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Title: **A prediction model for the accumulation of land to river debris at a downstream river section.**

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Title (in Dutch) Een voorspelmodel voor de accumulatie van land naar rivier puin in een stroomafwaarts gedeelte van een rivier.

Assignment: Master thesis

Confidential: no

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Nomenclature

List of acronyms and abbreviations

ADD: Antecedent dry days

ABPM: Average based prediction model

AMC1-3: Antecedent moisture condition 1 (dry) to 3 (wet)

BCDEPS: Baltimore County Department of Environmental Protection and sustainability

C: Cigarette butts

CB: Chips bags

CP: Configuration parameter

CSO: Combined Sewer Overflows

CWP: Center for Watershed Protection

FP: Fixed parameter

GLB: Glass bottles

GRB: Grocery bags

GSM: Greedy search method

HRU: Hydrologic response units

INT: Internal variable

IDW: Inverse distance weighted interpolation

IV: Input variable

JFW: Jones Falls Watershed

LR: Loading rate

M1: Model one. Experimental model one with precipitation only

M2: Model two. Experimental model two with surface runoff from precipitation only

M3: Model three. Experimental model three which includes street sweeping and antecedent rainfall.

M4: Model four. Experimental model four which includes wind.

ML: Marine litter

NN: Nearest neighbor (method/algorithm)

OV: Output variable

PB: Plastic bottles

PT: Polystyrene

PTM: Particle tracking method

SA: Simulated annealing

SRD: Specific river discharge

SWAT: Soil and Water Assessment Tool

TP: Thiessen Polygon

WPB: The Waterfront Partnership of Baltimore

WWTP: Waste water treatment plant

Conventions

The following conventions apply:

- A decimal separator is denoted with a point (.)
- A thousands separator is denoted with a comma (,)

List of symbols

Symbol	Description	Unit
A	Area of drainage area (smallest HRU used)	[m^2]
CN	Runoff coefficient for NRCS curve number method	-
$CN1/CN_I$	Runoff coefficient for AMC1	-
$CN2/CN_{II}$	Runoff coefficient for AMC2	-
$CN3/CN_{III}$	Runoff coefficient for AMC3	-
$CN_{1S}/CN_{2S}/CN_{3S}$	Runoff coefficient for AMC1-3 incl. slope correction	-
$CN_{i,k}$	CN value for land use group i belonging to sub watershed k	-
$CN_{i,ii}$	CN value for a specific land use group i and soil group ii	-
d_t	Transport distance from input point	[m]
E	Quantity of entrained debris	[kg]
$e_f(F, Ret)$	Entrainment factor	[kg/m]
F	River flow	[m^3/s]
$ff_{i,k}$	Fraction of sub watershed k allocated to land use i	[%]
$ff_{k,ii}$	Fraction of sub watershed k allocated to soil group ii	[%]
G	Waste generation rate person	[kg/person/day]
I_a	Initial abstraction (losses before surface runoff)	[mm]
k_p	Coefficient which relates surface runoff to debris inputs	[kg/m3]
k_w	Coefficient which relates wind speed and duration to debris inputs	[kg s/m^2]

$m_{AD,G}$	Anthropogenic debris generated on land	[kg]
$m_{D,A}$	Quantity of available debris on land	[kg]
$m_{D,I}$	Land debris inputs into river	[kg]
$m_{D,P}$	Quantity of debris removed by precipitation (surface runoff)	[kg]
$m_{D,W}$	Quantity of debris removed by wind (surface runoff)	[kg]
$m_{D,R}$	Quantity of debris removed by sweeping or other cleaning methods	[kg]
$m_{ND,G}$	Natural debris generated on land	[kg]
N	Baseload natural debris (stem, bark, leaves etc.)	[kg/day]
O	Model output: aggregated quantity of debris accumulated downstream	[kg]
Pop	Population size along the river banks	[persons]
Pop_r	Relative population size of sub watershed k to the whole watershed	-
P_b	Precipitation threshold value	[mm]
P	Precipitation total	[mm]
p	Propagation factor	-
P_5	Total antecedent precipitation 5 days prior to precipitation event	[mm]
Q_b	Surface runoff threshold value	[m3/s]
Q	Surface runoff over smallest HRU/drainage area used	[m3/s]
r	Percentage of mismanaged debris	[%]
$r_f(F)$	Retention factor	[m^{-1}]
Ret	Quantity of retained debris	[kg]
S	Potential maximum soil moisture retention after runoff begins	[mm]
SF	Seasonal factor, accounts for differences in tourism and outdoor presence of population	-
SS	Seasonal shedding factor for natural debris	-
Δt	Time interval	[day]
V	Wind speed	[m/s]
V_0	Threshold wind speed for wind generated surface runoff	[m/s]
W_A	Factor for wind generated anthropogenic debris	-
W_N	Factor for wind generated natural debris	-
α	Slope	[m/m]
λ	Initial abstraction ratio	-

Contents

Abstract

'A planetary crisis' [3], this ominous warning was given about the growing presence of anthropogenic debris in marine waters, plastic in particular. Debris accumulation in freshwater and marine water leads to a myriad of problems, such as decrease of aesthetic appeal, damage to nautical traffic, harm to flora and fauna and a potential risk to human health by contamination of human nutrition. Debris were defined in this report as *all undesired synthetic, processed or natural items or fragments that are being transported by rivers from land towards the marine ecosystem.*

One of the remedies to this problem is the extraction of debris in downstream sections of a river. Removal of debris downstream is advantageous for several reasons. Firstly, rivers are an important pathway for debris transport to the marine ecosystem. Secondly, ports and harbors are frequently located downstream, facilitating the removal of debris due to intrinsic interest of the local operators. Thirdly, downstream removal covers debris inputs from the whole length of the river. Fourth and finally, the downstream section is the last location where debris are still heavily concentrated in one area, before spreading out over the vast expanse of the marine waters.

In order to facilitate the effective removal of debris it is believed beneficial to perform removal operations during times of large accumulation of these debris. To achieve this, a prediction model can be developed aimed at predicting debris accumulation based on certain predictors.

Debris removal operations and hence debris prediction models should focus on macro debris (>5mm) for several reasons. Firstly, macro debris, though less numerous, constitute the majority of the weight. Secondly, micro debris can be found throughout the water column while macro debris are predominant at the surface, which makes debris removal easier. Finally, micro debris (<5mm) removal is currently not worth the cost.

Fluvial accumulation of debris fluctuates heavily due to the fluctuations of the factors causing this accumulation. From the observed datasets, accumulation can be categorized as a base accumulation with large pronounced jumps in the distribution, with peaks varying in size although other characteristics could be present as well. The following main characteristics were identified: jumps (temporary, fast change), seasonal fluctuations (temporary, slow change), trends (permanent, slow change), and steps (permanent, fast change). A prediction model should focus on jumps but will eventually, once implemented, need to account for the other characteristics, using time series analysis.

Debris inputs are mainly influenced by precipitation induced surface runoff. Antecedent dry days (ADD), total rainfall volume and rainfall intensity influence the impact of precipitation. Local soil and land use characteristics have a large influence on the effect of precipitation. Other factors include wind, government legislation, temperature, special events, urban development, tourism, waste management and public mentality. The impact of each of these factors is always synergetic with the presence of other factors. The propagation of debris through the fluvial system is affected by river discharge, which is often strongly correlated with upstream precipitation. Other factors are the presence of hotspots, vegetation, the slope of the riverbanks and fluvial geo- or anthropogenic morphology. Lateral transport

of debris is influenced by wind, input locations and hydrodynamic events like watercourse obstacles, confluence of tributaries and river bends.

Most existing debris input models are steady state and often consider a single source. If all micro debris models are excluded, Wan et al. (2018) [29] remains as the main benchmark spatio-temporal explicit model for the application envisioned in this report. This model proves its merit in the use of a detailed semi-distributed surface runoff model. It only accounts for surface runoff, waste management and public mentality however. Armitage et al. (1998) [47], though steady state, is more inclusive by including ADD. Existing macro debris propagation models are rare. Spatio-temporally explicit propagation models are either empirical stochastic models, numerical or analytical models. Their focus however is mostly on specific areas (e.g. ports). The empirical model is impractical since a mechanistic model is desired.

An analytical prediction model has been build and validated. Using the available data from the case study, the Jones Falls River (USA), the model was customized to this specific case study. During the development stage of the model, several issues were encountered. One of these issues pertained the accuracy of the weather data. Historic data, required for the model calibration and validation, was only available from distant weather stations, hence decreasing the accuracy of the data. Secondly, the data required to build the propagation model was unavailable and obtaining empirical by experiments was not feasible. Hence, the modelling of propagation was abandoned.

Four versions of the model were tested. The first version directly linked precipitation to river inputs, ignoring surface runoff. The second included lumped surface runoff calculations. The third was based on the second but included ADD and historic inputs while the fourth included both lumped surface runoff calculations and wind. The model versions tested in this report obtained a mean relative error (MRE) of 0.67 to 0.8 after validation and 0.59 to 0.65 after verification. A prediction model which simply uses historic daily average without any predictors, ranked lower with a MRE of 0.9.

While weather inaccuracies are deemed to be the most relevant factor, model assumptions and simplifications may also have had a considerably impact on model performance. These assumptions include simplifications in surface runoff modelling and averaging precipitation data over each day instead of considering precipitation events. The latter would better represent rainfall intensity. Finally, the quality and interpretation of the accumulation data used for calibration and validation may have decreased model performance.

The simplest model, which directly linked precipitation to debris inputs, managed to achieve an MRE of 0.73. This is considerably higher than a model which assumes steady state accumulation and this model would hence offer an opportunity for more effective debris removal. Accurate precipitation data is however crucial. As such one can expect a MRE < 0.73 using a more accurate weather dataset. While Wan et al. (2018) achieved a MRE of 0.14 on a specific sub watershed, such a model would require complex surface runoff modelling and their model performance is not guaranteed to be achievable for other cases.

1. Introduction

1.1. The problematic nature of debris in aquatic environments

The world has become increasingly aware of the problematic nature of the abundant presence of anthropogenic debris in the worlds waters, illustrated by figure 1. Debris can be defined in this context as undesired inanimate objects contaminating aquatic ecosystems[1]. Many of these debris are generated inland and transported by rivers to end up in marine ecosystems, where these debris become known as marine litter (ML). The EU states: *'Marine litter is a global concern, affecting all the oceans of the world. Every year, millions and millions of tons of litter end up in the ocean worldwide, turning it into the world's biggest landfill and thus posing environmental, economic, health and aesthetic problems'* [1]. A more recent and gloomy warning came from the UN oceans chief which called it '*a planetary crisis'* and mentioned that *'in a few short decades since we discovered the convenience of plastics, we are ruining the ecosystem of the ocean'* [3]. Perhaps one of the most shocking illustrations of the ML problem is the recent discovery of at least 17.6 tons of ML on Henderson Island in 2015, a remote pacific island located 5000 km from the nearest industrial or residential area [4].

Fig. 1. Floating debris [2].

This is not solely a problem concentrated around and created by emerging economies with poor waste management but also in more developed areas like the North Sea: *'Despite international, EU and national efforts to reduce the quantity of litter released into our seas over the last two decades, in many regions such as the North Sea, quantities of litter, especially plastic, are increasing'* [5]. The quantity of ML on Dutch beaches for instance has barely declined, researchers concluded based on monitoring studies [6].

A critical category of debris is plastics, due to their quantity, their persistence and the fact that an estimated 46% of plastics are able to float [7]. The major driver for plastic contamination is logically the consumption of plastic. The world produces currently nearly 20.000 plastic bottles of water per second, with 20% production increase expected for 2021 [8]. The absence of a market, where those demanding reduction (of plastic production) and those generating it negotiate a solution, means there is few intention to take action [9]. At the same time negative side-effects of plastic contamination are not being internalized by the producers and users of plastic (i.e. they do not incur the costs of these consequences) [9]. It is not surprising that growth predictions regarding the oceanic accumulation of plastic debris reveal an equally worrying increase. A recent study in Science states that: '*Without waste management infrastructure improvements, the cumulative quantity of plastic waste available to enter*

[1] A more elaborate look at the definition of debris will follow in section 2.

the ocean from land is predicted to increase by an order of magnitude by 2025' [10]. This is visualized in figure 2.

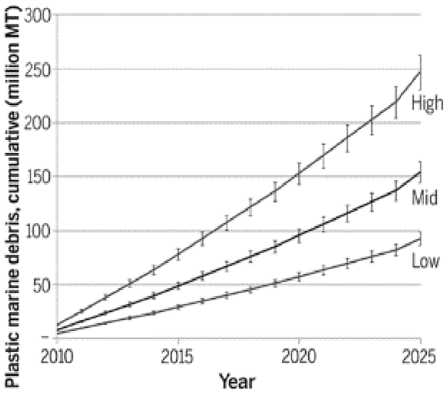

Fig. 2. Scenarios for cumulative quantity of ML entering marine waters [10].

Debris contamination brings a myriad of negative consequences. It damages living organisms either by entanglement, especially through 'ghost nets' or by ingestion [11]. It is especially worrying that ingested material can move up the trophic levels to end up in humans. Humans can also be injured by objects such as syringes and broken glass [12]. Other types of problems arise for the nautical traffic using these waters. Larger objects may damage propellers for instance, while intake pipes and valves may get blocked [12]. Certain debris, such as rope, fishing lines and nets may foul propellers and rudders [12]. Probably the most shocking illustration of the effects on nautical traffic is the sinking of a Korean passenger ferry in 1993 and the resulting death of 292 passengers after having its propeller shafts and propeller entangled by a nylon rope [12]. Furthermore, it may also negatively impact fishery: *'...torn nets, polluted traps and contaminated catches; if nets become choked with debris, the catch may be reduced'* [13]. The damage due to ML in the Asia Pacific Economic Cooperation (APEC) region, which includes most major economies around the pacific, has been estimated at 364 and 279 million dollars for the fishing and shipping industry respectively [14]. Since contamination is also not aesthetically appealing, it can damage tourism [15] and hence income to a region [16]. The damage of ML contamination on tourism in the Asia Pacific region has been estimated at 622 million dollars [14]. Following similar reasoning it can naturally also diminish perceived happiness among local residents.

Different mitigation approaches can be opted for to deal with this problem. Stricter penalization, new regulations/guidelines, improved waste disposal, improved law enforcement and awareness campaigns can be implemented to decrease supply of debris. Some facets however take time to change or may be hard to control such as the careless attitude of humans and the natural supply such as the waste generated by floods, which also includes natural products such as wood and plant debris. Moreover, with developing countries in mind which often lack sufficient waste disposal while simultaneously increasing their plastic consumption, it is hard to see the ML problem disappear anytime soon. Once discharged in the aquatic environment removal operations remain the sole option.

Removal operations are often performed in bays and ports downstream of rivers. A large benefit of removing downstream is that removed debris will not be discharged into the sea and oceans. It is estimated that approximately 80% of all ML in the global marine waters originate from land based sources [1]. A study of the coast of Europe has revealed that ML can even be found in large quantities at great depths of the Atlantic Ocean [17]. There is no doubt that cleaning these places would pose a tremendous challenge compared to the more confined and more accessible inland waters. Moreover, the closer cleaning operations are performed to the source, the less chance debris have to dissolve in smaller particles which are harder to remove. Finally, within inland waterbodies, contamination is more visible and nautical traffic is often more dense compared to seas and oceans which increases the nuisance and the risk of damage. In order to perform these operations with better effectiveness and efficiency, understanding debris accumulation from rivers is crucial.

1.2. Related work and research objective

Although recent discoveries and the growth of the problem in general have truly provoked the urgency to solve the problem of debris contamination, it should be noted that the cleaning of aquatic environments has begun far before the nature of the pollution problem was considered being problematic to the extent as it is perceived today. In 1942 already cleaning operations in the bay of San Francisco became common practice after an accident with a floatplane hitting some large floating debris [18]. In the US, the practice of using specialized equipment, so called skimmer boats, started in the early 1980's [19]. Nowadays it is common practices in many rivers, bays and ports and even the ocean [20]. A project named 'Port Waste Catch' was recently launched by the port of Rotterdam. The aim of that project is to encourage the private sector to come up with solutions which would enable the Port of Rotterdam to remove debris from its waters and hence contribute to the prevention of the plastic accumulation in the oceans [21]**.** This shows that port authorities are becoming aware of the useful contribution they could make in mitigating ML. The academic field and research institutions have also been increasingly engaged in the topic of ML contamination. From figure 3 it can be seen that the number of publications related to marine debris has grown immensely in recent years.

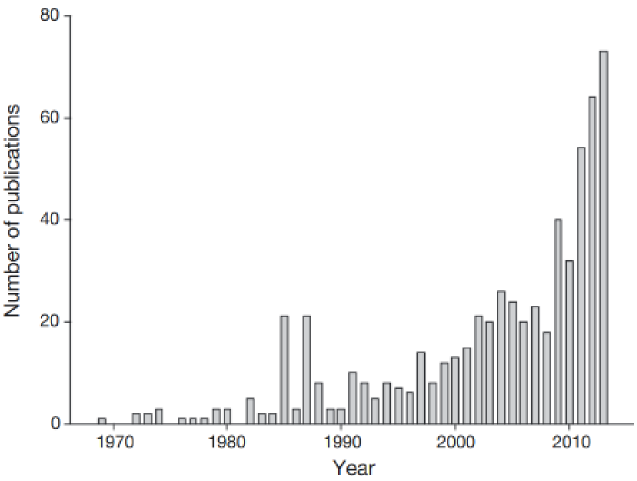

Fig. 3. Scientific publications related to marine debris [22].

1.2.1. Solution approaches

Several approaches can be conceived to make a contribution to improving debris removal operations in bays and ports downstream of rivers. Firstly, buying adequate/better equipment or adding equipment. Secondly, perform cleaning at locations with relatively high presence of debris. This means improving routing and smartly schedule the moments cleaning is performed. An example of this, is the study by Tol (2016) [23] which analyzed the performance of different routing methods of vessel in a port environment.

Thirdly and finally, one can further enhance performance by improving data quality and data availability w.r.t. spatial and temporal distribution. This can be achieved in multiple ways. Firstly, one can study the behavior of debris inside the debris removal area to gain knowledge on the spatial distribution of debris, i.e. study the system behavior. Lammerts (2016) [24] used numerical modelling to investigate the influence of various factors, which included disturbances such as river flow rate and wind, on debris behavior in a port environment. Secondly, this can be done using historic data or monitoring equipment to improve knowledge about the spatial and temporal distribution of debris. Martens et al. (2012) [25] for instance used debris mapping to enhance the performance of lobster trap removal. Wang et al. (2014) [26] and Wang et al. (2015) [27] studied the possibilities of using RGB cameras to detect floating debris. Thirdly, methods and technologies can be deployed which allows short term predictions regarding quantities of debris based on what is measured upstream. This approach could consist of using debris detection technology in the river, such as RGB cameras or infrared sensors. Alternatively, debris accumulation is not directly measured but linked to factors which contribute to and influence debris accumulation. Hence, debris accumulation is a latent variable which is inferred from other observable predictors. To achieve this, a debris prediction model can be developed which links data on the observable variable, the input, to a prediction value for the quantity of debris over time, the output.

This prediction model will be the focus of this report. A more elaborate analysis of the various solution approaches can be found in appendix B. This analysis shows that each solution has its challenges and limits but it is currently still hard to compare the various solution approaches. It should be noted that, fortunately, these solutions are not mutually exclusive and can hence be applied to complement each other.

1.2.2. Research question

Existing debris prediction models are rare. Deltares (2015) [28] applied data from river discharge to estimate accumulation and support ML removal efforts in a downstream bay. Lammerts (2016) did not account for fluctuations in accumulation whereas Tol (2016) in contrast used a rough estimation based on wind statistics to model accumulation. In short, these approaches to model accumulation, if used at all, are fairly simplified and not generalized. Recently, a more sophisticated model was developed by Wan et al. (2018) [29]. The model is spatio-temporal explicit and uses a semi-distributed surface runoff model to model precipitation induced surface runoff. It did however not account for debris propagation in rivers and also did not incorporate wind induced accumulation. To get a better understanding of the accumulation of debris by rivers, a generalized set of predictors for land-to-river-inputs and river propagation can be identified. Subsequently these factors can be used to make predictions of downstream accumulation which can be used by sweeping vessel operators to adjust their deployment accordingly. If this approach is successful and vessels are deployed more effectively it can contribute to a mitigation of outflow of debris to marine waters and a reduced presence of debris inside ports and bays[2]. This approach may also lead to an increase in quantity of debris removed per operational hour increases, which means more efficient operations.

[2] An overview of debris removal systems can be found in appendix B

This leads to the following research question:

Can a prediction model contribute to more accurate estimates of the accumulation of land to river debris at a downstream section of a river?

This question will be answered with the following sub questions:

1. *What are debris and how can temporal fluctuations of debris accumulation from rivers be characterized?*
2. *What factors influence the quantity of debris accumulating from a river?*
3. *How can these factors be incorporated in a prediction model, what existing models and modelling techniques are available and what are the challenges?*
4. *What is the performance of a prediction model, applied to a case study?*

1.3. Report structure and methodology

An outline of the report is depicted in figure 4. In the left column, each number identifies the corresponding sub question answered. In the right column the section numbers can be found. The problem analysis, covered in section 2, will address the definition of debris, the role of rivers in accumulation of ML and the temporal distribution of debris accumulation in rivers. A literature review will be conducted in section 3 to investigate which factors should be incorporated in an accumulation model. The next part of this literature study, section 4, will review existing accumulation models. Hereafter, a new model will be designed, which is covered in section 5. In section 6 this model will be verified and implemented and finally validated and evaluated in section 7. Modelling will follow a waterfall style design approach. A detailed overview of this modelling framework used to design, validate and evaluate the model can be found in Appendix J. The report finishes with the conclusions in section 9.

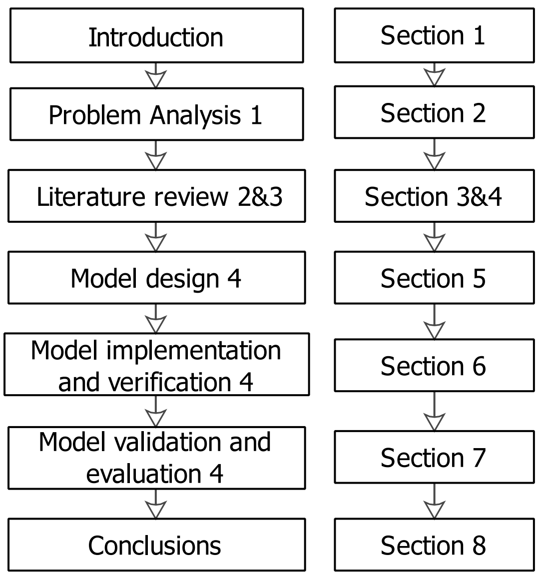

Fig. 4. Outline of the report.

2. Problem analysis

This section will start with a definition of debris, used within the context of this report. Since the use of debris terminology is frequently inconsistent, this section will clarify the terminology for the rest of the report. Doing so can also help to reduce the scope to those classes relevant in the context of this study. Understanding the origins and characteristics is crucial to understand the pathways and transport phenomenon related to them. This section will also aim to qualify and preferably quantify the contribution of rivers to the debris stock downstream, such as marine ecosystems and ports/harbors located downstream. The rest of the subsections explores the characteristics of temporal distributions and analyze historic accumulation data from existing rivers.

2.1 The definition of debris

'Debris' in the context of aquatic environments, is an umbrella term for numerous undesired inanimate objects found in aquatic environments. The term debris is used in numerous reports and papers, such as Lavers and Bond (2017) [4], Barnes et al. (2009) [7], Gregory (2009) [11] and McIlgorm et al. (2009) [14]. Frequently, 'debris' is further specified with a specific adjective such as 'anthropogenic', 'plastic' or 'marine'. Alternatively, marine litter (ML) is another term frequently used in reports and papers, such as Oosterhuis et al. (2014) [9], Mouat et al. (2010) [12], Lammerts (2016) [24] and Tol (2016) [23]. In the context of this study ML is however not the proper terminology as can be observed from the definition of ML:

'… all synthetic or processed items or fragments that have been discarded or lost either directly into the coastal and marine environments or somehow transported from land to the sea, e.g. by rivers or effluents, wind and land run-off' [30].

As the name suggest ML is specifically used in the context of marine ecosystems, which includes debris directly deposited in the marine ecosystem but inherently excludes riverine or any freshwater debris. Moreover, non-anthropogenic a.k.a. natural occurring items, such as wood trunks and branches, are not included in this definition, likely since they are naturally present and not as persistent as for instance plastic. Nonetheless, undesired natural items or fragments can still be harmful to nautical operations and negatively impact aesthetics so they should be included. The definition of ML can be rephrased as follows to obtain the definition for 'debris':

All undesired synthetic, processed or natural items or fragments that are being transported by rivers from land towards the marine ecosystem.

Henceforth, debris will be used throughout the report unless the context requires otherwise, in which case ML can be used, if applicable, or the term 'debris' will be extended with an adjective. An extensive analysis of debris can be found in appendix D.

From this analysis, several conclusions can be drawn:

- Plastic waste is the most abundant waste category due to its slow decomposition and the high consumption of plastics globally.
- Generally, natural debris account for the largest part of the mix of debris in developed nations while in developing populated nations, anthropogenic debris account for the majority of debris.
- For the time being the focus ought to be directed towards cleaning macro sized surface debris, particles larger than 5 mm, since the removal of smaller sized debris is generally not cost effective with current technological advancement.
- Quantified debris risk assessments are rare due to a lack of knowledge on certain harms and a lack of quantified data. Hence, it complicates the task of identifying the most critical debris. Currently, the goal should therefore remain to eliminate all macro sized debris from the river without distinguishing between specific debris.

2.2. Contribution of rivers to debris stock downstream

Since this report is centered on debris generated inland and aims to make a contribution to mitigating ML in marine waters, it is crucial to know the extent to which the creation of inland debris and rivers as a pathway contributes to this global contamination. Sherrington et al. (2016) estimated at least 5 up to at most 17 million tons of plastic per annum is introduced in total into the oceans [31] while Lebreton et al. (2017) estimated rivers introduced 1.15 to 2.41 million tons per annum [32]. This means at least 7% up to at most 48% of the total can be contributed to rivers which is a considerable range. However, even with 7% the amounts are significant and worth reducing. It should be noted that the geographical differences are large. The Yangtze River for instance accounts for 23% of the total of riverine input [32]. However one must also look at a more local level. Chinese rivers will predominantly contaminate bordering waters, the Chinese Sea and the Pacific Ocean whereas European and American inputs will largely dominate the North Sea and the Atlantic Ocean accumulation as demonstrated by Lebreton et al. (2012), with the data shown in Table 1 [33]. Therefore reducing debris from European rivers for instance is still crucial to mitigate contamination of local marine ecosystems. The local effect of American, European rivers on coastal waters, seas, beaches and harbors has been demonstrated in many different studies, such as Galgani et al. (2000) [34], Lattin et al. (2004) [35] and Claessens et al. (2011) [36] and Maria et al. (2007) [37]. Furthermore, Maria et al. (2007) notes 80% of the presence of ML on all global beaches is estimated to originate from riverine input. Finally, it is also worth mentioning, that the annual influx of the Danube River is estimated to be larger than the total mass of plastic in the total North Atlantic Gyre [38]. This seems excessive but it is important to realize that the vast majority of marine plastic is located on the sea floor as previously stated [31].

Table 1. Regional contribution (in %) to floating debris in the North Atlantic Gyre under 2 scenarios [33].

SOURCES	ACCUMULATION ZONE	
	North Atlantic Gyre	
Europe	24.004	16.836
Australia/New Zealand		
South America	5.317	6.570
Central & North America	64.299	65.771
Africa / Middle East	6.103	10.748
India		
South East Asia /Indonesia		
China		
Japan		
Russia	0.278	0.075
Total	100.000	100.000

Understanding the influence of riverine influx of debris on bays and harbors downstream is crucial to their operators if presence of debris is to be mitigated. It is important for them to realize that proximity to a river does not inherently imply any or significant influence. This can be illustrated with the waters around Hong Kong, a bay/harbor area downstream of the Pearl River which was studied on multiple occasions regarding debris. It was for instance hypothesized that the ML in the Western waters of Hong Kong would see fluctuations according to the wet and dry season which would increase river accumulations into the Pearl River Delta. This theory was confirmed by beach surveys by Cheung et al. (2016) [39] and surface water surveys by Cheung et al. (2018) [40].[3] An earlier study by Tsang et al. (2017) [41] in the waters more close to Hong Kong contradicted these results however by reaching opposite conclusions with respect to seasonality, i.e. a larger quantity during dry season was observed. It was suggested that the influence of point sources/local sources were more relevant in this case since the surveyed waters were relatively shielded from the outflow of the rivers. Noticeably, Tsang et al. unfortunately only surveyed micro plastics (<5 mm), these are generally more likely to originate from relatively steady state sources like sewage outflows. This seems more in line with the results obtained by Cheung et al. (2018) [40]. It is also plausible that some factors contributing to this particle presence were unknown and hence not accounted for in this study. In any case, these results prove being placed adjacent to a river (outflow) does not guarantee strong influence of the respective river. The origin of the accumulation in areas downstream should therefore be assessed separately for each case.

2.3. Temporal distribution of debris accumulation

Knowing the temporal distribution of debris entering the port/bay inlet over time, for instance on a day to day basis or even hour to hour, would eliminate uncertainty and cleaning operations can hence be optimized to deal with one predefined distribution. Differences in accumulation over time can be observed due to river characteristics and factors which determine the land to river inputs upstream, each with a certain variability over time. Furthermore, as a consequence of these factors each river will also show different debris characteristics [42] like quantity, variability and consistency. The route of debris which are generated upstream from land via a river towards a port/bay area is visualized in figure 5.

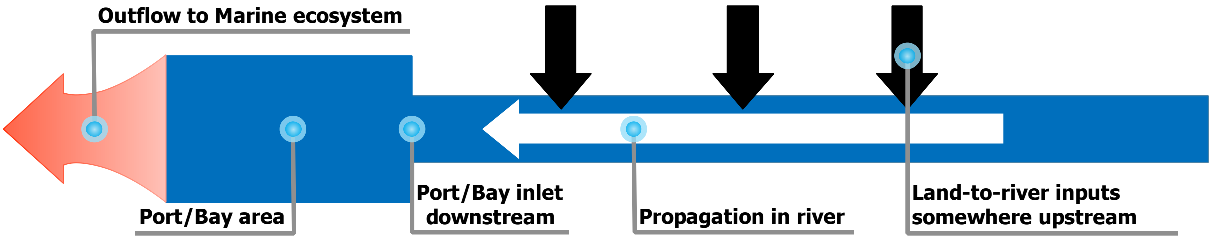

Fig. 5. The route of debris which are generated upstream and propagated through the river in downstream direction.

If the inlet point of a river into a port/harbor is approximated as a point in space the spatial dimension is eliminated, i.e. it becomes zero dimensional, and only a time dimension is left. This means it is

[3] A more elaborate analysis of this study can be found in appendix C.4.

assumed that knowledge pertaining the exact point of entering along the width of the inlet/entrance of the cleaning area is not necessary. It should be noted that even if the spatial component at the inlet is (assumed to be) non relevant, spatial distribution along the width of a river can still influence temporal distribution before it passes the entry point. This will be discussed in later sections. Removing the spatial component leaves a temporal distribution which can be presented in a cumulative way to obtain the quantity of debris entering of a certain time period. For instance a certain volume V entering at each time unit t, summed over a certain period of interest T, e.g. one hour. This is a discrete formulation, it can also be written in a continuous form using an integral, with Q as the flow. Both formulations can be found below:

$$\sum_{0}^{T} V^{t} \; or \int_{0}^{T} \frac{V(t)}{t} dt = \int_{0}^{T} Q(t)\, dt \quad (1)$$

This volume of debris can also be defined for certain debris categories. In a similar way as the equation above a summation and integral can be formulated as follows with debris categories i as a subset of I:

$$\sum_{0}^{T} \sum_{0}^{I} V_{i}^{t} \quad i \in I \; or \int_{0}^{T} \frac{V_{i}(t)}{t} dt = \int_{0}^{T} Q_{i}(t)\, dt \quad i \in I \quad (2)$$

2.4. Characteristics of temporal distributions

Temporal characteristics can be driven by events which are measurable or known to humans. These are the most interesting factors since these are plausible candidate input variables for predictive models. Some events however are hard to factor in and can be perceived as completely or highly random. A large illegal direct deposition of litter inside a river for instance or random stranding along the way. These events will give disruptions but their randomness imply they are best accounted for using statistics unless it is feasible to do continuous visual monitoring at strategic points along the way. For the first category of events, the length of the timespan over which their influences can be observed can be different. The smaller the timespan the more challenging it is to account for. The result of said influences can cause a temporary or permanent decrease or increase in the temporal distribution. Some events have time dependent probability distributions which often exhibit a seasonal tendency. This is illustrated in figure 6 for rainfall at a fictive location.

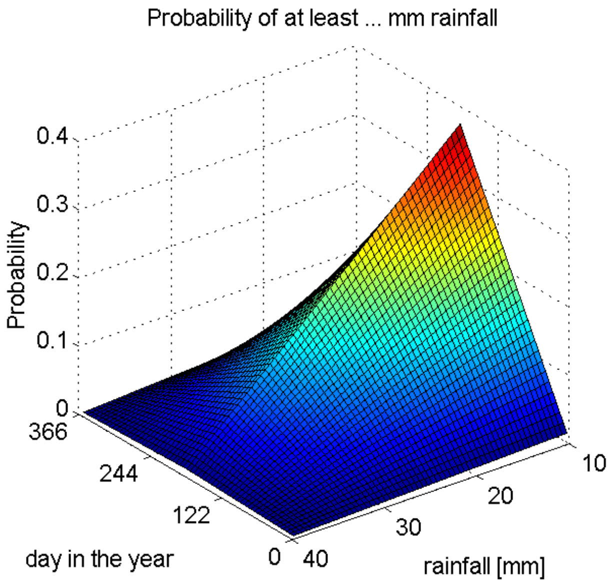

Fig. 6. Fictive time independent probability distribution (Generated with MATLAB®).

Various typical features of a debris accumulation distribution can be observed. First of all, the seasonal fluctuation or seasonal jump. This is a reoccurring increase/decrease in the distribution. This is generally a slow change which spans a longer time, multiple days to several months. Secondly, jumps or peaks in the distribution. These jumps occur generally for a limited amount of time, less than a week, and these jumps can be characterized by a fast change in accumulated debris. Since a fast and short change is harder to adapt to, these jumps are preferably predicted. Thirdly, trends. A trend is an increase or decrease of the average accumulation over a particular period. This can for instance be found if an annual moving average is computed. A trend is a slow change and is hence best adapted to by recording data on accumulated debris and computing the moving average. Fourth and finally, a step in the distribution. A single sudden event could trigger a permanent increase/decrease in the average accumulation of debris. Example distributions can be found in appendix E.

These features can be identified by two different characteristics:

- Rate of change
- Whether the change is permanent or temporary

Table 2 lists the above features including characteristics.

Table 2 Characteristics of temporal distributions of debris accumulation.

Seasonal fluctuation/Jump	Temporary	Slow change
Jump	Temporary	Fast change
Trend	Permanent	Slow change
Step	Permanent	Fast change

In order to assess the added value of a prediction model, one can identify two particular metrics to assess the distribution of debris accumulation; the mean absolute deviation d, and the mean rate of change cd. If a distribution deviates more from a constant line, it becomes more crucial to continuously adapt the cleaning schedule to the distribution in order to be both effective and efficient. This deviation, which is hence an indicator of the degree of flatness of the distribution, between a particular distribution f and a constant distribution c can be written mathematically for both a discrete and continuous function.

If there exists a constant distribution c with the following relation to distribution f:

$$\sum_{0}^{T} c(t) = \sum_{0}^{T} f(t) \quad or \quad \int_{0}^{T} c(t) = \int_{0}^{T} f(t) \quad (3)$$

Then deviation d can be written as follows:

$$d = \sum_{0}^{T} abs\big(f(t) - c(t)\big) \quad or \quad d = \int_{o}^{T} abs(f(t) - c(t)) \quad (4)$$

The rate of change is equally important. Adapting to slow changes is considerably easier than adapting to faster ones. Therefore the average absolute derivative can be used for a specific timespan T:

$$cd = \frac{1}{T}\sum_{0}^{T-1} abs\big(f(t+1) - f(t)\big) \quad or \quad cd = \frac{1}{T}\int_{0}^{T} a\frac{df}{dx} + C,$$

$$with\ \ a = 1\ if\ \frac{df}{dx} > 0\ and\ a = \ -1\ if\ \frac{df}{dx} < 0 \quad (5)$$

Two cases are to be identified since only the absolute value is relevant.

2.5. Real world data from river accumulation

Firstly, it must be demonstrated that river accumulation may indeed fluctuate over time and if so to what extent. Two investigate this, data from removal equipment can be used, for instance from stationary/passive removal systems. The first data source is depicted in Figure 7 [43] and shows debris weights observed at two debris retention booms in Hawaii. The second dataset has been retrieved from the website of the Harbor Wheel project in Baltimore (US) [44] which uses a passive removal system to collect debris flowing from the Jones Falls River. The Waterfront Partnership Baltimore (WPB) provided data for different dumpsters collected together with weight, volume, consistency and the date of removal. Because removal dates were irregular the weight of the dumpster(s) removed at a certain day have been divided by the number of preceding consecutive days without removal to obtain an accumulation per day. The results are shown in figure 8 for a seven months period (01-2015 until 07-2015). Both the largest and smallest fraction have been highlighted. The average accumulation by weight, 0.56 tons/day, measured over 48 months (5-2014 until 4-2018). A more detailed description of this calculation and other data, e.g. volumetric and consistency data, provided by the WPB can be found in Appendix F.

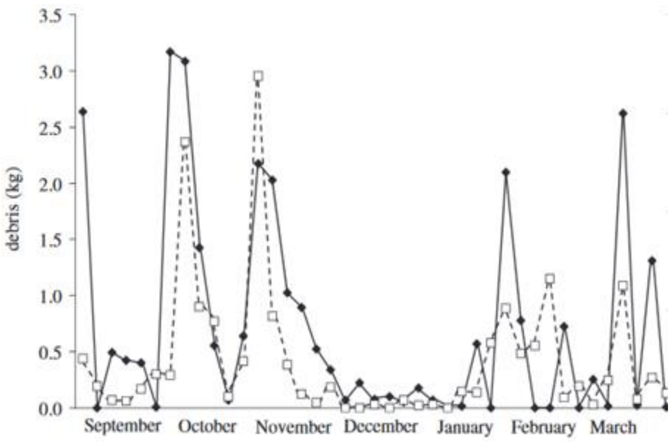

Fig. 7. Total anthropogenic debris (filled diamonds, solid lines) at debris retention booms in two watersheds in between monitoring events at the booms [43].

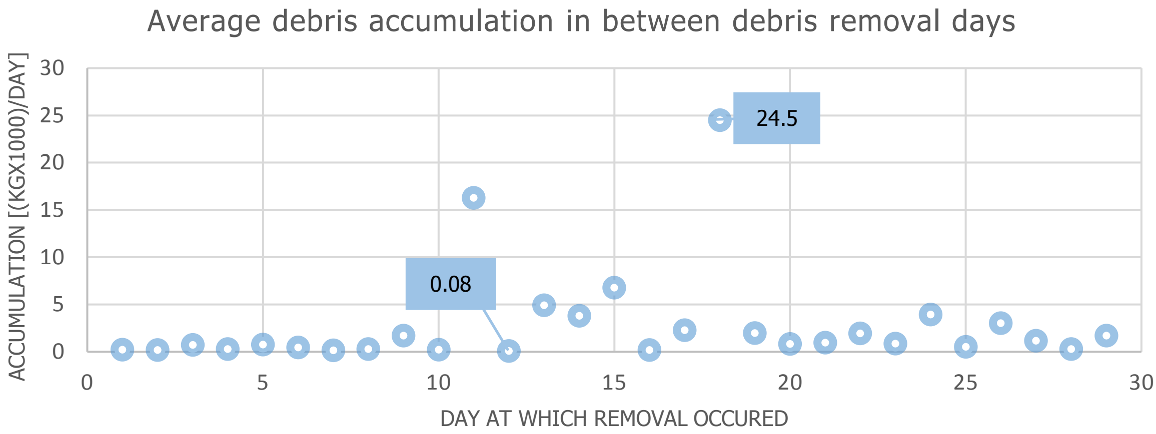

Fig. 8. Average accumulation in between debris removal days at the Baltimore Harbor Wheel [44].

Both data sets show large variations over time. It should be noted that the quantities collected from the Hawai'ian watershed are small hence few random debris arrivals might in theory skew the data. The second data set from Baltimore however confirms the presence of large variations. The absolute and relative differences are so large they suggest the arrivals are not pure random, e.g. random stranding, but instead suggest the presence of underlying factors driving these differences in accumulation.

The impact of such a distribution on the performance of debris removal operations depends on the goal of the operation, the equipment used and the removal strategy. The operations are likely to be a tradeoff between operation costs and removing debris. Since operating for peak accumulation is perhaps costly, a more reasonable strategy would aim to cover at least a certain percentage of the days with minimum effort. However, using the data used in figure 19, the 90% days ranked smallest by accumulation only account for 38% of the total accumulation. Hence the 10% days with the largest accumulation account for 62% of the accumulation, which proves the value of a prediction model.

Figure 9 on the next page shows debris accumulated at the Harbor Wheel over a 48 month period. Each blue point represents one month of accumulation in one specific year, as such each month has four data points (note that some data points are largely overlapping and hence barely distinguishable from each other). The blue trend line is a 6th degree polynomial fitted to the data. This was chosen since it fitted the data the best. The orange dots are the average weights for each month. Although the data set is small, from the data available, a clear seasonal pattern seems to emerge.[4] In total 813 tons of debris was removed over 48 months. The six months, April – Sept, account for 593 tons or 73% of the total. The three months, April - June, account for 383 tons or 47% of the total.

[4] To test the influence of outliers a trend line was fitted to the data after the largest data points for each month were removed, as shown in appendix E. Although less strong, the pattern remained clear.

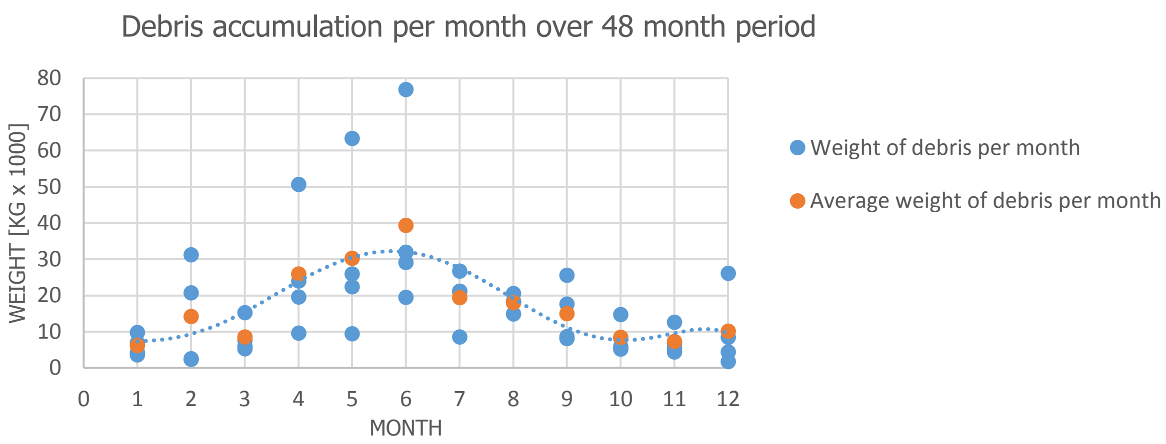

Fig. 9. Weight of debris accumulated per month, measured over 48 months [44].

2.6. Section summary

In short, plastic is globally the largest type of anthropogenic debris as commonly known. This is however location dependent with affluent regions of the world, due to being equipped with more capable waste management systems, facing more accumulation of natural debris with less affluent regions facing the opposite with anthropogenic waste being more abundant. Hence, both anthropogenic as natural debris should be accounted for. For the time being the focus ought to be directed towards cleaning macro sized surface debris, since the removal of smaller sized debris is generally not cost effective with current technological advancement. Most of the debris (in terms of weight), can be found in the top layer of the water column.

Debris accumulation from rivers contributes mostly to local water contamination, both sea and oceans, which implies that the common argument, that any action from small contributors is useless if large global contributors are not being handled first, is mostly false. Contamination of marine ecosystems should hence be mitigated through regional sources and pathways, such as rivers.

The accumulation characteristics observed downstream can be contributed to changes in the factors which cause land to rivers inputs and influence river transportation. This section identified four typical features which could be observed. Each of these features can be classified in two ways. Firstly, whether these changes are temporary or permanent and secondly, according to rate of change. Each of the four features are shown in table 3 on the next page. In the next section the factors as mentioned above will be classified according to these characteristics.

Table 3 Features and characteristics of temporal distributions of debris accumulation.

Feature	Characteristics	
Seasonal fluctuation/Jump	Temporary	Slow change
Jump	Temporary	Fast change
Trend	Permanent	Slow change
Step	Permanent	Fast change

Features which are classified as having fast temporary changes are the hardest to deal with w.r.t. debris removal since adjusting to these fluctuations, based on recorded removed quantities, is more difficult. Data from existing rivers shows large and fast deviations may indeed take place. Jumps were observed, whereas others where not observed. This can also be contributed to the short timespan over which the data was observed.

3. Literature study: Factors influencing temporal distribution

In this section factors influencing the temporal distribution of debris accumulation will be discussed. This way the possibilities of predicting this accumulation can be explored. There are multiple stages at which factors can exhibit any impact as depicted in figure 10. The terminology is discussed more in depth in appendix D.4.

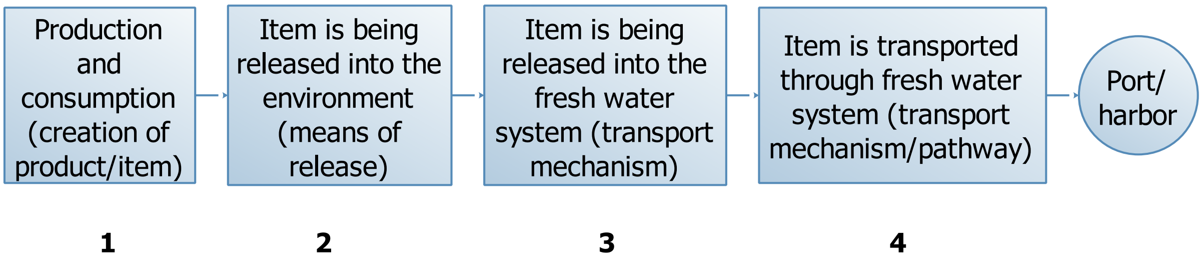

Fig. 10. Life cycle stages of debris from production to port/harbor.

It should also be noted that the impact of these factors may to a large extent depend on the geographical location. Hence special attention should be given to this. Life cycle stage 1-3 will be handled with the focus on precipitation in subsection 3.1 and on other factors in 3.2 whereas subsection 3.3 will discuss stage 4. The main focus will be on anthropogenic debris although the processes described in these subsections are also largely applicable to natural debris. Natural debris will be briefly separately discussed at the end of subsection 3.2.

3.1. Introducing debris into the river: Precipitation

Precipitation is the main factor driving seasonal differences in debris accumulation due to the seasonal tendency of rainfall in many areas around the world, as illustrated in figure 11. It shows estimates of the percentage of the total mass flow of debris discharging from each continent that can be contributed to the respective month. Note that the data has been smoothed to allow for a continuous graph.

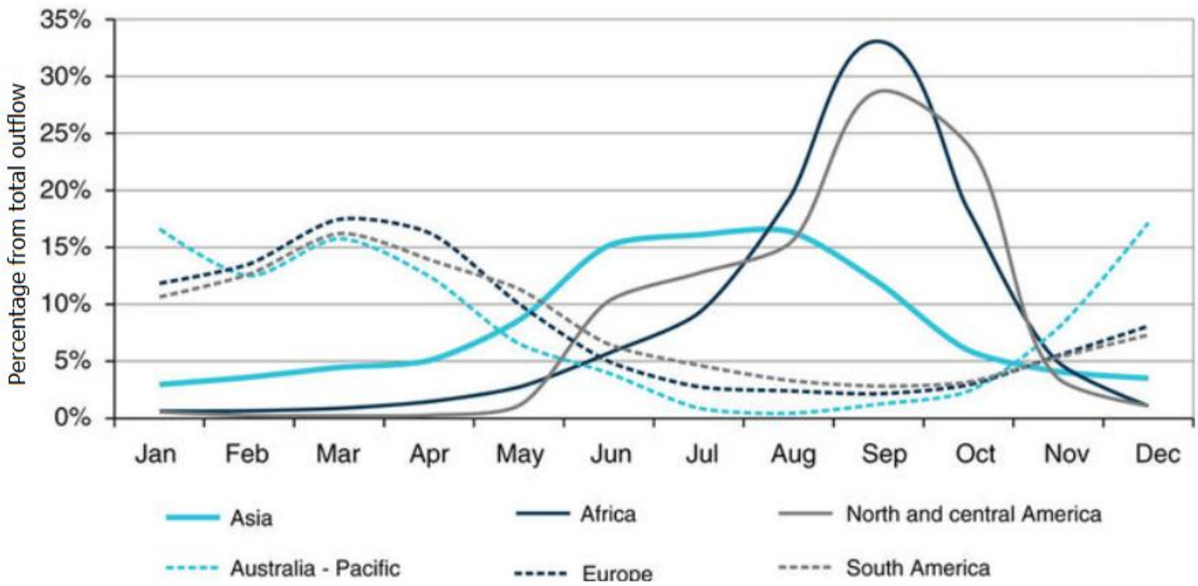

Fig. 11. Estimates of monthly contributions from rivers per continent [32].

Although these are estimates these seasonal differences appear large, especially in Africa and the North and central Americas. The link between rainfall and debris accumulation has been demonstrated by numerous papers and studies [29] [32] [35] [39] [45] [46] [47] [48] [49], in various regions. Ryan et al. (2009) emphasized the temporal characteristics caused by rainfall events: *'…the great temporal heterogeneity in plastic loads linked to rainfall events'* [50]. A study by Cheung et al (2016) at the mouth of the Pearl River delta found *'…distinct seasonal variations in the spatial distribution of plastic debris on the beaches of Hong Kong and demonstrated the importance of rivers as a source of marine debris. The changes were primarily caused by the sharp reduction in rainfall from the wet season to the dry season…'* [39]. Wan et al. (2018) specifies the role of surface runoff during these events: *'The mass of debris input from land is correlated with surface runoff values'* [29]. This heterogeneous temporal aspect of rainfall and the large potential influence it may have on the temporal distribution of debris accumulation implies it deserves a closer look. Precipitation and surface runoff are two key elements of the hydrologic cycle. As such it is helpful to have an overview of this system and the stocks and flows within this system, which can be found in Appendix F.

3.1.1. Antecedent dry days

The distribution of rainfall events over the year, or more specifically the quantity of antecedent dry days (ADD), plays an important role as mentioned by Prof. N. Harmitage, who has been extensively studying and characterizing solid waste from stormwater drains: *'The Long dry spells give greater opportunity to the local authority to pick up the litter, but also tend to result in heavy concentrations of accumulated rubbish being brought down the channels with the first rains of the season – the so-called "first flush" '* [5] [51]. An earlier study from South Africa found that the first flush over a 3 year period introduced on average nearly four times the quantity of debris compared to regular storm flushes [47]. This is confirmed by a study in two watersheds of the Los Angeles County (US). One study saw the highest trash quantities, in both years studied, during the first rainfall event [48] whereas the other saw the highest quantities during the first and second rainfall event respectively [49]. For the latter watershed the second rainfall of that particular year was much larger in terms of volume than the first (at least 20 times) which could explain why the second rainfall event delivered higher run-off of debris.

[5] 'This definition of first flush is not to be confused with another definition which points to the comparably large litter runoff early in an individual storm event.

First flush characteristics were also observed by Carson et al. (2013) [43] as shown in figure 12. The graph shows the retention of anthropogenic debris in an urban waterway in Hawaii alongside the rainfall in the respective watershed. Indeed, there seems to be a tendency of higher quantities of debris following the first flush (green arrow) compared to the second one, following it (red arrow). The last two peaks (blue arrow) however seem not to follow this trend. Reasons for this could be different rainfall patterns, both spatial and temporal. Higher intensity rains could create more runoff. It should also be noted the debris quantities are low hence large debris may skew the data. In addition, not all debris might be completely flushed by the first event, hence following rainfall events might still produce considerable debris. Moreover, debris flushing is not linearly correlated with volume (mm) of rainfall since a threshold value has been observed below which no significant debris is moved [29]. Finally, wind can also contribute as a means of release and/or a transport mechanism. So, although the coefficient of determination r^2 is merely 37%, i.e. 37% of the debris abundance can be explained by rainfall quantities, the data could be likely (much) better explained if one included more details on the rainfall patterns and perhaps other factors like tourism.

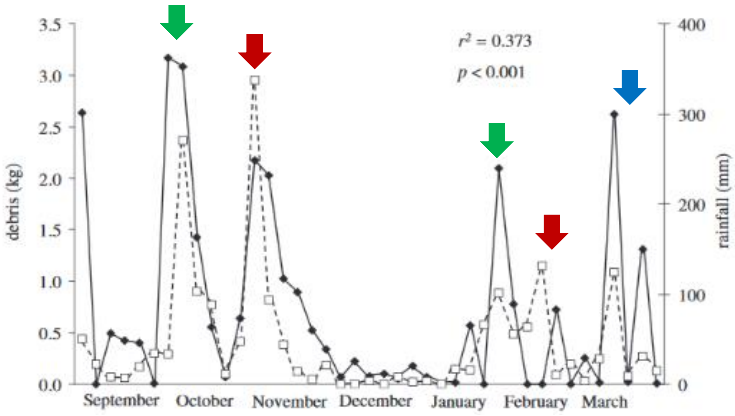

Fig. 12. Total anthropogenic debris (filled diamonds, solid lines) at debris retention booms in two watersheds and accumulated rainfall (open squares, dashed lines) in between monitoring events at the booms [43].

An earlier study by Kim et al. (2004) [52] in the same area, about two years earlier, found also that ADD influenced run off of debris (>0.5cm). The correlation found was however not very meaningful since in absolute terms the correlation was not strong and the variance of the data was deemed fairly large which means predictions will be hard to make. The correlation between Event Mean Concentration (EMC) [g/l], a metric for measuring the litter concentration in storm water runoff and ADD was described as follows:

$$EMC_{litter} = \varepsilon(ADD)^a(TR)^b \quad (6)$$

TR represents the total rainfall (cm) and ε, a and b are fitting parameters. The study mentions: '*There were few meaningful correlations of litter parameters with storm parameters such as total rainfall, antecedent dry days, etc. A decreasing trend in litter EMC was observed with total rainfall or total runoff volume. An increasing trend of EMC was observed with antecedent dry days'* [52].

3.1.2. Infiltration: soil characteristics and rainfall intensity

Kataoka et al. (2013) [53] studied the grass flux in rivers discharging into the Tokyo Bay area. The study found significant influence of flood events. The study estimated 24% of the annual inflow of grass occurred during one particular 10 day long flood event. The discharge during that particular time span was less significant, contributing 11% to the yearly input of freshwater. With such drastic short increases in influxes, increasing cleaning efforts during these days might very well be worth it from cost benefit point of view. An extreme example of the cumulative effect of long-lasting rainfall can be seen in figure 24. Discharge rates keep increasing due to consecutive days of rainfall.

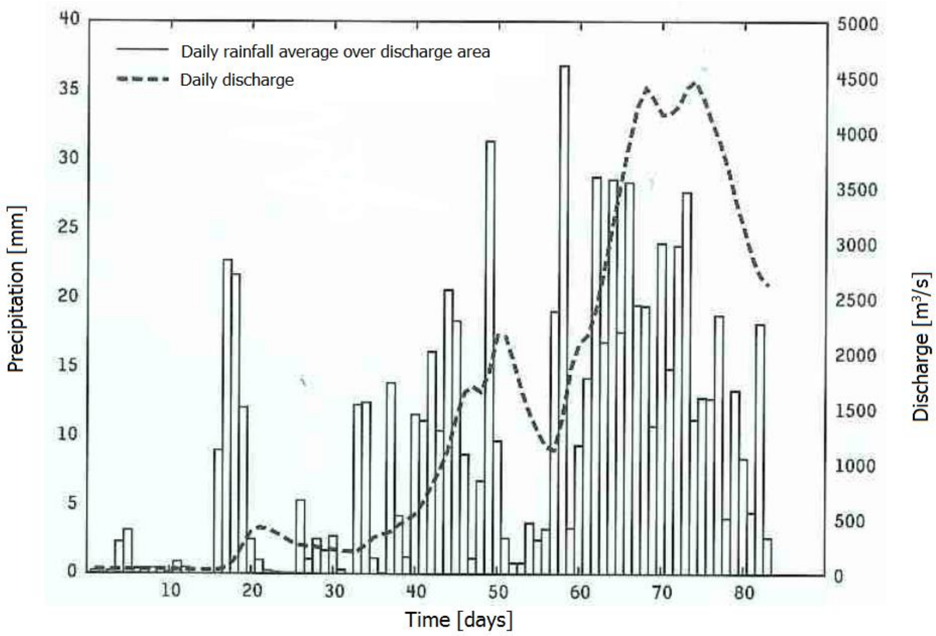

Fig. 13. Generated discharge of Maas River during consecutive days of heavy rainfall [54].

The ground cover plays an important factor in the extent to which rainfall leads to surface runoff towards the river. Urban development brings clear ramifications to surface runoff since urban areas with mostly impervious ground cover are much more susceptible to this phenomenon than natural vegetation and agriculture lands with much more pervious ground cover as shown in figure 14. The severity of this problem will depend on the quality of storm water handling.

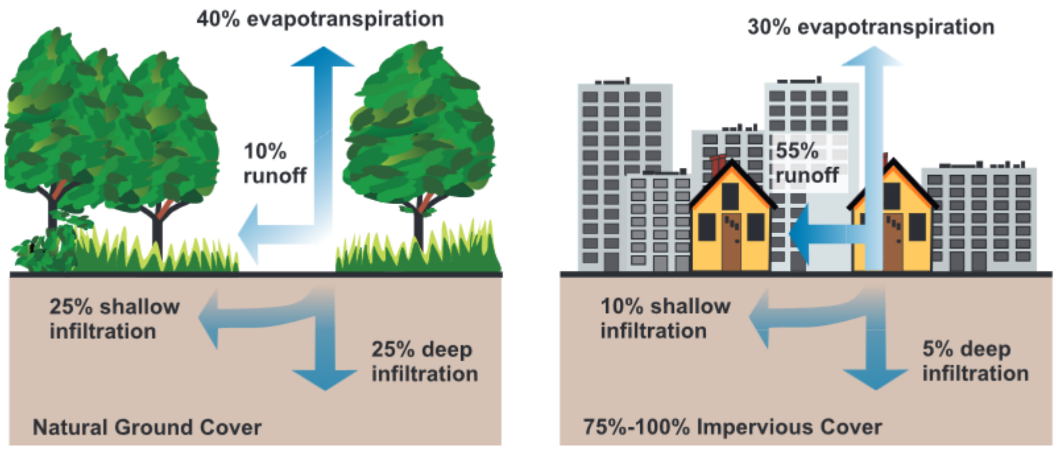

Fig. 14. Differences in surface runoff between two different ground covers [55].

Figure 14 shows typical numbers, however, infiltration behavior is extremely soil specific. In figure 15 two graphs visualize the infiltration rate for two types of soil: sand and clayey. Different soil types behave differently, clayey soils might become saturated after rainfall but sandy soils do not. On the contrary, water intake may increase after saturation. This has a large consequence for runoff behavior after precipitation.

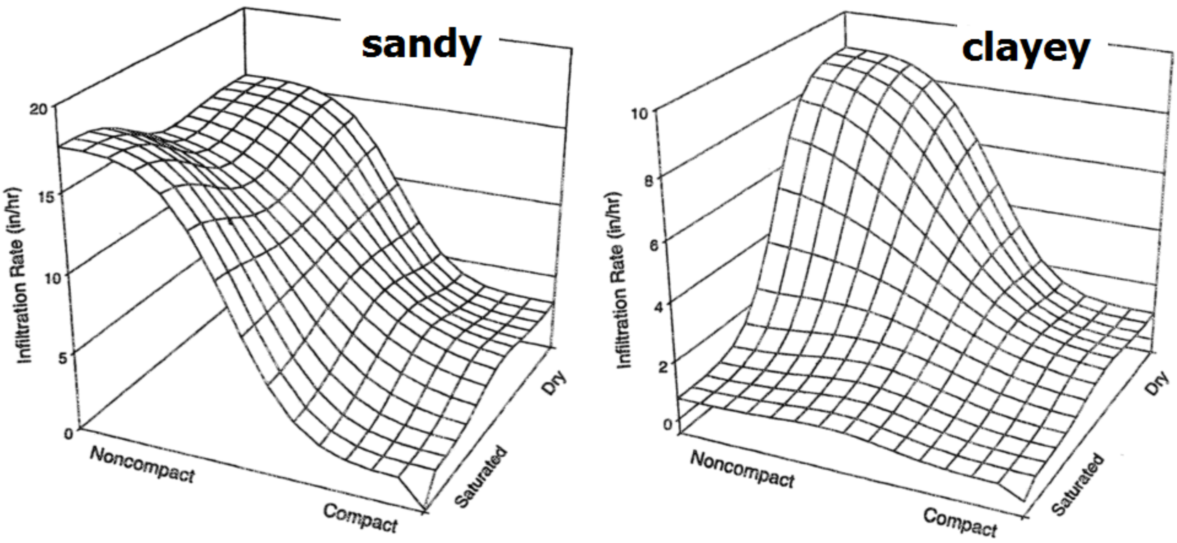

Fig. 15. Infiltration rate for two types of soil, depending on compactness and saturation rate [56].

An uneven distribution of (heavy) rainfall events on clay soils, for instance with a distinct raining season, may hence lead to increased runoff due to increased saturation. This becomes immediately clear if one looks at the base discharge of the river Geul in summer, displayed in figure 16, which is closely related to precipitation during the previous winter. The ground hence proves to have a long term buffering effect.

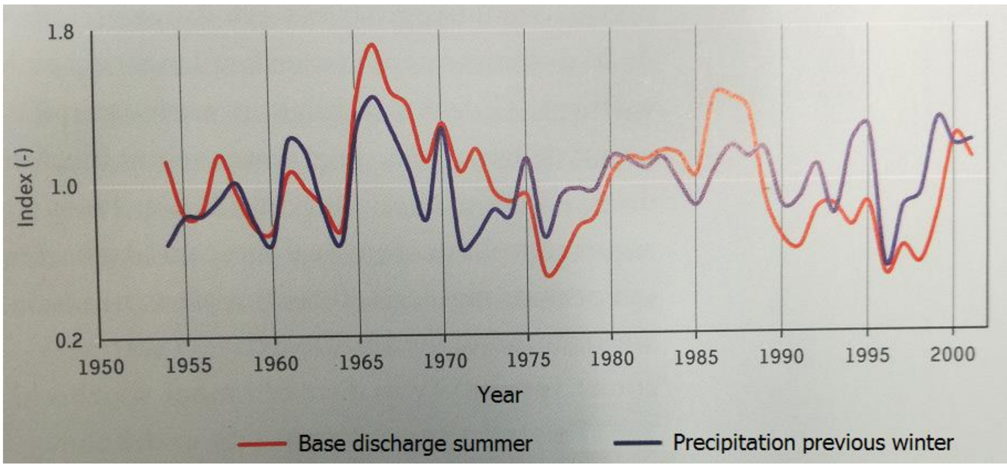

Fig. 16. Correlation base discharge summer of the river Geul and precipitation during previous winter [54].

Rain intensity is another critical factor to the level of surface run-off. High intensity rains may saturate the upper soil layer fairly quickly since water did not have time to infiltrate lower soil layers [56]. Finally heavier concentrated rain showers with large drops and hence high kinetic impact can generate crust formation, especially in locations with low vegetative cover, low organic matter, weak top soils and silty, clayey ground. Crusts form an impermeable seal over the soil beneath which drastically reduces infiltration rates and increases run off [57] [58]. For developed urban areas high rain intensity can lead to storm sewers/storms drains reaching capacity forcing water to run over generally impervious urban soils hence creating more runoff. The overflow of combined sewer systems (CSS) is worse, which is unfortunately a common result of heavy precipitation events. They aggravate the problem by introducing more waste from the CSS into the environment [59]. Williams and Simmons (1999) [60] for instance showed CSS was a major contributor to litter in the river Taff (UK). Fortunately many cities are nowadays aware of this issue and multiple projects were started which aim to reduce these overflows in multiple ways. Capacity is for instance increased (e.g. adding retention basins), new sewer systems are built to accommodate separate discharge and green infrastructure is being added (e.g. permeable soil like grass) [61]. The difference between CSS and separate systems is illustrated in Figure 28 on the next page together with an example of grass concrete, which can be used a green infrastructure.

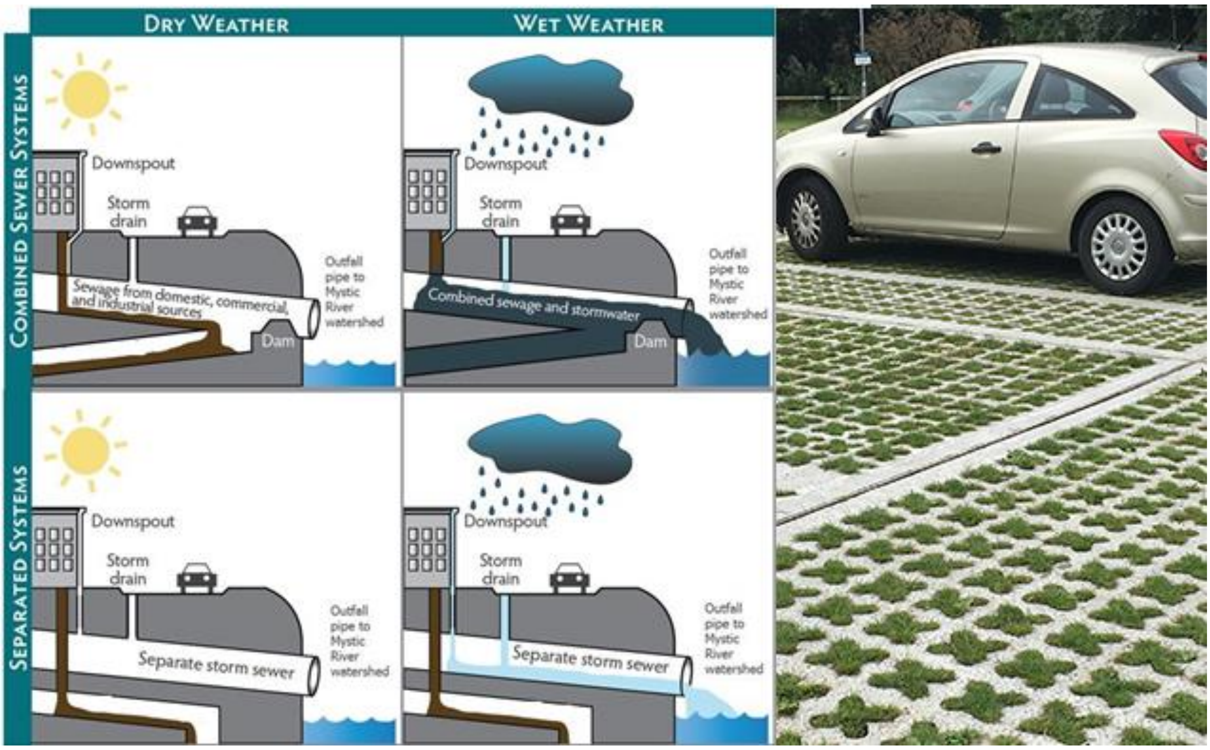

Fig. 17. A combined and separate storm water systems under wet and dry weather conditions (Left) [62]. A permeable parking space as an example of green infrastructure (Right) [63].

3.2. Introducing debris into the river: other factors

Other factors can also play a role: wind, temperature, special events, urban development, tourism, waste management and public mentality.

Wind can play an important role in the temporal distribution of debris accumulation from rivers, in multiple ways. Firstly, wind can act as a means of release (see appendix D.4 for definition). During wind (gusts) objects can be blown away from their intended place, e.g. from tables or landfills. Secondly it can act as a transport mechanism (see appendix D.4 for definition). In this case it has been released into the environment earlier, whether it is a landfill or any patch of street/land, and it is now being blown into the freshwater environment. Observations obtained by Alam et al. (2017) [45] for instance point to the influence of wind, especially during dry periods. Overall, quantitative studies w.r.t. wind as a means of release and a transport mechanism for debris are unfortunately rare. Subsection 3.3.2 will address wind more elaborately, especially in the context of river transport, including the temporal characteristics of wind. Wind applies to both anthropogenic and natural debris. The influence on the latter will also be touched upon later in this subsection when natural debris will be discussed.

Temperature and cloudiness, is a factor which can lead to daily and seasonal fluctuations. In certain regions where day to day weather fluctuations are common, pleasant temperatures and sun could motivate people to stay outdoors which means chances increase that waste does not end up in waste bins. This is deemed so since people are outside their domiciles, outside their personal property where waste bins are in general in less close proximity. The effect would be the greatest if followed by a heavy rainfall event which tends to flush any abandoned litter. So day to day differences could be observed but also seasonal differences (summer versus winter). Also in this case the extent to which this influence on debris accumulation is observed depends on the geographical location. Locations with stable weather patterns would observe less difference. This factor only applies to the accumulation of anthropogenic debris.

Special events such as festivals could perhaps influence the debris accumulation [64]. During such events many disposable food and drink packages are often just thrown on the event grounds and this might bring significant contamination especially when combined with heavy rainfall and wind occurrences. This factor is also merely applicable to anthropogenic debris.

Among long term influencing factors there is urban development and tourism or put in more general terms human presence. For tourism seasonal differences might be observed or sudden disruptions (e.g. due to terrorist attacks). For both, longer term trends might be observed. This factor is only applicable to the accumulation of anthropogenic litter although it can be argued increased urban development decreases biotic debris. This however is believed to be marginal since the accumulation pathways of debris such as rivers extent generally over a large distance which makes any observed decrease in biotic debris relatively small. Any changes in urban development and tourism can also fairly easily be compensated by another factor of relevance, namely the quality of local debris processing and presence of trash bins which can fall under the category waste management. This reasoning also applies to temperature and events.

Waste management is a crucial factor. Adequate waste collection for instance could decrease the amount of fly tipping. The correlation between mismanaged plastic waste and plastic load in the rivers has been studied by Schmidt et al. (2017) [65] and was found to be clearly positive, even when adjusting for the size of the catchment area. A study by Marais et al. (2004) in South Africa found the quantity of debris removed by street sweeping 33 to 100 times the debris caught in storm water runoff systems hence proving the necessity for good waste management [66]. A study by Cheung et al (2016) at the mouth of the Pearl River concluded that poor waste management in the river catchment area is the main culprit of the large quantity of litter and observed the toxic effect of combined precipitation and poor waste management: *'The current waste management system in the Pearl River Delta region is clearly ineffective at preventing municipal waste from entering the waterways, particularly during the rainy season'* [39]. Hence the quality of the waste management affects the relative difference observed between dry and wet seasons. Waste management includes:

- Availability and capacity of waste bins. The overflow of waste bins, see figure 18, create undesired uncontained litter which may be swept away by heavy rainfall. To avoid overflow of waste bins, waste collection should be done at a regular frequency. Absence of waste bins or waste collection may lead to fly tipping.
- Frequency of waste collection. See above.
- Landfills. Preferably landfills should be avoided but any existing ones should be well contained meaning they shouldn't border flowing water or be placed at windy areas. Wind or overflowing may introduce debris directly or indirectly into the environment [7].

Fig. 18. Waste bin overflow [68].

- Recycling rate and incineration rate. Landfill can be avoided through recycling and incineration [7].
- Street Sweeping. Regular street sweeping can prevent a lot of debris entering the storm water system as proved Marais et al. (2004) [66], in particular in areas with lack of waste bins, poor public awareness and poor waste collection.
- Sewage treatment. A shown in subsection 3.1.2 combined sewage and storm water discharge may lead to severe increase in contamination if high precipitation events are not properly taken care of.

Finally, public awareness might increase, for instance through education, which would make people less prone to discard their litter in public space or fly tipping. This might also lead to a demand for improved garbage collection and increased presence of trash bins. Both reduce chance of litter being release into the environment. Public awareness can lead to political action to ban certain products. Research from Maes et al. (2018) [68] suggests legislative action on plastic bags use led to a perceived drop in the presence of plastic bags in the North Sea. Where mentality change is generally a slow process legislative action can have a much more sudden impact. Political action can also have wider implications. It may influence waste management, affect the influence of festivals, urban development, tourism but also the extent of urban runoff by introducing more permeable areas in urban areas or hindering debris propagation through rivers by introducing debris removal systems[6].

It is important to realize how all these factors may influence each other. A bad waste management system is for instance a multiplier for land to river debris inputs by precipitation and wind. In a country with little rain or wind, a bad waste management system will have a small effect on debris accumulation unless it is directly deposited in the river (tributaries). Likewise, the necessity for street sweeping depends on the local mentality vis-à-vis street littering and the availability of public waste bins.

3.2.1. Natural debris

Natural debris are different compared to anthropogenic debris in several ways. Many factors do not apply to natural debris such as public mentality, legislative action, waste management, events and tourism. Urban development might influence natural litter deposition since cities often develop at the cost of green areas. Natural debris will often include branches or leaves. For both, wind is crucial but leaves are also largely affected by the type of vegetation which determines whether leave shedding occurs. Three cases can be distinguished:

- Non deciduous vegetation species; no shedding of leaves.
- Temperate deciduous species; seasonal shedding of leaves, leaf drop in autumn.
- Tropical and subtropical deciduous species; shedding during low rainfall period, often coincides with seasonality of precipitation patterns.

In the second case and the last case to a less extent vegetative debris will have a seasonal characteristic as far as leaves is concerned. Like anthropogenic debris, precipitation runoff can lead to the introduction of leaves into the marine environment. If rainfall happens during the shedding period an increase in debris accumulation can likely be observed. Bilby and Heffner (2016) [69] have studied the factors contributing to leaf delivery to streams. It was found tree type, tree height, tree age, wind speed and topography of the riparian zone to be of largest importance. The paper further mentions the close proximity of the trees to the stream and an increased slope of the riparian zone which leads to increased litter delivery: *'95% of annual litter input originates within 20 m of a stream in gentle terrain. Litter input can originate from beyond 25 m in steep riparian zones'* [69]. Precipitation was not mentioned however, perhaps since no strong runoff was observed, something more common in urban environments due to the impervious soil conditions.

The findings of Kataoka et al. (2013) [53] pertaining grass accumulation have been mentioned before. Like anthropogenic litter, grass flows could be linked to flood events. The exact cause is unfortunately not elaborated upon, more specifically whether surface runoff leads to inputs of grass into the river or whether it is increased currents which clean the riverbanks.

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[6] See appendix C for an overview of such systems.

3.3. River transport

According to Barnes et al (2009) [7] the main flow pattern of debris in rivers can be generally linked to the flow rate of the river where a process similar to sediment transport may be observed. Precipitation influences river discharge which affects flow velocities and hence temporal distribution. Precipitation induced discharge may happen in four different ways as shown in figure 19.

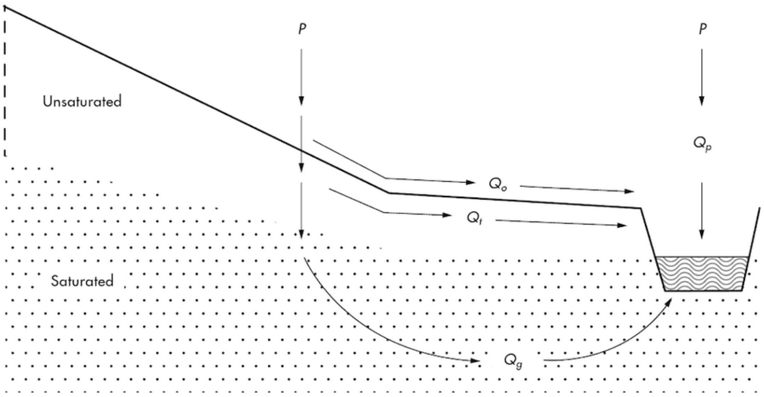

Fig. 19. Flow paths of precipitation P [70].

Each exhibits typical temporal characteristics. Surface runoff (Qo) is water which has not first infiltrated the soil. Together with direct riverine input (Qp) these cause a fast increase of river discharge during heavy rainfall events. Groundwater flow (Qg) and Throughflow (Qt) to a lesser extent have generally a much flatter discharge curve and the effects are hence felt over a longer time period with a lower discharge increase. Figure 20 shows a hydrograph which visualizes how a rain shower entails to additional river discharge and how different basin characteristics lead to different hydrograph shapes with different lag times. The lag time and shape could be an important consideration for prediction of debris after heavy rainfall.

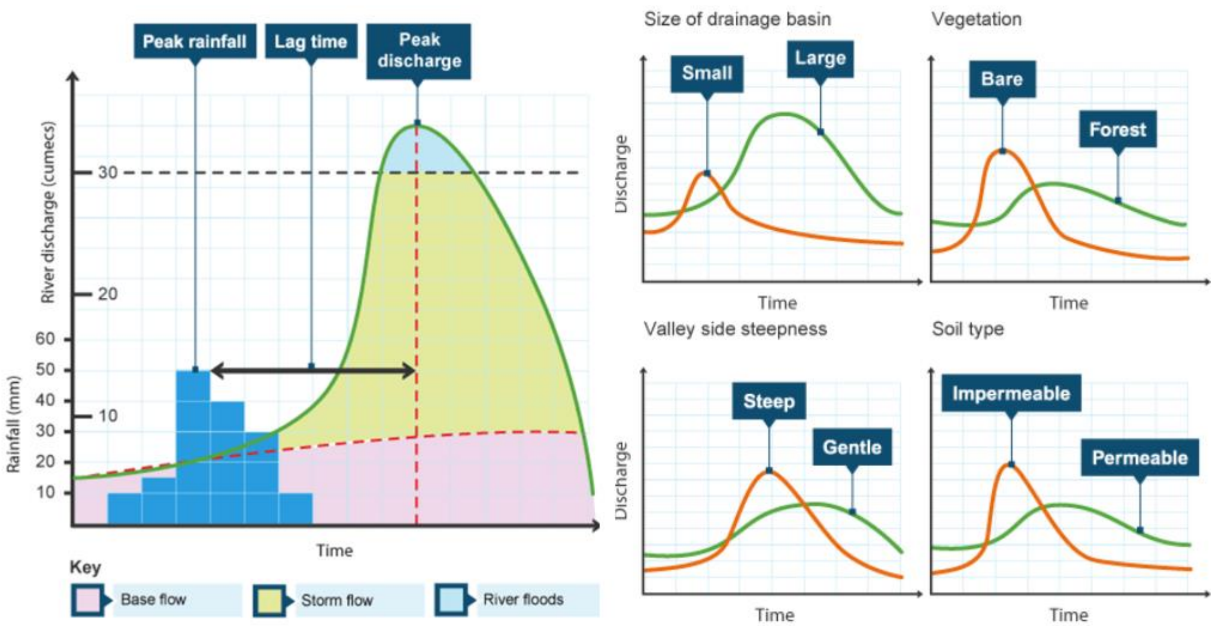

Fig. 20. Hydrograph of river discharge after heavy rainfall (L) and influence of basin characteristics (R) [71].

The increase of base flow due to increased groundwater is smaller and has consequently fewer consequences. The large bulge created by surface runoff and direct input called stormflow will however have a significantly larger impact so these flows should be carefully considered. The influence of through flow or subsurface flow depends on the soil type, topography and climate. For humid climates with dense vegetation and steep hillslopes with deep, permeable soils and narrow valley bottoms subsurface flow can become one of the dominant processes in the formation of storm flow [72]. For heavily vegetated surfaces, runoff will be comparatively low whereas arid surfaces are more vulnerable to surface runoff.

During fluvial transport of debris, a multitude of processes may take place, as depicted in figure 21.

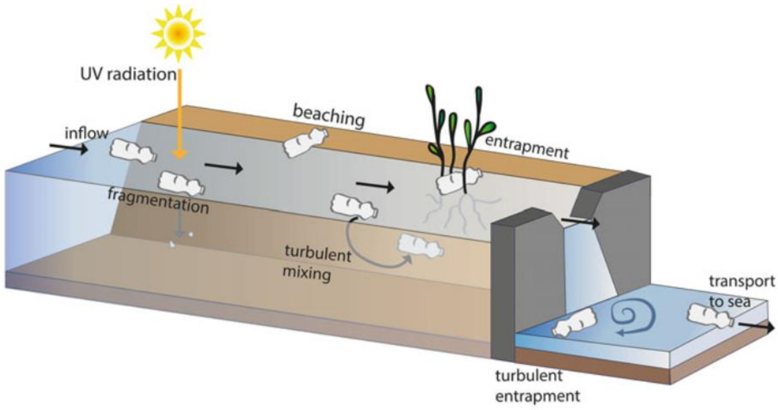

Fig. 21. Common processes involving debris during river transport [73].

Beaching and entrapment are processes which take place along the banks of the rivers which heavily influence the temporal distribution of the accumulation of individual debris items.

3.3.1. Empirical studies on fluvial transport of debris

Several studies have been dedicated to analyzing transport of debris in fluvial environments. The studies are summarized in table 4 (part 1) and table 5 (part 2) on the next page. These studies will be discussed more elaborately in this subsection and in appendix H.

Table 4. Empirical studies dedicated to transport of debris in fluvial environments (part 1).

	Transport phenomenon analyzed	Site characteristics
Williams and Simmons (1997) [74]	Transport time of debris	Small river 1 (0.6 m^3/s) and small river 2 (5.4 to 74 m^3/s)
Williams and Simmons (1997) [74]	Quantities and locations of debris on river banks, effect of flood events	Small river
Jang et al. (2014) [75]	Locations of stranding, transport time and time spent immobile	Large river (236 m^3/s avg. upstream[7] and 728 m^3/s avg. downstream[8])
Ivar do Sul et al. (2014) [76]	Retention and transportation of debris from river/creek banks and occasionally flooded high ground	Tidal creek (TC), River and high ground (HG). Bank slopes: 160° (river) and 110° (TC). Tides: 0-2.5 m. Flow: 0.005 m^3/s (TC), 0.5-25 m^3/s (river). Sediment: mud (TC), sand (river), sandy mud (HG).

Table 5. Empirical studies dedicated to transport of debris in fluvial environments (part 2).

	Flow conditions	Tracer(s) used	Length of stretch	Duration of measurement
Williams and Simmons (1997) [74]	Four different flow regimes	180 LDPE plastic sheets	1.3 and 2.2 km	n/a
Williams and Simmons (1997) [74]	Four flood events: 14, 24, 29 and 75 m^3/s	No tracers used, numerous debris as accumulated	100m bank length	Two and three months
Jang et al. (2014) [75]	Varying over tracking period	4(1st trial) and 11(2nd trial) tracking buoys, ≈250 mm	n/a	20, 24 and 55 days
Ivar do Sul et al. (2014) [76]		Margarine tub, plastic bag and cup, polystyrene and open, open squashed and closed PET bottle, 9 items per category per site	n/a	144 days (main data) although up to 6 months is mentioned

Williams and Simmons (1997) [74] studied temporal distribution of riverine debris and performed four separate experiments. During the experiments they released items distributed evenly over the width of the river. A strong correlation was found with the flow rate. At low flow rates entrapment and stranding was severe in a small river with high presence of vegetation. For a broader and deeper river, during high flow conditions items were much more mobile. A study on the same stretch of river during low flow conditions saw a much flatter response time. In general, for the arrival distribution, one can observe a more concentrated peak for the first arrivals with a long right tail. A high flow rate, low susceptibility of stranding of the items and a low level of vegetation will result in a more pronounced first arrival peak. More details on this study can be found in appendix H.

Finally, riverbanks were also studied by Williams and Simmons. After the banks were cleaned accumulation was observed. Observation revealed the vast majority of deposition occurred during flood events. The site characteristics however were such that it was prone to trap debris, i.e. many vegetation, such as shown in figure 22 [77] on the next page. The effect was named the 'Christmas tree effect' due

[7] Average over 2012 and 2013 for Nakdong Observation station Q1 [75]

[8] Average for Samrangjin observation site (Q6) [75]

to wrapping of litter around the branches. It was hypothesized that open surfaces with little vegetation would see an opposite effect, meaning they would get cleansed with rising stage. Moreover, it was also observed that once dislodged the items were generally not frequently deposited closely downstream but they were transported more than 45 meter. In the height the riverbank was divided in three parts. Movement between banks was infrequent but if it happened it was mostly upwards from lower to middle (the river did not reach the upper part) during increased flow events.

Fig. 22. ML stranding on vegetation [77].

Ivar do Sul et al. (2014) [76] investigated retention and movements of debris in a Mangrove forest. Different type of debris were released in three different environments, namely: a creek, a river and high ground. The observed movements suggest the shape and buoyancy (as long as it floats) of debris has limited influence in general. Not entirely surprising, debris were least retained along the river, with the creek not far behind, while the higher grounds performed significantly better. This suggests again flow rate is a factor of influence. More details on this study can be found in appendix H.

Long distance tracking has been studied by Jang et al. (2014) [75] which used satellite location tracking buoys to explore litter movements and found that debris tend to be trapped quite often, hence suggesting that relating discharge of litter to the flow rate of the river should be done with caution: *'Contrary to the generally held belief that most floating debris is quickly discharged during the rainy season, our results show that, at least in the Nakdong River, debris is frequently trapped on its path to the sea'* [76]. The study revealed that accumulation hotspots along the course of the river may trap debris for a certain undefined quantity of time. More detailed information such as the relation between specific reach characteristics and debris is unfortunately not present.
On the size of debris Van der Wal et al. (2013) [78] mentioned stranding and entrapment are especially common for larger items[9]. Finally, Aguilera et al. (2016) found artificial coastal breakwaters to enhance trapping compared to natural rocky ones and concluded complex structures leads to increased trapping of debris [79]. As this study does not directly involve movement patterns of debris it was omitted from table 4 and 5.

3.3.2. Wind

The lateral displacement of debris, along the width of the river is probably mostly determined by the wind. Other factors are hydrodynamic events which will be discussed in 3.3.3. Wind induced forces can push debris into the bank of the river where it might get stuck behind vegetation or other obstacles. This might strand debris for an undetermined period of time as demonstrated before and hence interrupt/delay to flow of debris. Studies on spatial patterns of litter such as Browne et al. (2010) [80]

[9] For clarification see the quote in appendix D.3.

have already shown the tendency of certain debris to become stranded along downwind sites. Lastly, wind parallel to the direction of the river flow can influence travelling time along the river. The extent to which wind influenced debris propagation this way is however not known and could very well be negligible, especially over relatively short distances. Lack of high obstacles along the banks combined with a wide stream improves conditions in which wind transport can occur. The entry location of the item into the river will also play an important role in the displacement of debris during wind conditions. If dropped leeward it is likely to be transported further than if dropped downward since in the latter case immediate stranding is possible.
Wind induced movements are caused by direct aerodynamic wind forces and wind induced surface currents. Debris with more buoyancy and more surface area above the water are logically more prone to direct wind forces. Wind induced surface currents will affect any debris. Lammerts (2016) [24] conducted particle experiments using numerical modelling and observed a large influence on surface debris. Kataoka et al. 2013 [53] demonstrated the effect of wind on surface currents in the Tokyo bay area and the resulting dynamics of floating debris. Since the study focused on grass the wind susceptible surface area was deemed negligible so it was estimated horizontal movements were largely due to currents. The dynamics of floating debris inside the bay showed a clear dependency on wind induced currents; at certain times these currents helped trapping the grass inside the bay while at other times the currents actually forced the grass out of the bay. Large debris (>0.05m^2) were investigated by Moy et al. (2017) [81] who spatial accumulation on Hawaiian Islands. Windward sites accumulated 76% of the total amount whereas leeward side accounted merely for 8.6% of the total. Finally, Kako et al. (2010) found winds directed towards shore to increase ML coverage on a Japanese beach [82].

Lammerts [24] demonstrated that wind speeds of 5 m/s (3 Beaufort) can already have a high impact on the horizontal spatial distribution of debris and described it as highly influential, although it is unfortunately not mentioned what the buoyancy and surface area of the particles were. Some parts in the world have annual means wind speeds (AMWS) which are significantly higher [83] than 5 m/s but some are also much lower. In general differences of AMWS between different global geographical areas is very large meaning this is a very location depended factor. However, not merely the mean but also occasional peak winds should be considered and local wind directions. For this reason, even if AMWS appears to be below the threshold of significance, wind should always be considered as a factor of influence. This raises the question how wind fluctuates over different timescales, this therefore deserves closer attention. Also with respect to monitoring frequency.

Wind is clearly a factor which needs to be monitored on a short time span as can be observed from figure 23 and 24. Figure 23 shows an example of a 24 hour measurement of wind speed and wind direction, measured at a weather station near Schiphol, Netherlands. It illustrates how wind speed and wind direction can fluctuate over a 24h period. Figure 24 shows similar data for a 10 minute period during a storm event which illustrates even better how fast significant wind velocity and wind direction fluctuations may occur, especially for storm events.

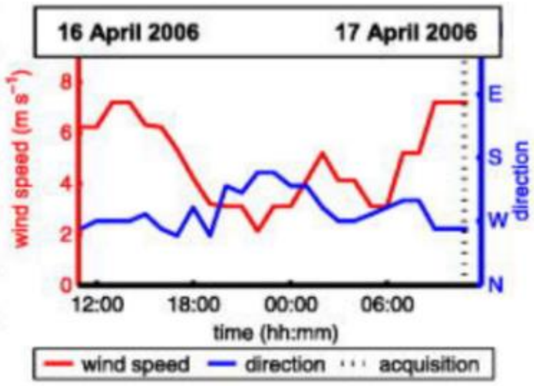

Fig. 23. Wind speed and direction near Schiphol, NL [84].

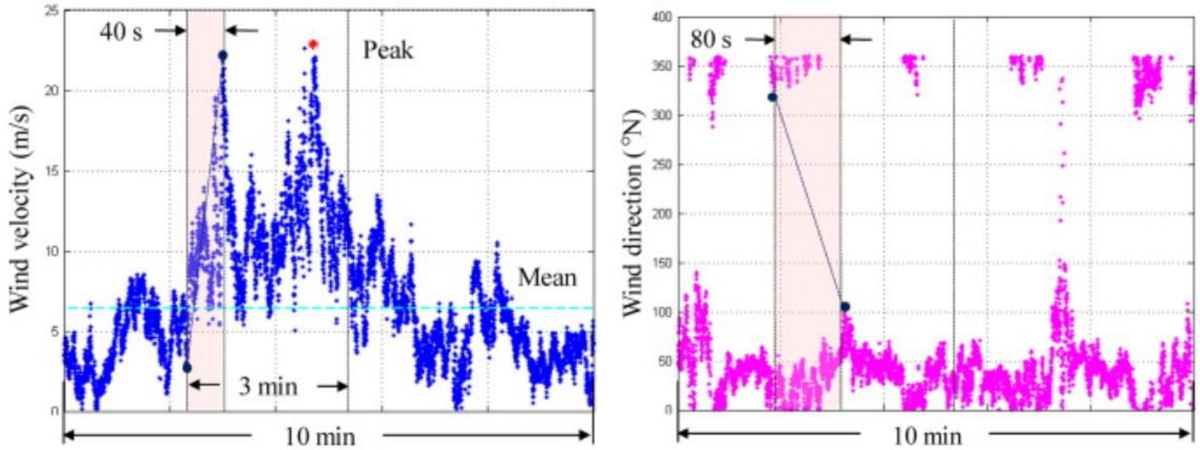

Fig. 24. Wind recordings, velocity and direction, during a thunderstorm event in Livorno port, Italy [85].

In addition, wind can have strong seasonal characteristics as can be seen in figure 25 which shows mean wind speed and directions in fall and winter (period 1, left) and spring and summer (period 2, right) for West Canada [86].

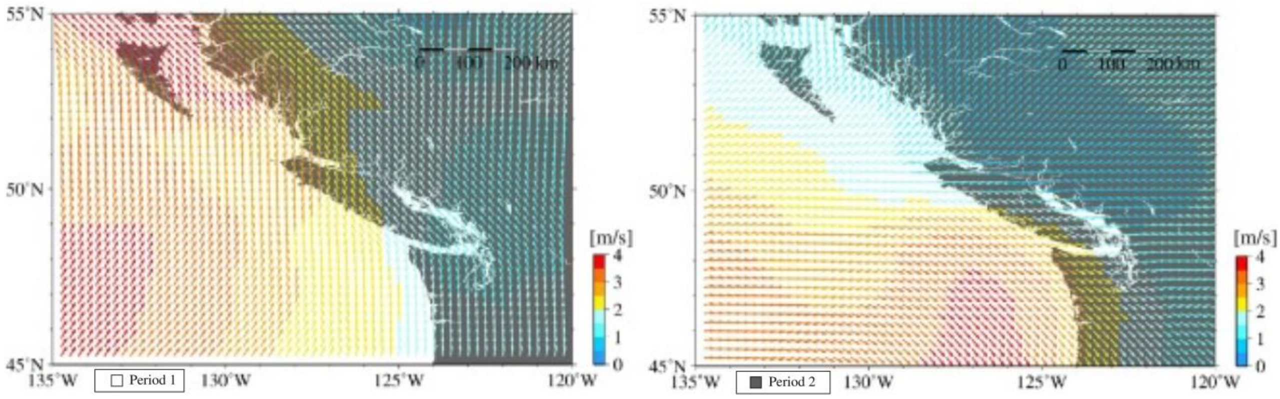

Fig. 25. Mean wind speeds and direction in period 1 (fall and winter) and period 2 (spring and summer) in West Canada [86].

3.3.3. Hydrodynamic events

Important hydrodynamic events may also play a role in lateral surface displacement, events like confluence of tributaries, watercourse obstructions and river bends [87]. Bends in the river create changes in the primary velocity profile as well an additional secondary velocity profile as illustrated in figure 26 [88]. The secondary profile V_s (in the red circle), induced by centrifugal forces will be directed outwards in the top section and inwards in the down section [89]. Multiple secondary currents can be found as shown in figure 27 with the main currents highlighted with the white arrows and the surface currents highlighted with the black arrows. Figure 46 also shows the differences in primary velocity.

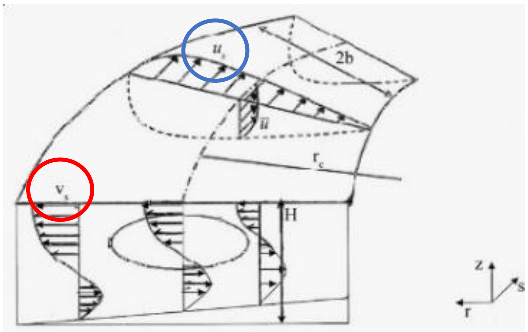

Fig. 26. Flow through river bends with primary, U_s, and secondary, V_s, velocity profile [88].

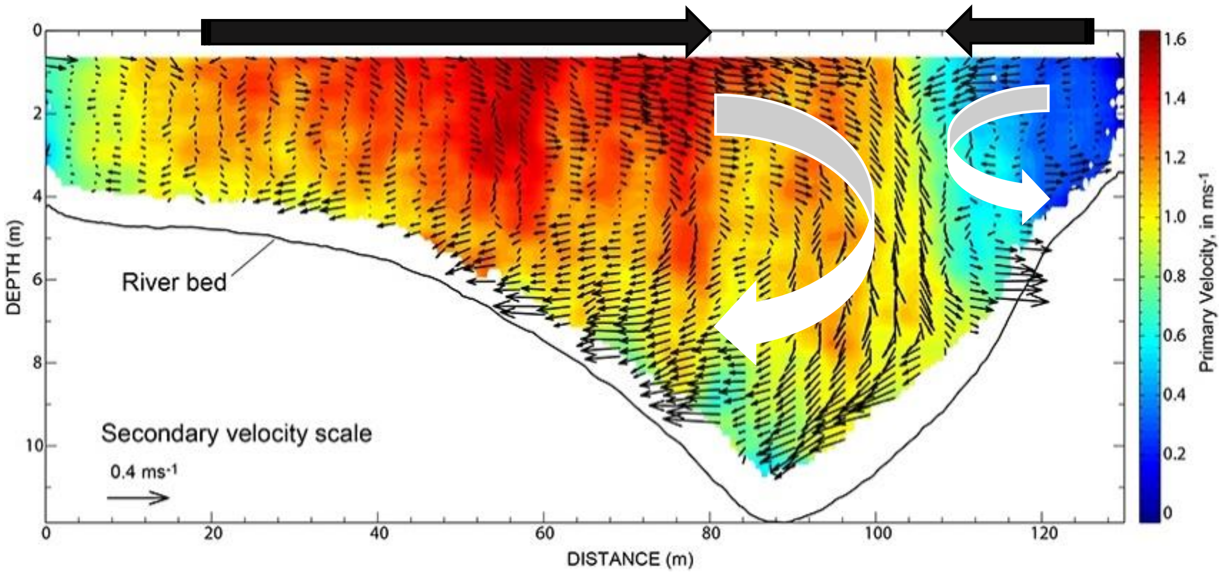

Fig. 27 MATLAB® generated primary and secondary velocity profile in a river bend profile [90].

Watercourse obstructions, like small islands, pillars can direct the flow around the object and at the back of the object circular currents emerge as shown in figure 28 [91]. This can lead to turbulent entrapment [73]. Lastly, the confluence of rivers also leads to a range of different flow patterns as shown in figure 29 on the next page, which may lead to the deflection of the main flow and the existence of stagnation zones and the creation of turbulent eddies which can influence lateral displacements [92]. Additionally one could observe a set of two counter rotating secondary flow patterns [93]. The existence and importance of these is situation dependent. Influencing parameters are confluence angle and stream velocity, and velocity ratio between both tributaries [93].

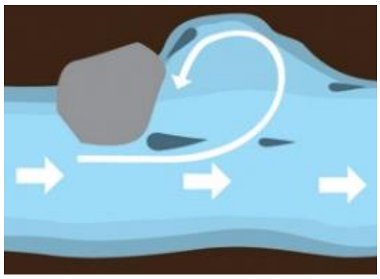

Fig. 28 Formation of eddies behind water obstacles [91].

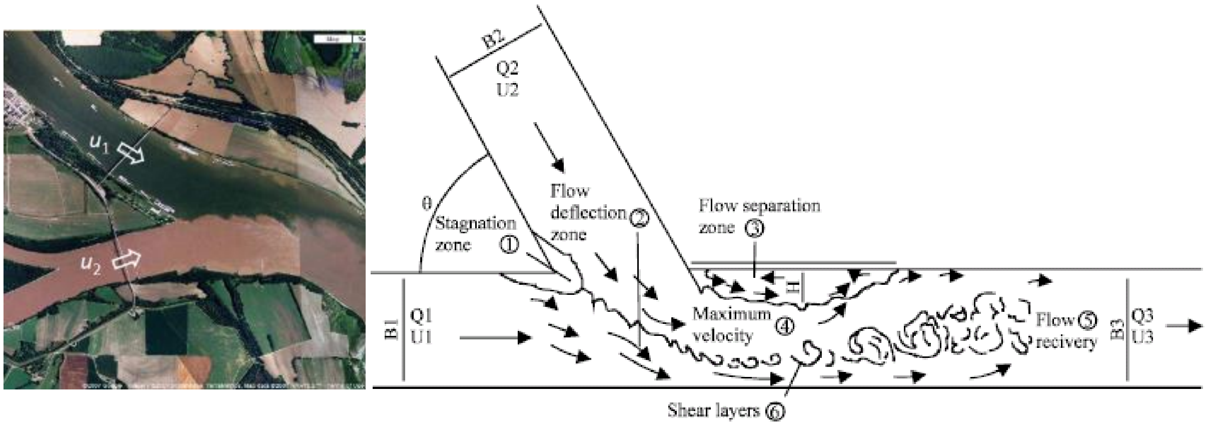

Fig. 29 Confluence of the Solimoes and Negro rivers, Brazil (L) [93]. Flow patterns at confluence (R) [92].

3.3.4. River discharge: velocity and water level

Based on the empirical studies discussed in 3.3.1. it is hypothesized higher discharge may influence interaction of debris with the riverbanks in the following two ways:

- A strong current (stream velocity) caused by stormflow makes it harder for debris to stick behind objects.
- Rise of the water levels increases interactions with higher sections of the riverbanks as suggested by Williams and Simmons (1997) [74].

Therefore it useful to understand how velocity and water level rise increase with higher discharge. Indeed, the increase in mean velocity is not directly proportional to the additional mean discharge since part of the discharge is accommodated by an increase in cross section such as an increased water level as shown by an example in figure 30.

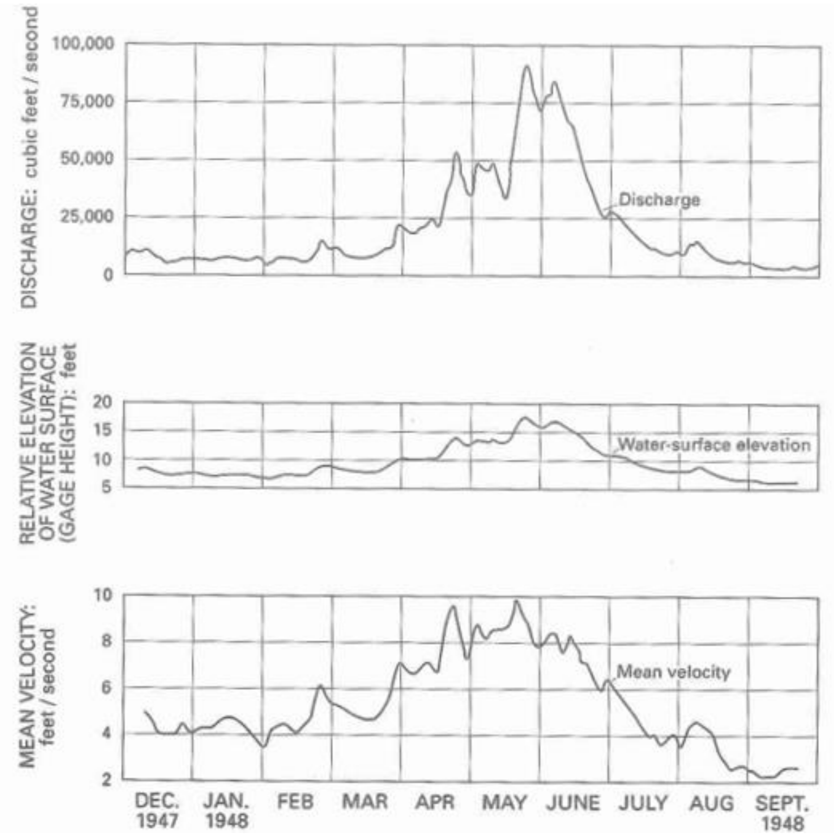

Fig. 30. Change in discharge, water surface elevation and mean flow velocity during a 10 month period at the Colorado River at Lees Ferry [94].

The mean river velocity can be calculated using equation 7, with the hydraulic radius R being defined as equation 8 [94]:

$$V = \frac{Q}{A} = \frac{R^{2/3}S^{1/2}}{n} \quad (7)\,, \quad R = \frac{A}{P} \quad (8)$$

V = Mean velocity [m/s]

Q = Discharge rate or Flow rate [m^3/s]

A = cross-sectional area [m^2]

R = hydraulic radius ([m]

S = Slope of the channel bed [m/m]

n = Manning roughness coefficient [s/$m^{1/3}$]

P = wetted perimeter [m]

It can be observed from both equations that the velocity grows less than linear with an increase of cross sectional area A. Since A is scaled down with P in equation 28 and with the power of 2/3 in equation 27. This is however the mean velocity. The flow rate is in reality not evenly distributed over the cross section of the channel due to friction with the channel contour, which is especially true for larger and deeper rivers [95]. An example of a straight river cross section with a stream velocity contour plot (isovel) is illustrated in figure 31. An isovel plot of a river bend was previously shown in figure 27 with the colors indicating primary velocities.

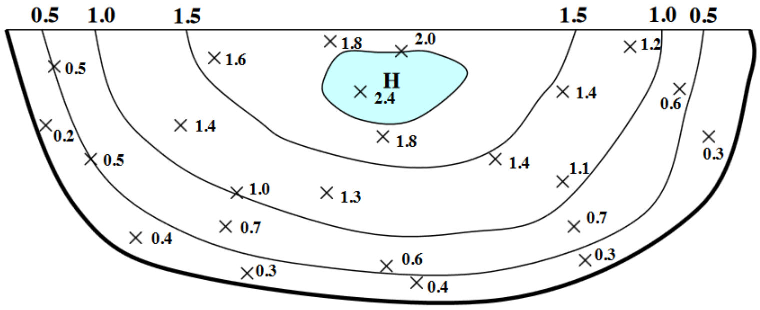

Fig. 31. Isovel diagram of a symmetrical river cross section [96].

Mean velocity fluctuations will have likely limited effect on interaction with the banks since velocities are relatively low there. In addition it means lateral position along the cross section is a crucial factor for the speed of displacement of debris and hence the temporal distribution of debris.

The hypothetic correlation between the loading rate, sometimes referred to as flux of debris in a river and river discharge has been investigated by Kataoka et al. 2013 [53] in the particular case of the rivers flowing into the Tokyo Bay area. A statistically significant relationship was found albeit the variability was large. A comparison of both are shown in figure 32 with the regression formula in the top left corner. Both loading rate LR and river discharge have been divided by the specific catchment area of the river under consideration. This yields a specific loading rate and a specific river discharge SRD. Correlation however does not mean causation hence it is not clear whether the higher discharge is related to current cleaning the riverbanks or surface runoff creating river inputs.

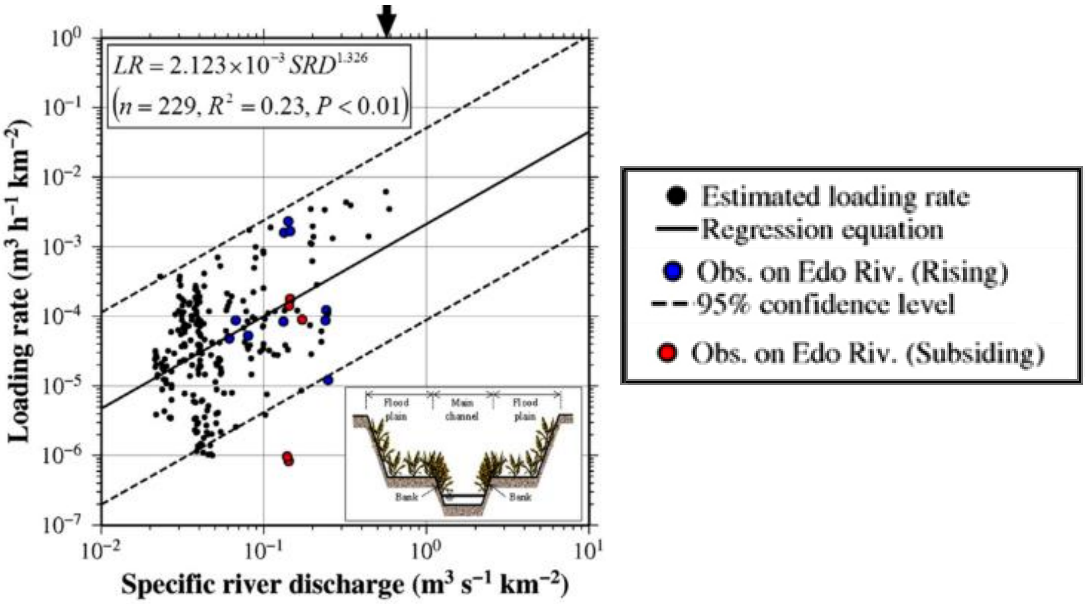

Fig. 32 A comparison between LR and SRD [53] using colored dots representing net samplings [97].

A notable observation is the difference observed between the rising stage and the subsiding stage: '*The LRs obtained by the net sampling in* [97] *were classified into two groups (i.e. the LRs in the rising stage and those in the subsiding stage). The rising (subsiding) stage is defined when the SRD increases (decreases) during the net sampling. The net sampling data indicates that the LRs in the rising stage were one order of magnitude larger than those in the subsiding stage'* [53]. This difference has however not been accounted for when calculating the regression formula. It is clear however from the observation that when observing the graph depicting the discharge over time, both the sign of the gradient and the value of the discharge itself should be taken into consideration.

3.4 Summary

For the introduction of debris into the river, runoff as a result of precipitation was found to be the largest factor. Important rainfall characteristics influencing the event mean concentration (EMS) were antecedent dry days (ADD), total rainfall volume and rain intensity. Governmental policies and legislation can logically also have major influence, especially on the usage of disposable items and waste management. Bans on or price steering of certain products proved a major contributor to reducing debris. Other factors include wind, temperature, special events, urban development, tourism, waste management and public mentality. In all cases the extent depends on the geographical location both with respect to physical topology, climate and anthropogenic related factors. Some combination of factors may have large synergetic effect, i.e. the combined effect is nonlinear. Especially the combination of climate factors and anthropogenic factors, such as precipitation and waste management, may have a reinforcing effect. For waste management, important characteristics are waste bin availability and capacity, waste collection, landfill characteristics, recycling and incineration rate, frequency of street sweeping and sewage treatment. Poor waste management can lead to more, public littering, fly tipping and CSO.

For river transport the main flow of debris can be related to the velocity of water, which is correlated to river discharge caused by precipitation. Caution is however advised since debris may strand or beach often and for long periods of time. Stranding is essentially a fairly random process although riverbank and river course characteristics will influence the likelihood of stranding events. Hotspots have been identified in the large Nakdong River (South Korea) where debris tends to be temporarily trapped whereas in the small Taff River (UK) the trapping effect of vegetation and flat riverbanks was proven. Floods proved to significantly alter litter presence along the riverbanks. Large scale deposition occurred during flood events but removal also occurred. It was hypothesized deposition occurs mainly on sites with trapping characteristics while removal is mostly restricted to areas with less trapping capabilities. This was unfortunately not thoroughly investigated. Factors influencing lateral transport are wind, input location and hydrodynamic events like watercourse obstacles, confluence of tributaries and river bends.

Table 6 on the next page summarizes all factors discussed above highlighting the corresponding stages it has influence on, according to figure 10 at the start of this section. Table 7 highlights the temporal characteristics as discussed in 2.4. The type of influence is categorized as peaks, trends and sudden disruptions whereas the rate of the change in accumulation is categorized in order from slow to fast as yearly, seasonal, daily and hourly.

Table 6. Effect of factor on respective life cycle stage(s).

Stage / **Factor**	Production and consumption (creation of product/item)	Item is being released into the environment (means of release)	Item is being released into the fresh water system (transport mechanism)	Item is transported through fresh water system (transport mechanism/ pathway)
Precipitation				
Wind				
Temperature				
Seasonal changes in vegetation (precipitation and temperature)				
Special events				
Urban development				
Tourism				
Waste management				
Public awareness				
Political policy/legislation				

Table 7. Temporal characteristics of factors.

Temporal character. / **Factor**	Type of influence	Rate of change: $cd = \frac{1}{T}\sum_{0}^{T-1} abs\big(f(t+1) - f(t)\big)$
Precipitation	Jump	Seasonal, hourly
Wind	Jump	Seasonal, hourly
Temperature	Jump	Seasonal, hourly
Seasonal changes in vegetation (precipitation and temperature)	Jump	Seasonal
Special events	Jump	Hourly
Urban development	Trend	Yearly
Tourism	Trend, Peaks	Seasonal, Yearly
Waste management	Trend, Step	Yearly (for trend), daily (for step)
Public awareness	Trend	Yearly
Political policy/ legislation	Trend, step	Yearly for trend), daily (for step)

4. Literature study: Modelling debris accumulation

All research and knowledge w.r.t. to debris accumulation by rivers has been described in subsection 3, whereas the modelling will be explored in this section. The debris accumulation model, which aims to model debris from source with the river as a pathway towards the downstream section of the river, can be subdivided in two parts as shown in figure 33: The riverine input model and the river propagation model.

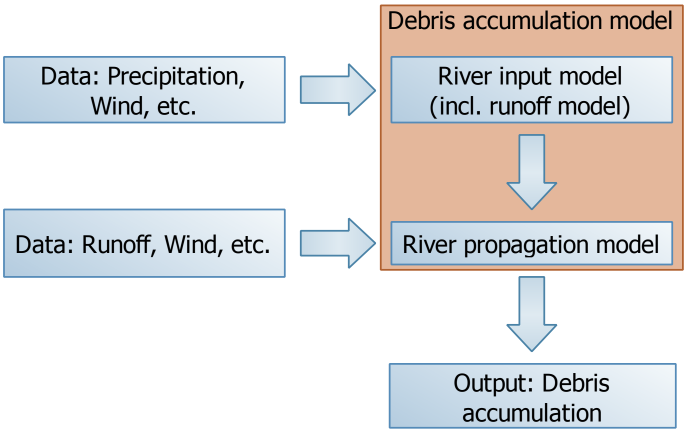

Fig. 33. Overview accumulation model and sub models, including data inputs.

From this figure it can be seen that each sub model relies on its own data input while the river propagation models also requires the output from the model above it. Modelling debris accumulation has multiple benefits. It does not only serve as a method to increase cleaning performance but may also improve knowledge pertaining the sources or geographical areas of debris over time, hence serving as a tool to pressure responsible authorities to act. Krelling et al. (2017) phrased it as follows: '*This uncertainty undermines the recognition that marine debris may be a transboundary issue in certain regions. Consequently, marine debris may be treated as a low priority issue by decision makers, especially from locations that are sources, but not sinks'* [98].

Various types of models can be found in literature. Models can be divided in different main categories as shown in figure 34, with the bottom layer being the most complex. 'Specific locations' refers to the specific location of an event like stranding, point of entry (into the river), etc. Factor representation refers to factors mentioned in section 3. Multi source, multi type/material and multi factor can be logically further subdivided according the quantity of sources/types/materials accounted for.

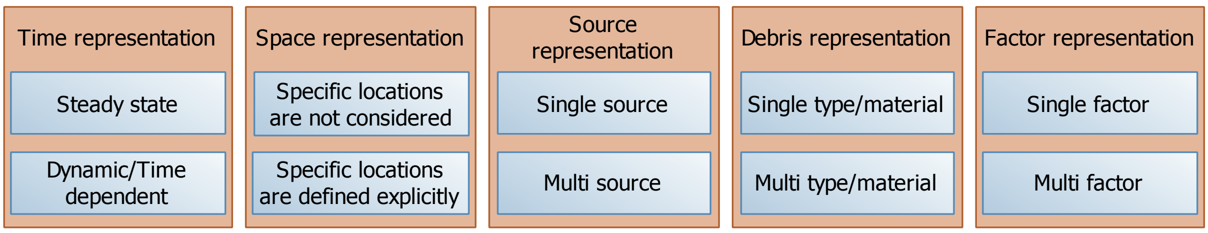

Fig. 34. Four ways of categorizing debris accumulation models.

In addition to these categories which are specifically applicable to debris modelling, mathematical models can be further subdivided in sub categories. For instance whether these are statistical (empirical) or mechanistic, stochastic or deterministic and analytical or numerical [96]. Figure 35 highlights those modelling approaches. It should be noted that hybrid models exist, in which different approaches are combined. The reason is that the total process modeled may consist of different sub processes which may need different modelling approaches.

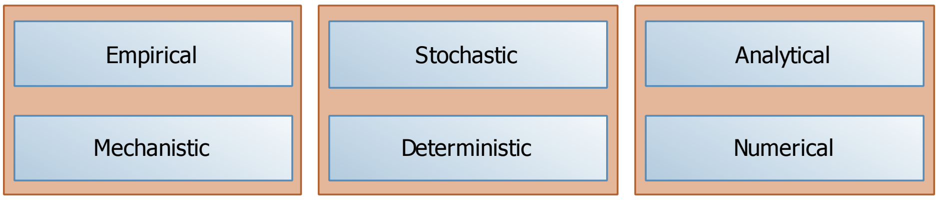

Fig. 35. Three ways of categorizing debris accumulation models.

In order to account for fluctuations in debris accumulation over a short time span, a dynamic model is required. Nonetheless, other models may give insight in how factors can be accounted for.

In the following subsections solutions to the two models from figure 33 will be explored in literature and different approaches assessed. Additionally, augmentations to existing models will be suggested and discussed. These changes will be worked out in section 5.

4.1. Modelling river inputs

Measuring the riverine inputs of debris is hard, especially since the sources are diverse and largely uncertain [29]. Logically, riverine debris inputs are not widely surveyed as pointed out by Malik and Manaf (2018) [99] and Rech et al. (2014) [42], hence the quantification of riverine inputs needs to largely rely on quantification methods which can estimate these inputs. Several estimation methods have been proposed for both macro debris, Wan et al. (2018) [29] and Armitage et al. (1998) [47], and micro plastics, Kooi et al. (2018) [73]. The latter presents an overview of several input and transport methods which all have been recently developed. Nizzetto et al. (2016) [100] is the only input model in the overview which is dynamic and multi-source since the other models merely consider a single point source like wastewater treatment plant (WWTP) effluents or consider a few point sources but only steady state. These models, including Nizzetto et al., also lack spatial resolution since emissions are lumped over a large area. An overview of these models, including models which randomly assume a number of debris accumulation, can be found in table 8 and 9. Debris propagation models which are not specifically calculating river inputs but nonetheless use an estimate or even a quasi-random number for the quantity of river inputs were also included in table 8 and 9. Each column, except the last represents a category from figure 47. The last column shows whether river inputs are specifically included. In some cases the number is not specific, for instance if river inputs are lumped with river propagation. In other cases the calculation is not comprehensive, if only a sub calculation for river inputs is considered.

Table 8. Overview of debris models for river inputs, part 1.

	Time	Space	Source(s)
Armitage et al. (1998) [47]	Steady state	Specific locations not considered[10]	Multi but lumped, uses a general figure for mismanaged debris
Meesters et al. (2014) [101]	Steady state, emissions assumed	Specific locations not considered	Soil, rain
Van Wezel et al. (2015) [102]	Steady state	Specific locations not considered	Sewage effluent (personal care, cleaning agents and paint)
Nizzetto et al. (2016) [100]	Dynamic, daily estimates	Specific locations not considered[11]	Multi source, sewage sludge, WWTP effluents, soil
Tol (2016) [23]	Dynamic, from a Weibull distribution fitted on historic data of debris removal	Specific locations not considered	Not considered
Lammerts (2016) [24]	Steady state, emissions assumed	Specific locations not considered	Not considered
Siegfried et al. (2016) [103]	Steady state, annual estimates	Specific locations not considered[12]	Point sources only. Sewage effluent (personal care, dust, tire wear and laundry inputs)
Besseling et al. (2017) [104]	Steady state, emissions assumed	Specific locations not considered	Not considered
Wan et al. (2018) [29]	Dynamic, daily estimates	Specific locations considered[13]	Multi but lumped, uses a general figure for mismanaged debris

Table 9. Overview of debris models, part 2.

	Debris	Factor	River inputs considered specifically?
Armitage et al. (1998) [47]	All macro debris, natural and anthropogenic	Rainfall volume, ADD and street sweeping	No, calculates debris accumulation into drainage system.
Meesters et al. (2014) [101]	Nano and micro plastics	Rainfall volume	Yes
Van Wezel et al. (2015) [102]	Micro plastics	Not considered	Yes
Nizzetto et al. (2016) [100]	Non buoyant micro plastics, 0.005-0.5 mm, five size classes	Rainfall duration and intensity	Yes
Tol (2016) [23]	Macro debris, buoyant	Wind	No, river inputs and river propagation are aggregated
Lammerts (2016) [24]	Macro debris	Not considered	No, random number for river accumulation
Siegfried et al. (2016) [103]	Micro plastics	Not considered	Yes
Besseling et al. (2017) [104]	Nano and micro plastics 100 nm to 10 mm, ten size classes	Not considered	No, random number for river accumulation
Wan et al. (2018) [29]	All macro debris, only anthropogenic	Rainfall duration and intensity	Yes

[10] The model allows to calculate the amount of debris generated for different land uses. How this translates to river inputs is not considered.
[11] Specific locations were not considered but quantities were specified for an area of 1250 km^2.
[12] Specific locations were not considered but quantities were specified for each cell on a 0.5° latitude × 0.5° longitude grid.
[13] The smallest spatial unit considered are the hydrologic response units used by the Soil and Water Assessment Tool (SWAT), which are areas within sub-basins with similar soil, land use and slope characteristics.

Henceforth, only the two macro debris models will be elaborated on since sources and input quantities are different for micro and macro debris. Moreover, Nizzetto et al. lacks sufficient spatial resolution.

As shown in section 3 precipitation and consequential runoff is an important factor in the fluctuations of riverine inputs. Modelling rainfall induced surface runoff has been an important topic of interest due to its value in flood forecasting [105], which helped pushing forward the progress in runoff modelling. A crucial factor in the quality of these models are precipitation measurements, measurements which are also necessary for the estimation of output from combined sewer overflows. Zhao et al. (2015) mentions how this is notoriously difficult: '*... Unfortunately, precipitation is also one of the most difficult atmospheric fields to measure, because of the limitations of surface-based observational networks and the large inherent variations in rainfall fields themselves'* [106]. Whether precipitation can be used in a useful way then depends on the level of detail required since a good estimate of the precipitation over the surface area might already be sufficient for a simple prediction model. Nizetto et al. (2016) for instance used a lumped model which spatially averages precipitation data over the whole catchment [100].

4.1.1. An estimation model for land to river inputs of macro debris

The flowchart presented in figure 36 represents a fairly comprehensive land to river debris estimation method recently developed by Wan et al. (2018) [29]. The method relies largely on the modelling of surface runoff from precipitation which was performed using SWAT (Soil and Water Assessment Tool), a model with built in databases to input the model. This flowchart needs to be repeated for every river basin flowing into the main channel, for each time step, e.g. on a daily basis as is prescribed by the SWAT model. The equations mentioned in the flowchart will be subsequently discussed starting with the maximum quantity of debris available for input.

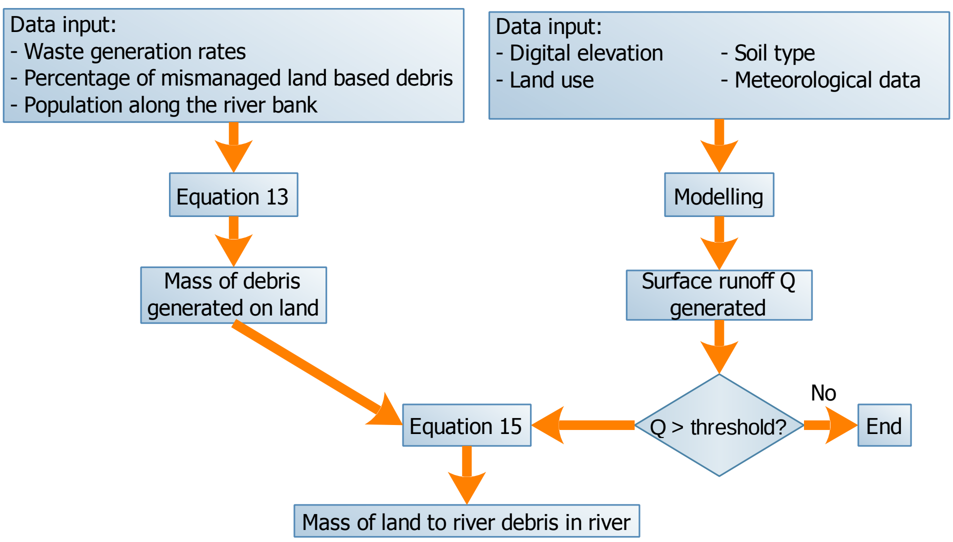

Fig. 36. Comprehensive flowchart of the estimation method used to calculate the mass of land to river debris in a runoff basin [29].

The following equation gives the daily mass of debris generated on land $m_{D,G}$ [kg] as given by Wan et al. [29]:

$$m_{D,G} = r \cdot G \cdot P \cdot \Delta t \quad (9)$$

r = percentage of mismanaged debris [%]

G = Waste generation rate person [kg/person/day)

P = Number of persons along the river banks [persons]

$\cdot\, \Delta t$ = time interval [day]

The size of the bank zone for the main channel used for determining P was defined as 50 km. This is an approximation for the average basin depths of the inflowing tributary rivers. Waste generation rates are obtained from Jambeck et al. (2015) [10] which defined mismanaged waste as follows: *'... material that is either littered or inadequately disposed. Inadequately disposed waste is not formally managed and includes disposal in dumps or open, uncontrolled landfills, where it is not fully contained'* [10]. It is however not clear how street cleaning has been accounted for. In subsection 3.2 research showed that street cleaning may have a large impact. Furthermore, the location of dumps and landfills is crucial but this data can be hard to obtain, especially for random dumps.

The daily accumulation of debris per day $m_{D,G}$ was used by the Wan et al. (2018) to calculate the quantity of debris available for land to river inputs. This is the maximum quantity which can logically not be exceeded by surface runoff, i.e. land to river inputs $m_{D,I} \leq m_{D,A}$. Accumulation however is not the true quantity available for surface runoff, a better definition of the total presence of litter $m_{D,A}$ should account for litter removed by street cleaning (or other) and surface runoff. Another shortcoming of the previous calculation method is that it does not include the number of antecedent dry days (ADD) and the 'first flush' effect discussed in subsection 3.1, which were deemed to be factors of influence.

Hence a more appropriate method to calculate the quantity of land debris available, $m_{D,A}$ is suggested:

$$m_{D,A}(t) = m_{D,G}(t) + m_{D,A}(t-1) - m_{D,S}(t-1) - m_{D,R}(t-1) \quad (10)$$

$m_{D,G}(t)$ = Daily generated anthropogenic debris as calculated in equation 13 [kg]

$m_{D,R}(t-1)$ = Daily quantity of debris removed (by sweeping or other) on the previous time step, e.g. day [kg]

$m_{D,S}(t-1)$ = Daily quantity of debris removed by surface runoff on the previous time step, e.g. day [kg]

$m_{D,A}(t-1)$ = Daily quantity of debris present at start of the previous time step, e.g. day [kg]

This process is visualized in figure 37.

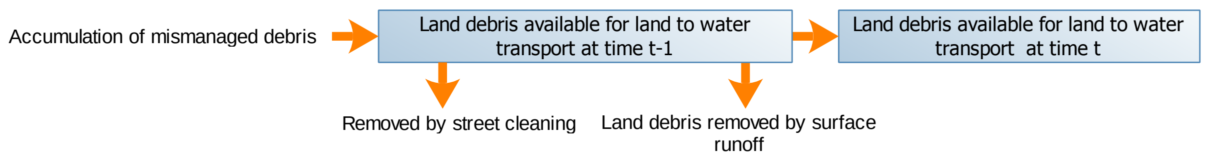

Fig. 37. Flow model to determine land debris available for land to water transport at time t.

Following the calculation of the available mass of debris, mass of debris inputs from land to river $m_{D,I}$ [kg] can be calculated as follows [29]:

$$m_{D,I} = \begin{cases} \sum_{i=1}^{n} k(Q_i - Q_b)\Delta t & m_{D,I} < m_{D,G} \\ m_{D,G} & m_{D,I} \geq m_{D,G} \end{cases} \quad (11)$$

Q_i = Surface runoff river basin [m^3/s]

Q_b = Threshold for surface runoff, below it no surface runoff [m^3/s]

k = coefficient which relates surface runoff to debris inputs [kg/m^3]

Δt = time interval [s]

n = number of outlets per river basin

If equation 10 is used, $m_{D,G}$ in equation 11 would be replaced by $m_{D,A}$. Q_b and k depend on composition of debris, land use amd slope and land use and slope respectively. Both parameters have to be determined by linear regression analysis using real world data. Figure 38 below illustrates the previous equation, especially with relation to surface runoff threshold Q_b and maximum available land to river debris $m_{D,A}$.

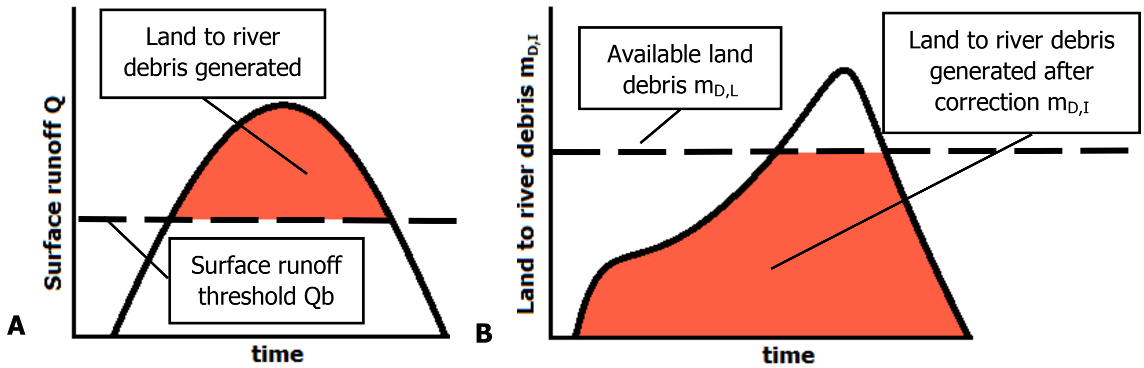

Fig. 38. Illustration of surface runoff threshold (A) and land debris available for land to river (B).

4.1.2. Model augmentation using the missing factors

Armitage et al. (1998) [47] presented an alternative set of steady state equations and in contrast to Wan et al. considered both street sweeping and ADD. The estimation method consists of a fixed debris loading rate and a variable debris loading rate to account for precipitation events. Equation 12 below calculates the fixed debris load in the waterways:

$$T = \sum f_{sci} \cdot (V_i + B_i) \cdot A_i \quad (12)$$

T = total debris load in the waterways [m^3/year]

f_{sci} = street cleaning factor for each land use [N/A]

V_i =vegetation load for each land use [m^3/m^2/year]

B_i = basic debris load for each land use [m^3/m^2/year]

A_i = area of each land use [m^2]

A range of possible annual values for different quality of cleaning services, different vegetation densities and different land use (like commercial, residential, industrial) respectively is given by Marais et al. (2004) [66]. Land use factors will be dependent on local mentality, availability of public waste bins, population density, local income, etc. Poor people will for instance be less likely to be concerned with litter disposal than rich people. The multitude of factors involved is adding to the complexity of defining these values and hence this geo dependency inherently means local surveys are necessary to acquire the local debris loading rates. In addition a variable storm load calculation is proposed to account for precipitation and resulting surface runoff [47]:

$$S = f_s \cdot \frac{T}{\sum f_s} \quad (13)$$

S = storm load in the waterways [m^3/storm]

f_s = storm factor

T = total debris load in the waterways [m^3/year]

$\sum f_s$ = sum of all the storm factors for all of the storms in the year

Storm factors account for the numbers of ADD. In conclusion, Armitage et al. gives a simple analytical method and includes ADD and street sweeping, Wan et al. however uses a more detailed model which also includes mismanaged landfills which means none of both method is clearly preferential. Adapting the Wan et al. method to account for ADD and street sweeping seems the best option to achieve the most accurate estimates.

Wind has not been accounted for in previous estimation methods although as argued in subsection 3.2 wind could also be a contributing factor for fluctuations in land to river inputs, especially in the dry months [45]. Wind inputs can be calculated largely in a similar way as rain. Likewise, one would expect a threshold value for transporting mismanaged debris and creation of additional debris. In addition however, wind is able to generate additional debris on land since strong winds can detach previously fixed items or move items from places where they would have been removed (like from outdoor furniture). Equation 10 previously defined for the calculation of land debris can be modified by adding wind generated debris and debris removed by wind runoff which is illustrated in figure 39. The modified equation, equation 14, can be found on the next page.

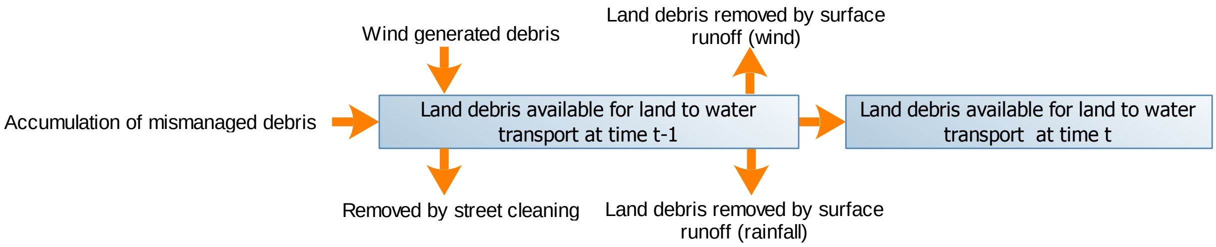

Fig. 39. Flow model to determine land debris available for land to water transport at time t, including wind.

$$m_{D,A}(t) = m_{D,G}(t) + m_{D,WG}(t) + m_{D,A}(t-1) - m_{D,W}(t-1) - m_{D,S}(t-1) - m_{D,R}(t-1) \quad (14)$$

$m_{D,WG}(t)$ = Daily generated anthropogenic debris by wind [kg]

$m_{D,W}(t-1)$ = Daily quantity of debris removed by wind runoff on the previous time step, e.g. day [kg]

Unfortunately as previously discussed in 3.2 research is extremely scarce w.r.t. to these processes. Modelling runoff could be performed using a CFD modelling program, e.g. Airflow Analysis, which requires data on local topography [107]. Such data can be obtained using airborne LIDAR data [107]. Unfortunately this type of computation is extremely computation intensive which makes sub daily or even sub hour calculations practically infeasible [107]. Therefore analytical approximations are perhaps more appropriate despite having a large discrepancy with the real values. This will be worked out in section 5, discussing detailed model design.

Seasonal effects of tourism can simply be accounted for by a factor. This is possible by adjusting P in equation 9 to account for the additional outdoor activity and tourists. For events roughly the same applies although events in general tend to generate more litter per person due to the large consumption of single use food packaging, plates, cutlery, cups, etc. which means an additional factor would be appropriate. One needs to take special consideration for weather conditions during the events since generally (depending on the type of event and location like country) event grounds are well cleaned after the event is finished.

Urban development is a slowly changing factor. This can be accounted for by adjusting P. Vegetation developments need to be monitored. This may require updates on vegetation coverage which can be obtained using airborne sensing like LIDAR. Shifts in public mentality can be measured in different ways. Quantified data could be retrieved, such as plastic production and the consumption of certain (single use) products, like cutlery and plastic bags. Furthermore, data from street cleaning and the number of dump sites encountered could provide insights on incorrect littering behavior and changing attitudes.

4.2. River propagation modelling

River propagation models for debris have been developed for both macro debris, Balas et al. (2001) [77] and micro debris, Kooi et al. (2018) [73].[14] An overview is presented in table 10 and 11.

[14] For an (exhaustive) overview of debris size classification, check appendix D.2.

Table 10. Overview of relevant river propagation models according to the categories specified in figure 34, part 1.

	Time	Space	Debris
Balas et al. (2001) [77]	Dynamic, 3 hour window simulated	Specific locations not considered, ≈2.2 km stretch of river	Plastic macro debris: LDPE sheets of 0.2x0.2 m
Nizzetto et al. (2016) [100]	Dynamic, daily	Specific locations not considered, Thames river catchment, >100km	Non buoyant Micro plastics, 0.005-0.5 mm
Tol (2016) [23][15]	Dynamic, daily	Specific locations considered, ≈13 km stretch of river	Macro debris, buoyant
Lammerts (2016) [24][16]	Dynamic, 7.5 seconds	Specific locations considered, ≈14 km stretch of river	Macro debris, in the top 1 meter of water
Siegfried et al. (2016) [103]	Steady state	Specific locations not considered, river length from rivers in Europe and North Africa	Micro plastic
Besseling et al. (2017) [104]	Dynamic, 36 seconds	Specific locations not considered, 40 km river stretch, divided in stretches of about 88 meter.	Nano and micro plastics 100 nm to 10 mm

Table 11. Overview of relevant river propagation models according to the categories specified in figure 34, part 2.

	River propagation considered specifically?	Factor	Modelling approach
Balas et al. (2001) [77]	Yes	Advection, Stranding along reaches, hotspots and vegetation	Empirical, stochastic
Nizzetto et al. (2016) [100]	Yes	Advection, settling and resuspension	Analytical
Tol (2016) [23]	Yes	River flow, wind, port compartments	Analytical
Lammerts (2016) [24]	Yes	Wind, river flow, tides, port compartments	Hydrodynamic, Numerical
Siegfried et al. (2016) [103]	Yes	Water abstraction, general retention	Analytical
Besseling et al. (2017) [104]	Yes	Advection, dispersion, biofouling, aggregation, degradation, settling, resuspension, burial	Hydrodynamic, Numerical

The simplest model from the overview above, Siegfried et al. (2016), assumes a simple estimation method which calculates river outputs using distance dependent retention factors and removal factors by water consumption. Additionally, two spatiotemporally explicit models are included which also take into account hydrodynamic processes. Many processes relevant for micro debris propagation however, as modeled by Besseling et al. (2017) [104], are very different from those for macro debris, e.g. biofouling, aggregation, settling and burial. The basic general transport models are nonetheless very similar. This is illustrated by equation 15, defined by Nizzetto et al. (2016) [100], which calculates the quantity of suspended micro particles and equation 16 which is a macro debris interpretation of equation

[15] In this overview, only the river propagation modelling through the port was considered. For debris propagation along the river towards the Port, see table 8 in subsection 4.1, since debris transport towards the port and river inputs were lumped together.
[16] See above.

15. Many micro debris specific processes were not included by Nizzetto et al., the level of detail being less compared to Besseling et al. which makes a comparison with macro debris more tractable.

$$\frac{dMP_{SUS}}{dt} = m_{eff} + \sum_{u}(A \cdot m_{OUT}) + L \cdot W \cdot (m_{ent} - m_{dep}) + m_{up} - m_{down} \quad (15)$$

$$\frac{dFD}{dt} = m_{ps} + \sum_{b}(m_{surf}) + L \cdot (m_{ent} - m_{ret}) + m_{up} - m_{down} \quad (16)$$

FD = Floating debris in river section [kg]

m_{ps} = Litter discharge from point sources along the reach [kg/s]

m_{surf} = surface runoff (wind and rain) from each adjacent basin b [kg/s]

m_{ent} = Entrainment of litter from reaches by river flow per reach length L [kg/m/s]

m_{ret} = Retention of litter by reaches per reach length L [kg/m/s]

m_{up} = Litter entering from upstream [kg/s]

m_{down} = Litter exiting downstream [kg/s]

m_{ps} and m_{surf} are output data from the land to river debris model, i.e. the river input model, whereas m_{up} and m_{down} are determined by advection rates at the start and end of the river section. What remains are entrainment and retention flows. Entrainment is mainly depended on the river flow rate as discussed in subsection 3.3, more specifically stage (gage height of water surface) and flow velocity. Logically, the quantity of debris retained is also relevant.

Retention, as discussed in subsection 3.3, is dependent on reach characteristics, watercourse obstructions, flow rate, wind induced displacement and river morphology which influences river hydrodynamics. Important hydrodynamic events which can influence lateral surface displacement are confluence of tributaries, watercourse obstructions and river bends [87] as discussed in subsection 4.3.3. In general all of these above hydrodynamic events above are complex, hence requiring intensive numerical modelling and more work is necessary on the integration of spatial and temporal scales of turbulent flows [87].

Some limited analytical methods exist however [108]. For instance on the lateral mixing of rivers. As visualized in figure 40 three types of transport phenomena in rivers can be identified: advection, turbulent diffusion, dispersion. Advection is transport due to bulk flow. Turbulent diffusion is due to turbulent motion and can for instance be created by ships, watercourse obstacles and river confluence as described above. Dispersion is displacement due to a non-uniform velocity profile in rivers, as visualized in figure 31 of subsection 3.3.4, which occurs due to shear with the riverbanks. It is a

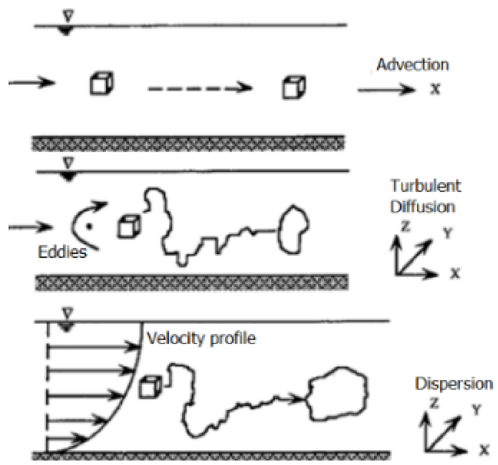

Fig. 40. Transport phenomena in rivers [108].

combined effect of advection and lateral diffusion. Estimations concerning lateral movements could be for instance deduced from lateral mixing.

The length L_m required for full mixing of a substance released in a river can be calculated with the following analytical equation [108]:

$$L_m = k\frac{U \cdot W^2}{N_y} \quad (17)$$

k = coefficient for entering point (side: 0.4, center: 0.1)

U = Mean velocity [m/s]

W = Mean channel width [m]

N_y = Transverse mixing coefficient [m^2/s]

Where N_y is defined as:

$$N_y = C_m \cdot Y \cdot u_* \quad (18)$$

C_m = dimensionless coefficient, typically 0.6 for slowly meandering natural channels, ±50%

Y = mean depth [m]

u_* = Shear velocity [m/s]

With u_* defined as:

$$u_*^2 = g \cdot Y \cdot S_o \quad (19)$$

g = gravitational constant [m/s^2]

S_o = bottom slope [m/m]

The main issue with these analytical calculations are the uncertainties concerning the dimensionless transverse mixing coefficient C_m and the bottom slope [89] [109]. Alternative proposals include the Manning roughness coefficient which estimation is also challenging [89].

Since analytical and numerical models of river hydrodynamics have their limitations and complexities, an alternative method to model propagation is to use empirically based statistical models. Balas et al. (2001) [77] developed a statistical riverine propagation model for the river Taff and looked specifically at stranding of macro debris, i.e. retention. The authors used discrete probability distributions like the Poisson, Geometric and Binomial distribution to model similar reach sections and vegetation. The monitoring study by Williams and Simmons (1997) [74] was used to calibrate the results. Four separate reach characteristics were identified based on their vegetation densities and debris sorted and counted. Only plastic sheeting was further considered as a category to calibrate since data pertaining river movements for different flow conditions was only available for plastic sheeting. The downside of this approach is that one preferably needs to do this type of calibration for each litter category since each category may have different movement patterns as shown in subsection 6.4. It is also important to identify relevant hotspots as demonstrated by Jang et al. (2014) [75] for the Nakdong river. Movement patterns for large rivers like the Nakdong will be less disturbed by vegetation compared to small rivers like the Taff. Hence hotspots likely play a more important role. Balas et al. did not account for wind induced movements since the river was small and well shielded by vegetation, however in large rivers these should certainly be included. Optionally, static debris removal operations can be included as retention. In this case these can be modelled as hotspots with probability of 1 of retention and probability 0 of entrainment.

4.3. Summary

Accumulation of debris from land to a downstream section of a river can be modelled using two separate sub models: a river input model (land to river) and a river propagation model. Estimation models exist for both micro and macro debris and can be divided into spatiotemporally explicit and steady state models. For the application envisioned in this report a spatiotemporally explicit is desired to observe fluctuations in time and space. Another feature is the number of sources considered by the models, many models consider for instance only one source. In this section two of the most promising existent models were presented for river inputs, namely Wan et al. (2018) and Armitage et al. (1998). Armitage is more inclusive since it incorporates ADD and street sweeping while Wan et al. uses a highly detailed river surface runoff model. To improve these models both can been combined. This can been achieved by augmenting the model of Wan with ADD and street sweeping. In addition, a solution has been proposed to include the following missing factors, as mentioned in section 3: wind runoff, urban development, events and tourism/temperature. For river propagation a statistical model can be used as developed by Balas et al. (2001). To complement that model, hotspots can be identified and wind can be modelled using windage factors. A detailed model will be worked out in the next section.

5. Model design

The previous section reviewed existing models of land to river inputs and river propagation and suggested improvements. In this section these improvements will be worked out in detail so it can be directly implemented into a coding language. The goal is to design a generic model which is able to predict anthropogenic and natural debris outputs downstream of rivers. Subsection 5.1 will discuss the modelling approach and specify the various model objectives, requirements and specifications. Next, subsection 5.2 and 5.3 will elucidate both parts of the main model, i.e. the design of the land to river input model and the river propagation model. Finally, the section is summarized in subsection 5.4.

5.1 Modelling approach

It is important to establish a design approach to guide the modelling process. Hence, a modelling framework is proposed, based on the waterfall model[17], which means it is generally a linear design process although iteration may be required. A simplified overview of the modelling approach without iterations is outlined in figure 41.

The first step sets the objective for the model. This objective depends on the implementation the model is aimed to fulfill and which goal is aimed for, i.e. the objective depends on the final user. The output of the model should also be specified. The objectives are high level and can as such be stated more vaguely while the requirements in contrast are more concrete, detailed elements to be included in the design. The requirements follow from the analysis of the literature as performed in section 3 and 4. In the design phase the actual prediction model is build. After the model has been worked out on paper, it should be coded before proceeding to the next steps. The verification phase takes place to ensure the design works as intended after which the model can be trained using a historical datasets of weather and debris accumulation, which represent the inputs and the outputs of the model. Training the model will calibrate all unknown model parameters. Once the model is trained, the model can enter the validation process where the performance of the model is measured. In order to test the added value of the most complex model, stripped down versions of this model will be included. Validating multiple versions should demonstrate the value of the various factors being implemented in the model. This is crucial since stripped down versions will have less inputs and are therefore easier to implement and are hence more widely applicable. The interpretation of the validation results depends however on the size and quality of the dataset

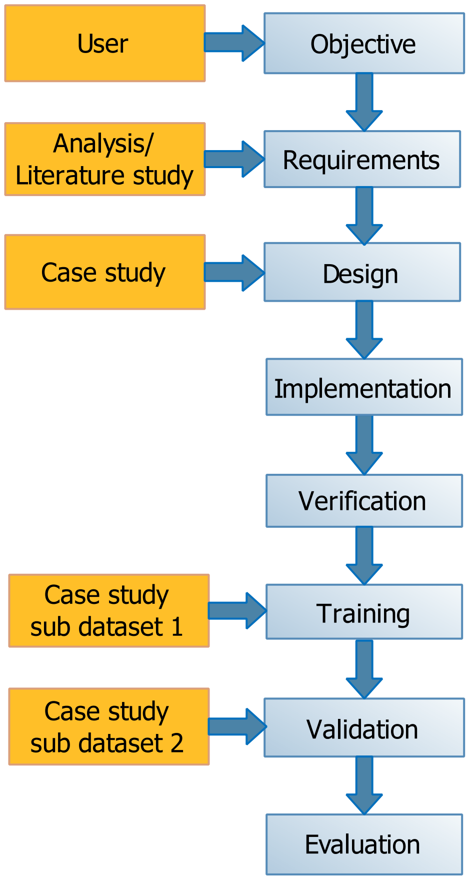

Fig. 41. The Modelling approach.

[17] An illustration of the modelling approach in waterfall style can be found in appendix J.

and the specific location of the dataset in general. This should be carefully assessed during the evaluation, where the validation results are evaluated.

Some steps will need external data/information. These external sources are highlighted in figure 55 by the yellow boxes. The objective depends on the user, the requirements are based on the analysis/literature study, the design phase depends on the case study and finally, the training and validation of the model is performed use the case study sub datasets.

5.1.1. Model objectives

The high level objectives of the model is to make a contribution to the prevention of accumulation of debris in marine ecosystems and to contribute to a reduction of debris present at any time in the port/bay area located downstream. Every actor involved in debris removal, to which any of the above objectives applies, can be called a user. Several actors are involved in debris removal, each with different main concerns, debris of interest, geographical focus and objectives. An overview can be found in table 12.

Table 12. User profiles of each actor involved in debris contamination.

	City harbor operator	**Nautical port operator**
Main concern:	Decreased aesthetic appeal	Damage to nautical traffic
Debris of interest:	Any visible debris, i.e. macro debris, natural and anthropogenic.	Any type, sizes prone to nautical traffic related damage, i.e. macro debris, natural and anthropogenic.
Geographical focus:	Respective harbor only	Respective port only
Main objective:	Minimizing debris in harbor leading to decreasing aesthetic value of harbor.	Minimizing debris in the harbor prone to cause damage to shipping vessels.
	Political authorities (i.e. national, provincial, municipal)	**Research groups and academics**
Main concern:	Economy and wellbeing of own citizens	Health and safety impact on Flora and Fauna, incl. humans.
Debris of interest:	Visible and debris, proven to inflict damage.	Anthropogenic debris high in abundance and risk.
Geographical focus:	Local, national or regional	National, regional or global
Main objective:	Minimizing presence of visible debris and minimizing presence and outflow of debris which has proved to inflict damage.	Minimizing outflow of debris to the marine ecosystem, known or suspected to be a danger to the health of flora and fauna, incl. humans.

Note that research groups and academics are not the operator or initiator of debris removal operations but may act as a lobby group to pressure and/or inform authorities. Even though these actors have dissimilar main objectives, they might share concerns as underlying motives or arguments to take action, hence creating secondary objectives. A port operator might very well feel he could contribute to a better environment, if not out of pure environmental friendliness perhaps at least to promote a green image of his port.

Each of the users described above (research groups and academics indirectly) are a potential user for the model and the model should be made to fit their needs. Users and applications can be from anywhere around the globe. The model is hence a general model, not custom build to a case. In order to make the model attractive and useful to the user several objectives can be added:

- The model should be practical to implement for a user.
- It should include the relevant factors, affecting land to river debris input and river propagation as discussed in the literature study.
- The model should have enough detail to make a relevant impact, i.e. improve on the situation without a model.
- The model design should be covered within a tractable timespan, i.e. within the context of this study.

The user of the model is assumed to be able to access data from the available weather stations and weather predictions, which can be used as an input to the model. The model should be simple to use and implement but inclusive. The relevant factors influencing debris accumulation should hence be included but the model should not be too computationally intensive and not require the need of expensive complex computer modelling. The initial design will therefore be analytical. Such a design would also benefit the last objective. A simple design may however conflict with the third objective. This can be evaluated during the validation stage of the modelling process. It might indeed be worth to include complex modelling such as the inclusion of hydrologic computer models by Wan et al. (2018), especially for rivers with larger debris accumulation and/or river basins with a mountainous surface topography. Depending on the application, certain data, such as soil and land use data might be hard to obtain or simply too intractable in terms of the sheer amount of data required. Hence, stripped down versions of the model will be tested as well.

The final model should output a quantity of debris, either mass or volume, arriving over a certain time window at a predefined section of the river. Removing debris in/after the most downstream cross section is obvious in many cases but in theory debris could be removed anywhere along the river. The unit for the quantity of debris and the length of the time window will follow Wan et al. (2018), i.e. mass and day respectively.

5.1.2. Model requirements

The model should calculate:

- the quantity of available anthropogenic and natural debris in a specific area, based on:
  - The number of inhabitants;
  - Season (tourism/seasonal shedding/outdoor presence of inhabitants);
  - The mass of mismanaged debris per person;

    - Wind force (wind generated debris).
- The mass of land to river inputs at a specific point along the river, based on:
    - The available anthropogenic and natural debris in a specific area;
    - Surface runoff from rainfall;
    - The number of antecedent dry days;
    - Surface runoff from wind;
    - Street cleaning.
- Calculate the mass of debris arriving over a day at the most downstream cross section of the river, based on:
    - The mass of land to river inputs at a specific point along the river
    - Retention of debris along river and reaches, based on:
        - River flow;
        - Hotspots;
        - Wind force and direction;
        - Passive removal devices placed along the river.
    - Entrainment of debris from reaches, based on:
        - River flow;
        - Hotspots.

5.1.3. Model design specifications

The following should be specified for the model:

- Input variables (IV). The input variables are values related to the factors described in section 4 and need regular updating. The timespan at which each input variable should be updated can differ. IV require the following specifications:
    - Units;
    - Domain;
    - Update scheme: Timespan between refreshing the input data.
- Configuration parameters (CP). The configuration of the model requires data on the specified river and its catchment area, as such the configuration parameters define the geographic region. Parameters are related to land and fluvial geometry and topography but also to natural and anthropogenic features and activities present in the area. CP can be completely undefined or can be predefined as a list of optional values. This data needs to be entered by the user once, although revision may be necessary on the longer term, e.g. on a biennial basis. CP require the following specifications:
    - Units;
    - Domain;
    - If applicable, update scheme: timespan between refreshing the configuration of parameters.

- Fixed parameters (FP). Fixed parameters are parameters which are predefined, i.e. they cannot be configured by the user. As such these are not updated, unless with new versions of the model. FP require the following specifications:
    - Units;
    - Domain.
- Internal variables (INT). Internal variables are relevant for internal calculations and are not visible to the user. Internal variables are dependent variables and depend on IV, CP, FP and/or other INT. Their update scheme and unit depends on these variables/parameters. The domain however can be predefined. Hence, INT require the following specification:
    - Domain.
- Output variables (OV). One or multiple output variables can be assigned to a model. These output variable are presented to the user. Since there are two sub models in series, the output of the first is will become input for the second model. The output of the second sub model is also the output of the total model. Outputs require the following specifications:
    - Units;
    - Domain;
    - Update scheme: Timespan in between updates.
- Model description. This is the actual model and includes the formulas, links, etc. which connect the inputs to the outputs. The model descriptions requires the following specifications:
    - Assumptions.

5.2. River input model

As concluded in section 4, the river input model will replicate the main structure of the model from Wan et al. (2018) [29] although modifications are necessary. Like the model described by Wan et al. the main structure of this model will have two branches. One branch calculates the available debris which are available for land to river inputs while the second branch calculates the inputs from land to river under the assumption that the available quantity of debris is limitless. An outline of the model is given in figure 42.

The presented model in this section is fairly detailed. As mentioned earlier, a simplified model might be a necessity depending on the case. The added value of the additional complexity will be tested in the validation phase.

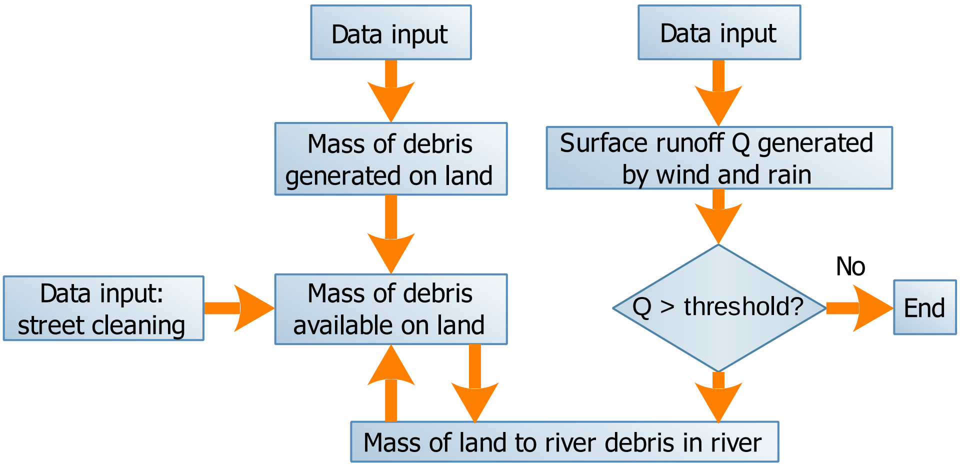

Fig. 42. Outline of the land to river input model.

5.2.1. Quantity of mismanaged anthropogenic debris generated

The following equation gives the daily mass of anthropogenic debris generated on land $m_{AD,G}$ [kg]:

$$m_{AD,G} = \frac{r}{100} \cdot G \cdot Pop \cdot SF \cdot \Delta t \quad (20)$$

This calculation is necessary to calculate an upper bound for the mass of generated anthropogenic debris available for land to river transport. r, the percentage of mismanaged debris, is a configuration parameter although it needs to be closely monitored. Especially governmental policy and legislation can have a major impact over a short time period. Recently the Waterfront Partnership in Baltimore used data from removal operations to support the ban on Styrofoam containers [110], a major category of debris in the Jones Falls River, traversing Baltimore[18]. Infrastructure improvements, like improved storm drains, can have a large effect on the quantity of debris observed in the river although such improvements take more time be implemented. Values for r can be obtained from Jambeck et al. (2015) [10].

G, the quantity of waste generated per person per time unit, is a configuration parameter since it can be assumed this will only gradually change. The configuration parameter Pop is the population in a respective area. Since urban development is accounted for by Pop , it needs to be updated about every few years, the frequency of updating largely depending on the demographic changes in the specific area. An important consideration is the width of the river bank considered. This depends on local topography and the local storm drain system. The seasonal factor SF has not been included by Wan et al. The input variable SF has been included to account for tourism and the outdoor presence of the local population which may differ with different seasons. Tourism affects population size whereas outdoor presence increases littering. Whether this factor is relevant is largely dependent on the geographical area. The time interval Δt is largely determined by the desired output interval and the interval at which other input variables can and need to be updated. An obvious time interval could be a 24 hour time

[18] See appendix F for data on common debris removed in Baltimore.

interval. The time interval is a configuration parameter. An overview of the aforementioned variables and parameters is listed in table 13.

Table 13. Description of variables and parameters used in equation 20.

	Description	Unit	Domain	Type	Update scheme
r	Percentage of mismanaged debris	[%]	0-100	CP	Once every few years
SF	Seasonal factor, accounts for differences in tourism and outdoor presence of population	-	≥1	IV	Twice, sometimes a few times a year
G	Waste generation rate	[kg/person/day]	≥0	CP	Once every few years
Pop	Population size along the river banks	[persons]	≥0	CP	Once every few years
Δt	Time interval	[day]	1	CP	Never, unless desired
$m_{AD,G}$	Anthrop. debris generated on land	[kg]	≥0	INT	-

5.2.2. Available anthropogenic debris generated by wind

Not included in equation 20 is wind generated debris. At regular wind speeds (<14m/s, <7 Beaufort) this is likely not playing any role of significance but it might certainly do so during storm conditions (>25m/s, >9 Beaufort) as becomes evident from the overview of damage characterizations at different wind speeds [111]. In severe storms, flying objects transported by wind may add additional risk of creating additional debris upon impact [112]. Estimation models of generated debris exist but have only been found for hurricane strength storms.

The U.S. Army Corps of Engineers (USACE) Emergency Management staff has suggested the following equation for urban areas [113]:

$$Q = H \cdot C \cdot V \cdot B \cdot S \quad (21)$$

Q = Quantity of debris generated in an area [m^3]

H = Number of households

C = storm factor, accounts for wind speeds [m^3]

V = vegetation multiplier

B = commercial/business/industrial multiplier

S = Precipitation multiplier

There are some downsides however to this formula. This formula may work for large urban areas which includes a large portion of households. To investigate smaller areas which are generally or totally commercial/business/industrial however, this formula will not work very well, at least with the multipliers given in the document. The factors proposed for C, V, B and S where based on empirical data from historic storm events with hurricane strength. In order to extrapolate the data one has to assume the data patterns continue at sub hurricane wind speeds. Due to the lack of other data sources it is assumed one can extrapolate data patterns into sub hurricane strengths.

Figure 43 shows the storm factors C plotted for 5 different hurricane strengths. These 5 storm factors were divided over two data sets since it was hard to fit a trend line to a single data set.

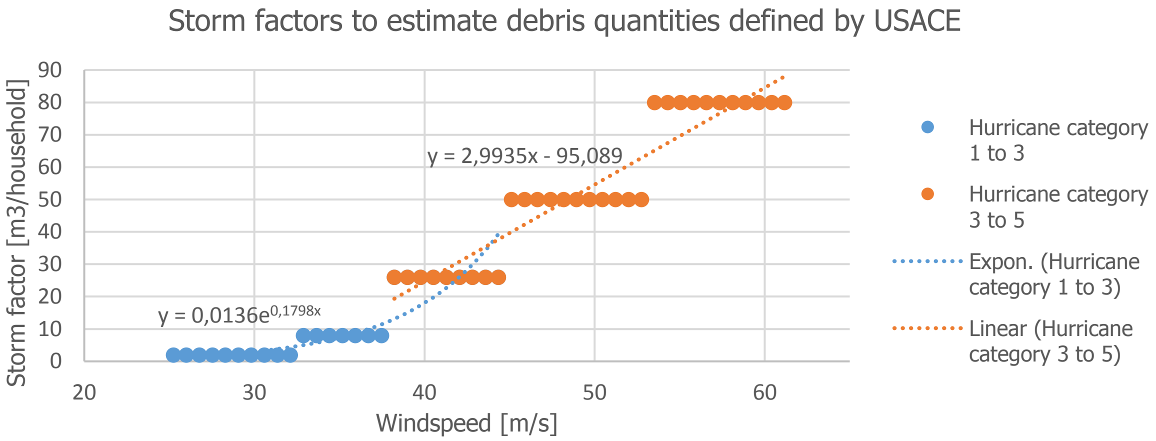

Fig. 43 Storm factors to estimate debris quantities as defined by USACE [113] with fitted trend lines.

Using the exponential equation to extrapolate to lower wind speeds however gives unreasonable high estimates. A storm event of 10 m/s (5 Beaufort) in an area of almost 40,000 households (100,000 people divided by 2.6 persons per household) would generate more than 3000 m^3, which would be more than the quantity of debris collected by the Harbor Wheel (see Appendix F) in 48 months. It was also be at least 1000 times the quantity of debris calculated by equation 20 using US data from Jambeck et al. (2015) [10]. This approach is hence abandoned. Without other data sources, the remaining solution is to compare the outputs of the river accumulation model with actual accumulation data using meteorological data and conclude whether adjustments during wind events are necessary. To account for wind generated debris a factor W_A could be added to equation 20:

$$m_{AD,G} = r \cdot G \cdot Pop \cdot SF \cdot W_A \cdot \Delta t \quad (22)$$

A description of W_A can be found in table 14.

Table 14. Description of additional variables and parameters used in equation 22.

	Description	Unit	Domain	Type	Update scheme
W_A	Wind factor	-	≥1	IV	Every time interval Δt defined in table 13

5.2.3. Available land to river debris, natural debris

Vegetation load was not considered by Wan et al. The presence of natural debris depends on the amount and type of vegetation along the river banks, the occurrence of seasonal shedding and heavy wind events which can generate additional debris. Obtaining the necessary data to calculate the available natural debris in the same way as anthropogenic debris is significantly more tedious than anthropogenic debris however. This is because littering not only varies with species but also with meteorological conditions, altitude, stand age and site quality [114]. As such, surveys from certain sites cannot be readily translated to other areas [114] and large annual variations can be observed for the same tree and site [115]. As study into wind generated forest debris during storm conditions also reveals the complexity of factors contributing to debris production. Tree and stand characteristics appear to be the best predictors, above sustained wind speed [116]. For this reason, a preferred alternative is likely to use historic data on natural litter accumulation.

$$m_{ND,G} = N \cdot SS \cdot W_N \cdot \Delta t \quad (23)$$

A description of variables and parameters used in equation 23 can be found in table 15.

Table 15. Description of variables and parameters used in equation 23.

	Description	Unit	Domain	Type	Update scheme
$\boldsymbol{N}$	Baseload natural debris	[kg/day]	≥0	CP	Every few years
$\boldsymbol{SS}$	Seasonal (shedding) factor	-	≥1	IV	Twice, sometimes a few times a year
$\boldsymbol{W_N}$	Wind factor	-	≥1	IV	Every time interval Δt
$\boldsymbol{m_{ND,G}}$	Quantity of natural debris generated on land	[kg]	≥0	INT	-

5.2.4. Calculating the quantity of total available debris

Following the calculation of the quantity of generated debris follows the calculation of the quantity of anthropogenic debris available for day t:

$$m_{D,A}(t) = m_{AD,G}(t) + m_{D,A}(t-1) - m_{D,P}(t-1) - m_{D,W}(t-1) - m_{D,R}(t-1) \quad (24)$$

$m_{AD,G}(t)$ = Daily generated anthropogenic debris as calculated in equation 30 [kg]

$m_{D,R}(t-1)$ = Quantity of litter removed (by sweeping or other cleaning methods) on the previous day [kg]

$m_{D,P}(t-1)$ = Quantity of debris removed by precipitation on the previous day [kg]

$m_{D,W}(t-1)$ = Quantity of debris removed by wind on the previous day [kg]

$m_{D,A}(t)$ = Quantity of debris present at day t [kg]

$m_{D,A}(t-1)$ = Quantity of debris present at start of the previous day [kg]

This formula accounts for antecedent dry days by including historic surface runoff from rainfall. Wind runoff and sweeping has also been included. The calculation of debris inputs from wind is described in 5.2.7, whereas the calculation of rainfall from surface runoff is described in 5.2.5 and 5.2.6 respectively. Data on sweeping quantities and sweeping schedules has to be provided by local authorities so it can estimated how much and when litter is removed from the streets. This process is visualized in figure 44.

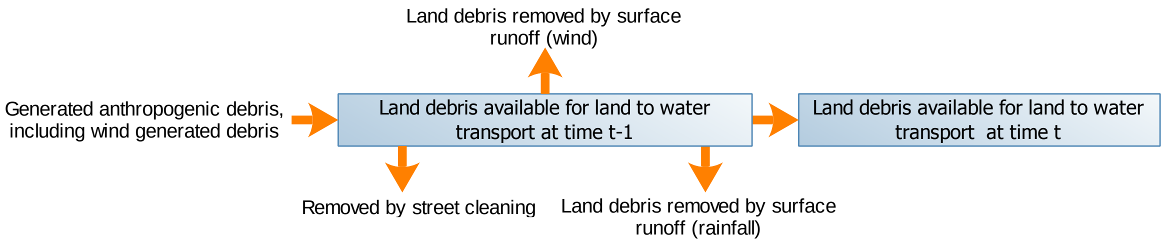

Fig. 44. Flow model to determine land debris available for land to water transport at time t.

A description of variables and parameters used in equation 24 can be found in table 16.

Table 16. Description of variables and parameters used in equation 24.

	Description	Unit	Domain	Type	Update scheme
$m_{D,A}$	Debris available for land to water inputs	[kg]	≥0	INT	-
$m_{D,P}$	Land debris removed by surface Runoff from precipitation	[kg]	≥0	INT	-
$m_{D,R}$	Daily quantity of debris removed, by sweeping or other methods	[kg]	≥0	CP	Never, unless updated data is available
$m_{D,W}$	Land debris removed by surface Runoff from wind	[kg]	≥0	INT	-

5.2.5. Calculating river inputs from rainfall surface runoff

Surface runoff from precipitation can be calculated using weather stations. The density of weather stations varies from region to region, largely according to population density but also according to local GDP as richer regions are likely better equipped. Data from available weather stations should henceforth be interpolated over the available watersheds. To obtain a grid of reliable rainfall data points may be challenging however, as brought forward in the previous section, due to the large fluctuations in the precipitation fields [106] but the only solution without increasing the number of rain gauges or using remote sensing data. The latter method however is more suitable for mean values and fails to cope with rainfall extremes [106]. Therefore, interpolation will be used using the available rain gauges. Various methods can be used to do this: Nearest neighbor (NN), Spline, Thiessen Polygon (TP), Inverse Distance Weighted Interpolation (IDW) and Kriging [117] [118]. Their performance depends on various factors, such as rainfall intensity [117]. Among NN, TP, IDW and Kriging, Meiling et al. (2017) [117] found the best performance for NN during low rainfall events. The other methods in contrast performed better during high rainfall events which is not surprising since NN is almost by definition very sensitive to outliers. Overall there was not much difference between TP, IDW and Kriging as methods performed slightly better or worse depending on the error metric used. Keblouti et al. (2012) [118] assessed the performance of Spline, IDW and kriging and found IDW to perform best with IDW scoring a 6.9% mean error with a 4.9% standard deviation. It should be noted that both studies were performed over a large area, 1429 m^2 and 5173 m^2 respectively, with only 10 and 15 rain gauges respectively. Based on the results from these studies it is assumed that IDW and NN can be used with sufficient reliability. It is noteworthy however that IDW, although to a less extent than NN, may be sensitive to outliers. Moreover, the distribution of rain gauges is also important to consider as it generally preferred to have a more evenly distributed grid of measurements instead of clustered pairs spaced distant from each other.

The NN method looks for each previously undefined data point on the grid which measurement is closest, in this case in Euclidean space, and simply copies that measurement. The IDW method calculates a spatial average from available measurements. Close measurements get a higher weight than distant measurements. As such a weighted average is defined:

$$z_p = \frac{\sum_{i=1}^{n} z_i \cdot d_i^{-p}}{\sum_{i=1}^{n} d_i^{-p}} \quad (25)$$

z_p = value of predicted point calculated with power function p

z_i = value of measured point i

d_i = distance between measured point i and predicted point

p = power parameter

n = number of measurement points

To be able to calculate z_p a number of specifications are necessary. Firstly, the power parameter p should be defined. P defines the degree to which closer measurement points are given more weight with respect to more distant measurement points. IDW with p → ∞ equals NN. The second specifications defines which measurements are used. There are two extremes: fixed search radius and fixed number of measurements. A combination could also be used. For instance if the number of measurements are fixed as long as the search radius does not exceed a certain threshold. Meiling et al. (2017) used a fixed radius and a power parameter of 2 although the latter may depend on the topographic profile of an area [117].

Surface runoff from rainfall depends on population, soil characteristic, slope and land use within a sub watershed. Combining data on the latter three one can create areas of the similar soil characteristic, similar slope and similar land use. These areas are called hydrologic responds units (HRU) [29] and can be very small. Observing maps from the Jones Falls Watershed for instance in figure 45 this becomes immediately obvious as the spatial distributions of various land uses and soil groups are very heterogeneous. Each color represents a separate land use or soil group respectively. In order to keep the problem tractable one could decrease the number of categories, i.e. lump categories or lump the data over each sub watershed. If a high level of detail is desired it is recommended to use the SWAT model since this is specifically designed to perform this task.

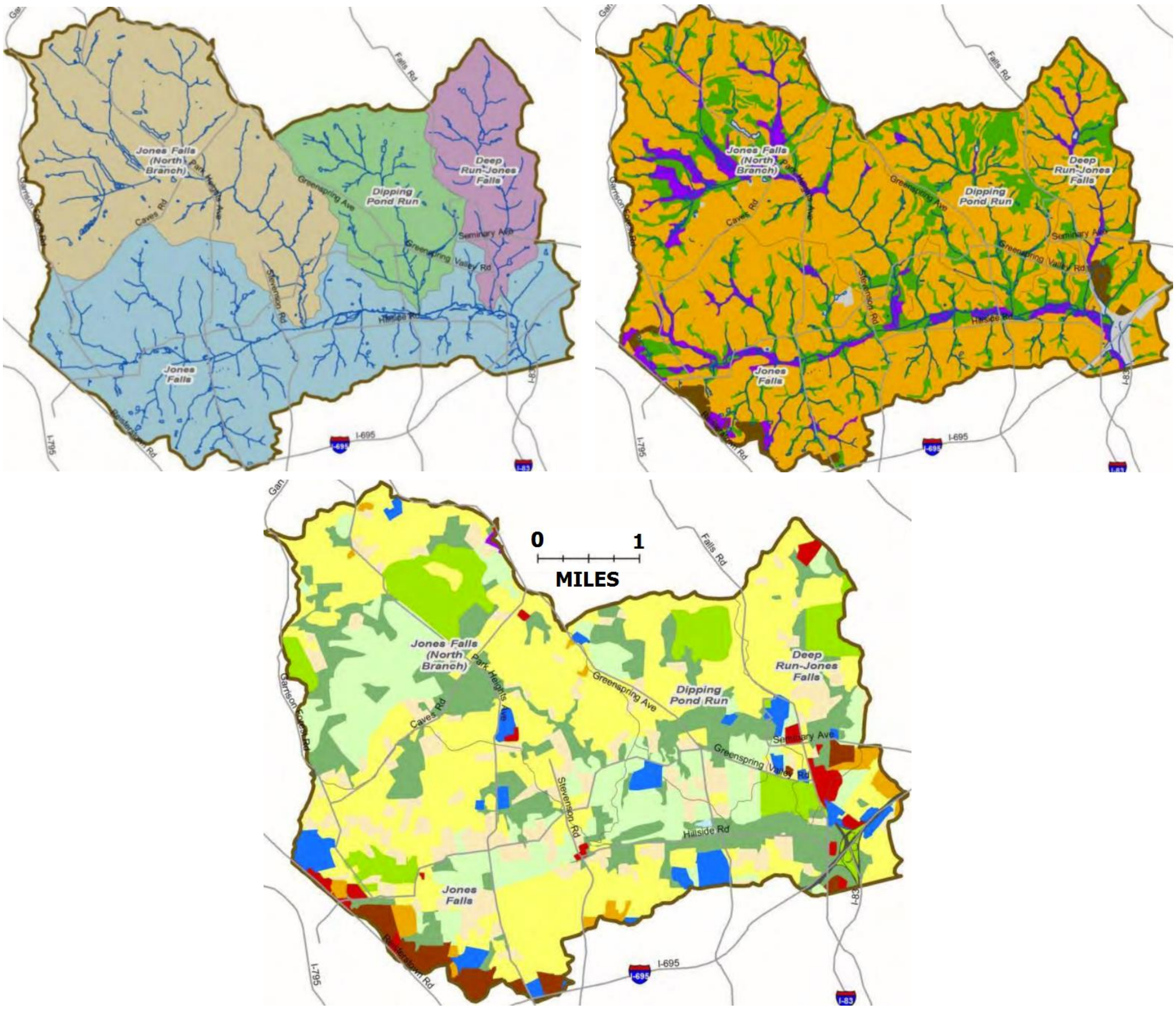

Fig. 45. The Upper section of the Jones Falls watershed with sub watersheds (top left), soil groups (to right) and land use (bottom) [119].

If lumped quantified data is available for each sub watershed as opposed to graphical/mapped data as shown in figure 45 and if spatial distribution of land use, slopes and soil characteristics is very heterogeneous, one could make the decision to use this lumped quantified data instead. In that case it is assumed that this will not generate significantly different results compared to evaluating each smallest possible HRU separately as done by default in SWAT. This assumption may significantly decrease the quality of the estimation but a more accurate method would be a very time consuming operation.

The calculation of rainfall induced land to river debris can now follow using equation 11 in subsection 4.1.1:

$$m_{D,P} = k_p(Q - Q_b)\Delta t \quad (26)$$

Note that this formula, in contrast to equation 11, does not sum over the number outlets. Instead, the land to river input will be calculated separately for each outlet first as the location of the outlet is relevant for the river transport model. An outlet is equal to the smallest HRU used. This can be a river section in a specific sub watershed. Inputs are then averaged over the river section. An overview of variables and parameters with description can be found in table 17.

Table 17. Description of variables and parameters used in equation 26.

	Description	Unit	Domain	Type	Update scheme
$\boldsymbol{k_p}$	Coefficient which relates surface runoff to debris inputs	[kg/m^3]	≥0	CP	Every few years
$\boldsymbol{Q}$	Surface runoff over smallest HRU/drainage area used	[m^3/day]	≥0	INT	-
$\boldsymbol{Q_b}$	Surface runoff threshold value	[m^3/day]	≥0	CP	Every few years

The configuration parameters k_p and Q_b depend on the amounts and composition of debris on land but also on land use and slope [29] and values can hence hardly be applied to other locations [29]. Wan et al. (2018) [29] has determined these values based on empirical observations in the same area as their prediction model was applied to. The established values for three regions differed quite a lot. The k values ranged between 0.67 and 2.71 kg/m^3. The Q_b values ranged between 4.78 and 24.02 m^3/s. A higher k_p value corresponded to a lower Q_b value which makes sense. More research is needed to create a database of k_p and Q_b which can be then be applied without the need for empirical testing for each new application. This is complicated however due to large quantity factors influencing these values. Not only land use and slope should be accounted for, but also the way storm water is handled and the quantity of debris present on the ground. Hence, currently, values have to be determined empirically. Once data on debris quantities is obtained, linear regression can be used using a two-step iterative process described as follows [29]:

'The procedures begin with setting an arbitrary value for Q_b and proceed through two-step iteration:

1. *The sum of squared deviations of input mass from the line mi=0 is calculated for data for $Q_i < Q_b$, and this sum is added to the sum of squared deviations of input mass from the least squares linear regression line, $k(Q - Q_b)\Delta t + \varepsilon$ (where Q_b is now fixed), then fitted to data for $Q_i \geq Q_b$.*
2. *The value of Q_b is increased by a small amount and step 1 is repeated.*

The iteration stops when the minimum sum of squared deviations is found. The corresponding values of k_p and Q_b are taken as the best estimates.'

5.2.6. Calculating surface runoff from precipitation

The surface runoff Q is not equal to the rainfall. The volume of water from precipitation is distributed over surface storage, infiltration and evapotranspiration[19]. In figure 14 in subsection 3.1.2 a set of example values were shown for a natural and urban environment. The different values represent the

[19] See appendix G for the hydrologic cycle

extent to which rainfall has an effect on generating land to river debris. More specific numbers for various types of soil and land use however exist.

A range of models exist to calculate surface runoff [120]:

- Lumped parameter models, e.g. curve number method and the rational method [121].
- Semi-distributed models, e.g. TOPMODEL and SWAT.
- Distributed models, e.g. MIKESHE, VELMA.

Each model has its own drawbacks and advantages. Lumped parameter models require less detailed input data, hence 'lumped'. Distributed are more complex, are data intense and computationally intensive. Semi-distributed models fall in between [120].

The NRCS (SCS) curve number method calculates an estimate for total runoff volume [121]. It is widely applied, as it is versatile and straightforward in its approach with a large database of empirical values which relates various soil types and land uses to surface runoff [122]. Nonetheless, it is not without limitations, as its discrete approach inherently leads to illogical jumps. The dependency of soil conditions on antecedent rainfall is also poorly described and discrete [122]. Moreover, one needs to consider its empirical origin meaning that certain parameters can be (slightly) different for certain areas. Adjustments have been suggested to adjust formulae and parameters but this generally complicates the model and these suggestions are based on empirical data which may not apply to all so these adjustments should considered carefully. Finally, the heterogeneous nature of the spatial distribution of precipitation should be considered. This can be a major contributor to deviations between the estimated and true surface runoff and also an important reason for differences in empirically obtained parameters and equations. It can be defined as follows [121]:

$$Q = \frac{A}{1000} \cdot \frac{(P - 0.2S)^2}{(P + 0.8S)} = \frac{A}{1000} \cdot \frac{(P - I_a)^2}{(P - I_a) + S} \quad for\ P > I_a \quad (27)$$

With I_a defined as follows [146]:

$$I_a = \lambda \cdot S \quad (28)$$

In equation 32 the initial abstraction $I_a = \lambda \cdot S$ with the initial abstraction ratio λ equal to 0.2, which is the number originally used after the development of this formula. Recent research however found lower estimates to be more appropriate with λ equal to 0.05 [123] [124] or even 0.01 [123]. According to Xiao et al. (2011), a dynamic ratio is likely better although it has been stressed that Q is more sensitive to S (defined by CN, see equation 32 below) than λ [125]. The same paper also listed λ values between 0.24 and 0.01 which were calculated as being optimal. Without any further evidence to support any of these values, it is hence assumed an initial abstraction ratio λ equal to 0.05 is appropriate for future calculations of runoff modelling. The potential maximum soil moisture retention S for metric units is defined as follows [121]:

$$S = \frac{25400}{CN} - 254 \quad (29)$$

A description of variables and parameters used in equations 27- 29 can be found in table 18.

Table 18 Description of variables and parameters used in equations 30 - 32.

	Description	Unit	Domain	Type	Update scheme
$\boldsymbol{A}$	Total land area of drainage area	[m^2]	≥0	CP	Never
$\boldsymbol{CN}$	Runoff coefficient	-	≥30 and ≤100	CP	Every few years
$\boldsymbol{I_a}$	Initial abstraction	[mm]	≥0 and <30	INT	-
$\boldsymbol{S}$	Potential maximum soil moisture retention after runoff begins	[mm]	≥0 and <593	INT	-
$\boldsymbol{P}$	Rainfall total	[mm]	≥0	IV	Every time interval Δt
$\boldsymbol{\lambda}$	Initial abstraction ratio	-	0.05	FP	-

CN depends on soil and land use combination but also on the antecedent moisture condition (AMC) which depends on antecedent rainfall and slope [126]. Other factors such as air temperature (which affects evaporation) are generally ignored. Three moisture conditions exist: AMCI (dry), AMCII (average) and AMCIII (wet). The category can be assigned using the 5 day antecedent precipitation P_5. A P_5 between 23 and 40 mm equals AMCII while more or less rainfall equals AMCIII and AMCI respectively [127]. CN factors are given for AMCII which can be converted into the other two. Hence, this procedure can defined as follows in mathematical formulation:

$$CN = \begin{cases} CN_I & P_5 < 23\ mm \\ CN_{II} & 23\ mm < P_5 < 40\ mm \\ CN_{III} & P_5 > 40\ mm \end{cases} \quad (30)$$

Multiple empirical formulae exist to achieve conversion from CN2 (belonging to AMCII) to CN1 and CN3 [126]. The performance of various formulae was tested by Mishra et al. (2008) [126] and although the difference in performance was not large, the following equations performed best:

$$CN_I = \frac{CN_{II}}{2.2754 - 0.012754 \cdot CN_{II}} \quad (31)$$

$$CN_{III} = \frac{CN_{II}}{0.430 + 0.0057 \cdot CN_{II}} \quad (32)$$

Slope can be accounted for by replacing CN_{II} with CN_{2s}, where the latter is CN_{II} adjusted for slope [128]:

$$CN_{2s} = \left[\frac{CN_{III} - CN_{II}}{3}\right] \cdot [1 - 2 \cdot \exp(-13.86 \cdot \alpha)] + CN_{II} \quad (33)$$

For steep slopes, 14% < α <140%, Huang et al. (2006) [129] found the following formula to yield better results:

$$CN_{2s} = CN_{II} \cdot \left(\frac{322.79 + 15.63 \cdot \alpha}{\alpha + 323.52}\right) \quad \forall\, 0.14 < \alpha < 1.4 \quad (34)$$

A description of variables and parameters used in equations 30-34 can be found in table 19.

Table 19 Description of variables and parameters used in equations 33-37.

	Description	Unit	Domain	Type	Update scheme
$\boldsymbol{CN_{II}}$	Runoff coefficient for AMC2	-	≥15 and ≤100	CP	Every few years
$\boldsymbol{CN_I}$ **and** $\boldsymbol{CN_{III}}$	Runoff coefficient for AMC1 and AMC3	-	≥15 and ≤100	INT	-
$\boldsymbol{CN_{1s}}$**-**$\boldsymbol{CN_{3s}}$	Runoff coefficient for AMC1 to AMC3 incl. slope correction	-	≥15 and ≤100	INT	-
$\boldsymbol{P_5}$	Total antecedent precipitation 5 days prior to runoff calculation	mm	≥0	IV	Every time interval Δt
$\boldsymbol{\alpha}$	Slope	m/m	>0	CP	Every few years

The calculation of Q hence proceeds as follows, for each rainfall event:

1. Find area for each HRU, i.e. land use, slope and soil combination, present in drainage area.
2. Find CN factor for each HRU. Tables are available for AMCII.
3. Find slope for each HRU.
4. Calculate CN_{2s}.
    a. For slopes >14%, use equation 34
    b. Otherwise, use equation 33
5. Calculate P_5.
6. Use equation 30 to determine correct AMC.
7. If AMCI on AMCII, use 31 or 32 using CN_{2s} calculated in step four.
8. Use equation 29 to calculate potential maximum soil moisture retention S.
9. Use equation 28 to calculate initial abstraction I_a.
10. Finally, P > I_{a}, calculate surface runoff volume Q using equation 27.

5.2.7. Calculating river inputs from wind

Modelling wind force near the ground is complex, especially in urban environments [130] as wind speed alters in the vertical plane depending on local surface roughness and objects surrounding the particular location [131], but also in the horizontal plane depending on surrounding objects [130]. Like rainfall, the relation between wind and debris removal from land is best understood through empirical research. An alternative may be CFD modelling to shed more light on this process. Unfortunately, any research on this topic was not found. The quantity of debris blown from land could be modelled using a quadratic relation between wind speed, due to the quadratic relation between wind speed and wind force. In addition, the quantity is increasing with the duration of the wind force since a longer duration means more chance for debris to reach the river. In the equation below a proportional relation is assumed which is an appropriate assumption if the wind direction is not fluctuating (significantly) as this would mean that wind forces (partially) cancel each other out. Under changing wind conditions the duration would have a relation with inputs which is less than linear. For a specific area with predefined land use and population, the continuous measurement of wind speed the quantity of debris created by a single wind event would look as follows:

$$m_{D,W} = k_w \cdot \int (V^2 - {V_0}^2) \cdot t_w dt \quad (35)$$

For a discrete measurement this would look as follows, with i being a measurement:

$$m_{D,W} = k_w \cdot \sum_i ({V_i}^2 - {V_0}^2) \cdot t_{w,i} \quad (36)$$

The parameter V_0 is used in a similar way as the precipitation parameter Q_b in equation 26. It represents the minimum wind speed at which the debris of interest with smallest resistance to wind force start to move. The equation above assumes wind direction has no influence on the quantity of inputs. This can be assumed for a river with spatially well distributed tributaries branching of from the river and/or spatially well distributed inputs into the storm water system draining in the river. Finally, values of k_w and V_0 differ with rainfall as both rainfall and wind influence land to river inputs. Therefore this formula is preferably first applied to wind events without rainfall. The presence of snow will also alter these values as debris tend to be trapped under and in snow which significantly increases resistance to wind force.

It should be emphasized that wind speed differs altitude due to surface friction and turbulence or shielding effects of surrounding objects at low altitude. The values obtained for k_w and V_0 for a specific weather station (or combination of weather stations) are therefore not directly transferable to other weather stations (or another combination of weather stations). This makes interpolation also notoriously difficult. Keeping a fixed set of measurement station after k_w and V_0 have been established is therefore recommended.

A description of variables and parameters used in equations 35 and 36 can be found in table 20 on the next page.

Table 20. Description of variables and parameters used in equation 36 and 36.

	Description	Unit	Domain	Type	Update scheme
k_W	Coefficient which relates wind speed and duration to debris inputs	[kg s/m^2]	≥0	CP	Never, unless better estimates become available
t_W	Duration of wind event	[s]	≥0	IV	Every time interval Δt
V	Wind speed	[m/s]	≥0	IV	Every time interval Δt
V_0	Threshold wind speed for wind generated debris	[m/s]	≥0	CP	Never, unless better estimates become available

5.2.8. The river input model: output

The output from the river input model $m_{D,I}$ is the cumulative quantity of wind and precipitation induced runoff. However, lastly, it should be checked that cumulative quantity of surface runoff from rainfall $m_{D,P}$ and surface runoff from wind $m_{D,W}$ cannot exceed the mass of available debris on land:

$$m_{D,I} = \begin{cases} m_{D,P} + m_{D,W} & m_{D,P} + m_{D,W} < m_{D,A} \\ m_{D,A} & m_{D,P} + m_{D,W} \geq m_{D,A} \end{cases} \quad (37)$$

A description of variables and parameters used in equations 37 can be found in table 21.

Table 21. Description of variables and parameters used in equation 37.

	Description	Unit	Domain	Type	Update scheme
$m_{D,I}$	Land debris inputs into the river	[kg]	≥0	INT	-

5.3. River propagation model

The quantity of river propagated debris is dependent on advection (speed of river), retention, and entrainment. In order to simplify the river transport modelling, a certain lumped retention and entrainment factor can be assumed. Hence, it is assumed debris composition is constant and no specific retention and entrainment factors for separate debris categories are accounted for. Besides these factors, retention and entrainment will depend on the distance from the downstream river section. A longer distance will result in more retention and entrainment since the chances of deposition and dislodging debris becomes larger if distance is longer. River discharge, i.e. the flow, is also a factor, as demonstrated in section 4.3 and can be accounted for by adjusting retention and entrainment factors accordingly.

Retention of debris, in total weight, is proportional with the transport distance from discharge point to the downstream end of the river and the quantity of debris released in the river. The retention of debris can be described by the following formula:

$$Ret = d_t \cdot r_f(F) \cdot m_I \quad (38)$$

In this formula r_f was included as a function of the flow F. Literature studies demonstrated an inverse relationship with the flow of water. However, it was also shown that during the subsiding stage of a flood event a lot of debris is deposited. This deposition is high as flood events carry a lot of debris carried from land. Noticeably, for rivers for which the discharge is not predominantly dependent on precipitation but also snow melt during the melting season, such as the Vistula in Poland [54] this statement logically does not hold to the same extent. Values for $r_f(F)$ need to be determined empirically. For channels with steep and smooth riverbanks zero retention could be assumed but hotspots may still need to be identified. For rivers with flat and unsmooth riverbanks empirical data is necessary and empirical studies like Williams and Simmons (1997) [74] can hence be conducted.

Entrainment can be described in a similar way, now being proportional to the transport distance and an entrainment factor dependent on the flow of water. In contrast to $r_f(F)$, the parameter $e_f(F)$ will have a positive relationship with the flow F as the force of the water and the height of the water will dislodge more debris. Entrainment depends on historical retention also since the quantity of deposited debris determines how much debris are available to be dislodged.

$$E = d_t \cdot e_f(F, Ret) \quad (39)$$

A description of variables and parameters used in equations 38 and 39 can be found in table 22.

Table 22. Description of variables and parameters used in equation 38 and 39.

	Description	Unit	Domain	Type	Update scheme
$\boldsymbol{d_t}$	Transport distance from input point	[m]	≥0	CP	Never
$\boldsymbol{E}$	Quantity of entrained debris	[kg]	≥0	INT	-
$\boldsymbol{e_f(F, Ret)}$	Entrainment factor	[kg/m]	≥0	CP	Never, unless better estimate becomes available
$\boldsymbol{F}$	River flow	[m^3/s]	≥0	IV	Every time interval Δt
$\boldsymbol{Ret}$	Quantity of retained debris	[kg]	≥0	INT	-
$\boldsymbol{r_f(F)}$	Retention factor	[m^{-1}]	≥0	CP	Never, unless better estimate becomes available

Finally, the output of debris downstream can be computed as follows, by summing over all the debris input from each of the k sub watersheds:

$$O = \sum_k m_{D,I} + E - Ret \quad (40)$$

A more simplified approach would be to combine E and Ret into a single factor, which also accounts for the distance from input location to downstream accumulation point. As such, the quantity of debris inputs is multiplied by a propagation factor. This factor would also have to be acquired by conducting an empirical study.

The output becomes now as follows:

$$O = p \cdot \sum_{k} m_{D,I} \quad (41)$$

A description of variables and parameters used in equation 40 and 41 can be found in table 23.

Table 23. Description of variables and parameters used in equation 40 and 41.

	Description	Unit	Domain	Type	Update scheme
$\boldsymbol{O}$	Model output: Aggregated quantity of debris accumulated downstream	[kg]	≥0	OV	Every time interval Δt
$\boldsymbol{p}$	Propagation factor: Accounts for retention and entrainment during river transport	-	≥0	CP	Never, unless necessary, for instance if passive removal systems are created along the river

5.4 Summary

In this section the modelling approach was discussed for this and subsequent sections, and a model was worked out based on the objectives, requirements and desired specifications.

The objectives of the model were defined, partly based on the user profile. The main objectives of the model is to reduce the outflow of debris towards the marine ecosystem and to limit the quantity of debris within a port/bay area downstream. Secondary objectives are as follows:

- The model should be practical to implement for a user.
- It should include the relevant factors, affecting land to river debris input and river propagation as discussed in the literature study.
- The model should have enough detail to make a relevant impact.
- The model design should be covered within a tractable timespan, i.e. within the context of this report.

An analytical approach has been chosen, in order to satisfy the first and last objectives. Within an analytical approach, the second objective can still be achieved granted that the necessary data is available. It might conflict however with the third objective. After validation, the third objective can be evaluated and model adaptations can be proposed.

Requirements where listed based on the literature report earlier in the report. First, the model should be able to calculate the quantity of available debris on land. Secondly, the model should calculate debris and specific points along the river. Finally, the model should be able to calculate daily arriving debris at a downstream section of a river. The model should account for wind, seasonality, street cleaning, fluvial hotspots and antecedent dry days among others.

The first part of the initial detailed design covered the modelling of generated debris on land. Anthropogenic debris has been a fairly straightforward copy of the formula used by Wan et al. (2018). An additional seasonal factor was proposed. This section looked into wind generated debris but found that data was severely lacking. A wind factor was proposed to account for this. This should however be studied more in dept. The available quantity of natural debris on land was also discussed. The synergy of factors leading to the presence of natural debris was found to be complex and not easily transferable to various places. It was proposed to include a base load and seasonal factor, based on historic data. For the total availability of debris, the quantity of debris available debris, a formula was presented which takes into account the historic inputs of debris and debris removal by street cleaning.

Calculating the actual debris inputs from rainfall is complex. This section covered this process and also discussed suitable methods for interpolating weather stations. Calculating the actual debris inputs from wind is equally, if not more complex. A simplified formula was proposed, similar to the formula used for rainfall induced inputs. This formula linked the square of the wind speed to the inputs using a linear relationship and a threshold wind speed.

Finally, river propagation was discussed. Modelling retention and entrainment of debris with existing empirical studies would be hard due to limited amount of studies. It is also complicated by the fact that these processes are highly river specific and can hence not be readily used for other rivers. The proposed simplified method would simply use a multiplication factor for propagation. Such a factor would also account for the distant covered towards the downstream area.

6. Implementation

In the previous section, a debris prediction model was designed. In this section, the model will be applied to a case study. First, subsection 6.1 lists the hardware and software used for implementation of the model. Subsequently, subsection 6.2 and 6.3 are dedicated to the case study and the implementation thereof. Necessary model adaptations will be discussed as well, since it might be necessary to make some adjustment to the model depending on the available data. Finally, the verification of this adapted model will be covered in subsection 6.4 and the section is summarized in subsection 6.5.

6.1. Hardware and software used for implementation

The implementation of the model is performed in MATLAB version R 2014a, running on a HP EliteBook 8570w, with an Intel® core™ i7-3630QM 2.4 GHz processer and 8GB DDR3 PC3-10600 SDRAM memory. The operating system is Windows 7, 64 bit.

6.2. Case study description

In order to train and validate the model, the model will be applied to a case study. A dataset of debris accumulation large enough and sufficient in quality is hard to obtain but fortunately the WPB, the agency responsible for the Baltimore Harbor Wheel, a passive debris removal system in Baltimore, is providing debris accumulation data which should be both qualitatively and quantitatively sufficient to train and validate the model. Data has been recorded since May 2014. The date at which a certain threshold of debris has been accumulated is included in the data. This threshold is small enough and the timespan over which data has been collected is large enough to allow for training and validation. Moreover, the accumulation of debris, at an average of 565kg per day (see appendix E), is large enough to be useful. Figure 46 shows the Jones Falls watershed (JFW) and the location of the debris removal system. The watershed can be described as having a relatively flat surface topography, with height differences of at most 100 meters, and is covered mostly by urban area and forest. More (detailed) information on the debris removal system and the Jones Falls Watershed can be found in appendix F and I respectively.

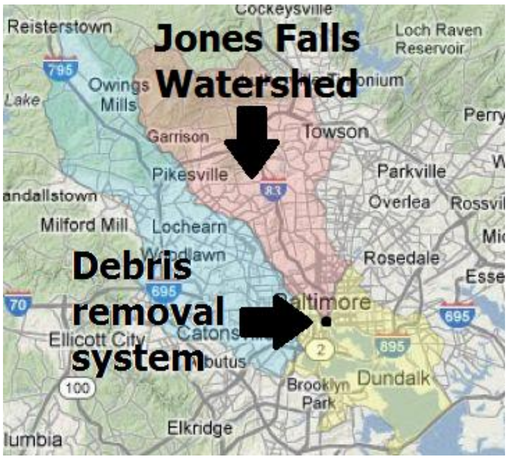

Fig. 46. The Baltimore Harbor Wheel and the Jones Falls Watershed [132].

Baltimore itself can be described as a seasonal location with a clear seasonal distribution of temperature [133]. It is relatively dry, monthly rainfall totals are low [133], but (heavy) rain and wind events do occur [134] [135]. On average days with precipitation occur 111 days per year [133].

6.3 Case study parameters and model adjustments

The Center for Watershed protection (CWP) and the Baltimore County Department of Environmental Protection and Sustainability (BCDEPS), responsible for compiling data on/managing the JFW, have subdivided the watershed in sub watersheds which were each grouped together in one of the three sets of sub watersheds. An overview of the different (sets of) sub watersheds can be found in figure 47 below. The three watershed characterization reports published by the CWP and the BCDEPS list data separately for each sub watershed [119] [136] [137]. These reports also provide the population data for each sub watershed.

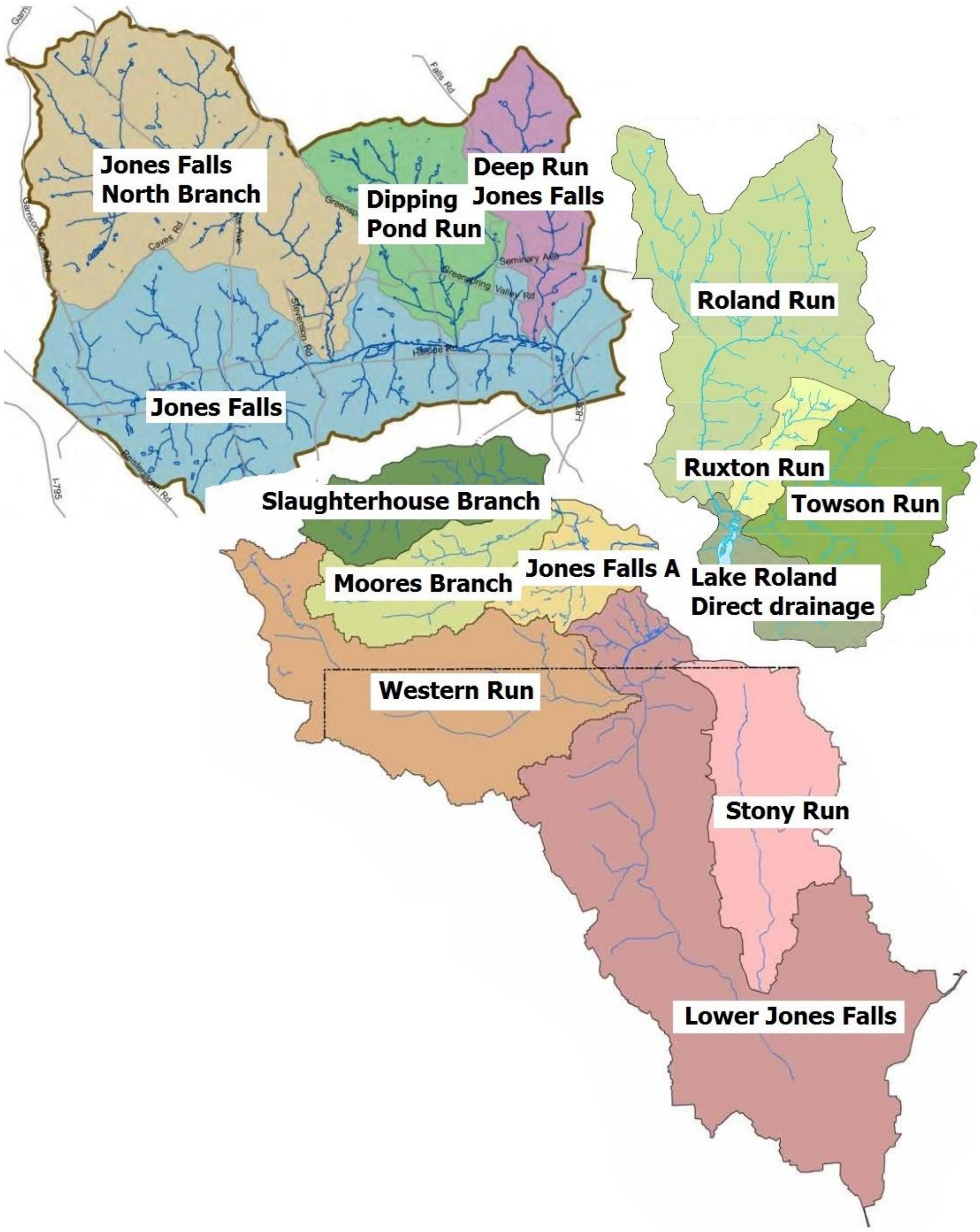

Fig. 47 Overview of the sub watersheds of the JFW, as reported by the CWP and BCDEPS [119] [136] [137].

Unfortunately, the dataset of accumulated debris provided by the WPB does not include separate data for natural debris. Hence, natural debris will not be considered for training and validation of the model. The data set provides aggregated mass, volume and separate data on the quantities of various anthropogenic debris. A second issue is that the mass and volume of debris includes natural debris. Hence, using quantities as a measurement is the sole option. In this case, equation 20 in subsection 5.2.1 is unsuitable and the quantity of generated debris would have to be estimated based on the available data. This has also benefits however. Wan et al. (2018) did not account for M_{adg} during the calibration of their parameters, though in reality, better values may be found if it constraint was accounted. Furthermore, the value for M_{adg} were fixed based on national estimates for waste generation rates and percentage of mismanaged debris, defined by Jambeck et al. (2015). While these national estimates may be sufficiently accurate for getting rough estimates for the fluvial outflow of debris from any country, better results may be obtained by fitting the data to M_{adg}, i.e. make M_{adg} adapt to the data. A detailed overview of the WPB dataset data, including debris types, can be found in appendix F.

Weather data is obtained from *'weather underground'* [138]. Historic data is only available for weather stations located on the three airports surrounding Baltimore, namely Carroll Country Regional Airport, Martin State Airport and Baltimore/Washington International Thurgood Marshall Airport. A map is shown in figure 48. The weather data from each of these stations will be interpolated for the various sub watersheds using equation 25. It is assumed this can be performed with sufficient accuracy. The distance has been calculated using latitude and longitude data from the weather stations and the central points of each sub watersheds which have been approximated by manual selection. For each of the weather stations, the following is obtained: date, time of measurement, wind speed and rainfall. Rainfall measurements are summed over each day, weighted according to the timespan in between consecutive measurements. This means, to be more precise that hourly rainfall data are summed. Six measurements, taken every 20 min, with each 1 mm of rainfall per hour registered, and all other measurements zero, yield a total of 2 mm rain. A similar approach is adopted for wind measurements, with the main difference that wind speeds are squared before being summed. A better approach would be to account for a specific rain and wind events and account for intensity, since a short outburst of precipitation will likely yield more debris than a some volume of water spread over a long time span. Since this approach is more challenging, the first approach will be adopted. It is assumed that this yields sufficiently accurate results.

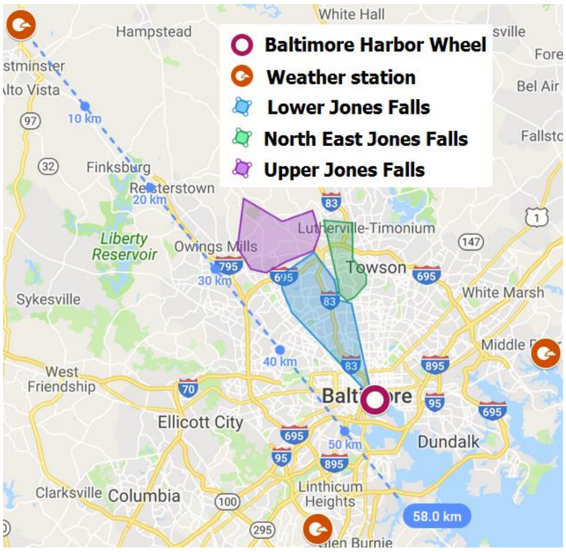

Fig. 48. Overview of the three sets of sub watersheds and weather stations.

CN values required for the surface runoff from precipitation have been computed using land use, soil and topographic data for each sub watershed. Ideally, each combination of land use, hydrologic soil group and slope is considered as a separate HRU but the necessary data is hard to obtain and is deemed too intractable for the scope of this report. Instead $CN2_{i,k}$ values are first calculated for each land use group i belonging to sub watershed k, using the amount of soil group ii as a percentage of the total area of sub watershed k:

$$CN_{i,k} = \sum_{ii} ff_{k,ii} \cdot CN_{i,ii} \quad (42)$$

This method of calculation assumes the soil distribution of the total watershed is comparable to the soil distribution for each land use within that watershed. Potential maximum retention S, initial abstraction I_a and subsequent surface runoff $Q_{i,k}$ are now calculated separately for each land use group i belonging to sub watershed k. The surface runoff $Q_{i,k}$ is calculated as follows:

$$Q_{i,k} = ff_{i,k} \cdot A \cdot \frac{(P - I_a)^2}{P - I_a + S} \quad (43)$$

Finally all Q values are summed over the whole watershed. Infiltration through overland flow from other HRU are ignored. Hence, only direct vertical deposited is considered. The parameters of equation 42 and 43 are being described in table 24.

Table 24 Description of all new variables and parameters used in equation 42 and 43.

	Description	Unit	Domain	Type	Update scheme
$CN_{i,k}$	CN value for land use group i belonging to sub watershed k	-	≥15 and ≤100	INT	Never
$CN_{i,ii}$	CN value for a specific land use i and soil group ii	-	≥15 and ≤100	FP	Never
$ff_{i,k}$	Fraction of sub watershed allocated to land use i	[%]	≥0 and ≤100	CP	Never, unless deemed necessary
$ff_{k,ii}$	Fraction of sub watershed k allocated to soil group ii	[%]	≥0 and ≤100	CP	Never, unless deemed necessary

Modelling river propagation requires unfortunately data which is currently unavailable. It is likely that the amount of debris going downstream will be related to surface runoff, since the Jones Falls is fed by precipitation (and occasionally local snowmelt). This factor is hence for a large part covered by the parameters related to surface runoff, i.e. the value of p from equation 41 is ignored and accounted for by adjusting the values of k_w and k_p in equation 26 and 36 respectively. Considering the riverbanks of the Jones Falls, and under low flow conditions also protruding vegetation throughout the river, it is likely that debris blew into the river from surface runoff will likely strand quickly and will only be brought after a large rainfall event. It is hence expected that heavy wind events, if these have any effect at all, should add more debris after each rainfall event than would be expected, just based on rainfall data alone.

6.4. Verification

The verification of the model is performed by changing the model input and configuration parameters and checking whether the model generates sensible values for the internal variables and output variables. It will first be checked whether these variables do not exceed their domain. Secondly, for variables which have a technically unbounded domain, e.g. ≥0 for the 5 day antecedent rainfall, it will be checked whether these yield plausible values.

In order to perform verification, the input parameters, namely wind speed (m/s) and rainfall (mm) will be varied in combinations, where each takes either zero or a large value for all entries. This is shown in table 25, which shows the verification test plan.

Table 25. Verification test plan.

	Rainfall [mm]	Wind [m/s]
Verification test 1	0	0
Verification test 2	0	25
Verification test 3	10	0
Verification test 4	10	25

In all of the above combinations it should be checked whether input variables and internal parameters for each weather station and each sub watershed yield correct/plausible results. Configuration parameters are checked only once since these do not depend on the processing of different data sources. Parameters will be assigned possible values or if not available plausible values and subsequently checked after running the model in one of the four test modes. Some additional internal parameters, used to implement the model in the software, are also included for verification.

Verification will be performed over a six day time span. Due to recursive nature of the model and equation 24 in particular, day one is predefined, so the number of days fully processed by the model is confined to 5 consecutive days. The predefined value is zero, meaning zero debris are forced into the river.

Special attention will be paid to the conservation of mass. First, the quantity of debris inputs from each sub watershed into the river is smaller or equal than the available quantity of debris on land. Secondly, the debris input from land to river are smaller or equal than the amount of debris generated by wind and/or rainfall (depending on the test mode). Thirdly, the output equals the sum over all debris inputs. The output of the last test should be larger or equal than the output of test 3 and 4. Lastly, input equals output, i.e. the quantity of generated debris after five days equals the quantity of debris equals the quantity of debris removed by wind and rain plus the quantity of debris removed street sweeping plus the quantity of debris available on land. The latter are the debris not removed by wind and rain. A detailed overview of these equations per test and the parameters used for verification can be found in appendix L.

An overview of the verification sheet used to check all values can be found in Appendix M. The model has passed each consecutive test and was hence approved for training and validation.

6.5 Summary

This section covered the implementation of the case study and the verification of the model. The Jones Falls River (Watershed) provides a suitable case study for the debris prediction model. The Waterfront Partnership of Baltimore (WPB) provided debris accumulation data which enables training and validation of the model. The dataset covers a timespan of circa 4 years. The dataset does unfortunately only contain data on full bins, i.e. if a weather event creates less than one bin of debris, the data is not recorded until the bin is full.

Data on the 14 separate sub watersheds the Jones Falls River watershed comprises of, is provided by watershed reports compiled by The Center for Watershed protection (CWP) and the Baltimore County Department of Environmental Protection and Sustainability (BCDEPS).

Unfortunately, no historic weather data from within the watershed is available. Historic wind and rainfall data are hence collected from three weather stations surrounding the main watershed. Although interpolation will be applied, the distance of these weather stations from the watershed will significantly impact the reliability of the obtained weather data.

The availability of certain data forces unfortunately several adjustments to the model. First, since natural and anthropogenic debris are lumped together in the weight measurements, debris quantities will have to be used. This means, the quantity of generated debris cannot be obtained in the original way. Instead this would have to be estimated as a model parameter. A benefit is that this offers the opportunity to better adjust this value to this specific area.

Moreover, detailed data on soil composition and ground cover is not available, at least not in a format through which it can be readily implemented within a tractable timeframe. Hence, a formula is adopted which assumes a specific soil type is distributed over each soil cover according to its fraction in the total soil composition.

The processing of weather is a tradeoff between model complexity and model accuracy. In order to reduce model complexity, daily rainfall measurements and the square of daily wind measurements are summed for each day. Hence, specific weather events are not considered.

After the model, including the above adjustments have been implemented, the model has been successfully verified.

7. Model validation

The previous section discussed a case study and model adjustment to the model designed in section 6, which was deemed necessary to process the case study. Section 7 also covered the verification of the model. In this section the model parameters will be calibrated, which is also referred to as 'training the model'. Finally, the results of the model validation are presented and discussed. The section starts with a brief overview of forecasting theory in subsection 7.1 which supports the evaluation of model performance. Subsection 7.2 discusses the experimental plan for the training and validation of the model. It is followed by the theory and results for the calibration of the model parameters in subsection 8.3 and the results of the validation process in subsection 7.4. The results are discussed in subsection 7.5. The section is summarized in subsection 7.6.

7.1 Forecasting

Since a debris prediction model concerns the prediction of an event into the future it makes sense to use forecasting theory to train said model and evaluate its forecasting errors. Forecasting differentiates itself from predictive modelling in the sense that it explicitly deals with the notion of time and the future in specific. It is often used to support decision making and is hence frequently used in governments, universities and businesses. Examples include air quality forecasts, climate forecasts, sales and demand forecasts and forecasting future behavior of processes in process control [139].

The act of forecasting relies on the analysis of historic data, identifying a pattern and using this pattern to make a forecast. Forecasting is hence grounded on the assumption that this pattern remains true in the future [139]. Nonetheless, forecasting theory provides methods to detect pattern changes which enables the user to rerun the analysis and adapt the forecasting model to the outcome of the new analysis.

Quantitative forecasting models can be categorized in two types of models [139]:

- Univariate forecasting models. These models forecast solely on the basis of historic values. On the basis of a historic time series patterns have to be recognized and extrapolated. Any causal relationship with external variables is hence not explicitly included.
- Causal forecasting models. These models revolve on the explicit relationship between the forecasting variable, i.e. the dependent variable and the causal variable, i.e. the independent variable.

In the context of prediction of debris accumulation, both models are relevant although the focus will be on causal forecasting modelling. The independent variables identified by literature were:

- Rainfall
- Wind
- Distribution of rainfall (and wind), i.e. to simulate first flush characteristics.

The causal relation between these factors and accumulation of debris may change however as for instance quantity of mismanaged waste changes. Such a variable is more difficult to track and measure and is hence preferably implicitly accounted for by using time series analysis. Changes in the causal relation between the above factors and accumulation should be monitored and can be observed by continuously examining the data for trends or disruptions, i.e. data patterns. Solutions to this issue are discussed after discussing 'forecasting errors'.

7.1.1. Forecasting errors

There are several ways to present forecasting errors. These can be used as a KPI to compare the performance of the prediction models. The definition of a forecasting error e_t at time t, e.g. the discrepancy between predicted accumulation $\hat{y}_t$, and actual accumulation y_t, is defined as follows [139]:

$$e_t = y_t - \hat{y}_t \quad (44)$$

In literature several forecasting KPI are used/proposed: ME/MBE, MAE/MAD, MSE, RMSE, (M) APE and MRE/ARE [139] [140] [141] [29]. Summing these error over a timespan with n predictions, leads to the mean error ME:

$$ME = \frac{\sum(y_t - \hat{y}_t)}{n} \quad (45)$$

A mean error shows whether the predictions tend to follow the mean of the actual values or whether values tend to be over or under predicted. Therefore, since it shows the bias in the model, it also referred to as the mean bias error (MBE). It does not show however the average size of the error. For this purpose the mean absolute deviation/error, MAD/MAE, can be used:

$$MAE/MAD = \frac{\sum|y_t - \hat{y}_t|}{n} \quad (46)$$

Another common metric is the mean square error MSE. Like MAE, MSE makes all errors positive. The difference is that larger errors have a larger impact on the overall metric due to the errors being squared.

$$MSE = \frac{\sum(y_t - \hat{y}_t)^2}{n} \quad (47)$$

Alternatively, the RMSD can be used, which is simply the square root of MSE. This metric has the same units as the data set.

The absolute percentage error APE and mean absolute percentage error MAPE, are less interesting from the perspective of debris prediction as absolute deviations are more important than relative deviations, as seen over the whole time series. It is however useful to compare any of the above KPI with the mean actual accumulation (MAA). This is useful to compare with sites with different levels of accumulation. Comparison can be achieved by dividing any metric, e.g. MAE, by MAA: MAE/MAA. This value should be as small as possible. Wang et al. (2018) uses specifically this metric, named the average relative error ARE or alternatively the mean relative error MRE, which can be defined as follows [29]:

$$MRE = \frac{\sum |y_t - \hat{y}_t|}{\sum y_t} \quad (48)$$

ME/MBE, MAD and MRE will used to measure model performance. ME/MBE shows the model bias but does not reveal the size of the errors which is arguably the most relevant metric. The RSME measures the size of the error, although it specifically useful if outliers are undesired. In other circumstances, this metric can be hard to interpret [141]. Hence, the MAD is deemed more appropriate. MRE will be used as it reflects on the size of the error with respect to the mean of the actual values. A large error for a small mean is worse than a large error for a large mean. Moreover, this allows for comparison between studies.

7.1.2. Monitoring forecast accuracies

If forecasting will eventually be used to predict debris accumulation, model parameters may need to be adjusted to changes in the implicit independent variables. In order to trigger parameter adjustments or notify the user to make parameter adjustments, a tracking signal TS can be used. TS works for one sided errors, i.e. predictions which consistently overestimate or consistently underestimate reality, and is defined as follows [140]:

$$TS = \frac{\sum (y_t - \hat{y}_t)}{MAD} \quad (49)$$

A certain threshold for TS would then trigger a warning. For fluctuating errors this wouldn't work, since errors would cancel each other out. A solution to this approach would be to use the absolute magnitude error over a period instead or in addition.

Continuous forecast adjustments can be made without human intervention. This would not always work but it may work certain cases, such as when the errors grow in a linear matter. Adjusting for the errors could then be performed using moving linear regression and double exponential smoothing [140]. Whether this works depends on the type of causal model. Revisiting the model parameters may be needed for more complex models, other than linear models. Storing historic data for the independent and dependent variables is therefore paramount.

7.2. Experimental Plan

The experimental plan consists of testing various versions of the river input model in order to check the added value of the numerous additions which add to model complexity. The base case is the simplest model, a model which merely accounts for rainfall, without taking surface runoff, street sweeping, antecedent rainfall and wind into account. The second case includes surface runoff calculations and is similar to the approach from Wan et al. (2018) [29]. The third case will introduce antecedent rainfall and antecedent removal of debris. The last case will introduce wind. These variations of the model will be tested in this order. For model M3 and M4 the best out of the previous two and three models respectively is used to build upon. An overview is shown in table 26.

Table 26. Overview of model variations used in experimental plan.

Description model variation and main assumptions	Model name and acronym
Precipitation only. $\boldsymbol{m_I = m_{D,P} = k_p(P - P_b)\Delta t}$. Main assumptions: rainfall is by far the dominant factor. Wind, antecedent removed debris, street sweeping and land use and soil data have limited influence.	Model one (M1)
Surface runoff from rainfall only. $\boldsymbol{m_I = m_{D,P} = k_p(Q - Q_b)\Delta t}$. Approach Wan et al (2018) [73]. Main assumptions: rainfall is by far the dominant factor. Wind, antecedent removed debris and street sweeping have limited influence.	Model two (M2)
Complete model excluding wind. If better performance is generated with precipitation only, detailed surface runoff modelling will be ignored. Main assumption: Wind has negligible influence.	Model three (M3)
Wind included. Depending on the performance of the previous four experiments, the best will be used in E4.	Model four (M4)

In order to better assess the overall model performance of these models, a 'clueless' prediction model has been added during validation. This average based prediction model (ABPM) simply uses the daily average of the training set and predicts daily quantities of accumulation based on this daily average. Each of the models above should at least perform better than this model.

The WPB dataset includes accumulation data for several debris categories. The aforementioned models will initially be applied to an aggregated set of debris categories. After concluding these results it will be evaluated whether separate debris categories should be included. Each debris category may have a slightly different behavior, especially with respect to wind or with how much ease each debris category manages to go through the grid spanning the storm water drain inlets. Cigarette butts for instance are sufficiently small to fit through the grid. Glass bottles for instance are less vulnerable to wind induced transport than plastic bottles, due to their higher weight. Plastic bags in contrast are highly vulnerable to wind induced transport.

The following six debris categories are included in the WPB dataset, each listed with acronym:

1. Plastic Bottles (PB)
2. Polystyrene (PT)
3. Cigarette Butts (C)
4. Glass Bottles (GLB)
5. Grocery Bags (GRB)
6. Chips Bags (CB)
7. Aggregated, PB + PT + GRB + CB

The aggregated category is the summation of a subset of the other categories. Not all categories have been included in the aggregated version since cigarette butts would dominate the data due to the much larger quantities involved whereas glass bottles are negligible in comparison to the other categories.

Since the datasheets only provides data, i.e. date and number of items, once a full bin is removed, model output will need to match this. Hence, daily outputs of the model will be summed over the days where measurements in the datasheet are unavailable up to the date a bin of debris is removed. Furthermore, since some weather events generate so much debris that it can fill multiple bins, data from bins removed on the same day are added together. This is illustrated with the example in table 27. In this example bins were removed on day 2 and 6. For day 6, for instance, the model outputs of day 3, 4, 5 and 6 were summed and compared with the actual data, which are the daily totals as shown in table 27. The summation of bins is done by preprocessing the WPB data set.

Table 27. Example of a comparison between the model outputs and the actual data.

	Day					
	1	2	3	4	5	6
Quantity of debris in bin 1		110				80
Quantity of debris in bin 2		100				120
Quantity of debris in bin 3						150
Totals actual data		210				350
Daily outputs for the model	30	60	0	120	500	0
Output totals for the model		90				620
Absolute error		120				270

The total WPB datasheet contains data from May 2014 to July 2018. May is skipped to make the dataset even numbered for convenience. This means there are 50 months of data. Half of these months will be used for training, i.e. the first 25 months, whereas the last 25 months are used for validation. More details can be found below in table 28.

Table 28. Specifications training and validation data.

	Training data	Validation data
Number of days	756	758
Starting date	6-06-2014	1-07-2016
End date	30-06-2016	28-07-2018

7.3. Calibration of the model parameters

In order to train the model, i.e. calibrate the model parameters, values for the parameters must be found which minimizes the error between the actual values of the dependent variables, here denoted as y_t and the predicted dependent values, here denoted as $\hat{y}_t$. In the initial debris prediction model defined by Wan et al. (2018), the predicted values were said to be defined by the following equation, formulated in the general form of a linear regression model:

$$y_t = \alpha + \beta \cdot x_t + \varepsilon_t \quad for\ Q > Q_b \quad (50)$$

$$with\ \alpha = -k_p \cdot Q_b\ and\ \beta = k_p$$

And:

$$y_t = 0 + \varepsilon_t \quad for\ Q < Q_b \quad (51)$$

Constrained by the daily available debris:

$$\alpha + \beta \cdot x_t < c \quad (52)$$

$$with\ c = M_{adg}$$

The goal in this optimization problem is to estimate the values for k_p and Q_b and thus α and β, which minimize the error terms. This leads to the following debris prediction model, with $\hat{\alpha}$ and $\hat{\beta}$ being estimates for the parameters α and β, and $\hat{\varepsilon}_t$ being the residual at time t:

$$y_t = \underbrace{\hat{\alpha} + \hat{\beta} \cdot x_t}_{\hat{y}_t} + \hat{\varepsilon}_t \quad for\ Q > Q_b \quad (53)$$

$$y_t = 0 + \hat{\varepsilon}_t \quad for\ Q < Q_b \quad (54)$$

Constrained by the daily available debris:

$$\hat{\alpha} + \hat{\beta} \cdot x_t < c \quad (55)$$

$$with\ c = M_{adg}$$

Wan et al. (2018) applied linear regression analysis to find the values for k_p and Q_b but did not account for the constraint in the process of fitting the data to this linear relationship, i.e. the following procedure was followed:

1. Find estimates for k_p and Q_b based on linear regression analysis, ignore M_{adg}.
2. Calculate debris inputs.
3. Constrain if debris inputs exceed M_{adg}.
4. Calculate model performance.

Including M_{adg} is necessary as was discussed in section 6. Since M_{adg} will now also be estimated, as argued for in subsection 6.3, the constraint becomes as follows:

$$\hat{\alpha} + \hat{\beta} \cdot x_t < \hat{c} \quad (56)$$

Now, best values (ideally the optimal values) are to be found for three parameters, namely k_p , Q_b and M_{adg} for the model variant using surface runoff as a predictor.

7.3.1. Greedy search

In order to find these optimal values, a first optimal solution will be acquired based on a basic greedy search method (GSM). This method converges to a minima of the function by decreasing the solution space of the model parameters in subsequent iterations. This method resembles a basic pattern search method described by Davidon (1991):

'Enrico Fermi and Nicholas Metropolis used one of the first digital computers, the Los Alamos Maniac, to determine which values of certain theoretical parameters (phase shifts) best fit experimental data (scattering cross sections). They varied one theoretical parameter at a time by steps of the same magnitude, and when no such increase or decrease in any one parameter further improved the fit to the experimental data, they halved the step size and repeated the process until the steps were deemed sufficiently small' [142].

The idea is to select for each parameter a certain number of steps, or (exploratory) moves, for the algorithm to make, in such a way that it yields a tractable calculation time. In addition, a solution space should be selected and the matter in which the steps are divided over this solution space. The solution space is the space of all possible solutions from which a subset, or neighborhood structure, is chosen to be tested by the algorithm in subsequent steps/moves. This subset is called a lattice and the size of the number of steps on this lattice determines the lattice resolution. The steps/moves can be divided over this search space in different ways, for instance on a linear scale or on a logarithmic scale, as shown in the equations below for parameter α, with S_α being the number of iterations performed for parameter α :

$$\alpha = a + b \cdot step, \quad for\ step = 1, 2, \dots S_\alpha \quad (57)$$

$$\alpha = b \cdot 10^{step}, \quad for\ step = 1, 2, \dots S_\alpha \quad (58)$$

After all the solutions for each step have been computed, the solutions are observed and the regions with promising solutions are used for the next solution space. The best solution is the incumbent. Note that the combined solution space for all generated solutions is multi-dimensional, one dimension per parameter. 100 steps for each parameter will hence yield 1 million solutions in a three dimensional space. In the next iteration, the step size is decreased accordingly, i.e. depending on the solution space. The best solution in this iteration becomes the new incumbent. Subsequent iterations are performed until improvements in new solutions compared to the incumbent become negligible.

The advantage of this procedure is that it is simple and the procedural parameters are fairly straightforward to acquire, without the necessity for much experimentation. It is also flexible as the solution space is manually adjusted to promising regions.

The downside of this procedure is that it can only guarantee a local minimum. It solely proceeds to areas where the solutions are found to be better than the surrounding solutions, but since the step size is initially large, it may overlook a global optimum. It also becomes vastly more complex or intractable when the quantity of parameters increases. It is hardly suitable for a parameter space beyond three dimensions as multi-dimensional matrices are hard to analyze manually. For model 4, iterations are therefore run multiple times. Within each run, rainfall parameters are kept constant while the other parameters are varied. This is performed for a set of rainfall parameters, based on the outcome of the earlier models, i.e. with a smaller solution space.

7.3.2. Simulated annealing

A more sophisticated approach would include a non-greedy metaheuristic. Such a metaheuristic is simulated annealing (SA), an established algorithm part of a larger group of nature inspired metaheuristics, which moves to new solutions based on memory less probability, inspired by the annealing process of metals [143]. It uses the metropolis criterion a as an acceptance function, meaning all improving moves are accepted and all worse moves are accepted with a certain probability. This probability is initially large and moves slowly down, making the algorithm increasingly greedy.

This algorithm requires the following algorithm parameters to be selected:

- Starting temperature (T0)
- Cooling schedule
- Cooling rate/cooling factor

In addition to the above algorithm parameters, a solution space/state space should be defined. This means defining the domain of each of the model parameters, i.e. three parameters in model 1 to 3 and five parameters for model 4. Moreover, a neighborhood structure should be selected in order to move to a candidate solution.

The starting temperature and cooling schedule will be based on experimentation, together with results from the previous greedy search method. The neighborhood structure will be based on binary numbers. Each neighbor is essentially 1 digit away from the incumbent solution [144]. The changing digit is chosen based on stochastics. Using SA requires discretization of the solution space and also requires the solution space to be significantly reduced to make it more tractable for the algorithm to solve. This will be achieved based on results from the previous greedy search method and based on an analysis of the weather data and data on the downstream accumulation of debris. This procedure is elaborated on in appendix M, together with an overview of the simulated annealing algorithm.

Building a simulated annealing method is time consuming, especially considering the time involved with tuning the algorithm parameters. For five dimensions, an adaptive neighborhood might even be required to cope with large solution space [145]. Therefore, this approach is first tested on model 1 and only considered for subsequent models if the quality of the solutions significantly outperforms the results of the greedy search method.

7.3.3. Training results

The training results are shown below in table 29, with the population ratio Pop_r equal the population of sub watershed k divided by the total population of all sub watersheds:

$$Pop_r = \frac{Pop(k)}{sum(Pop)} \quad (59)$$

Below the calibrated values, the model performance can be found, represented by the MAD and MRE. Based on the values of M1 and M2, the M2 method of calculating the relation between rainfall debris inputs has been adopted for the subsequent two models. It should be noted however that the difference in performance is small. In the same way, based on the values between M2 and M3, the M2 method of calculating the quantity of available debris, has been adopted for M4.

Table 29. Training results: values of the calibrated parameters and model performance.

	M1(GSM)	M1(SA)	M2(GSM)	M3(GSM)	M4(GSM)
k_p [#debris/mm/day]	0.06	0.0209	>=1	3.4E-05	0.002
P_b [mm]	1.5	1.2	n/a	n/a	n/a
Q_b	n/a	n/a	0.01	0	0.012
k_w	n/a	n/a	n/a	n/a	9E-06
V_0	n/a	n/a	n/a	n/a	0
$Madg$	$Pop_r \cdot 5598$	$Pop_r \cdot 5661$	$Pop_r \cdot 5822$	$Pop_r \cdot 812$	$Pop_r \cdot 5766$
MAD	6834	6820	6664	7360	6644
MRE	0.61	0.6	0.59	0.65	0.59

Figures depicting the actual and predicted series, with the parameter values as given above, can be found in Appendix N.

7.4. Validation results

The validation results are summarized in table 30 below.

Table 30. Validation results: model performance.

	M1(GSM)	M1(SA)	M2(GSM)	M3(GSM)	M4(GSM)	ABPM
ME	-1107	-1237	-1600	-4921	-2154	858
MAD	8997	8932	8509	9853	8278	11130
MRE	0.73	0.72	0.69	0.8	0.67	0.9

Detailed results, specifically graphs, are included in appendix O. The following figures are included:

- A comparison between the predicted and actual accumulation of debris (the dots representing the values were connected by lines to improve readability). This direct comparison gives a clear visual insight in how both time series compare to each other.
- A comparison between the actual values of accumulation of debris with line fit and the predicted values with line fit in two separate graphs. A graph was added with the difference (residuals) between predicted and actual values with line fit. This shows the trend of the residuals.
- The mean error (ME) for different validation sets, ranging from a short to a long time span. This shows if and how fast the bias of the model decreases towards zero. The following timespans are included:
    - 1 month
    - 2 months
    - 5 months
    - 9 months
    - 12 months
    - 15 months
    - 19 months
    - 22 months
    - 25 months
- The mean absolute deviation (MAD/MAE) for different validation sets as listed above. It shows if and how fast the MAD decreases towards zero for longer timespans.

7.5 Analysis

7.5.1. Validation analysis

Overall, one can conclude that the performances of all models score comparable although the third model sticks clearly out as the worst. M1, M2 and M4 score considerably better than the average based prediction model. The performance of all models, MRE, is however much lower than the performance achieved by Wan et al. (2018), which scored an MRE between 0.14 and 0.22 depending on the region. The training performance is better than the validation performance, as it should be, but nonetheless, the performance remains underwhelming.

The poor model performance could either be due to the data validity or model assumptions. If the weather stations are located too distant from the location of interest, inaccurate weather observations may render the data invalid. As mentioned earlier, rain showers may be very local. Data invalidity may also arise at the data source used to train and validate the model. For instance, if data is misinterpreted or incorrectly recorded. Finally, the large number of assumptions, especially for the calculation of surface runoff, may have severely affected model accuracy. Wan et al. (2018) used for instance a detailed hydraulic surface runoff model. Other important assumptions included the processing of rainfall and wind measurements. Threating these as events may have yielded significantly better results if data was sufficiently accurate. An important model assumption which should not be overlooked is, that a forecasting model assumes that an historic trend propagates in the future, which might not be the case. Although trend adjustment techniques exist, these were not applied here. This would however not explain the poor training performance.

The figures from the validation and sensitivity analysis will be discussed below.

A comparison between the predicted and actual accumulation of debris (the dots representing the values were connected by lines to improve readability). This direct comparison gives a clear visual insight in how both time series compare to each other.

From these figures one can indeed observe that predictions do differ significantly from the actual values. Some peaks and values overlap but the majority of points appear random.

A comparison between the actual values of accumulation of debris with line fit and the predicted values with line fit in two separate graphs. A graph was added with the difference (residuals) between predicted and actual values with line fit. This shows the trend of the residuals.

For this series of graphs it is noteworthy to observe that while the actual values go down, the predicted values go up. The most straightforward explanation is that somehow, despite worse weather conditions, less debris manage to reach the river. Debris are either less present on land or better contained on land. This could for instance be due to regulatory changes for packaging or improvements in waste management and increased street sweeping. Improved storm drains can also have a tremendous impact. Measures include: less storm drain overflows, improved storm drain filters and sewage grids/storm drain covers.

A closer look at the data in figure 50 reveals indeed a clear change in the trend of debris accumulation in the downstream area of the Jones Falls River. In contrast, this trend is not observed for precipitation in figure 49.

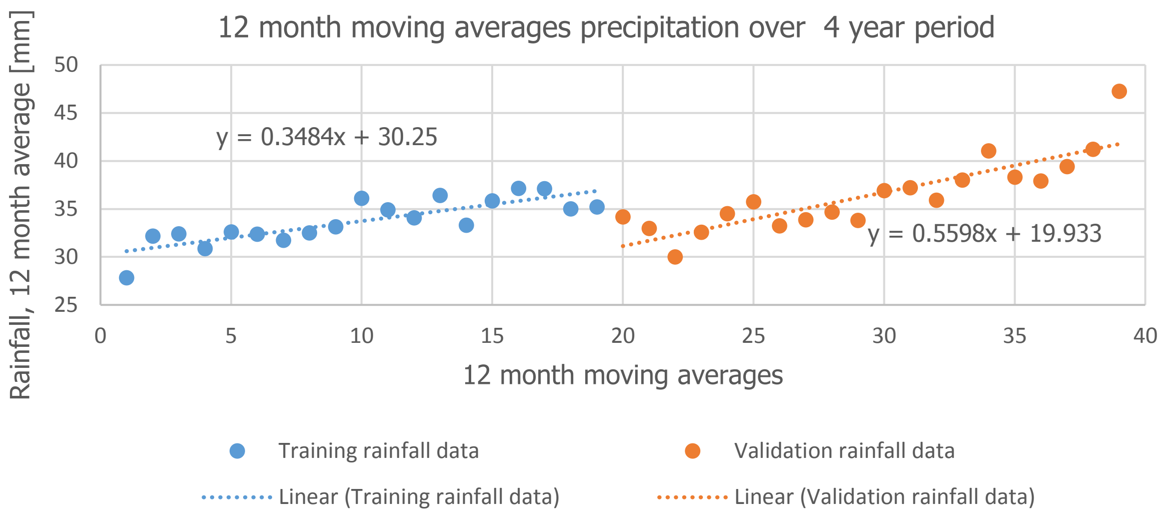

Figure 49. 12 month moving averages precipitation over a four year period.

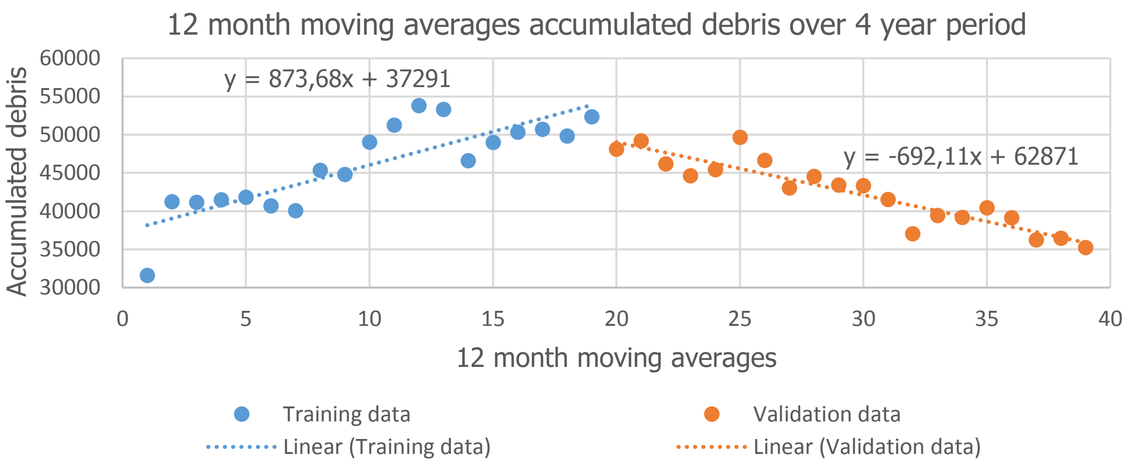

Figure 50. 12 month moving averages accumulated debris over a four year period.

As precipitation increases over the span of validation data, the predicted debris accumulation values also move (slightly) up. Since the actual debris accumulation data goes down, the mean of the residuals logically increases.

If this trend is accounted for in the predictions, a MAD of 6013 can be obtained for the training of M4 using the GSM. The MRE is 0.53. For the validation a MAD of 7163 is obtained and a MRE of 0.58. Hence, the performance is significantly better.

The mean error (ME) for different validation sets, ranging from a short to a long time span. This shows if and how fast the bias of the model decreases towards zero.

The ME of all models moves towards zero for all models and similar speed, about 2000 debris quantities per 10 months. All models would reach a zero bias in 35 months if the trend continues, except M3 since it starts with a worse bias.

The mean absolute deviation (MAD/MAE) for different validation sets... It shows if and how fast the MAD decreases towards zero for longer timespans.

The MAD does not decrease over increasing timespans, and even increases in two cases. This can be explained, as for longer timespans more discrepancy between actual and predicted values would be incurred due to what was observed above, namely the observation that precipitation and debris show opposite trends.

7.5.2. Sensitivity analysis

For the sensitivity analysis the model parameters will be varied separately to test the influence of the parameter on the overall mode performance. It aims to answer the question to what extent the model performance is sensitive to a change in a specific parameter. In order to achieve this, each parameter will be varied separately while keeping the other parameters constant. M4 has been selected as it performed based during validation. MAD is used to evaluate model performance. For each parameter, two parameter models are used to evaluate each parameter:

1. Linear. For the linear parameter model each parameter has been divided by 1000 to define the step size. 1000 iterations are evaluated below the optimal value and 1000 iterations are evaluated above the optimal value, hence 2000 iterations in total. Each iteration, the parameter is increased by the step size.
2. Logarithmic. For the logarithmic parameter model, the first iteration is 1E-9 and subsequently multiplied by 10 until 1E10.

For the threshold wind speed V0, a different linear parameter model is selected as the optimal value of V0 equals 0. For V0, 40 equally spaced values of V0 are selected, ranging from 1 to 40 m/s (hurricane strength). The results of the sensitivity analysis are given in appendix P.

First of all it can be noticed that the optimal values generated by the training data set are not the optimal values for the validation data set. This is not surprising. The influence of k_p is relatively small, as long as k_p is ≥ 1E-5. The reason is that the influence of k_p is eventually limited by M_{adg} which caps the total input of debris. In contrast, it can be observed that the influence of M_{adg} is relatively large. For values in the range of 1E5 and above, MAD increases excessively to eventually top out just over 1.3E7. It is however not guaranteed to be always the case. Other configurations with comparable performance can be found which decrease the influence of M_{adg}. Dividing k_p by 100 for instance decreases MAD by 3% while dividing k_p by 100 increases MAD by 17%. A lower k_p value will inherently decrease the effect of M_{adg} as the current average value for M_{dp} stands at 1E5 debris per sub watershed per day, which is much higher than the value of M_{adg} which is 5766 debris for the whole watershed or 2888 per sub watershed on average.

The effect of Q_b is limited as values above a certain threshold, means no surface runoff will be able to trigger debris inputs. This means that the effect of precipitation is zero. Below a certain value, the threshold values become extremely small compare to the actual surface runoff, which means its effect becomes negligible.

The wind related coefficient k_w has a small contribution to the overall performance around the optimal value. From both figures concerning k_w it can be observed that the effect of halving or doubling k_w has a minor effect. For values ≥ 10-6, the performance becomes quickly worse to eventually be bounded by M_{adg} between 4E5 and 5E5. The contribution of the wind related threshold value V_0 is negligible for all values. One can hence conclude that the wind, using the data as provided and in accordance with the model assumptions, does not contribute in any way to the accumulation of debris. If it would be contributing, raising the threshold above all values in the dataset should decrease performance.

Indeed, the average M_{dw} value is 1.8 quantities per sub watershed per day, while the average M_{di} value equals 80 quantities per sub watershed per day and the average M_{dp} value equals 1E5 quantities per sub watershed per day. MAD for k_w = 0, yields 8210 which is merely 0.8% different than the MAD for the calibrated, i.e. 8278. A simple plausible explanation could be that the wind speeds observed in this area are simply too low to influence debris deposition. The maximum daily average wind speed was merely 10.7 m/s and 8.8 m/s respectively, which counts as a fresh breeze.

The reason that M4 performs significantly better than M2 seems to be coincidence. For this specific dataset, the calibrated values happen to fit the validation set better than the values calibrated for M2. This is a plausible hypothesis as the performance of the calibrated models for the training set, barely differ with 0.3% difference.

7.5.3. Analysis of weather and accumulation data

The analysis of the input data should set some light on whether the poor performance of the models can be contributed to the quality of the input data.

For wind, the following correlations were obtained after an analysis of the training input data, i.e. 756 daily wind averages of the three weather stations, North, South and West:

Table 31. Correlation coefficients wind at weather stations North, South and West.

	North	South	West
North	1		
South	0.82	1	
West	0.85	0.81	1

The correlations are strong and statistically significant. For precipitation, a similar analysis is pursued, now with daily rainfall totals over the same 756 day period. The correlation between the weather stations for rainfall is moderate. The correlation between West and North is at the low end of moderate. The rest of the values are at the high end of moderate correlation. It is hence plausible that the precipitation data is not accurate enough.

Table 32. Correlation coefficients precipitation at weather stations North, South and West.

	North	South	West
North	1		
South	0.59	1	
West	0.36	0.63	1

A closer look was also given to the rainfall and accumulation data. Rainfall data was generated by the model, using the data from the weather stations and accumulation data is data provided by the WPB. This data is presented in figure 51 for a subset of the training data, 09-06-2015 to 08-09-2015. The colored cells in the rainfall columns day 1 to 8 highlight the day at which bins of debris were registered. Each column marked with 'rainfall…' shows one of the days since the previous removal day, with the daily rainfall sums marked in each cell. The accumulation data column shows the amount of debris, as registered by the WPB. In the methodology as used in this report, the second line would predict zero debris as the rainfall amount is zero. Hence, the obtaining a 27250 debris difference for that particular debris removal day. It is interesting to observe that large quantities of debris accumulation were assigned to days without rainfall but directly following a day with significant rainfall. Debris removal at such days was marked in red with the other days marked in dark grey. These observations could arise for the following reasons:

1. Rainfall has actually fallen on the watershed but is too local to be picked up by the weather stations.
2. The accumulated debris actually corresponds to the rainfall at the previous day but was only collected the day afterwards. Not surprising if rainfall fell in the late evening, if river propagation takes a few hours or if removal operations takes so long, if multiple bins need to be removed, that operators also needed the next day. Bins could ten have been registered on these days.

Number of days in between removal	Accumulation data [#debris]	Precipitation sum [mm]	Rainfall [mm] on day 1	Rainfall [mm] on day 2	Rainfall [mm] on day 3	Rainfall [mm] on day 4	Rainfall [mm] on day 5	Rainfall [mm] on day 6	Rainfall [mm] on day 7	Rainfall [mm] on day 8
8	31780	24,0	16,1	1,0	0,2	1,6	0,0	0,0	0,0	5,2
1	27250	0,0	0,0							
2	11660	0,0	0,0	0,0						
3	11680	7,0	1,3	0,1	5,6					
3	10740	6,3	0,0	0,0	6,3					
6	23410	26,6	3,3	0,7	18,3	0,0	1,4	3,0		
4	21780	20,3	0,0	3,0	14,0	3,2				
1	8150	0,0	0,0							
8	10270	16,8	0,0	5,4	0,8	0,0	1,5	0,0	1,0	8,0
1	10250	0,0	0,0							

Figure 51. A closer look at the rainfall data generated by the model and accumulation data provided by the WPB.

7.6 Summary

In this section the model was trained, validated and the results were subsequently discussed. For the calibration of the model parameters and the validation of the model, forecasting theory was applied to evaluate model performance. ME, MAD and MRE were selected as suitable KPI to evaluate model performance.

Four versions of the model were tested, in order to evaluate to added value of model extensions and complexity. Model M1 uses precipitation as the sole independent factor and ignores surface runoff. Model M2 uses a simple surface runoff model to test the benefit of a more detailed approach to calculating rainfall induced debris inputs. Model M3 takes into account historic inputs and model M4 included wind as a predictor for debris inputs. Finally, a baseline prediction model (ABPM) was added for comparison. This model, based its predictions on the average daily inputs of the training dataset.

The exact form of M3 and M4 was based on the training performance of M1 and M2 for M3 and the training performance of M1 to M3 respectively for M4.

The models were trained and validated using aggregated debris quantities of plastic bottles, polystyrene, grocery bags and chips bags. Each category was more or less similar in size. The training data included 756 days and the validation data included 758 days.

The models were calibrated using a greedy manual search method (GSM) and simulated annealing (SA) respectively. Since GSM performed comparable to SA for parameter calibration of M1, only GSM was applied for the subsequent models. The MRE obtained after training of the models, ranged from 0.59 to 0.61 for M1, M2 and M4 while M3 achieved 0.65. The validation of the models yielded the following MRE: 0.73 (M1 GSM), 0.72 (M1 SA), 0.69 (M2), 0.8 (M3), 0.67 (M4) and 0.9 (ABPM).

Though all models scored better than the baseline ABPM model, they scored much worse than Wan et al. 2018), which scored between 0.14 and 0.22 for various sub watersheds. From the analysis it appeared that accurateness of weather data is a likely cause, as rainfall data from the three weather stations were only moderately correlated. But several model assumptions may also have severely decreased the achievable performance with these models, most noticeably the processing of rainfall measurements and the simplification of the surface runoff process. From observations in the dataset as obtained from the WPB, it was found that the quality of said dataset with respect to this study may have hampered a successful analysis of the data.

Upon analysis of the graphs and data generated by the model and a sensitivity analysis of the parameters it was found that wind was negligible. The reason is likely the low wind forces registered within the dataset. M4 scored however better than M2 but this can simply due to parameter values which favor the validation dataset. The MRE achieved at the parameter calibration was similar, both 0.59.

8. Conclusions and future research recommendations

'*A planetary crisis*' [3], this ominous warning was given about the growing presence of anthropogenic debris in marine waters, plastic in particular. Debris accumulation in freshwater and marine water leads to a myriad of problems, such as decrease of aesthetic appeal, damage to nautical traffic, harm to flora and fauna and a potential risk to human health by pollution of human nutrition.

Remedies are looked for in different areas but this report focuses specifically on the extraction of debris in downstream sections of a river. Downstream removal of debris is advantageous for several reasons. Firstly, rivers are an important pathway for debris transport to the marine ecosystem. Secondly, ports and harbors are frequently located downstream, facilitating the removal of debris due to intrinsic interest of the local operators. Thirdly, downstream removal covers the debris inputs from the whole length of the river. Fourth and finally, the downstream section is the last location where debris are still heavily concentrated in one area, before spreading out over the vast expanse of the marine waters.

In order to facilitate the effective removal of debris it is believed beneficial to perform removal operations during times of large accumulation of these debris. To achieve this, a prediction model can has been developed aimed at predicting debris accumulation based on certain predictors. An answer to each of the proposed research questions, will be formulated in subsection 8.1. Future research recommendations are addressed in subsection 8.2.

8.1. Conclusions

- *What are debris and how can temporal fluctuations of debris accumulation from rivers be characterized?*

Debris can be categorized in many ways, with the top level categories dominating literature being location, size, material, type/product, risk and origin.

Debris can be categorized in two main categories: anthropogenic debris and natural debris. The mix of debris in areas with adequate waste management and low human presence is generally skewed towards natural debris, while areas with poor waste management and high human presence face the opposite.

With current technology, debris removal operations generally focus on macro debris, >5mm, which constitutes the largest amount of debris in terms of weight and especially in the top layer of the water, which is where debris removal equipment generally operates. The removal of micro debris, <5mm, from freshwater ecosystems is currently not worth the costs.

Debris which are found in marine waters are predominately originated from neighboring land masses, even if these land masses contribute relatively less to the global supply of marine debris. The exact number for the fluvial contribution of debris to the marine ecosystem remains unclear but estimates range from 7% to 48% of the total.

Risk assessments of debris are rare due to the lack of knowledge, data and the difficulty of monetizing certain harm. Hence, risk assessments are often performed in qualitative way. The most crucial debris are plastics due to their abundance, toxicity and longevity. Types with particular shapes pose additional risk such as monofilament, plastic bags, fruit nets and other debris with holes. Their shape poses risk to rudders, propellers and marine life. Certain brittle materials like foam need to be removed as soon possible since their brittle nature makes them highly vulnerable to mechanical degradation. Though the degree of risk may differ, all anthropogenic debris and also many natural debris pose a certain risk to human activities and/or marine life.

Fluvial accumulation of debris fluctuates heavily due to the fluctuations of the factors causing this accumulation. From the observed data, accumulation can be categorized as a base accumulation with large pronounced jumps in the distribution, with peaks varying in size. This can for instance be related to weather events. Over a longer time span, one or multiple years, seasonal effects can be observed. This can be due to seasonal presence of human activity or due to weather events. Moreover, trends can emerge with the mean accumulation gradually growing or declining. This can be due to growing human presence, increase public awareness or improving waste management. Finally, one can observe an abrupt step in the mean accumulation, likely due to infrastructure adaptations or legislation. Briefly summarized, the following characteristics can be found: jumps (temporary, fast change), seasonal fluctuations (temporary, slow change), trends (permanent, slow change), and steps (permanent, fast change). A prediction model should focus on jumps but will eventually, once implemented, need to account for the other characteristics, using analysis of historic data or tracking tools.

- *What factors influence the quantity of debris accumulating from a river?*

Debris inputs are mainly influenced by precipitation induced surface runoff. Precipitation related factors are antecedent dry days, total rainfall volume and rainfall intensity. The effect is jumps in the distribution of debris accumulation. Government legislation mainly affects trends and steps through the impact on consumption of disposable products and incorrect waste disposal. Other factors include wind, temperature, special events, urban development, tourism, waste management and public mentality. Each of these factors has their own temporal effect and place in the life cycle of waste it acts upon. The impact of each of these factors is always synergetic with the presence of other factors. The impact of heavy rainfall with poor waste management and poor public mentality is particularly severe. Local soil and land use characteristics have a large influence on the impact of precipitation. Soils which are more hydrophobic inhibit the percolation of water and will force more overland flow, creating more surface runoff.

Once debris enter the fluvial system, river transport of debris is related to the velocity of water, which is correlated with the river discharge. River discharge is often directly related with upstream rainfall. Stranding of debris may occur, especially in so called 'hotspots', areas which facilitate the retention of debris. Chance of stranding is increased by flat or shallow riverbanks, presence of vegetation and fluvial geo- or anthropogenic morphology. Lateral transport of debris is influenced by wind, input locations and hydrodynamic events like watercourse obstacles, confluence of tributaries and river bends.

● *How can these factors be incorporated in a prediction model, what existing models and modelling techniques are available and what are the challenges?*

Accumulation of debris can be modeled with two separate sub models: a river input model and a river propagation model. Currently, some models exist for micro and macro debris and can be divided into spatiotemporally explicit and steady state models. A spatiotemporally explicit model is desired to observe fluctuations in time and space.

Most existing input models are steady state and often consider a single source. If all micro debris models are excluded, Wan et al. (2018) remains as the main benchmark model for the application envisioned in this report. This model proves its merit in the use of a detailed semi-distributed surface runoff model. This model is however not exhaustive as it only takes into account surface runoff. Armitage et al (1998), though steady state, is more inclusive in some respects as it includes ADD and street sweeping. While ADD is fairly straightforward to implement, street sweeping would require detailed sweeping schedules and would be intractable for large river basins with many municipalities. Modelling surface runoff poses a major challenge as developing and operating a detailed surface runoff model requires a large amount of data and expert knowledge. Simple models may be insufficient. Obtaining accurate rainfall data may also be challenging in certain areas since precipitation fields can be fairly concentrated. The numerous points of entry to a river also means that severe simplifications of the model are often hard to avoid.

Introducing the other factors into the model can be challenging as it leads to an excess of parameters to be estimated. Permanent changes in accumulation are best adapted to by recording accumulation and applying tracking tools. Seasonal effects are fairly easily implemented and can best be implemented by introducing a seasonal multiplication factor, after studying historic data. Studies on wind induced debris movements are extremely rare, except for hurricane strength winds, but simple analytical estimation models can be developed for areas with high medium wind speeds.

Natural debris was not considered by Wan et al. (2018). Estimating the natural debris production on land is significantly more tedious than estimating the presence of anthropogenic debris on land. Therefore, historic data in combination with observations is preferably used to adapt removal operations.

For river propagation models several modelling techniques were observed: numerical modelling, analytical modelling, stochastic and deterministic. While small river sections can be approached numerically, large sections of rivers are best approached by obtaining empirical data. Hotspots would also have to be identified using either numerical modelling or visual observations. Discharge characteristics are also crucial to link propagation to discharge and precipitation. General numbers for propagation are unfortunately barely available as studies are rare and whatever data is available is not readily used for other rivers as it tends to be very site specific.

● What is the performance of a prediction model, applied to a case study?

In order to test the performance of a prediction model, an analytical model was designed, implemented, calibrated and validated. The case study provided the necessary data and hence, the model was customized to the specific case study and the available data. During the development stage of the model, several issues were encountered. One of these issues pertained the accuracy of the weather data. Historic data, required for the model calibration and validation, was only available from distant weather stations, hence decreasing the accuracy of the data. Secondly, the data required to build the propagation model was unavailable and obtaining empirical by experiments was not feasible. Hence, the modelling of propagation was abandoned.

Four versions of the model were tested. The first version directly linked precipitation to river inputs, ignoring surface runoff. The second included lumped surface runoff calculations. The third was based on the second but included ADD and historic inputs while the fourth included both lumped surface runoff calculations and wind. The model versions tested in this report obtained an MRE of 0.67 to 0.8 after validation and 0.59 to 0.65 after verification. A prediction model which simply uses historic daily average without any predictors, ranked lower with an MRE of 0.9.

While weather inaccuracies are deemed to be the most relevant factor, model assumptions and simplifications may also have had a considerably impact on model performance. These assumptions include simplifications in surface runoff modelling and averaging precipitation data over each day instead of considering precipitation events. The latter would better represent rainfall intensity. Finally, the quality and interpretation of the accumulation data used for calibration and validation may have decreased model performance.

● *Can a prediction model contribute to more accurate estimates of the accumulation of land to river debris at a downstream section of a river?*

The simplest model, which directly linked precipitation to debris inputs, managed to achieve an MRE of 0.73 on this specific case study. This is considerably higher than a model which assumes steady state accumulation and this model would hence offer an opportunity for more effective debris removal. Accurate precipitation data is however crucial. As such one can expect an MRE < 0.73 using a more accurate weather dataset. While Wan et al. (2018) achieved an MRE of 0.14 on a specific sub watershed, such a model would require complex surface runoff modelling and their model performance is not guaranteed to be achievable for other cases. Finally, while the more complex models did not generate added value in this study, it is important to stress that better performance may be obtained when applied in other locations and/or using more accurate weather data.

8.2. Future research recommendations

Several future research recommendations can be proposed:

- Currently debris surface runoff from wind has not been well studied, especially for wind speeds below hurricane speed. While wind is generally not considered the main predictor for debris accumulation, it may be relevant in certain areas. One could study the effect of wind for different debris on different soils.
- More empirical data should be gathered on the movement of debris in rivers. If more empirical data becomes available it becomes possible to build a database of different types of river sections. Ideally, even a propagation model is built and tested.
- The current dataset of accumulation set used for this model was not build with the intention of calibrating and validating a prediction model. Ideally, such a dataset should be build. In addition, data from relevant weather stations should be stored as weather stations often perform measurements but fail to store the data. The area researched in this report, counted dozens of weather stations but only a minor part had stored historic data. Using this data, another attempt can be given to test the modelling approach in this report.
- This study explored whether a prediction model could help to better understand debris accumulation and obtain a more accurate estimate of this accumulation. However, it also useful to understand to which extent this information can contribute to a more effective removal of debris. In order to accomplish this, simulations can for instance be performed.
- Other areas of debris removal could be researched. Many areas such as debris removal with RGB camera guided autonomous vessels are currently being investigated. While it shows promising results, more testing is needed, for instance on operating under nocturnal conditions, as debris outflow does not stop at night.

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For convenience, book (section) s, reports and conference/journal papers are indicated as follows:

- Book (section)s: **(BK)**. Number of books: 15.
- Papers: **(P)**. Number of papers: 94.
- Reports: **(R)**. Number of reports: 26.

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Appendices

Appendix A: Scientific Paper

This appendix contains the scientific paper, a compulsory part of the thesis.

A prediction model for the accumulation of debris in rivers

Abstract – The accumulation of natural and persistent anthropogenic debris in particular, within aquatic ecosystems, brings along a myriad of ramifications. By reducing these debris, damage to nautical vessels and harm to marine life can be mitigated. Rivers are an important pathway of debris towards coastal harbors, ports and marine ecosystems. To contribute to a more effective proactive removal of these debris from rivers, a prediction model can be developed, which can identify a temporal distribution of accumulation. This paper proposes a new prediction model by identifying a comprehensive set of predictors, through which land to river inputs can be predicted. A case study is used to evaluate the performance of several model versions, differing in complexity and predictors.

Index terms – Forecasting, predicting, marine litter, anthropogenic debris

I. Introduction

Within the context of this paper, debris are considered as all undesired synthetic, processed or natural items or fragments that are being transported by rivers from land towards the marine ecosystem. Once these debris have entered the marine ecosystem, the anthropogenic debris become known as marine litter. Rivers are an important pathway for marine litter. Plastics are the most significant category of debris, accounting for 50 to 80% of all debris, due to their consumption, floating capabilities and persistence. It is estimated that globally 1.14 to 2.41 million tons of plastic is yearly transported from land to the marine ecosystems [1]. The rest of the items includes a wide range of mostly low density debris, including Styrofoam [2], rubber, glass (bottles), metal (cans), paper, textile, processed wood and aluminum-plastic hybrids (chips bags) [3] [4]. A few examples of damage resulting from debris contamination in aquatic ecosystems includes fouling of rudders and propellers [5], blockage of intake pipes and valves [5], ingestion, suffocation and entanglement of marine life [6] and reduction of aesthetic appeal [7].

A broad range of remedies can be conceived, such as stricter penalization, new regulations/guidelines, improved waste disposal, improved storm water treatment, better law enforcement and awareness campaigns. Once discharged in the aquatic environment, removal operations remain the sole option. In this case, passive removal devices can be considered, especially for rivers without nautical traffic. Finally, active removal of debris can be attempted. Multiple solution directions can be researched to achieve more effective active debris removal operations. These solution directions include vessel routing [8], modelling spatial distribution [9], mapping debris presence using historic data [10] [11], autonomous debris recognition and removal [12] [13] [14] and the prediction of debris accumulation [15] [16]. The latest development in debris accumulation prediction modelling is currently the most sophisticated spatio-temporally explicit attempt and focuses on detailed precipitation induced surface runoff modelling [16]. Nonetheless, despite being detailed in the approach of modelling one particular factor, it is not comprehensive in terms of predictors. The objective of the research in this paper is the development of a more comprehensive prediction model for the accumulation of debris from rivers which means expanding the set of predictors used by the model. This research aims to identify these predictors, explore existing modelling approaches and test the performance of several versions of the prediction model developed in this study.

The paper is structured as follows. A literature review, discussing literature related to predictors and modelling approaches, is presented in section II. In section III, a model is developed and model versions are presented. In section IV the models are validated using a case study and performance levels are compared. Conclusions and recommendations are presented in section V.

II. Literature review

A. Predictors for land to river inputs

Predictors can be categorized according to their impact on the temporal distribution of debris accumulation. Firstly, the rate of change caused by a predictor, i.e. the derivative as a function of time. Secondly, whether the induced impact is temporary/cyclic or permanent. Predictors may have a large synergetic effect.

The main predictor for land to river inputs is precipitation induced surface runoff, as proven by many studies [17] [18] [19]. Surface runoff is related to the duration of rainfall event, the intensity of an event, slope, land use and soil (state). The duration influences the chance of debris to be displaced from their initial location to the storm drains/rivers. It also increases the chance of soil saturation, which reduces the ability for a soil to absorb the water, hence causing more overland flow. High intensity rainfall can quickly saturate the top layer of the soil [20] and may induce crust formation which decreases the permeability of the top soil [21]. A major factor can also be the distribution of antecedent dry days (ADD). Dry periods in between precipitation events give time for debris to build up in between these events, giving rise to a so called 'first flush'. This phenomenon was registered in several studies [22] [23] [24] [25]. Waste management is a crucial factor [18] [26]. Waste management includes availability and capacity of waste bins, frequency of waste collection, landfill quality, recycling and incineration rate, frequency of street sweeping and sewage treatment. For areas with more pronounced wind events, wind can become a relevant factor, especially during periods of minor precipitation [19]. Unfortunately few research has been performed on this. This is also true for other predictors which have less impact. Several predictors have been conceived as having potential impact: public mentality, legislation, large events, temperature, tourism and urban development.

B. Factors for river propagation of debris

River propagation is strongly correlated to river discharge [27] [28], which is generally correlated to local precipitation [29]. Discharge controls water velocity and water level. Other factors including vegetation levels, riverbank slopes and fluvial geo-/anthropogenic morphology. Debris might be trapped for long times at so called hotspots [30]. Lateral displacement of debris is further influenced by wind, input location and hydrodynamic events like watercourse obstacles, confluence of tributaries and river bends.

C. Land to river inputs, modelling approaches

Existing debris accumulation estimation and prediction models have been evaluated, including those for micro particles. Many of these models are either steady state, account for a subset of sources, account only for a subset of the factors or are not spatially detailed [8] [9] [31] [32] [33] [34] [35] [36] [36]. The most promising models are Wan et al. (2018) [16] and Armitage et al. (1998) [31]. Wan et al. (2018) does however not consider other factors other than precipitation and estimates of daily generated debris. Waste management is incorporated by calibration of a parameter. It succeeded however in achieving a decent model performance. Armitage et al. (1998) is not a prediction model but an estimation model and is therefore steady state. It however includes street sweeping explicitly and ADD. Neither of those models include any of the other suggested predictors as these models, most likely because these predictors are not relevant to the location these models apply to.

D. River propagation of debris, modelling approaches

Existing macro debris propagation models are rare. Spatio-temporally explicit propagation models are either empirical stochastic models, numerical or analytical models [8] [9] [32] [37] [38] [39]. The focus of the numerical and analytical macro debris models however is mostly on specific areas (ports). Numerical modelling of large river stretches would also be impractical. The empirical model is not suitable since a more mechanistic model is desired in order to make a model more generic. Propagation models for micro debris are not suitable due to large difference in processes involved.

III. Development of a prediction model

A. Model design

Modelling propagation was abandoned as obtaining empirical data required to calibrate a model was not feasible. Instead, the model of Wan et al. (2018) was augmented with the missing factors from Armitage et al. (1998). The calculation of the quantity of anthropogenic debris available for day t is obtained as follows:

$$m_{D,A}(t) = m_{AD,G}(t) + m_{D,A}(t-1) - m_{D,P}(t-1) - m_{D,W}(t-1) - m_{D,R}(t-1) \quad (1)$$

Using the available quantity of debris after the previous day $m_{D,A}(t-1)$, it is feasible to represent antecedent dry days. An overview of variables and parameters with description can be found in table 1.

Table 1. Description of variables and parameters used in equation 1.

Name	Description	Unit
$m_{AD,G}$	Quantity of anthropogenic debris generated on land	[m^3], [kg] or [#debris]
$m_{D,A}$	Debris available for land to water inputs	[m^3], [kg] or [#debris]
$m_{D,P}$	Land debris removed by surface runoff from precipitation	[m^3], [kg] or [#debris]
$m_{D,R}$	Daily quantity of debris removed, e.g. by sweeping	[m^3], [kg] or [#debris]
$m_{D,W}$	Land debris removed by surface runoff from wind	[m^3], [kg] or [#debris]

This formula accounts for antecedent dry days by including historic surface runoff from rainfall. Wind runoff and sweeping has also been included. The calculation of debris inputs from wind is described in 6.2.7, whereas the calculation of rainfall from surface runoff is described in 6.2.5 and 6.2.6 respectively. Data on sweeping quantities and sweeping schedules has to be provided by local authorities so it can estimate how much and when litter is removed from the streets. This process is visualized in figure 1.

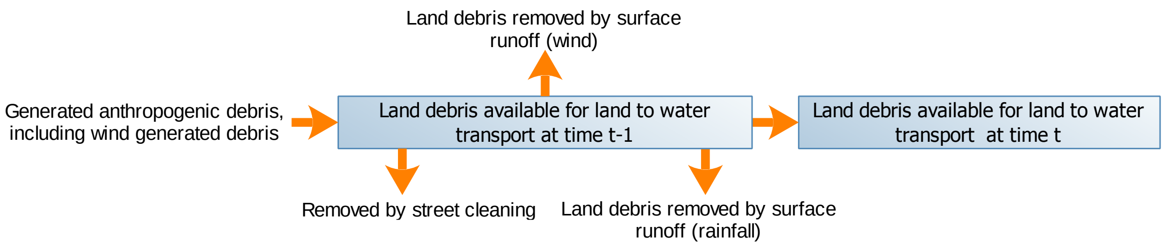

Figure 1. Flow model to determine land debris available for land to water transport at time t.

Similar to Wan et al. (2018), the quantity of rainfall induced land to river debris is calculated as follows:

$$m_{D,P} = k_p(Q - Q_b) \cdot \Delta t \quad (2)$$

Note that this formula, in contrast to Wan et al. (2018), does not sum over the number outlets. Instead, the land to river input will be calculated separately for each outlet first as the location of the outlet is relevant for the river transport model. An outlet is equal to the smallest HRU used. This can be a river section in a specific sub watershed. Inputs are then averaged over the river section. An overview of variables and parameters with description can be found in table 2.

Table 2. Description of variables and parameters used in equation 2.

	Description	Unit
k_p	Coefficient which relates surface runoff to debris inputs	[m^3/m^3], [kg/m^3] or [#debris/m^3]
Q	Surface runoff over the smallest HRU/drainage area used	[m^3/day]
Q_b	Surface runoff threshold value	[m^3/day]

The quantity of debris blown from land could be modelled using a quadratic relation with the wind speed, due to the quadratic relation between wind speed and wind force. In addition, the quantity is increasing with the duration of the wind force since a longer duration means more chance for debris to reach the river. For discrete measurements, the estimated quantity of debris from a single event would look as follows, with i being a measurement:

$$m_{D,W} = k_w \cdot \sum_i ({V_i}^2 - {V_0}^2) \cdot t_{w,i} \quad (3)$$

An overview of variables and parameters with description can be found in table 3.

Table 3. Description of variables and parameters used in equation 3.

	Description	Unit
k_w	Coefficient which relates wind speed and duration to debris inputs	[kg · s/m^2]
$t_{w,i}$	Time in between measurements	[s]
V_i	Wind speed for measurement i	[m/s]
V_0	Threshold wind speed for wind generated debris	[m/s]

The quantity of debris inputs is calculated as follows:

$$m_{D,I} = \begin{cases} m_{D,W} + m_{D,P} & m_{D,W} + m_{D,P} < m_{D,A} \\ m_{D,A} & m_{D,W} + m_{D,P} \geq m_{D,A} \end{cases} \quad (4)$$

An overview of variables and parameters with description can be found in table 4.

Table 4. Description of variables and parameters used in equation 4.

	Description	Unit
$m_{D,I}$	Quantity of land to river inputs	[m^3], [kg] or [#debris]

The above formulas need to be applied for all sub watersheds. Once these inputs have been calculated for all sub watersheds, all inputs can be summed to obtain the quantity of daily accumulated debris.

B. Model versions

Various versions of the river input model are tested in order to check the added value of the numerous additions which add to model complexity. The base case is the simplest model, a model which merely accounts for rainfall, without taking surface runoff, street sweeping, antecedent rainfall and wind into account. The second case includes surface runoff calculations and is similar to the approach from Wan et al. (2018) [73]. The third case will introduce antecedent rainfall and antecedent removal of debris. The last case will introduce wind. These variations of the model will be tested in this order. For model M3 and M4, the best one out of the previous two and three models respectively is used to build upon. An overview is shown in table 5.

Table 5. Overview of model variations used in experimental plan.

Description model variation and main assumptions	Model version
Precipitation only. $m_I = m_{D,P} = k_p(P - P_b)\Delta t$. Main assumptions: rainfall is by far the dominant factor. Wind, antecedent removed debris, street sweeping and land use and soil data have limited influence.	M1
Surface runoff from rainfall only. $m_I = m_{D,P} = k_p(Q - Q_b)\Delta t$. Approach used by Wan et al (2018) [73]. Main assumptions: rainfall is by far the dominant factor. Wind, antecedent removed debris and street sweeping have limited influence.	M2
The complete model excluding wind. If better performance is generated with precipitation only, detailed surface runoff modelling will be ignored. Main assumption: Wind has negligible influence.	M3
Wind included. Depending on the performance of the previous four experiments, the best will be used in E4.	M4

In order to better assess the overall model performance of these models, a 'clueless' prediction model has been added during validation. This average based prediction model (ABPM) simply uses the daily average of the training set and predicts daily quantities of accumulation based on this daily average. Each of the models above should at least perform better than this model.

IV. Model validation

A. Case study

In order to train and validate the model, the model will be applied to a case study. A dataset of debris accumulation large enough and sufficient in quality is hard to obtain but fortunately The Waterfront Partnership of Baltimore, the agency responsible for the Baltimore Harbor Wheel, a passive debris removal system in Baltimore, is providing debris accumulation data which should be both qualitatively and quantitatively sufficient to train and validate the model [40]. Data has been recorded since May 2014. The date at which a certain quantity of debris has been accumulated is included in the data. This threshold is small enough and the timespan over which data has been collected is large enough to allow for training and validation. Moreover, the accumulation of debris, at an average of 565kg per, is large enough to be useful. Figure 2 shows the Jones Falls watershed (JFW) and the location of the debris removal system. The watershed can be described as having a relatively

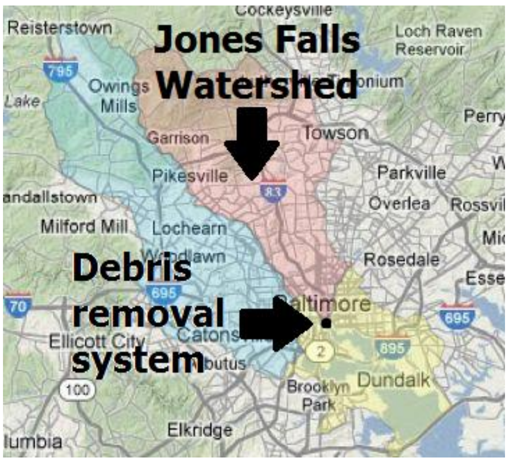

Figure 2. The Baltimore Harbor Wheel and the Jones Falls Watershed [41].

flat surface topography, with height differences of at most 100 meters, and is covered mostly by urban area and forest. Four sub watersheds can be identified.

The availability of certain data forces unfortunately several adjustments to the model. First, since natural and anthropogenic debris are lumped together in the weight measurements, therefore quantities of several debris categories are used instead. These categories are; plastic bottles, polystyrene, grocery bags and chips bags. The quantity of generated debris is calibrated. A benefit is that this offers the opportunity to better adjust this value to this specific area. Since the street cleaning schedule is too complex to include, it will be lumped together with the quantity of generated debris. Moreover, detailed data on soil composition and ground cover is not available, at least not in a format through which it can be readily implemented within a tractable timeframe. Hence, a formula is adopted which assumes a specific soil type is distributed over each soil cover according to its fraction in the total soil composition.

The processing of weather is a tradeoff between model complexity and model accuracy. In order to reduce model complexity, daily rainfall measurements and the square of daily wind measurements are summed for each day. Hence, specific weather events are not considered. Weather data is obtained from '*weather underground*' [42]. Historic data is only available for weather stations located on the three airports surrounding Baltimore, namely Carroll Country Regional Airport, Martin State Airport and Baltimore/Washington International Thurgood Marshall Airport. A map is shown in figure 3. The weather data from each of these stations will be interpolated for the various sub watersheds using inverse distance weighted Interpolation.

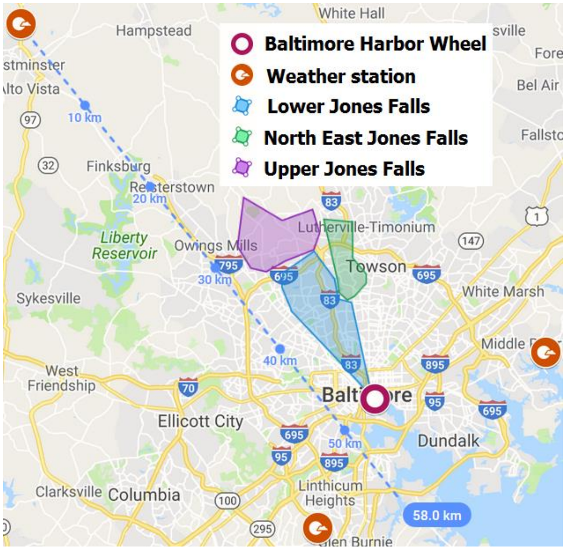

Figure 3. Overview of the three sets of sub watersheds and weather stations.

B. Experimental plan

The implementation of the model is performed in MATLAB version R 2014a, running on a HP EliteBook 8570w, with an Intel® core™ i7-3630QM 2.4 GHz processer and 8GB DDR3 PC3-10600 SDRAM memory. The operating system is Windows 7, 64 bit. The model versions are first calibrated using a greedy search method (GSM) and simulated annealing. Since simulated annealing achieved comparable results as the GSM after calibrating M1, subsequent models were calibrated using GSM only. After calibrating the model parameters and validating the model, a sensitivity analysis is applied to all model parameters.

C. Results

The training results are shown below in table 6, with the population ratio Pop_r equal to the population of sub watershed k divided by the total population of all sub watersheds:

$$Pop_r = \frac{Pop(k)}{sum(Pop)} \quad (5)$$

Below the calibrated values, the model performance can be found, represented by the MAD (mean average deviation) and MRE (mean relative error). Based on the values of M1 and M2, the M2 method of calculating the relation between rainfall debris inputs has been adopted for the subsequent two models. It should be noted however that the difference in performance is small. In the same way, based on the values between M2 and M3, the M2 method of calculating the quantity of available debris, has been adopted for M4. The validation results are summarized in table 7.

Table 6. Calibration results: values of the calibrated parameters and model performance.

	M1(GSM)	M1(SA)	M2(GSM)	M3(GSM)	M4(GSM)
k_p [#debris/mm/day]	0.06	0.0209	n/a	n/a	n/a
k_p [#debris/m^3/day]	n/a	n/a	>=1	3.4E-05	0.002
P_b [mm]	1.5	1.2	n/a	n/a	n/a
Q_b	n/a	n/a	0.01	0	0.012
k_w [#debris · s/m^2]	n/a	n/a	n/a	n/a	9E-06
V_0 [m/s]	n/a	n/a	n/a	n/a	0
$Madg$ **[#debris]**	$Pop_r \cdot 5598$	$Pop_r \cdot 5661$	$Pop_r \cdot 5822$	$Pop_r \cdot 812$	$Pop_r \cdot 5766$
MAD [# debris]	6834	6820	6664	7360	6644
MRE	0.61	0.6	0.59	0.65	0.59

Table 7. Validation results: model performance.

	M1(GSM)	M1(SA)	M2(GSM)	M3(GSM)	M4(GSM)	ABPM
ME	-1107	-1237	-1600	-4921	-2154	858
MAD	8997	8932	8509	9853	8278	11130
MRE	0.73	0.72	0.69	0.8	0.67	0.9

Though all models scored better than the baseline ABPM model, they scored much worse than Wan et al. 2018), which scored between 0.14 and 0.22 for various sub watersheds. Based on the results it could be concluded that wind did not have any influence which can largely be contributed to the lack of wind in the case study area during the studied period. It is likely that weather inaccuracies may have decreased model performance significantly, as the precipitation from the weather stations was moderately correlated. Nonetheless, model assumptions and simplifications may also have had a considerably impact on model performance. These assumptions include simplifications in surface runoff modelling and averaging precipitation data over each day instead of considering precipitation events. The latter would better represent rainfall intensity. Finally, the quality and interpretation of the accumulation data used for calibration and validation may have prevented good results.

V. Conclusions and recommendations

Four versions of the model were tested. The first version directly linked precipitation to river inputs, ignoring surface runoff. The second included lumped surface runoff calculations. The third was based on the second but included ADD and historic inputs and the fourth included wind. While Wan et al. (2018) obtained MRE values between 0.14 and 0.22, the model versions tested in this report obtained a MRE of 0.67 to 0.8. A prediction model which simply uses historic daily average without any predictors, ranked lower however with a MRE of 0.9. Despite the relatively poor performance obtained by all versions of the proposed prediction model, the simplest model, which directly linked precipitation to debris inputs, managed to achieve a MRE of 0.73. This is considerably higher than a model which assumes steady state accumulation and this model would hence offer an opportunity for more effective debris removal. Accurate precipitation data is however crucial. As such one can expect a MRE < 0.73 with more accurate weather data. While Wan et al. (2018) achieved a MRE of 0.14 on a specific sub watershed, such a model would require complex surface runoff modelling.

Several research recommendations can be proposed. Currently debris surface runoff from wind has not been well studied, especially for wind speeds below hurricane speed. While wind is generally not considered the main predictor for debris accumulation, it may be relevant in certain areas. One could study the effect of wind for different debris on different soils. More empirical data should be gathered on the movement of debris in rivers. If more empirical data becomes available it becomes possible to build a database of different types of river section. Ideally, even a propagation model is built and tested. Secondly, the current dataset of accumulation set used for this model was not build with the intention of calibrating and validating a prediction model. Ideally, such a dataset should be build. In addition, data from relevant weather stations should be stored as weather stations often perform measurements but fail to store the data. The area researched in this report, counted dozens of weather stations but only a minor part had stored historic data. Using this data, another attempt can be given to test the modelling approach in this report. Thirdly, as a lumped surface runoff model was used, better results could be achieved using a semi-(distributed) debris surface runoff model, like SWAT. Other areas of debris removal could be researched. For instance, debris removal with RGB camera guided autonomous vessels is currently being investigated. While it shows promising results, more testing is needed, for instance on operating under nocturnal conditions, as debris outflow does not stop at night.

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Appendix B: solution approaches to enhance debris removal operations

Since the costs of debris removal may costs an enormous amount of time and effort [45] and debris contamination is a major issue as was demonstrated, it is worth investigating debris removal performance can be further enhanced. Assuming debris removal is with an active, i.e. non stationary, system[20] there are multiple ways to achieve this, which will be explored in this section. Human controlled vessels would likely benefit most from this solution due to the labor costs involved although it would certainly also benefit operations with autonomous vessels. An overview of existing methods of debris removal can be found in appendix B. Subsection B.1 will present overview of the conceivable solution approaches using system representation. Subsections B.2, B.3 and B.4 will subsequently elaborate on each of these approaches.

B.1. Debris removal as a system: different solution approaches

To understand the different solution approaches it is helpful to represent debris removal as a system, as shown in figure 52. The disturbances to the system are the accumulation of debris, wind and flow rate, whereas the inputs are the routing and scheduling of the sweeping vessel. The outputs at time t are the outflow $O(t)$ of debris towards the marine ecosystem and the debris accumulated $A(t)$ inside the removal area. As debris outflow and accumulated debris fluctuate over time as debris is accumulating and removed, the total outflow of debris and the total debris accumulated can be represented as the integral of $O(t)$ and $A(t)$. The desired (total) output is in both cases equal to zero. The feasible routing and scheduling options depend on the equipment available.

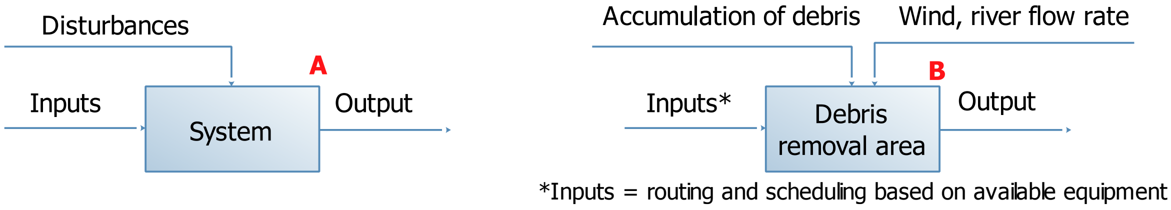


Fig. 52. General system representation (A), System representation of debris removal, open loop system (B).

Various approaches can now be attempted to improve the performance. Firstly, buying adequate/better equipment or adding equipment. Secondly improving the presence of cleaning in a spatial way, i.e. perform cleaning at locations with relatively high presence of litter. This means improving routing and smartly schedule the moments cleaning is performed. An example of this, is the study by Tol (2016) [23] which analyzed the performance of different routing methods of vessel in a port environment. This work focused on the inputs while make assumptions about system behavior.

One can further enhance performance by improving data quality and data availability w.r.t. spatial and temporal distribution. This can be done in multiple ways. Firstly, one can study the behavior of debris inside the debris removal area to gain knowledge on the spatial distribution of debris, i.e. study the system behavior. Lammerts (2016) [24] used numerical modelling to investigate the influence of various

[20] There are two types of debris removal systems: passive and active systems. For more, see appendix B.

factors, which included disturbances such as river flow rate and wind, on debris behavior in a port environment. This way disturbances like wind and river flow rate fluctuations are measured and input (routing) is adapted. The relation between the disturbances and location of debris is inferred from work like Lammerts. Secondly, this can be done using historic data or monitoring equipment to improve knowledge about the spatial and temporal distribution of debris. Output is used to adapt input at the next debris removal attempt, which is depicted in figure 53A on the page. Finally, methods and technologies can be deployed which allows short term predictions regarding quantities of debris based on what is measured upstream. This is a feedforward approach, depicted in figure 53B, since information regarding anticipated accumulation of debris becomes available before debris removal has started. A feedforward approach could consist of using debris detection technology in the river, such as RGB camera's or infrared sensors. Alternatively, debris accumulation is not directly measured but linked to factors which contribute to the accumulation. Hence, debris accumulation is a latent variable which is inferred from other observable variables.

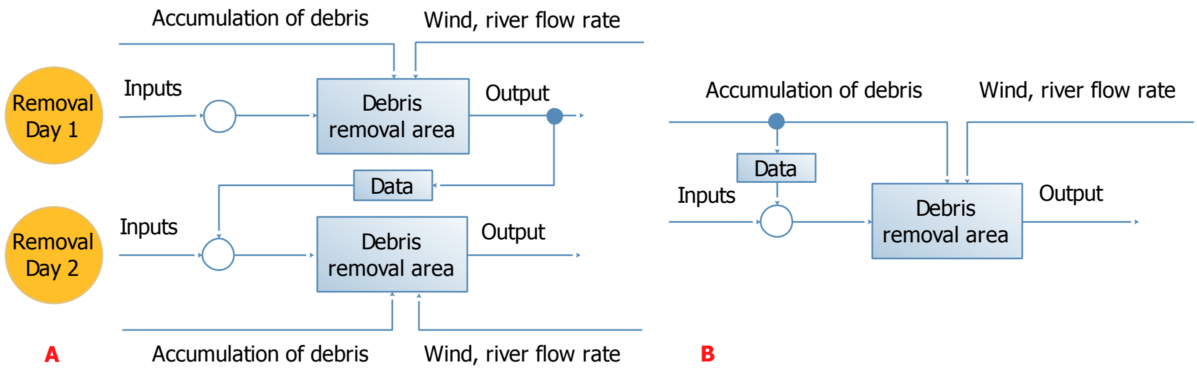


Fig. 53. Improved debris removal system; historic data approach (A) and feedforward approach (B).

B.2. Using historic data

Tol (2016) used an educated guess on the debris accumulation. Spatial distribution was modelled using zero dimensional hotspots. In reality debris hotspots may indeed exist but will in contrast be more spread out. If for instance detailed historic data can be collected on the exact litter quantities and locations where debris have been found debris removal can be improved. It is even possible to find temporal data patterns which can be linked to factors deemed relevant in the accumulation of debris. Ranmarine technology [146] for instance aims to collect data from their autonomous sweeping vessels to focus operations at locations where litter has been historically abundant.

Figure 64 on the next page illustrates how such a hotspot map could be visualized using a geographical information system (GIS). Martens and Huntington (2012) [25] investigated whether lobster trap removal could be performed more effectively and efficiently using a spatial map of likely debris accumulation hotspots. The area surrounded by the blue line shows the cleaning area where red to green denotes areas of high to low probability of finding litter. The researchers managed to decrease the search area by 95%. Performing spatial analysis using such mappings can hence contribute to performance assessments and steer future cleaning operations.

Another illustration of GIS based spatial mapping of historic data is Bennet-Martin et al. (2016) [147] who visualized litter densities for coastal sites as shown in figure 65. In literature, GIS based spatial mappings of debris have also been used to link factors like Ekman flows and winds to the spatial distribution of debris on coastal land. Examples are Kataoka et al. (2017) [86] and Moy et al. (2017) [81].

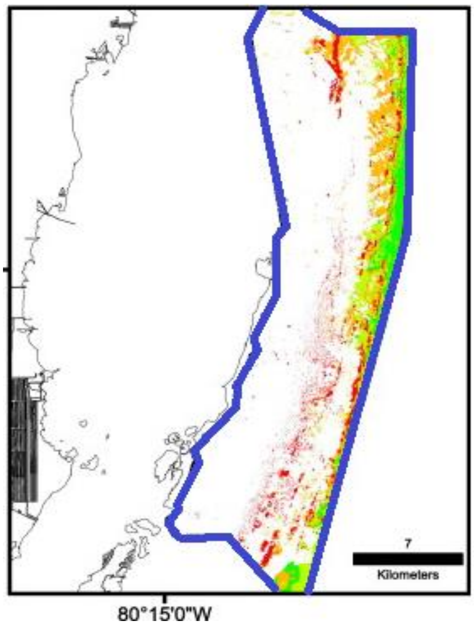


Fig. 54. Spatial map visualizing likelihood of finding lobster traps. Red to green denotes high to low probability of finding traps [25].

There are downsides to this approach however. Using historic data is unfortunately not very robust to fast fluctuations. Trends and steps in the accumulation to a lesser extent, could be adequately dealt with using a moving average or single/double exponential smoothing which uses respectively k historic data points and exponentially decreasing weight factors to decrease the importance of older values. Temporary peaks in the distribution with a large rate of change

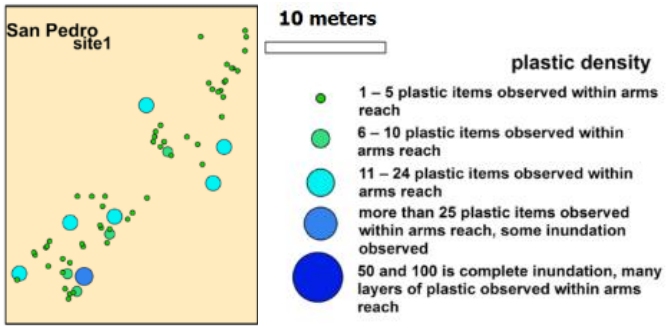


Fig. 55. Spatial mapping of plastic items in Belize [147].

however, are harder to deal with. As demonstrated in section 2, accumulation may fluctuate in a very short span of time, by several magnitudes. Hence, this approach may be useful to detect spatial distribution patterns but its contribution towards addressing accumulation, is likely limited.

The second downside is the required equipment to detect debris quantities. In order to create a GIS spatial mapping of debris, each piece of debris must be recognized in situ so it can be linked to a specific location. For small debris this may prove challenging.

B.3. The feedforward approach: Using sensors to monitor debris

Detection of debris before they accumulate downstream is an attractive solution since it involves a direct measurement of the expected flow of debris. The feasibility of this approach depends however on the performance of the sensor system.

The performance of such sensor systems on the detection of debris can be assessed based on the following performance criteria [148]:

1. Spatial resolution;
2. Spectral resolution;
3. Temporal resolution;
4. Quality of post processing.

Spatial resolution refers to area per pixels available. High spatial resolutions means smaller objects can be detected. Spatial resolution depends on the equipment but it can also be improved by decreasing the distance between the object and the equipment. Spectral resolution refers to the quantity of available bandwidths within the electromagnetic spectrum. RGB cameras have three, multispectral has more and hyperspectral equipment has the most. A higher spectral resolution means spectral signatures can be more easily distinguished from each other, hence undesired objects are easier identified. Even specific plastics can be identified [149]. Temporal resolution influences detection rate. It refers to how often the desired area to be monitored is covered. This is for instance relevant for sensors which have a certain rotation schedule to cover a certain surface. For expensive sensors it is most likely desired to scan the surface instead of having more sensors with a fixed angle and position. The quality of the post processing and availability of (spectral) databases is also crucial as the algorithm involved should translate sensor data into useful information. If machine leaning is used, the quantity and quality of training plays are role. Trade-offs may be involved such as between performance and memory requirements, energy demand and computational intensity [27].

Various technologies can be applied to detect debris. An overview by Veenstra and Churnside (2012) [150] can be found in table 33. These sensors can generally be classified into active and passive types. Passive sensors merely receive signals whereas active sensors transmit and receive. Other relevant factors, namely size, costs and the existence of debris (Shape/material) data sets for post processing, where also considered.

Table 33. Overview available sensors for sensing of floating debris [150].

	Sensor Type	Class	Relative size	Existence data set	Cost
1	RGB video	Passive	Small	Yes	Low
2	RGB (high-res) camera	Passive	Small	Yes	Low
3	Thermal imaging/IR	Passive	Small	Limited	Medium
4	Multispectral imaging	Passive	Small	No	Medium
5	Hyperspectral imaging	Passive	Large/Medium	No	High
6	LIDAR	Active	Large	Yes	High
7	Radar	Active	Large/Medium	No	High

Active sensors are attractive since these can be used both at night and under all weather conditions. These types of sensors are however expensive and large. Hyperspectral imaging is attractive as it can collect many spectral signatures. Unfortunately it also expensive and impractical. Thermal imaging has benefits for nocturnal operations during which floating debris may be observed. It is questionable however how this would work for small surfaces. RGB is limited in functionality but overall cheap and practical.

Literature pertaining the close distance monitoring of floating debris is scarce and has only recently been published. Due to the low costs and compact size, RGB is the only technology which has been considered so far in this context. Tan et al. (2014) proposed an unmanned surface vehicle (USV) system with RGB sensors dedicated to debris observation [26]. To cope with the limited angle of a single camera a rotating schedule has been developed to minimize rotating energy while decreasing the chance of missing debris, based on arrival probability of said debris. Since it concerns a floating platform able to perform long term operations, it was faced with additional challenges which are generally not applicable to cameras mounted on fixed structures. Nonetheless, the designers achieved their goal of developing an algorithm which successfully identifies many debris.

Wang et al. (2015) [27] aimed to build and study a monitoring system placed on a buoy. The main achievements of this work have been the computationally efficient method of debris detection and the energy efficient method of transmission.

Both algorithms revolved around background subtraction or equivalently foreground extraction. The aim is to have the foreground equal all debris captured in the image. This task is complicated by changing light reflections in the water which might result in false positives. These reflections can occur for instance due to waves or swaying trees [27]. False negatives generally occur due to a large distance between object and sensor and/or high color similarity [26]. Results from both papers are presented in figure 56.

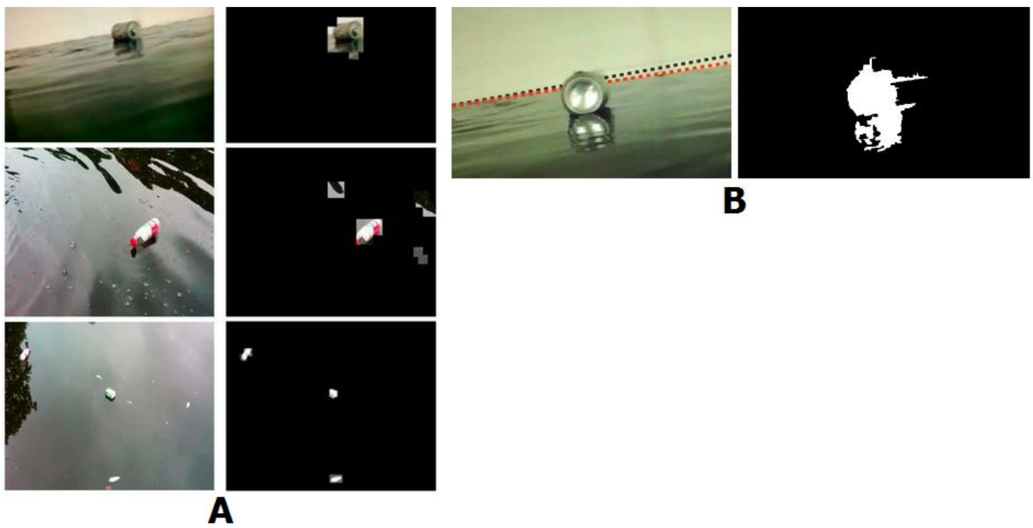


Fig. 56 Original image and foreground obtained from experiments using method A [27] and B [26].

Both methods perform reasonably well with different debris. For 56A it seems all macros debris can be detected (>5mm) however smaller objects, smaller than circa 30mm, are not detected. The foreground image in the middle of figure 56A shows some environmental reflections obtained a false detection whereas the foreground image in 56B is larger than the real object, largely due to reflections. It is also not clear how performance deteriorates with decreased sunlight, for instance sunset or dawn.

To be able to monitor fluvial debris, monitoring equipment can mounted on fixed structures like bridges. Even if it does not span every part of the river, it can still be relevant under the assumption that the observed flow of debris along a partial width of the river is indicative of the flow of debris as a whole. More research is however needed. How well does it perform other various circumstances, for instance during nocturnal operations. For RGB, the support of lights could for instance be tested under nocturnal conditions.

B.4. The feedforward approach: Using a predictive model

The third solution is an indirect approach to obtain an estimate of the flow of debris. To achieve this, data on the factors driving the accumulation of debris should be obtained. This data can then be fed into a model which ten outputs an indication of the debris accumulation which can be expected. The underlying assumption behind this approach is that these factors are measured with more ease than then the flow of debris floating in the river. Once the data is fed into a probability model, the model calculates a number for or a range of values for the predicted flow of debris. The value of the output variable can hence be discrete or continuous. Models can include a numerous modelling techniques ranging from relatively simple like decisions trees, fuzzy logic, and a simple set of analytical equations to more complex like stochastic discrete modelling, neural networks, numerical modelling other complex time stepped dynamic simulation. Depending how the model is built, the output value will be discrete or continuous.

Prediction modelling has been used in various forms in the context of water quality of which solid debris contamination is a subset. A daily water quality forecasting system, the WATERMAN system has been developed for coastal waters in Hong Kong [151]. With the application of neural networks and linear regression the relevant parameters influencing bacterial concentration could be identified, for instance antecedent rainfall, hydro dynamical conditions and historic concentrations [152]. Simple decision trees could be used for predictions, illustrated in figure 57 for the likelihood of algae bloom. Long term predictions of ML accumulation has been attempted by Kako et al. (2014) [153] who estimated future ML beach accumulation developments using numerical hydrodynamic modelling and particle tracking models (PTM). Modelling approaches which have been developed for land to river debris and river propagation, are discussed in the section 4. This method has also some downsides. There must be a sufficiently strong link between the factors contributing to land to river inputs and the accumulation of

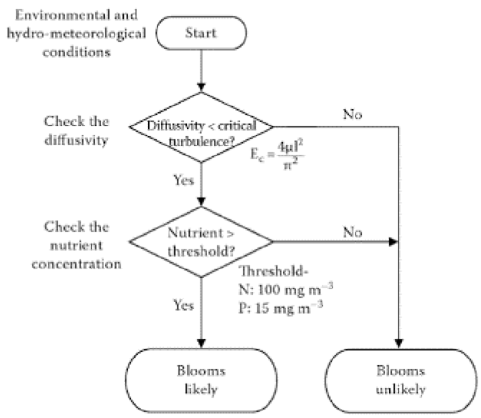


Fig. 57 Decision tree for algae bloom likelihood predictions [151].

debris downstream. Moreover, it should be feasible to obtain, for instance though measurements, quantitative data on these factors.

B.5. Appendix B summary

Three solution approaches were proposed in order to improve the removal of debris better anticipate debris accumulation, one feedback approach and two feedforward approaches. The feedback approach uses historic data to discover patterns in the spatial distribution of debris. This data can be used to locate debris likelihoods on a map. The downside is that this approach is not suitable to anticipate on large a fast fluctuations in debris quantity over time. It requires also certain technological advancement in debris sensing.

Two feedforward approaches were considered. The first approach consists of direct detection of debris using sensors. RGB cameras are the most likely technology, costs and practicality considered. It is however limited in functionality, although the full capabilities have not all been tested yet. It also lacks in terms of spatial performance, which means there is a relatively large size threshold for debris to become visible.

In the last feedforward approach a predictive model is considered which enables users to obtain an estimate on debris accumulation. This can be achieved by collecting data on, e.g. measuring, factors contributing to this accumulation. The success of this approach depends however on the strength of the link between these factors and the actual accumulation and whether these factors can be measured adequately.

It is clear all methods have their limits. In order to deal with fluctuations, a feedforward approach can certainly bring large benefits. Experience with both feedforward approaches is too limited and research too scarce to make solid conclusions on which approach would be the better alternative. It can also be argued all three approaches could complemented each other. In this report however the last feedforward approach will be explored.

Appendix C: Debris Removal equipment and operations

The cleaning of debris in different environments has become an increasingly applied practice. So far, most of the cleaning has been performed in inland waters. Passive and active cleaning methods are applied. Passive means use a stationary location where debris are being collected. ML is being supplied by the current of the water. Active means use a cleaning vessel which can be moved around, for instance after visual observation of ML. Passive systems are mostly suitable for locations with significant currents such as rivers and oceanic currents, whereas active systems are often used in more confined areas where debris tend to accumulate, such as ports. In general passive systems are used proactively, they operate in a continued near uninterrupted manner, whereas active systems are mostly reactive, meaning after visual inspection, since operating costs are higher. The latter applies especially to operations which have high human involvement. Another way of operating active systems is to clean at predefined intervals which is not necessarily reactive but it would make sense to change the cleaning route and schedule accordingly to save time and money. It should be noted that ML cleaning systems also exist for riverbed/harbor bed litter. These operations only exist as active systems and are often performed in litter prone waters (canals) or before dredging operations to clear the waterbed from obstructive litter [154]. Tol (2016) [23] provided an overview of some common passive and active ML cleaning systems currently in operation however this overview was far from comprehensive and many new systems have recently been designed and applied.

Appendix C.1 discusses a classification of ML systems and Appendix C.2 and C.3 will complement the overview of Tol and present actual state of the art concepts and existing technology for passive and active systems respectively.

C.1 Classification of ML removal systems

Table 34 on the next page shows a classification of passive and active systems based on different levels of technical advancement. Note that skimming the water surface with a sieve, illustrated in figure 58, is included as mechanized removal to emphasize manual removal does not occur in the specific type of operation.

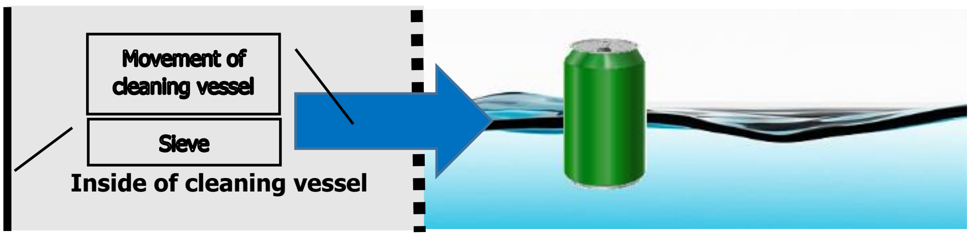


Fig. 58 skimming the water surface, a simple method of active debris removal.

Furthermore, it should be clarified that systems with intelligent navigation have the ability to intelligently adjust their routes, for instance based on previous collection locations of debris. This geo-localization of debris when these are being encountered and collected is called passive tracking. A more advanced method applies active tracking or ML detection, i.e. detecting debris from a distance, before they have been caught. The most advanced system would then also apply direct identification of debris.

Identification is useful for performance assessment but this is generally not necessary to perform before the item has been removed. Both passive and active cleaning can also have onboard sorting facilities which is shown in the last column.

Table 34 Level of technical advancement of different passive and active cleaning systems.

	Passive cleaning	Active cleaning	Sorting facility
Simple ↓ **Advanced**	1. No moving elements 2. Moving elements (e.g. propelled by river current) 3. Engine powered moving elements (e.g. with solar polar and electric motor)	1. Manual onboard navigation, no onboard engine, manual removal of ML. 2. Manual onboard navigation, onboard engine, manual removal of ML. 3. Manual onboard navigation, onboard engine, mechanized removal of ML. 4. Remote controlled navigation (human onshore), onboard engine, mechanized removal of ML. 5. Automated navigation (no human involved), onboard engine, and mechanized removal of ML. 6. Automated and intelligent navigation, passive tracking, onboard engine, mechanized removal of ML. 7. Automated and intelligent navigation, automated debris detection, active tracking, onboard engine, mechanized removal of ML. 8. Automated and intelligent navigation, automated debris identification, active tracking, onboard engine, mechanized removal of ML.	1. No Sorting 2. (Semi-)manual sorting of debris 3. Automated sorting of debris

C.2 Passive systems

Passive systems can be generally put in four categories: no moving elements, with moving elements and moving elements powered by an engine. An example of the first and simplest method of passive cleaning can be found in the river Thames where the Port of London Authority (PLA) placed stationary, passive marine litter collectors at 16 carefully selected locations. These so called 'Passive driftwood collectors (PDCs)' collect around 400 tons of litter annually in the river Thames [155]. These collectors contain no moving elements and are fed by the water current which moves through a sieve.

An example of a more advanced system is the 'Inner Harbor Water Wheel', pictured in figure 59A. This single device, installed in Baltimore (USA) around 2014 collected an average of 15.25 tons per month over 38 months, i.e. 183 tons per annum [44]. The device has been smartly placed at the exit of the river, just before the river flows into larger waters. Floating barriers extend as arms to guide litter towards to collector. The conveyor which transports the ML into a trash bin is actuated by the stream of water. Additional power can be provided by solar panels. More information on this inner harbor water wheel can be found in appendix F, including a more detailed illustration of the system.

Another example which works in a similar way is a recent invention from the Netherlands [156]. The working principle is explained as follows: The river water powers a waterwheel which drives a gear connected to two larger teethed wheels. Each wheels has four vanes which work as scooping platforms scooping the debris out of the water. Once a vane has reached an upright/vertical position the debris fall into a gutter which drains into two accumulation pools. The water in the pools ensures the survival of fish which are to be removed manually.

A functionally advanced passive system is the 'CTU system' from SK international [157]. It is equipped with a waste processing system which enables personnel to separate waste and is capable of shredding the plastic waste.

The above systems have the main disadvantage that they obstruct the waterway which can be a nuisance to marine traffic or it requires the systems to be deployed at the cost of effectiveness. The bubble barrier [158] is a recent invention currently test which aims to solve this problem. It uses a screen of bubbles released from an underwater pipe located at the bottom of the river to block ML. By placing it an angle the flow of the river naturally guides it towards collection equipment along the riverbanks. This working principle is illustrated in figure 59B. The system can cover the complete width of the river and does not disturb the marine traffic doing so.

The above systems all require surface currents to deliver ML which is not the case for the following system. The people behind the Seabin Project developed submerged trash bins [159], pictured in figure 59C, where water and rubbish flow in at the top and a pump removes the water at the bottom so the water continues streaming in. The pump can be powered by solar energy for instance. The system can be attached to the quay or mooring emplacements at locations prone to see accumulation of ML. The working principle enables the user to place it at locations which do not or barely experience naturally flowing water like lakes and bays.

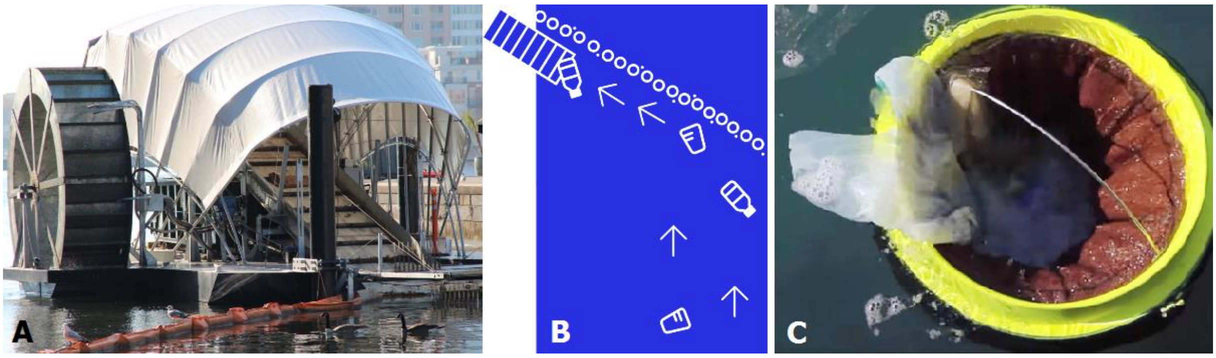


Fig. 59. Three passive systems: the Baltimore harbor wheel [44] (A), the bubble barrier [158] (modified) (B) and the sea bin project [159] (C).

From the first two examples it is clear that even with passive collection methods large quantities of litter can be collected. Data provided by the operators from both systems also illustrate and support the statement that rivers, as an entry point of marine litter to the oceans and seas, should not be ignored.

C.3 Active Systems

Active operations are mostly performed with special purpose designed ships. The advantage is that they are less obstructive but they are deemed more costly in operations [23]. Different levels of technologic advancement exist for active cleaning.

The first level is a type of operation where the navigation and the removal of litter requires human interference/operation. This is typical for removal operations of non-standardized larger items such as shopping carts and bikes. Manual sweeping of smaller items is also possible but would only be a viable choice if the operations are occasional and small scale.

The second level requires special purpose cleaning vessels which are generally larger. Port authorities or other parties responsible for cleaning larger waterbodies, like bays, would generally benefit from these type of vessels. That way the litter can be scooped out of the water by navigating through the litter as illustrated in figure 58 at the start of this section. The system can be as simple as just a hole between two sealed hulls through which the litter enters. A little more advanced could be a system which uses an automated conveyor to lift the litter and drops it in a bin, as illustrated in figure 60A. Another option, illustrated in 60B, is a floating front loader which can also dredge litter further below the water surface, carried in the water suspension, or even on the bedload. For the latter the front loader needs to be controlled by the navigator.

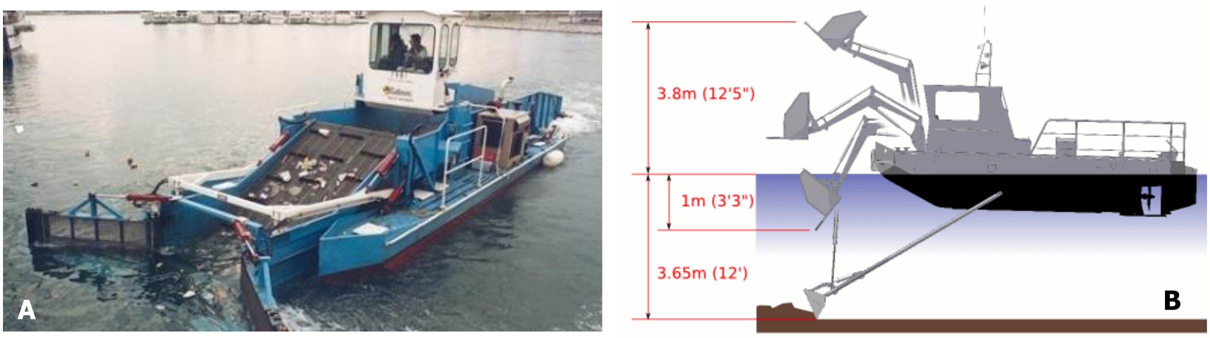


Fig. 60 An active cleaning system with automated conveyor [160] (A) and front loader [161] (B).

The third level is a fully automated system. These type of systems are still state of the art technology. Recently (halfway 2016) testing has started to use automated cleaning vessels from RanMarine Technology, called WasteShark, in the port of Rotterdam [162] which are able to clean garbage, up to 500kg or 550 liter in one time for the larger version, by themselves. The drones can navigate either by remote control or autonomous (predefined path). One of the large benefits is long operation times (16 hours per day) and machine learning [146]. If data can be stored on the quantity of litter removed at different locations, the litter density over the port surface can be mapped and accumulation spots can be better identified for future cleaning operations.

Another novelty in this class of automated systems is SeaVax from Bluebird marine systems, another cleaning vessel which should be able to contribute to cleaning oceanic litter [163]. This system also aims to recycle recovered plastic. The inventors claim a modified version should be able to operate in rivers as well. The vessels are currently in the small scale testing phase and the inventors are looking for investors. The aforementioned WasteShark and the SeaVax can be seen in figure 61A and 61B respectively.

The advantage of automated solutions is that they can be deployed more often since costs are much cheaper. For inland waters it can be argued that removing the necessity for human operation makes it more attractive to deploy smaller vessels (without steering cabin) which are more energy efficient due to their size. A fleet of these vessels which are being deployed more often means the chances of marine debris escaping to open water or becoming a hinder diminishes.

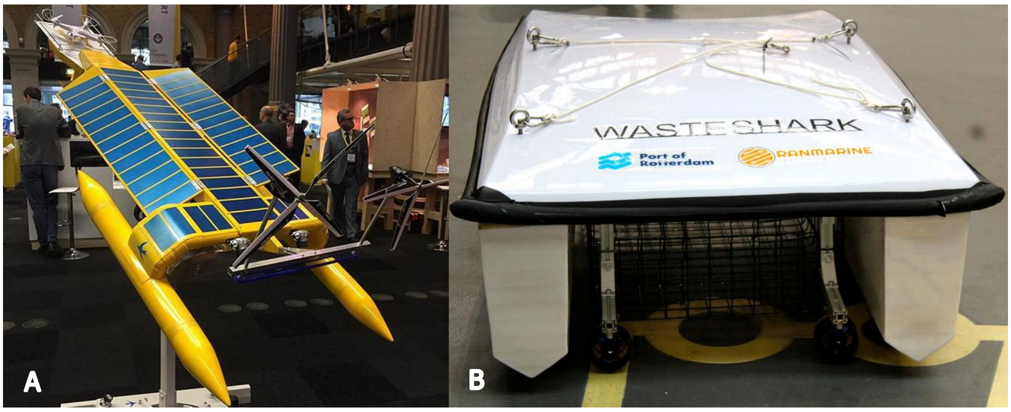


Fig. 61. Two active automated sweeping solutions, the SeaVax [164] (A) and the WasteShark [165] (B).

C.5. Appendix C summary

In recent years a range of new designs was released for ML removal systems, spurred by the growing awareness concerning ML pollution. Most of these designs are still in the concept or test phase but they prove ML removal may radically improve in the next decade. The main directions of improved are sought in a larger focus on automation, scaled up deployment and improved methods of removal, which all may highly increase removal efforts. Careful site selection remains crucial to make sure the litter streams are tackled which are either large or inconvenient with respect to their location.

Appendix D: Analysis of debris

This appendix is a supplement to section 2. It elaborates on the classification of the various characteristics of debris. Doing so can help to reduce the scope to those classes relevant in the context of this study. Understanding the origins and characteristics is also crucial to understand the pathways and transport phenomenon related to them. Moreover, since the interpretation of debris terminology is often inconsistent, this section will also clarify the terminology for the rest of the sections. An overview of the classifications for debris as discussed in this appendix, can be found in Figure 62 below.

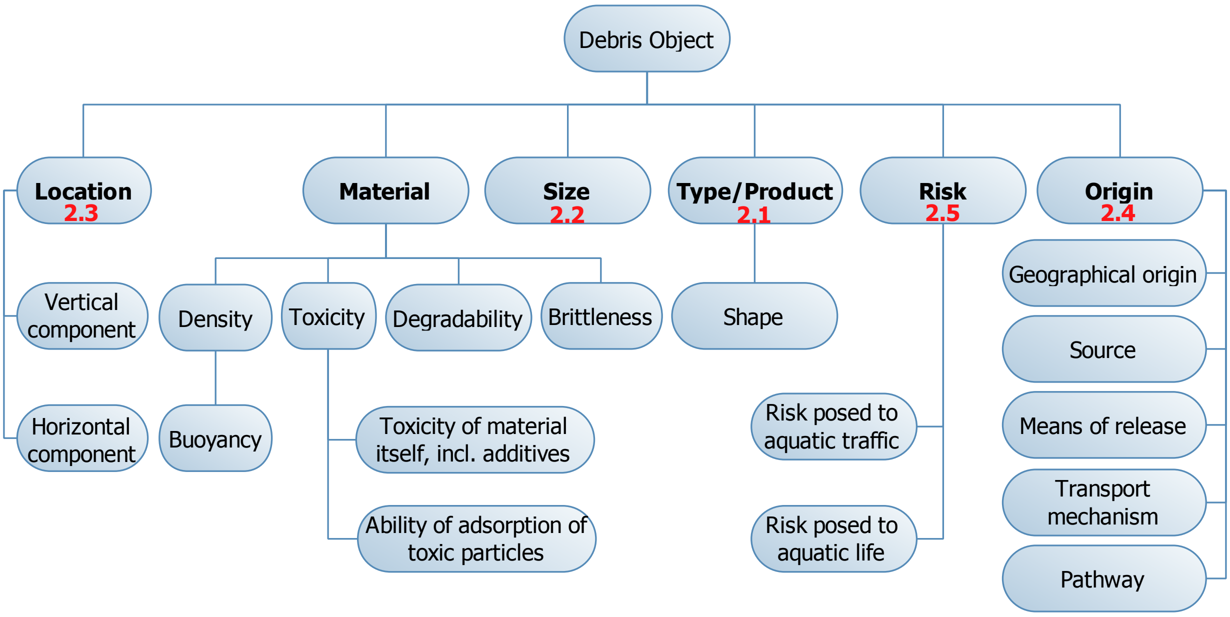


Fig. 62. Debris classification overview.

The second level, highlighted in bold, describes the main categories used for classification found in research papers. Thereunder sub classifications follow which represent a characteristic implied by the level above. The red numbers denote the subsection from this appendix in which the corresponding category is being described in. Note that different categories falling under 'material' are discussed in one or more subsections to which it is relevant, with toxicity for instance being discussed in subsection D.5. After addressing the classifications, the appendix is finished with a short summary highlighting the important points.

D.1. Type/product and material

A primary classification of debris is according to type/product and/or material. The product itself and the material it is made of are often labeled together as a category, e.g. 'plastic bottles' or 'paper towels'. This is the reason these are also grouped together in this subsection. Type/product can be relevant in terms of shape. Fishing nets for instance are particularly harmful since they can lead to 'ghost fishing', when sea animals get trapped inside. Important material characteristics are density, toxicity, (chemical) degradability and rate of mechanical fragmentation, i.e. brittleness. Toxicity will be discussed in subsection D.5.

Object with a significantly higher density than water, such as metal, will immediately sink whereas light plastics and wood will float. Hence fluvial transport of floating debris only concerns low density materials. The density of various types of marine litter materials are shown in figure 63. US data revealed that around half (46%) of the plastic waste was buoyant in 2006 [7].

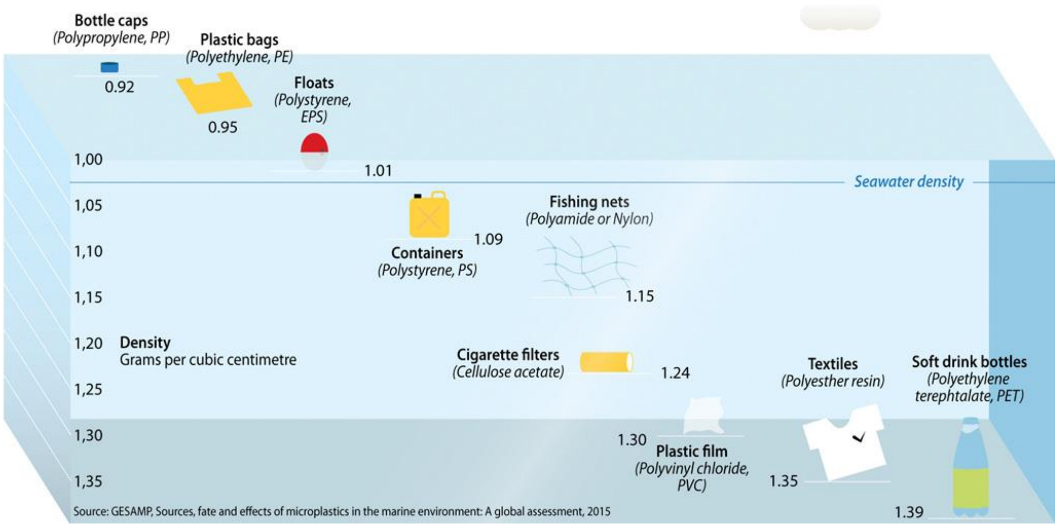


Fig. 63. Density of various types of marine waste [166].

Degradability shows the extent to which a material persist in the environment. Figure 64 highlights a range of typical marine litter items and their degradation rate. Among the worst scoring types of waste are plastic products. Unfortunately, the majority of all anthropogenic ML added to the environment can be classified as plastic [167]. More elaborately: *'Despite the uncertainty, estimates from around the world are reasonably consistent in estimating plastics to comprise approximately 10 per cent of municipal waste mass. In contrast, plastics comprise 50–80% of the waste stranded on beaches, floating on the ocean surface and on the seabed'* [7]. For this reason many papers focus solely on plastic ML. Natural debris have generally a much higher degradation rate than synthetic anthropogenic items.

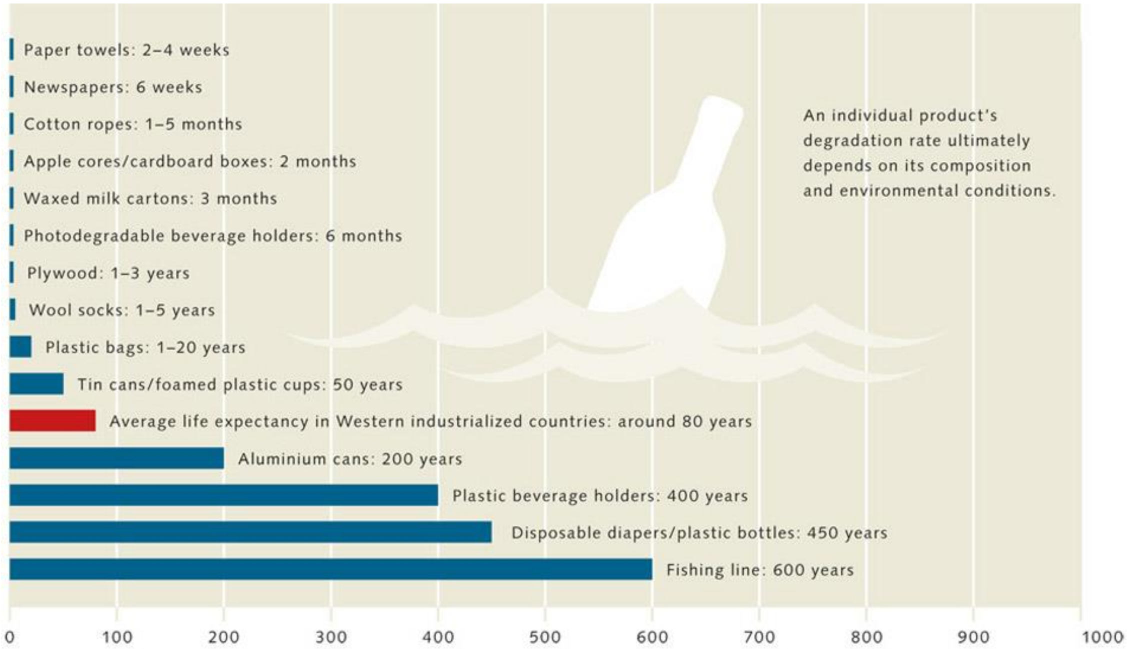


Fig. 64. Marine waste degradability [13].

Brittleness is important since it is an indicator for short term fragmentation. Noticeable chemical degradation may take decades whereas mechanical fragmentation can go much faster. Weak brittle materials, like glass and foam polystyrene, are particularly vulnerable. Foam polystyrene, like Styrofoam, is often used for (food)-packaging and insulation and is vulnerable to wind forces due to its low density. This is likely the reason it is often found in aquatic environments, for instance in the coastal waters of France where about 10% of the items consisted of foam polystyrene [168]. In Southern California foams accounted for over 70% of the number of particles surveyed from river accumulation and foamed polystyrene accounted for 11% of the total mass [169].

D.1.1. Geographical differences

The geographical differences are major, especially if the ratio between anthropogenic and natural debris is considered. Debris collection data from the Tokyo bay reveals that merely 4% (by volume) of all debris are from anthropogenic origin as can been seen in figure 8, left. A study in the river seine in Paris revealed a comparable number. *'…vegetal debris was predominant and represented between 92.0% and 99.1% of total floating debris by weight.' 'Plastic debris represented 0.8–5.1% of total debris by weight...'* [170]*.* Japan and France are developed countries whereas in developing countries anthropogenic debris may account for a much larger part of the total. For Malaysia for instance Malik and Manaf 2018 [99] identified an average rate of over 70% for non-natural, non-organic debris, as shown in figure 65, right.

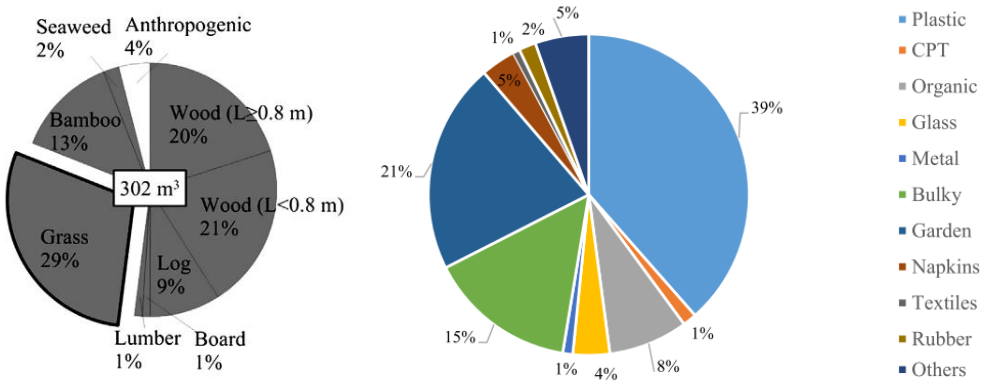


Fig. 65. Distribution of debris origin in Tokyo bay (L) [53] and Sungai Batu watershed (R) [99].

It can be seen natural debris can certainly not be discarded, even though their environmental impact will be lower. Among anthropogenic debris, fishing equipment becomes a marginal group however since its origin and presence is heavily skewed towards marine waters. It should be noted that many studies, for instance on litter movements, will consider specific types of debris, often plastics, which is often carefully chosen based on surveys on abundance of debris types. Hence conclusions may have to be extrapolated to other debris groups.

D.2. Size

Size is a relevant classification since it affects the ease at which it can be removed from the waters. Furthermore, size affects the threat it poses to aquatic life and nautical traffic. Large objects might damage rudders and propellers while smaller object are prone to be ingested by aquatic life and block intake pipes of boats and ships. Additionally, particle size does influence litter movements. Van der Wal et al. (2013) notes that larger plastic waste in the Meuse, discharged somewhere upstream, tends to be removed quite often: '*It seems that larger plastic items that float at the water surface are prone to stick to vegetation on river flood plain, dykes and pile up against hydraulic structures, like sluices and hydropower stations. Items are often remove from these locations because they block water flow, damage dyke slopes, hamper the use of an area or decrease its aesthetic value. For the river Meuse, it is suspected that these larger items are removed or rapidly degrade to smaller particles, micro plastics, since relatively small amounts of larger plastic items are only found up to Dordrecht'* [78]. This observation makes sense as larger items are more susceptible to stranding such items are generally removed upstream. Size is also a crucial vector in vertical distribution, as will be explained in appendix D.3. Consequently, data about particle size might help to improve modelling of particle behavior which in turn helps to improve spatial and temporal predictions.

According to Ten Brink et al. (2016) [171] common classification separates ML by defining **micro** litter (<5 mm) and **macro** litter (>5 mm), occasionally extended with '**nano**'(<1μm), '**meso**' (<25 mm) and '**mega**' (>1 m).

The latest report of the Joint Group of Experts on the Scientific Aspects of Marine Environmental Protection (GESAMP) mentions that in contrast to downstream micro plastics removal, the downstream macro plastics removal is generally worth the effort of taking action: *'Whilst the benefits of action against macro plastics often outweigh their costs, downstream clean-up actions focusing on micro plastics are unlikely to be cost-effective, underlining the need for upstream preventative measures on sources…. Acting on macro plastics may be easier to justify, as the social, ecological and economic effects are easier to demonstrate'* [15]. The removal of macro plastics however also benefits the mitigation of micro plastics since plastics tend to degrade and fragment into smaller pieces [15]. Small particles should not be neglected however if the combined weight of small particles is comparable or larger than large ones. A sampling study from Moore et al. (2011) [169] reveals that in general small particles (1 mm – 4.75 mm) largely exceeded large particles (>4.75 mm) while in terms of weight large particles largely exceeded small particles. 85% of all weight could be contributed to large particles despite large particles merely contributing 9% of all particles. A similar observation was found in the waters around Hong Kong. As shown in table 2 and 3 in subsection 2.4, during the rainy season in the east section over 99% of all weight could be contributed to macro plastics whereas they only accounted for 16% of the total count.

Nonetheless, removing smaller particles may become cost efficient in the future. For this reason, larger micro particles (1-5 mm) should not be simply ignored although the main focus should be on macro particles.

D.3. Location

The spatial distribution of debris in both the vertical and the horizontal component, impacts the transportation of debris and how and where it can be removed from the waterbody. For the vertical component, generally three distinguishable positions could be identified, here elaborated by Van der Wal et al. (2013) for the specific case of rivers:

'The transport of plastic litter in rivers occurs through different transport modes: a minor fraction floats on the water surface, a major fraction is transported in suspension in the water column and a small fraction is transported as part of the bed load transport near the bottom of a river' [78].

The water surface can be further subdivided into different states of buoyancy, defined below in figure 66. This is especially relevant for the susceptibility of a particle to wind induced transportation and hence horizontal spatial distribution. Additionally, one can add non transport states like sediment [36]. Sediment is relevant as this can be used to perform research on spatio-temporal behavior of debris.

Fig. 66. Three different surface states of ML particles [76].

From surveys in numerous rivers it appeared that the majority of debris in rivers is located near the surface: *'In the presented research performed by SK International it appeared that 98% of all the debris was present in the most upper meter of the water column, whereby the majority of the debris appeared in the upper halve meter of the water column. Therefore, marine litter can effectively be removed in* *the port of Rotterdam by cleaning vessels that only filter the upper layer of the water column'* [23]. For marine waters in contrast, 94% of all debris by estimates [31], is located on the sea floor. This underlines the argument to remove riverine litter, as soon as possible, before it sinks and becomes virtually inaccessible.

Size is an important indicator for vertical distribution, generally larger sized debris are predominantly located at the surface whereas smaller particles can be found more spread throughout the water column. A survey by Lattin et al. (2004) [35] found that large particles, > 4.750 mm, accounted for over 87% of the total weight at the surface, whereas 0.355-0.709 mm accounted for merely 1.3%. In the mid column these numbers where respectively 25% and just over 30% while at the bottom large particles dropped to 3.9% whereas small particles increased to 42%, hence skewing heavily towards smaller particles. Density of particles is logically also affecting vertical distribution. Since important plastic groups have a density smaller than water, see subsection 2.1 figure 6, plastics generally float.

In terms of horizontal locations one can distinguish specific waterbodies or subsets thereof. Examples would include rivers, ports, bays, river mouths, seas and oceans. Other important distinguishable locations for debris (particles) are floodplains/riverbanks [78], beaches [39]. These are non-transport states but as debris may be transported both to and from these states to and from water they are still relevant in the transport of debris. Moreover, as these are subject of many research studies w.r.t. ML, they may be indicators of ML pathways and temporal and spatial distribution.

D.4. Origin

The 'origin' of debris can be conceived on different levels. On a global scale the extent of the plastic contamination problem and the contribution thereof to the world's largest waterbodies can first of all be related to different countries. From figure 67 it can be observed that the quantity of mismanaged plastic varies significantly from country to country. The most significant quantities of mismanaged plastic can be found in developing Asian nations whereas in developed areas like the United States or the EU the percentage of mismanaged plastic is much smaller. Consequently this leads to regional differences in terms of ML quantity: '*In European waters, up to 100,000 pieces of litter visible to the naked eye were counted per square kilometer on the sea floor. In Indonesia, the figure was even higher – up to 690,000 pieces per square kilometer'* [13].

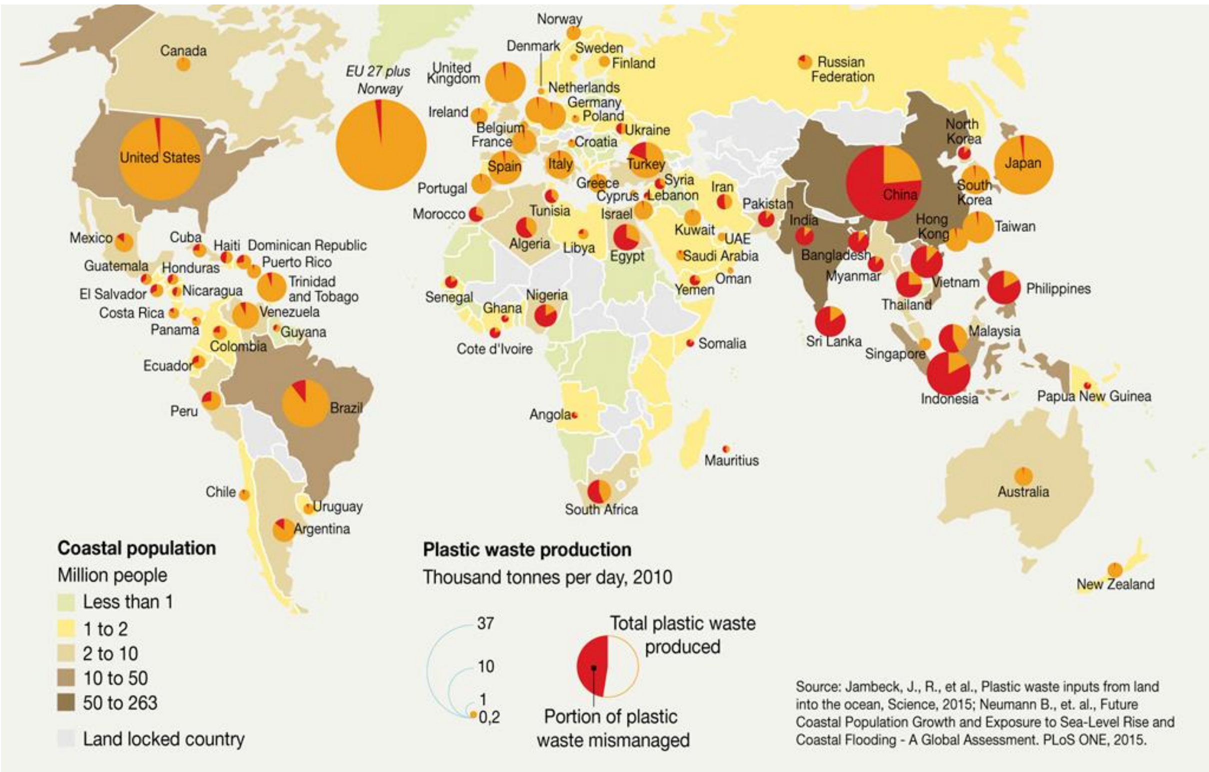


Fig. 67. Worldwide map of produced and mismanaged plastic [10].

Several sources of litter can be identified which shows the origin of debris. An exhaustive terminology (highlighted in bold) is used in a report by the Joint Research Centre of the EU to identify how debris ends up in our oceans: '*…**source*** to *indicate the economic sector or human activity from which litter originates but specify further the **means of release** to indicate the mechanism or the way in which a given item leaves the intended cycle and/or enters the natural or urban environment and becomes a problem. The **geographic origin** can thus be defined by the geographic location of the source and where the release took place'*[30]. Hence geographic origin can be a country but also on a sub country level such as a beach or the riparian zone of a river. Rivers are sometimes identified as a source or entry point of ML even if they act largely as a way to transport it, which makes sense from the point of view of the water body the river is discharging in. However, from a more holistic viewpoint 'pathway' is the appropriate terminology to use. To avoid this confusing terminology, it is useful to extend the terminology with 'transport mechanism' and 'pathway': *'… **transport mechanisms**, which move litter into and within the marine environment from various land- and sea-based sources. We consider a **pathway** to be the physical and/or technical means by which litter enters the marine environment'*[30].

In general most scientific papers also distinguish between terrestrial sources and marine based sources. Galgani et al. (2015) [172] list an exhaustive group of potential terrestrial sources: recreational use in coastal areas, general public litter, industry, harbors, unprotected landfills, fly tipping, sewage overflows, extreme events and introduction by accidental loss [172]. Globally the majority of the litter is estimated to be land-based although the book also warns clear geographical differences should not be overlooked. Regions with a litter mix skewed more towards ocean based sources include the North Sea and the US

West coast. Other regions, such as the Mediterranean Sea and the South Chinese Sea exhibited larger quantities of land-based sources [172]. This can be illustrated by surveys in the Celtic sea which linked 65% of the litter to fishing whereas in the Gulf of Lion for instance merely 2.7% on average was linked to fishing [34]. Therefore locally different courses of action are perhaps appropriate.

D.4.2. Contribution of rivers to debris stock in downstream bays and ports

The influence of riverine influx of debris on bays and harbors downstream has been already discussed in section 2. Here, the results of Cheung et al. (2018) [40] will be discussed more elaborately. The results are presented in table 35, for large debris, and table 36, for micro particles, also reveal interesting differences between small and large particles. Particles are indeed more numerous and heavier in all locations and all size classes in rainy season compared to dry season. For large particles a larger increase in weight can be observed, both mean and median, which suggests a skew towards heavier debris. Median values have been included since mean values can be severely skewed by outliers. Moreover, West shows a larger increase compared to East. Micro plastics however show a tendency towards smaller particles, since weight shows considerably less increase than count. Moreover, East shows a larger increase compared to West. Hence micro particles might be more affected by local sources, such as traffic or sewage outflows for instance. Differences between small and large particles reveal precaution is warranted when considering such micro plastic surveys to make conclusions for larger debris.

Table 35. Quantity of large litter (⩾4.75 mm) found in the waters around Hong Kong [40].

	Rainy season		Dry season	
	West (x times dry season)	East (x times dry season)	West	East
Mean number [count/m^3]	1.450 (22)	0.911 (12)	0.066	0.079
Mean weight [mg/ m^3]	198.768 (28)	79.767 (38)	7.001	2.098
Median weight [mg/ m^3]	9.274 (30)	20.111 (19)	0.308	1.070

Table 36. Quantity of micro plastics (0.355–4.75 mm) found in the waters around Hong Kong [40].

	Rainy season		Dry season	
	West (x times dry season)	East (x times dry season)	West	East
Mean number [count/m^3]	6.932 (22)	4.911 (31)	0.322	0.158
Mean weight [mg/ m^3]	0.370 (1.3)	0.210 (9)	0.289	0.023
Median weight [mg/ m^3]	0.325 (6)	0.221 (13)	0.051	0.018

D.5. Risk

Risk assessments are rare [173], which can be contributed to a scarcity of data and knowledge pertaining certain processes. Hence, risk is not often included as a classification but it is of crucial relevance nonetheless. Removing the debris with the highest risk is after all the most effective method of removal if one aims to mitigate the burden of ML. The risk R is defined as the probability of a harmful event E occurring, P(E), times the loss in case of a harmful event, L_E. This can be denoted as follows, summed over all possible events:

$$R = \sum_{all\ possible\ events} P(E) \cdot L_E \quad (60)$$

As demonstrated, the risk consists of two parts, the probability part and the loss part. The probability is the quantification of the number of incidents expected while the loss is the monetization of said incidents. The probability depends on the following:

- Characteristics of the debris. Determines the type of events possible and how likely the event is when it encounters life (e.g. marine animals) or maritime operations (e.g. fishing or shipping). It also determine the physical processes taking place during the existence of the debris (e.g. biofouling or degradation).
- Pathway (the route a debris will take through the environment), which depends on:
  - Geographic origin;
  - Time of release;
  - Characteristics of the debris (buoyancy for instance);
  - Removal efforts along the route;
  - Random component for horizontal diffusion [33].
- Geographic presence of life or maritime operations the harm is inflicted upon. If the pathway of the debris crosses any of these geographic presences, interaction may occur.

It is not surprising assessing this probability is difficult. Pathways can be modelled using numerical modelling [33][24]. This should however be done for each port/fluvial outflow and under various climatological scenarios. Physical processes could also be modelled, although knowledge on some processes like sinking of ML fragments through biofouling is still premature [174]. Pathways of debris would have to be subsequently be mapped onto areas of maritime activity, nautical routes and fish and marine life habitats. This approach has been attempted by Schuyler et al. (2015) [175] for several sea turtle species. Habitat maps were mapped onto global marine plastic distributions, which was modelled based on data obtained from ocean drifting buoys, to predict exposure levels to plastic pollution.

C.5.1. Qualifying harms

Another approach is to merely look at historic data, i.e. registered incidents. The number of incidents can help to estimate the probability of an incident. This approach not without flaws since it may be a challenging task to trace back the origin of the debris. A certain debris released in one place may pose problems in one place while the same debris released elsewhere may not pose any problem since the pathway is different. In other cases the specific debris involved in the incident or even the incidents themselves may not be registered at all. Nonetheless this is the most straightforward way to get a first glance at problematic debris. Various harms can be identified. Harms are a qualification of an event whereas an incident is a harmful event, a single realization of a harm. The main harms can be classified as follows [173]:

- Harm to biota
    - Ingestion;
    - Entanglement;
    - Smothering;
    - Transport of biota/invasive species.
- Socio economic harms
    - Harms to nautical traffic;
    - Harms to fisheries and aquaculture;
    - Harms to human health;
    - Decrease in aesthetics (beaches, water banks and water surface).

Ingestion may lead to rupture of intestines, choking, blocking of the digestive system and effects related to the release of toxic elements [173]. Not only the toxicity level of the material plays a role but also the ability of the material to adsorb hazardous particles. Research has shown that different plastics show very different adsorption rates and capacities [176]. Also additives, such as toxic chemicals for enhancing material performance can add to the level of risk [177]. Different studies on animals have revealed harmful effects of certain additives used in plastics. Examples include hormonal effects such as increased estrogen levels and reduced testosterone productions [178]. Size plays a role since only specific size ranges of plastics can be ingested. It also affects the risk of blockage and rupture of intestines. The size would also play a role in whether the animal would be able to mistake it for food. Furthermore, degradability is also relevant. A shorter presence in the aquatic environment naturally decreases chances of coming in contact with marine life. The vertical location is a factor, which is influenced by density. Surface based debris can be seen by birds, whereas debris located on the ocean floor are much less susceptible of ingestion by marine life. Close to shore the chances increase that debris are blown ashore and become a risk for livestock [12]. Hence the horizontal component, influenced by buoyancy affects the class of animals affected. Finally the shape of the object could be relevant in the sense that it can be more susceptible to blockage or cause internal bleeding. Similarly, the same factors except toxicity are relevant for the extent of the risk of entanglement [11]. Long flexible debris and debris with holes are particularly risk prone. Hence, entanglement can often be contributed to ropes and nets, of which many are discarded or lost by fisheries [173]. Some inland generated debris may also pose a risk such as plastic ribbons, plastic bags and packaging with holes like cup carriers, plastics bags and fruit nets. Smothering occurs when organisms, like sponges and corals are covered by for instance plastic sheeting. This may lead to reduced fitness and mortality [173]. Transport of biota may lead to transport of invasive species and disruption of ecosystems. This risk is amplified by debris with low degradability such as plastics [173]. Other risks exists but these seem largely related to fishing equipment and larger debris.

Harms to nautical traffic include fouled propellers and rudders and blocked intake pipes [12] [173]. The risk of fouling is clearly with debris which are long and flexible, like ropes and nets. In general, nautical harms are affected by size, shape, degradability and location of the debris. The horizontal location is perhaps even more relevant as a factor compared to marine life since nautical traffic is more bound to traffic routes, transport hubs and as such the spatial spread of nautical traffic is very homogeneous. In port environments traffic for instance is very dense. Out in the open seas and oceans, especially away from the marine traffic routes the risk posed by objects drastically diminishes. However, if an incident occurs in such remote locations, ramifications for the crew might also be more severe, rescue becomes more costly. Surveys identified risk prone areas as shallow waters like rivers, river mouths and ports [173]. Logically, vertical position influences the risks involved. Debris at the depth of intake pipes, propellers and rudders are most likely to inflict damage. According to a Dutch survey from 2012 [179], found that smaller ships are more susceptible to perceiving inconvenience due to debris since propellers and intake pipes from larger vessels are deeper below the surface of the water. The focus of that study was however on sea litter and it does not clarify which type of litter has caused the damage, which would understandably be hard to point out in some cases when damage is only noticed at a later moment. Japanese fishing studies also reached a comparable conclusion concerning the vulnerability of ship sizes [14]. Risks of blocking intake pipes is related to size and shape.

Fishing is mostly affected by similar harms as nautical traffic. Fishing specific harms include contaminated catches, debris accumulated in fishing hauls, blocked sorting/selectivity grids used by trawlers or damaged equipment like teared nets [12] [173]. Sharp and heavy objects, like oil drums [12], may damage nets while all types of large macro debris may contaminate and block fishing equipment. Within aquaculture, harms include contamination of fish farm sites and fouled propellers. Hence any floating debris and debris prone to foul propellers will affect aquaculture.

Human health is affected in various ways. Firstly life may be at stake due to fouled propellers and rudders as the Korean accident mentioned in the introduction proved. Removing debris from fouled propellers and rudders is a dangerous job [12]. Swimmers might become entangled, with the biggest risk posed by derelict fishing gear like ropes, nets, lines and wires [12] [173]. Furthermore, on beaches there is a risk for visitors to hurt themselves on sharp objects such as glass and needles [12]. Finally, ML, especially (contaminated) micro plastics, may be unintentionally ingested after eating contaminated shell (fish). These (contaminated) particles may be toxic, carcinogenic or mutagenic [173].

Decrease in aesthetic value is brought by any floating debris or debris in suspension which is washed ashore. Macro particles, especially larger macro particles are most visible and hence lead to the largest decrease in aesthetic value. Surveys indicate visible litter on beaches is considered a serious source of annoyance by visitors [173] [180]. These surveys do not distinguish between natural and anthropogenic litter, but it is highly plausible that anthropogenic litter would be considered worse if similar quantities are considered.

D.5.2. Quantification and monetization

The next step is quantifying and especially monetizing these harms. Monetizing the harm equals calculating the expected loss in case of a harmful events in risk terminology. According to Bertram et al. (2014) monetizing is feasible in specific cases but in many cases it is a gross approximation or simply infeasible [181]. Since studies have usually a limited geographic scope, it is often necessary to translate the results into the area of interest. Methodologies such as benefit transfer are however hard to apply with sufficient reliability [181].

Entanglement is the most easy to quantify due to visible presence of litter, but it is predominantly caused by abandoned fishing gear which is not the litter typically supplied by rivers and floating in port environments which decreases the relevance to this study. Moreover, direct mortality appears to be irrelevant on animal populations as a whole [173]. Ingestion is another important harm, which is deemed to me much more relevant but for which quantified effects are unfortunately considerably more difficult to obtain. Sub lethal effects are hard to quantify since other factors contribute to decreased fitness level of animals [173]. Quantitative data for smothering and transportation of invasive species is also not sufficiently available to make reliable estimates [182]. In general, monetizing of harms on animal life and ecosystems is extremely hard although it works well in specific cases, if the animal has direct commercial value. Gilardi et al. (2009) [183] for instance performed a cost benefit analysis by calculating monetized benefits of removing derelict fishing gear merely by examining the commercial value of crab, a marine animal prone to get entangled. For non-commercialized animals the only remaining option is to obtain an estimate of the financial value marine life via willingness- to-pay surveys. Such surveys were used by Lord (2016) to estimate the effects of plastics on marine ecosystems but data is unfortunately not available [182]. It is far from ideal to rely on such data however, especially if these values of harms which are directly quantifiable in terms of money. Costs responders say they are willing to pay via these surveys and costs they are actually willing to pay if implemented might differ significantly.

Data on registered incidents of entanglements and ingestion is available for certain species [173] [184]. Figure 68 below shows the type of debris affecting individuals and species. Encounters with individuals was mostly with rope and netting (57%), followed by plastic fragments (11%), plastic packaging (10%), other fishing related debris (8%) and finally micro plastics (6%). Other categories except other or unknown, were each less than 0.04% and hence negligible. It shows shipping and fishing debris dominate, especially for entanglement whereas plastic fragments and micro plastics largely dominate for ingestion. Encounters by species is less skewed: 24%, 20%, 17%, 16% and 11% respectively. Glass, metal and paper score between 0.38% and 0.65%, not negligible but small nonetheless.

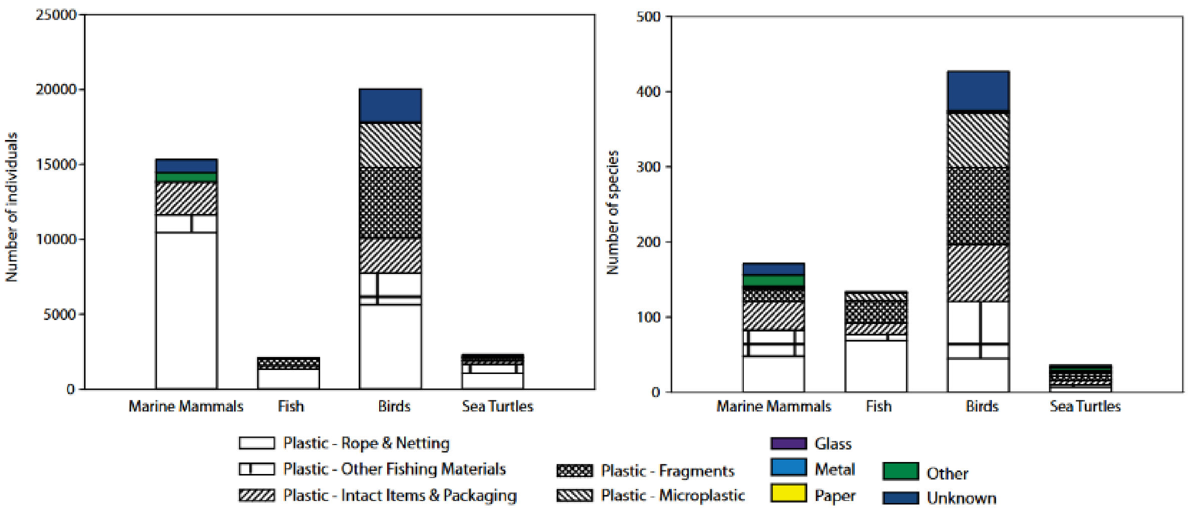


Fig. 68. Incidents of entanglement and ingestion reported by debris class, for individuals and species [184].

Thresholds could be established with the maximum percentage of animals which are allowed to be affected. Once the threshold is breached, urgent action on mitigating relevant debris is advised. Examples of thresholds are very limited however and those which exist are more or less arbitrary. The EcoQO target [185] specifies plastic particles in Fulmar stomachs in the OSPAR region; less than 10% should carry more than 0.1 grams of plastic. This is however more based on what is practically achievable than on the true level of risk. This is not surprising as it was demonstrated the effects of ingestion are hard to quantify. A recent publication [186] did an attempt to assess the impact of plastic debris on earth's ecosystem using the 'Planetary boundary concept'. Chemical pollution, one of the boundary threats most related to plastic pollution has however not been quantified yet. Standards, for instance for toxic metals leaching from plastic litter, however do exist. Kako et al. (2014) [153] suggests that within 10 years a small but significant number of beaches the standard might be exceeded.

Instead of quantifying, an elegant approach to assess risk could be ranking which can be obtained by expert elucidation. Wilcox et al. (2015) [187] used over 200 expert opinions to create a ranking of various ML debris based on the threat they pose on three types of marine animals, as shown in figure 69. The paper ranks chemical contamination (here mentioned as separate category) lower than entanglement or ingestion. It emphasizes however that the understanding of ecotoxicology is limited.

Item ID	Item name	Rank of expected impact			
		Mean	Bird	Turtle	Mammal
6	Buoys/traps/pots	1	1	1	1
7	Monofilament	2.3	3	2	2
8	Fishing nets	2.7	2	3	3
14	Plastic bags	5.7	4	9	4
17	Plastic utensils	5.7	7	4	6
1	Balloons	6.7	8	5	7
4	Butts	7.3	5	12	5
2	Caps	7.7	9	6	8
9	Food packaging	8.7	10	7	9
12	Other EPS Packaging	9.7	11	8	10
11	Hard plastic cont.	11.3	6	13	15
16	Plastic Food Lids	11.3	13	10	11
18	Straws/Stirrers	12.3	14	11	12
19	Takeout containers	15.3	15	18	13
3	Cans	15.7	17	14	16
15	Beverage bottles	16	12	17	19
20	Unidentified Plastic Fragment	16.3	16	19	14
5	Cups&plates	16.7	18	15	17
10	Glass bottles	17.7	19	16	18
13	Paper bags	20	20	20	20

Fig. 69. Ranking of ML debris based on expected impact to marine life [189].

Harms to nautical traffic, fishing and aquaculture are considerably easier to put financial value on. A survey among UK ports revealed fouled propellers was by far the most common harm [12], followed by blocked intake pipes. A survey among Portuguese fishing vessels found the same. For the UK, ropes were the most important culprit of fouling, followed by nets, plastic and wire. Another UK survey revealed the most common types of debris accumulated in fishing hauls were ropes, plastic, bottles and wire [12]. A Spanish survey found plastic bottles to be the most common type of debris [12]. The most common types of debris found to be of nuisance in UK fish farms were ropes, plastic and wood [12]. Costs are available, like the costs of rescue missions due to fouled propellers, costs of lost fishing time and costs of the actual disentangling. Overall, cost estimates remain however limited in quantity and geographical spread and if available, data is often aggregated.

For human health quantifying and monetizing is harder. Loss of human life is very rare and putting a financial value on human life is obviously not trivial. Moreover, minor incidents like cuts are rarely registered. Regarding the intake of contaminated food, concentrations are generally so low the risk is deemed negligible, especially since fish stomachs are often removed before served. A larger risk is present however with shellfish, like mussels or oysters which are consumed with the complete digestive system [49]. Nonetheless, consumption of these is generally low.

Aesthetic value is in some cases hard to quantify. Signs of contamination can lead to a perceived degradation of life quality of the local community. This type of parameter is not very suitable for monetization. However, removal costs could be used instead [12]. Since debris are often removed, for instance from beaches, removal costs could be used to monetize the presence of debris.

Loss of tourism can be estimated with surveys. Surveys can provide answers with respects to the behavior of tourists and the average spending of tourists can then be used to monetize. The quantification through surveys may however lead to some inaccuracy since the opinions of the respondents might not be constant over time and their travel choice will also depend on information provided on the presence of litter which introduces a bias into the surveys. It may also be hard to translate the results of said surveys to other geographical areas, especially because it largely depends on the available alternatives in the region. A survey like this was put out by Krelling et al. (2017) [182] and found that 15 litter items/m^2 would deter 85% of users causing up to US$8.5 million local losses. Such data can be used to put a financial value on litter. It is however nonlinear and as mentioned earlier, it depends on the available alternatives.

Data on risk for specific items is unfortunately too scarce to make comparisons. Lord (2016) [184] made calculations on the risk of plastics and obtained a cost of $56 per metric ton of plastic and $21 per metric ton of alternatives. A closer look however at the calculation reveals it simply looked at loss estimated due to ML for several economic sectors and multiplied this with estimates of the percentage of plastics in ML (50%-80%). It ignores however which debris actually contributed to the damage. Hence this figure is too vague to be practical.

One can conclude risk assessments are rare due to a lack of knowledge on certain harms and a lack of quantified data. Data is simply too scarce to make reliable comparisons based on costs per debris. Incidents have not been researched or incidents or debris involved in incidents are simply not registered. Many harms are also not very suited to be monetized since these include harms to ecosystems and biota. This in contrast to loss of man hours or repairs, which can be easily monetized. It is possible however to indicate the debris most prone to affect certain harms as summarized in table 37.

Table 37. Summary of the types of debris responsible for different harms.

	Type of debris responsible	**Example debris**
Ingestion	Small macro debris and micro particles.	Cigarette butts, plastic bottle caps, primary and secondary micro plastics.
Entanglement	Long flexible debris and debris with holes.	Ropes and nets, plastic packaging, plastic ribbons, plastic bags and packaging with holes like cup carriers, plastics bags and fruit nets.
Smothering	Large sheets.	(Large) plastic bags.
Transport of biota/ invasive species	Any long lasting floating debris	Plastic fragments and items.
Harms to nautical traffic	Long flexible debris	Ropes, nets, plastic bags.
Harms to fishing and aquaculture	Long flexible debris, heavy sharp objects and floating litter.	Ropes, nets, plastic bags, oil barrels, wood, household plastic and foam.
Harms to human health	Mostly sharp objects.	Glass and needles.
Decrease in aesthetics	All types of floating litter.	Natural debris, household plastic, foam.

Ranking of debris is a possible alternative since this avoids putting a value to debris. This can be achieved by expert elucidation. Such surveys are limited however. Moreover, since these are ordinal scales their applicability is limited compared to interval and ratio scales. Another alternative is standards, one standard and one target was reviewed in this subsection but the target reviewed in this subsection was essentially based on feasibility instead being a scientifically established threshold to minimize risk. This means the usage of standards is limited, especially in the geographical sense since feasibility is geographically depended. The standard concerned toxic leaching from plastic. Prediction models revealed this threshold may be breached on many Japanese beaches in the future.

Within the marine environment fishing debris, like ropes, nets and monofilaments, pose the biggest risk, whereas plastics are second. Certain plastic items are of bigger risk, predominantly single use plastics from household garbage/disposal and single use plastics used in public, e.g. bags, fruit nets and products with holes as these can lead to entanglement. Fishing debris are however mostly discarded at sea. Natural debris are only relevant in downstream areas of a river like bays and ports where there are mostly affecting aesthetic value and aquaculture.

D.6. Appendix C: summary

In short, plastic is globally the largest type of anthropogenic debris as commonly known. This is however location dependent with affluent regions of the world, due to being equipped with more capable waste management systems, facing more accumulation of natural litter with less affluent regions facing the opposite with anthropogenic waste being more abundant. Hence, both anthropogenic as natural litter should be accounted for.

Debris accumulation contributes mostly to local water contamination, both sea and oceans which implies the common argument, that any action from small contributors is useless if large global contributors are not being handled first, is largely untrue. Contamination of ecosystems should hence be mitigated through regional sources and pathways.

For the time being the focus ought to be directed towards cleaning macro sized surface litter, since the removal of smaller sized litter is generally not cost effective with current technological advancement.

Finally, risk assessments are rare due to a lack of knowledge on certain harms and a lack of quantified data. Many harms are also not very suited to be monetized since these include harms to ecosystems and biota. This in contrast to loss of man hours or repairs, which can be easily monetized. For the aforementioned reasons standards, which indicate a certain threshold value for each debris category, are also rare. The alternative could be to use ranking, for instance through expert elucidation. The downside is the limitation of ordinal scales compared to interval and ratio scales. Such rankings are also very scarce and are not comprehensive. The only ranking discussed in this section is not comprehensive as it only pertains a subset of harms. Since performing a quantitative comparison for all debris on all harms is infeasible, a qualitative comparison was performed to identify the most critical debris w.r.t. to various harm categories. One of the most crucial debris categories are plastics, especially bags, fruit nets and products which contain holes. The most crucial debris are fishing debris such as ropes, nets and monofilament fishing line. These items however are generally to originating from land based sources. Natural debris are mostly harming inland nautical traffic and aesthetics and play a crucial role due to their abundant presence. Plastic items can be found on the streets as these are frequently littered as single use plastics or around public waste bins which reached maximum capacity. These plastics can also be found on dumping grounds for general household waste. Natural debris are logically originating from areas with vegetation which means their abundancy depends on vegetation levels.

Appendix E: Example distributions

This is a supplement to subsection 2.4. Figure 70 below shows a fictive example of a temporal distribution of debris accumulation influenced by one or multiple factors with such characteristics. If the timeline is measured in weeks weekly differences can be observed but in addition there also appear to be seasonal tendency with a considerable surge in accumulation from somewhere around week 14 to 25 and week 39 to 49. Hence, there can be jumps in the distributions which span a short time while there can also be seasonal fluctuations or seasonal Jumps. In figure 70, the reference accumulation quantity is zero whereas a larger reference quantity is also possible. In that case jumps can logically be negative.

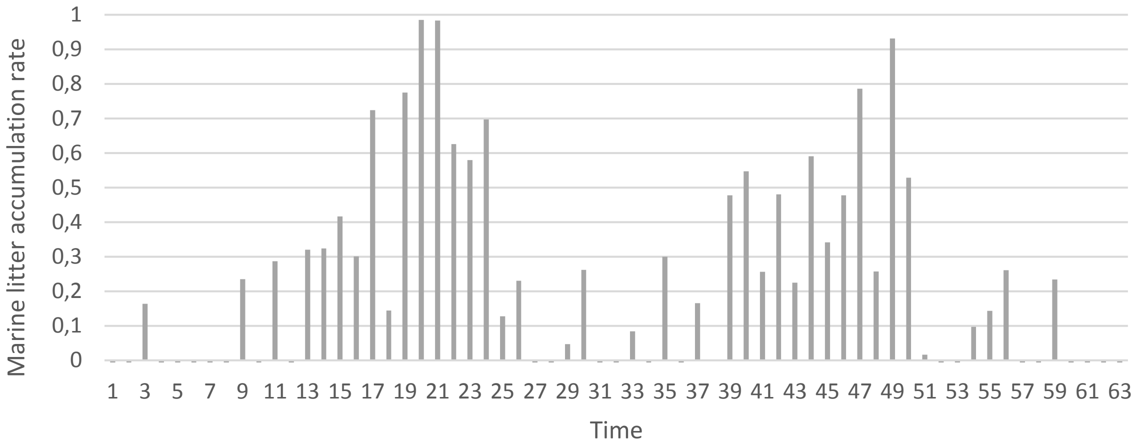


Fig. 70. Visualization of a temporal litter distribution with repetitive nature.

The graph in figure 71 shows an accumulation pattern which can be seen as a trend where accumulation rates are slowly increasing over time and an accumulation pattern where a sudden event leads to a step in the accumulation rate. Both are permanent, i.e. not repetitive in nature.

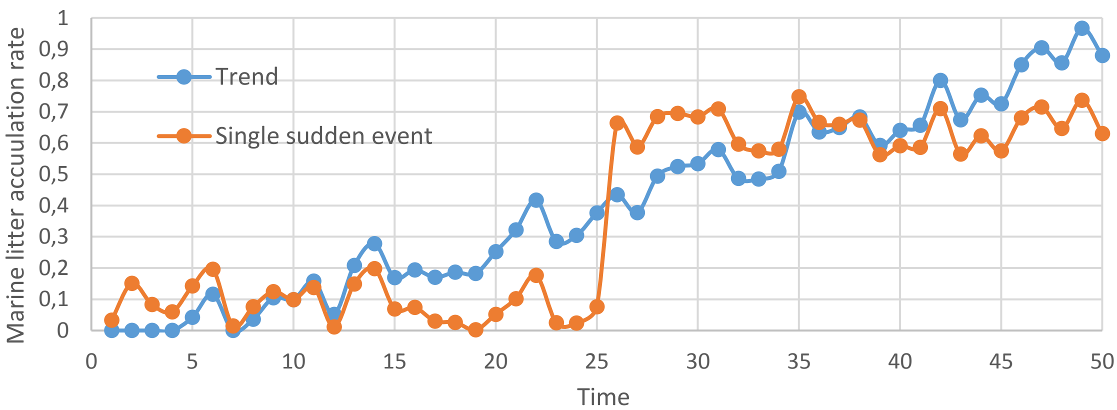


Fig. 71. Visualization of varying litter quantities over time due to trends or single sudden events.

Secondly, the shape and size of different distributions can be analyzed. Figure 72 below shows two arbitrary distributions of debris accumulation, distribution 1 and 2 respectively. Distribution 1 and 2 essentially have equal cumulative accumulation over the timespan shown but their shape differ significantly from each other. Distribution 1 has two small peaks whereas distribution 2 has a single large peak. Distribution 3 is a scaled version of 1, this means the cumulative accumulation is also scaled, in this case with a factor 2. The shape is exactly similar. Distribution 4 has the same cumulative accumulation as distribution 2. The shape however has changed. The accumulation is less concentrated around a single point but more spread out, the distribution is more flattened. The extreme version is the brown distribution which is completely constant over time. Finally, any of these accumulation patterns with similar shape and size could be observed but then shifted over time.

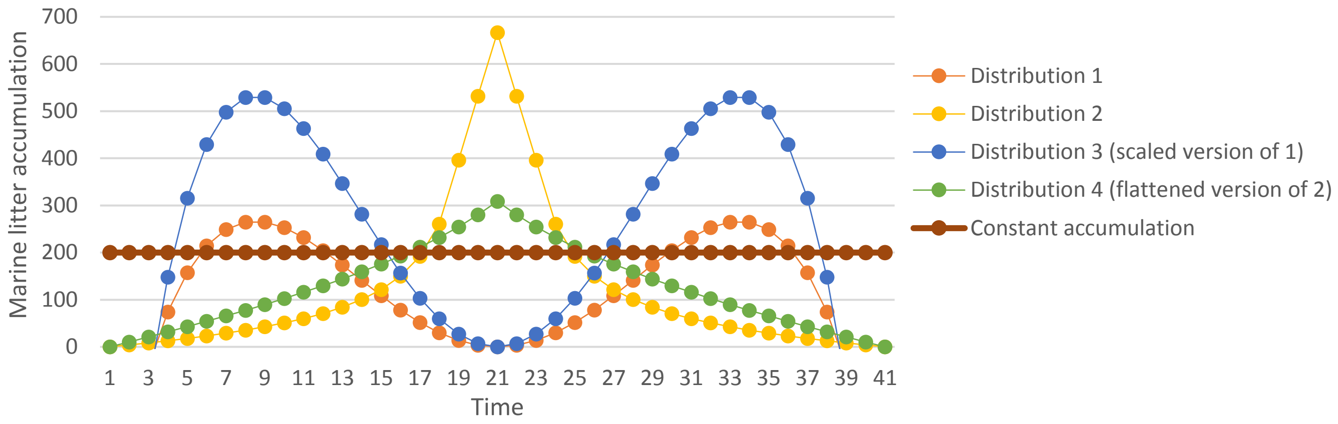


Fig. 72. Visualization of different temporal distributions of marine litter accumulation.

Appendix F: The Baltimore Trash Wheel: background and calculations

The Waterfront Partnership of Baltimore (WPB) has been removing debris flowing from the Jones Falls River using a passive removal system since may 2014 [110]. The Jones Falls riverwatershed, depicted in figure 73, is 103 km2 to 150 km^2 large [44] and is home to about 200.000 people [188]. The Jones Falls itself is 28.8 km long. The system, depicted in figure 74, is located in a tidally activated location [189] and scoops the debris from the water using a water wheel activated conveyor which transports the debris into a dumpster. In case the water wheel is not sufficient the conveyor can be powered by solar panels. Dumpsters can be removed from the back after which trashed can be properly disposed off.

Fig. 73. Drainage basin of the Jones Falls River [44].

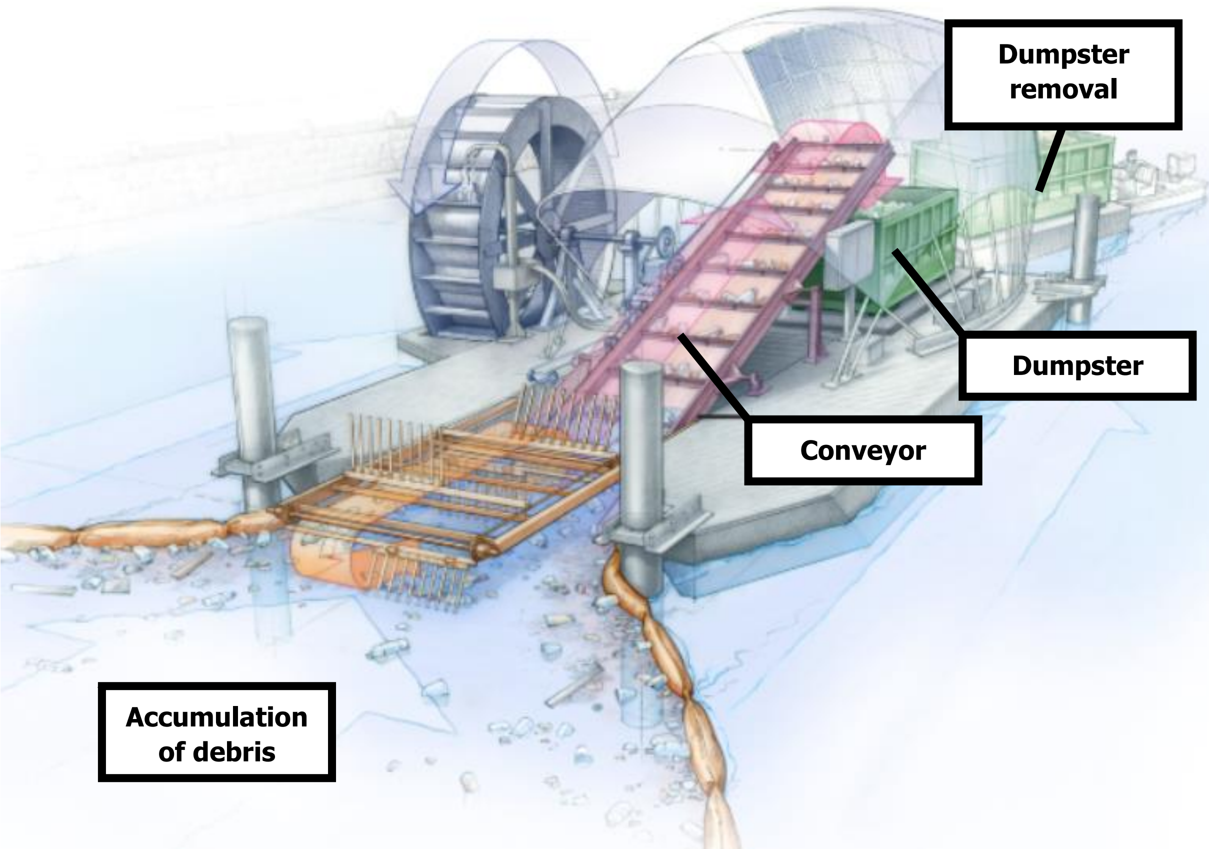


Fig. 74 Illustration of the Baltimore Harbor Wheel Project [110].

The WPB has provided data on its website pertaining the weight, volume and consistency of dumpsters since the start of the operations in may 2014. This data can be used to perform calculations and statistical analyses. The weight and volumetric data provided by the WPB is aggregated data which includes natural debris, like twigs, leaves and branches. On several important items, separate data is given on the number of important debris items. A snip of the excel data file provided is shown in figure 75.

Dumpster	Month	Year	Date	Weight (tons)	Volume (cubic yards)	Plastic Bottles	Polystyrene	Cigarette Butts	Glass Bottles	Grocery Bags	Chip Bags	Sports Balls
262	May	2018	31-5-2018	3,38	15	2130	2240	11000	9	650	2350	2
	May Total			**37,94**	**165**	**17120**	**17100**	**102000**	**50**	**7720**	**19360**	**27**
263	June	2018	3-6-2018	3,35	15	2340	2580	12000	11	1130	1760	5
264	June	2018	3-6-2018	3,17	15	1890	2130	14000	6	870	1590	4
265	June	2018	5-6-2018	4,19	15	1420	1650	8000	3	590	1020	3
266	June	2018	5-6-2018	2,6	15	1280	1330	9000	3	630	1170	2

Fig. 75. A snip of the excel data file provided by the WPB.

F.1 Calculation method subsection 2.5

The data points in figure 8 of subsection 2.5 were calculated using the data provided by WPB for a seven month period (01-2015 until 07-2015). The calculation of the first eleven data points can be found in table 38. These data points, shown in the last column (column E), were calculated by dividing column D by column C. Column D represents the cumulative weights. This means each day at which measurements occurred where considered as a separate data point. Days at which multiple measurements occurred (due to large accumulation), like 20-4-2015, where aggregated (see column D, row 11). Row C is the number of consecutive days in between measurements. C2 for instance notes 11 days, as the measurement on 23-1-2015 occurred 11 days after the previous measurement, 12-11-2015. In total 29 data points where considered.

Table 38. Data and calculation steps used to calculate data points in figure 19 in subsection 3.2.

	Date	Weight [kg x 1000]	Consecutive Days	Cumulative Weight [kg x 1000]	Scaled Cumulative Weight [kg x 1000]
Column:	**A**	**B**	**C**	**D**	**E**
Data Provided by WPB or calculated?	Provided by WPB [67]	Provided by WPB [67]	Calculated	Calculated	Calculated
1	12-1-2015	2.87	13	2.87	0.22
2	23-1-2015	2.00	11	2.00	0.18
3	26-1-2015	2.14	3	2.14	0.71
4	4-2-2015	2.54	9	2.54	0.28
5	9-3-2015	3.82	5	3.82	0.76
6	13-3-2015	1.83	4	1.83	0.46
7	27-3-2015	2.02	14	2.02	0.14
8	8-4-2015	2.50	9	2.50	0.28
9	10-4-2015	3.41	2	3.41	1.71
10	19-4-2015	1.83	9	1.83	0.20
11	20-4-2015	3.84	1	16.27	16.27

	20-4-2015	3.22			
	20-4-2015	3.03			
	20-4-2015	2.64			
	20-4-2015	3.54			

This way of calculating is not optimal however as days with large quantities accumulated are not always properly handled. This is because days with large amounts of accumulated debris and a long period preceding without dumpsters being removed will score low as the amount removed on that day is divided by the consecutive days in column C. Among the data points used in figure 8, 76 and 77 this is specifically true for data point 17. A cumulative weight of 18.20 tons was measured on that day but due to the 8 preceding consecutive days the scaled cumulative weight was only 2.28. As such peaks in the distribution may be underestimated.

The same calculation was also performed for volumetric data, except that the units have been converted from cubic yards to cubic meters. The data points can be found in figure 76 below. It can be seen the distribution of volumetric data points shows a similar pattern as the weight data points. The smallest and largest number have been highlighted and coincide with the smallest and largest number for the weight data. The average volumetric accumulation, 2.1 m^3, measured over 48 months (5-2014 until 4-2018) has been plotted as a green line on the top of the data points.

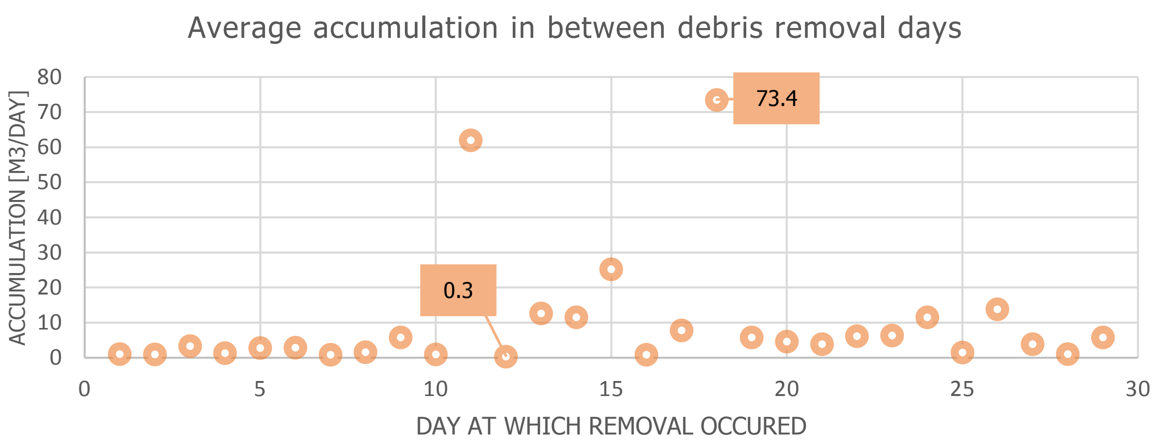


Fig. 76. Average accumulation in between debris removal days, in volumetric terms [44].

In figure 77 the ratio between volume and weight has been plotted. The smallest and largest number have been highlighted again. The data shows the can vary significantly which means the consistency of the debris can also vary significantly. The average ratio, measured over 48 months (5-2014 until 4-2018) has been plotted as a green line on the top of the data points.

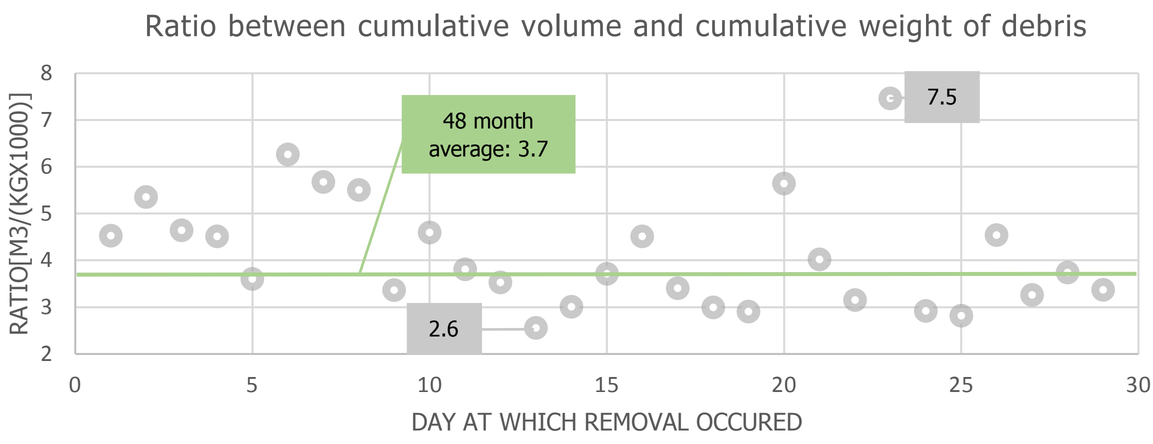


Fig. 77. Ratio between cumulative volume and cumulative weight of debris [44].

F.2 General Data on the Harbor Wheel debris removals

In the period May 2014 to April 2018 a total of 813 tons was removed and 3006 m^3 of natural and anthropogenic debris [44].

Table 39 shows the consistency of the dumpsters illustrated using various main categories of debris. The quantities have been summed of the period May 2014 until April 2018 by counting the number of items corresponding to each category. The percentages have been calculated as a percentage of the sum of all quantities. Unfortunately it excludes natural debris. Cigarette butts are by far the largest category in terms of numbers but are likely to be much smaller in terms of volume and weight. If cigarette butts are excluded, plastic and polystyrene dominate all categories, at least with the data provided by the WPB.

Table 39. Consistency of dumpsters aggregated over 5-2014 to 4-2018 period [44].

	Plastic Bottles	Polysty-rene	Cigarette Butts	Glass Bottles	Grocery Bags	Chip Bags	Sports Balls
Quantity	519,010	618,837	10,003,600	7,851	383,707	505,739	3,520
Percentage	4.31%	5.14%	83.07%	0.07%	3.19%	4.20%	0.03%

In addition to the above mentioned figures, one website [110] mentioned 140.000 Styrofoam containers are removed monthly. This would add up to 6,720,000 items over 48 months and make it second, not far behind cigarette butts.

Figure 78 shows the weight of debris per month as described in subsection 2.5. For the grey data set the largest numbers were removed for each month to test the influence of outliers. A bulge around the summer months remains.

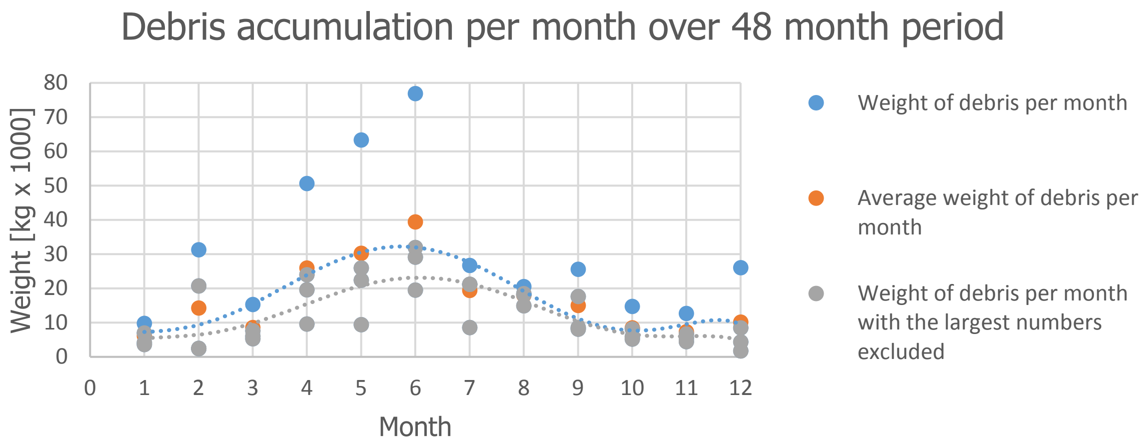


Fig. 78. Weight of debris accumulated per month, measured over 48 months [44].

Appendix G: The hydrologic cycle

This is a supplement to section 3. To understand the relations between precipitation and debris accumulation and the origins of river discharge, it is necessary to understand the hydrologic processes involved. The main processes happening between the rainfall event and the eventual discharge are shown in figure 79.

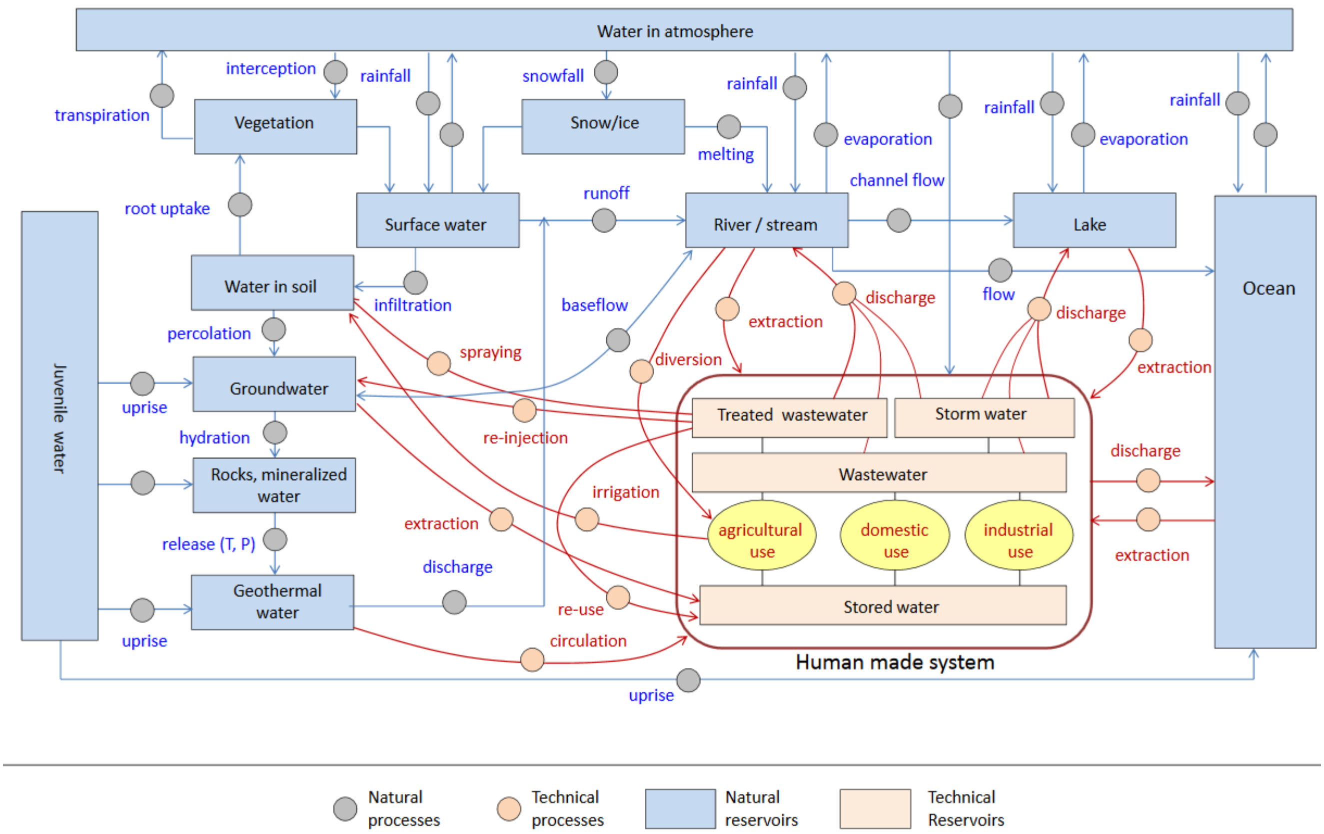


Fig. 79. Comprehensive overview of hydrologic processes [190].

This schematic overview can be viewed as being a system representation since it can be described as a system, using the Delft Systems Approach terminology: '*a collection of elements that is discernable within the total reality. These discernable elements have mutual relationships and (eventually) relationships with other elements from the total reality'* [191]*.* The systems overview shows the internal relationships (e.g. processes such as rainfall) between the different elements (e.g. river/stream). Two main subsystems are highlighted in red and blue, namely natural and anthropogenic reservoirs. Both contain elements of interest. With this system representation, arbitrary black boxes can be drawn over different parts of the hydrologic system. Basic equations of preservation of continuity can now be established [192], also referred to as the hydrologic budget:

$$I - O = \Delta S \quad (61)$$

I = Inputs

O = Outputs

ΔS = Change in Storage

Hence, drawing a black box around river/stream, our subsystem of interest, will yield equation 8 below.

$$\begin{aligned} baseflow\ (source\ of\ river +\ groundwater\ effluent) +\ runoff + melting + rainfall \\ + (wastewater + treated\ wastewater + stormwater) discharge - evaporation \\ - channel\ flow\ to\ lake - flow\ to\ ocean - extraction - diversion \\ = change\ in\ river\ water\ storage \quad (62) \end{aligned}$$

The flows within this equation are relevant for understanding the flow of debris but also to understand the discharge velocity of a river which influences the movement of debris through the system. The size of these streams are depended on the respective river and season. Wide shallow rivers in warm weather might for instance see more evaporation, relatively, than deep rivers in colder weather. Also due the seasonal characteristics of rainfall and melting, the significance of wastewater discharge might increase significantly during low flow conditions as noted by Ji et al. (2008): *'For example, wastewater discharges to the Blackstone River can account for up to 80% of the total river flow in summer'* [95]*.*

Since it was ascertained that surface runoff is a crucial component of debris transport a black box can also be drawn around surface water which yields the following equation:

$$\begin{aligned} dripping\ from\ vegetation + rainfall + snow\ and\ ice\ melt - infiltration - runoff - evaporation \\ = total\ surface\ water\ storage \quad (63) \end{aligned}$$

It is important here to consider which part of the rainfall is being infiltrated, what is the quantity of water which can be stored at the surface and which part leads to runoff.

Appendix H: Details empirical studies fluvial transport of debris

This appendix expands on the study of Williams and Simmons (1997) [74] and Ivar do Sul et al. (2014) [76]. Williams and Simmons (1997) [74] studied temporal distribution of riverine litter and performed four separate experiments, which are summarized in table 40.

Table 40. Overview of experiments on riverine litter movements performed by Williams and Simmons [74].

Study	River Stretch	Length	Flow conditions	Number and type of tracers
1	River Cynon	1.3	Low, 0.6m^3/s	180 LDPE sheets
2	River Taff, Radyr Reach	2.2	High, 74 m^3/s	180 LDPE sheets
3	River Taff, Radyr Reach	2.2	Low, 5.4 m^3/s	180 LDPE sh. + 180 pantyliners
4	River Taff, Radyr Reach	2.2	Moderate, 17.7 m^3/s	180 LDPE sh. + 180 pantyliners

During the experiments they released items distributed evenly over the width of the river. A strong correlation was found with the flow rate. At low flow rates, study 1, entrapment and stranding was severe, all plastic sheets released were entangled before 80 meter and even after one month the vast majority had still travelled less than 100m. The second study was performed at another river, broader and deeper, during high flow conditions and found 80 out of 180 sheets to arrive within 3 hours, the vast majority in a time span of 15 minutes. The third study on the same stretch of river during low flow conditions saw a much flatter response time. A couple of plastic sheets arrived after almost 3 hours whereas the first pantyliners (smaller in size), also released, arrived 30 minutes later. Merely 9 tracers arrived after the following 7 hours. The fourth experiment during moderate flow conditions saw 59 plastic sheets and 30 pantyliners arrive within 4 hours.

The temporal distribution of litter items for study 2 and 4 is visualized in figure 80. Three observations can be made. Firstly, both show a clear positive skew (a long right tail). Secondly, the distribution under high flow conditions is much narrower, as far as the main bulk of the arrivals is concerned. Thirdly, regarding study 4, pantyliners were lower in number in comparison to the sheeting, even though the same number was released which indicates higher stranding susceptibility.

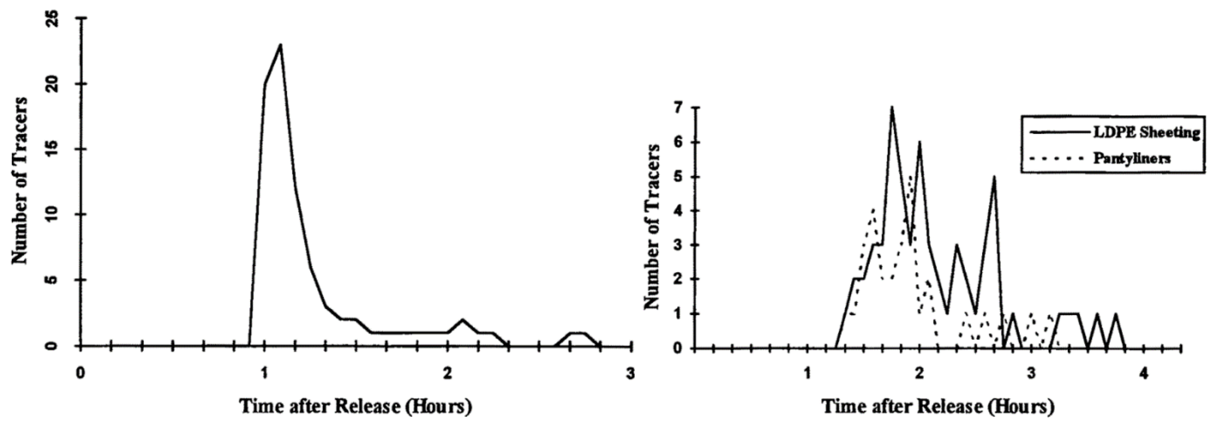


Fig. 80. Arrival pattern study 2 (left) and study 4 (right) [101].

Ivar do Sul et al. (2014) [76] investigated retention and movements of debris in a Mangrove forest. Different type of debris were released in three different environments and the movements during 144 hours were observed around the deposition area of $20m^2$. Firstly, a tidal creek was observed with low flow rate, bank slope of 110 degree from water surface and width 20m. Secondly a river with high flow rate, bank slope of 160 degree from water surface and width 400m. Thirdly and finally high ground which was occasionally flooded during high tides. The items surveyed were cap closed plastic bottles (negatively buoyant), open plastic bottles (negatively buoyant), squashed plastic bottles (neutrally buoyant), plastic bags, 200ml cups, polystyrene blocks and open margarine tubs. 27 items of each category were released with each deposition area starting with 21 items, 3 items per category. As shown in figure 81B Margarine tubs were transported most easily while the bags and cups were initially fairly well retained but once moved they were not observed somewhere else which means they moved significantly. The other types did not show significant differences, especially not the bottles among them. The results suggest the shape and buoyancy (as long as it floats) of debris has limited influence in general. After 144 hours 75% of the items disappeared completely from the surveyed area although after six months the higher ground still contained seven items. Not entirely surprising, litter was least retained along the river, with the creek not far behind, while the higher grounds performed significantly better, see figure 81A. This suggest again flow rate is a factor of influence.

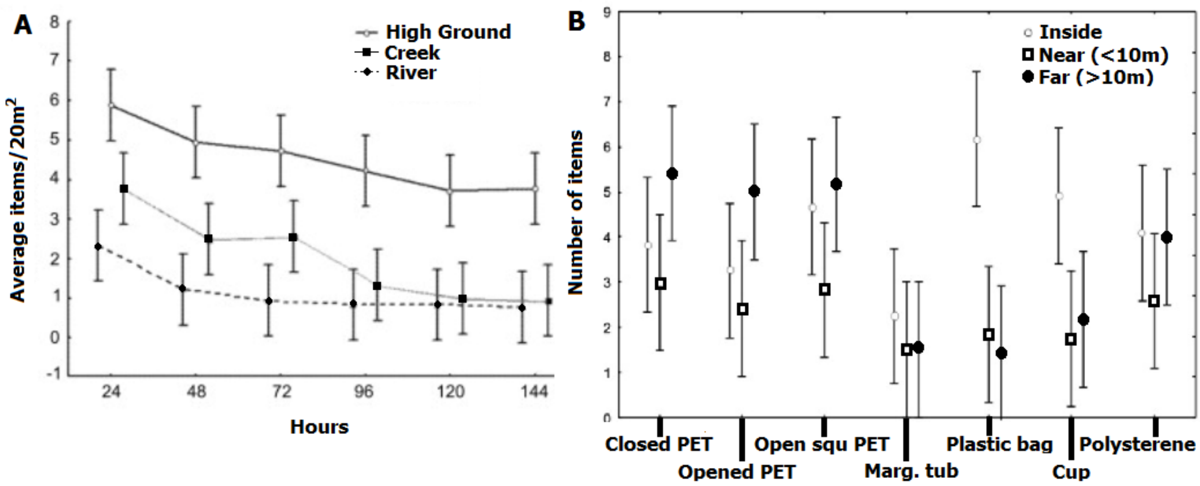


Fig. 81. Average numbers of items per deposition area over time for each habitat (A) [76]. Number of items surveyed in, near or far from the deposition area, per litter category (B) [76].

Appendix I: Data on the Jones Falls watershed

Figure 82 below shows a rough land use map of the JFW. Figure 83 on the next page shows a map of the JFW watershed plotted over an elevation map of the area.

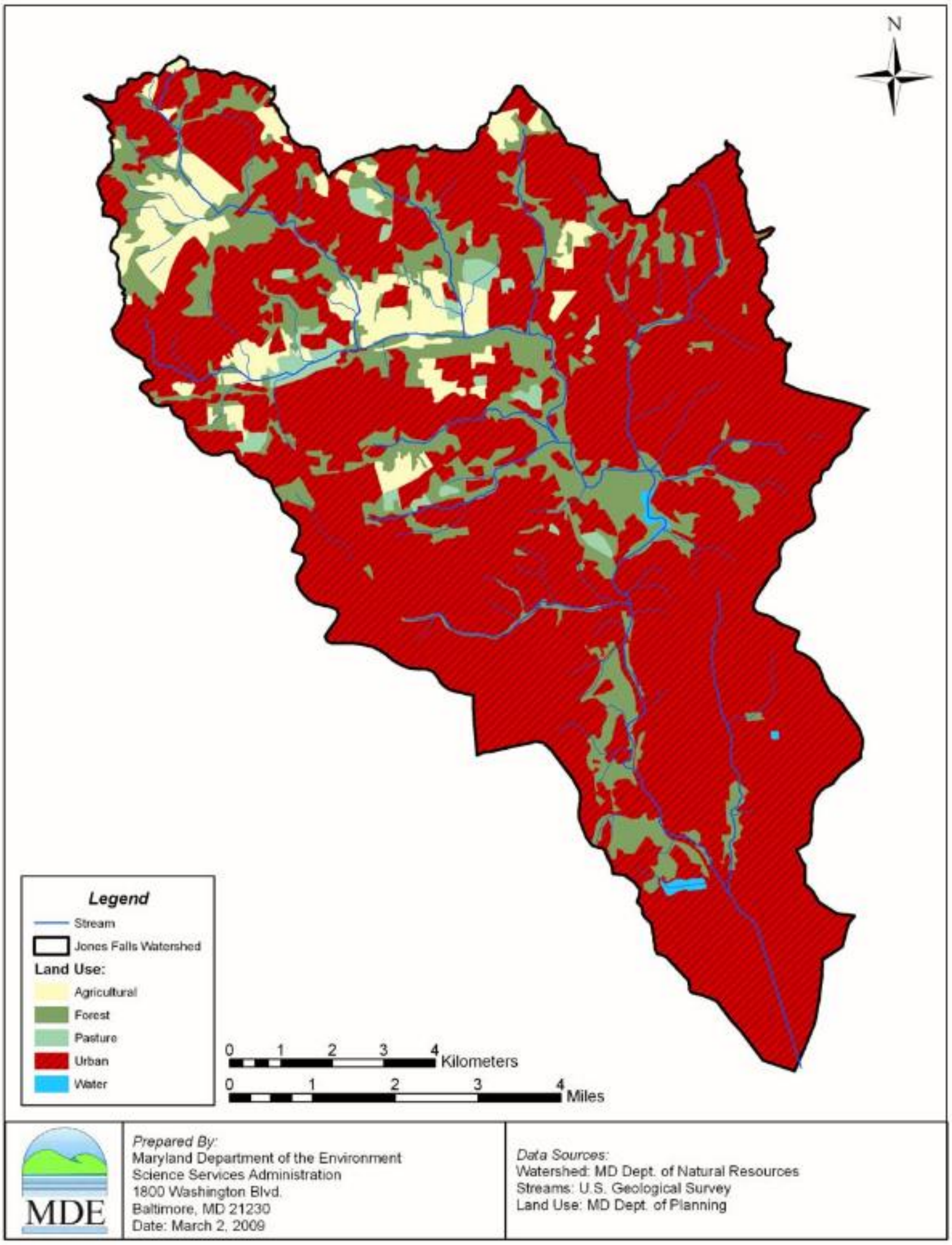


Fig. 82. Land use map Jones Falls watershed [191].

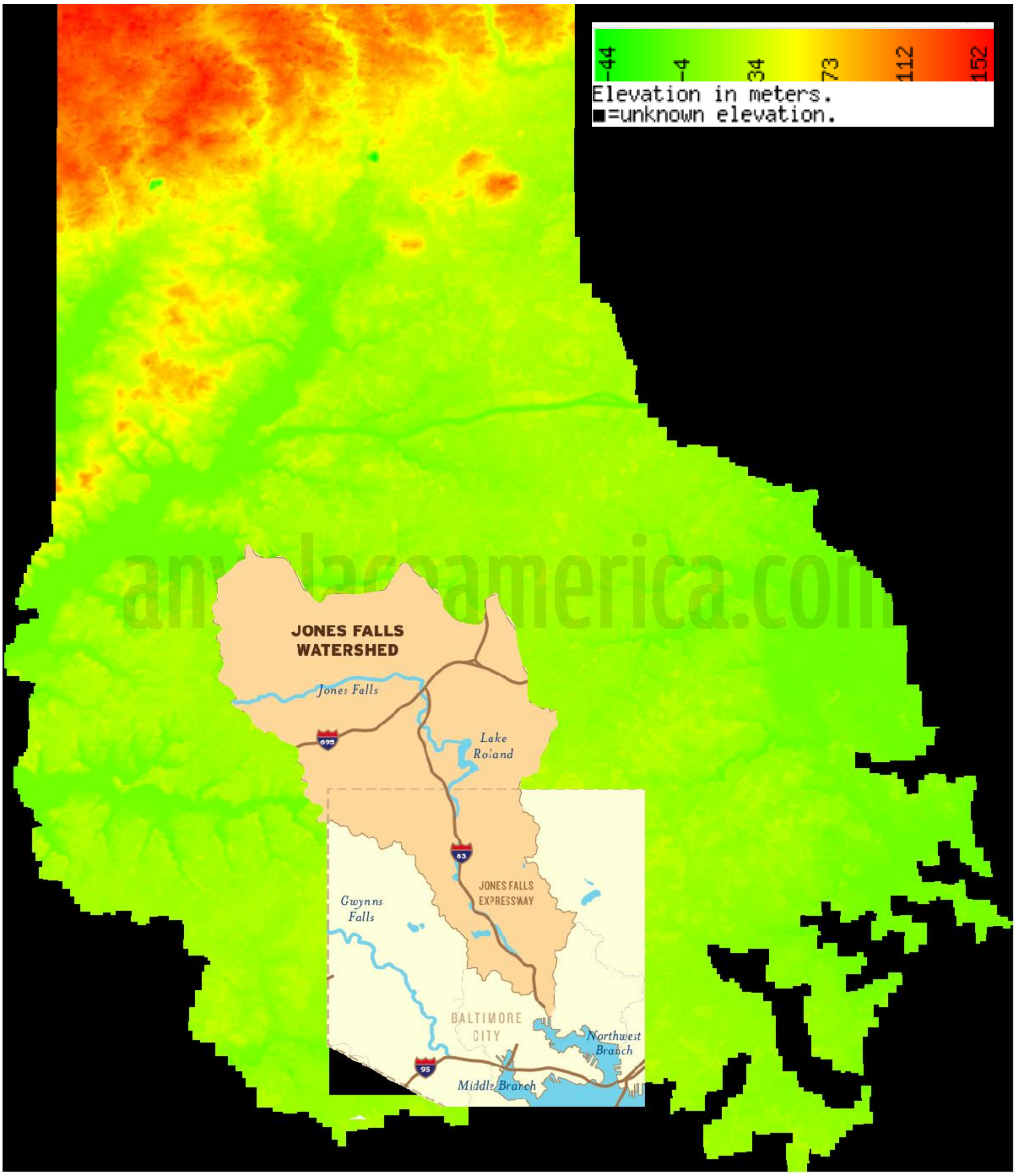


Fig. 83. Elevation map with JFW, modified from [193] and [44].

Table 41 shows land use data for all 14 Jones Falls sub watersheds [119] [136] [137]. The numerical order of the sub watersheds (e.g. U1 to U4) is identical to the order presented in the report, i.e. U1 corresponds to the sub watershed in the first row and U4 corresponds to the sub watershed in the last row.

Table 41. Land use data for all 14 Jones Falls sub watersheds.

Land use	Percentage of total area of sub watershed belonging to corresponding land use [%]													
	Upper JF				North East JF				Lower JF					
	U1	U2	U3	U4	E1	E2	E3	E4	L1	L2	L3	L4	L5	L6
Agricultural facilities	0	0.8	0	0	0	0	0	0	0	0	0	0	0	0
Cropland	5.4	7.4	9.6	19.9	0	0	0	0	0	0	0	0	0	0
Orchards	0	1.6	0	0	0	0	0	0	0	0	0	0	0	0
Pasture	1.1	7.2	3.2	0	1	0	0	0	0	0	0	0	0	0
Ultra low residential (agriculture)	0.9	5.1	6.9	2.8	0	0	0	0	0	0	0	0	0	0
Ultra low residential (forested)	9.2	5.4	7	5.1	0	0	0	0	0	0	0	0	0	0
Low density residential	44.7	35.6	36.8	42.1	19	11	53	27	47.9	21	11.3	7.6	5	6
Medium density residential	1.2	0	2.9	0.4	41	25	12	16	8.8	21.6	8.6	46.8	50.2	8.6
High density residential	2.3	0	4.7	0	6	12	0	8	7.4	13.3	18.3	17.9	11.1	32.3
Forest	0	0	0	0	0	0	0	0	24	27.9	43.5	5.1	4.9	12.3
Decidious forest	14.6	24.1	15.2	18.7	6	7	0	19	0	0	0	0	0	0
Evergreen forest	0	0	0	0.1	0	0	0	0	0	0	0	0	0	0
Large lot forest	0	0	0	0	1	2	6	11	0	0	0	0	0	0
Wetlands	0	0	0.1	0	0	0	0	4	0	0	0	0	0	0
Open urban land	12.7	10.2	4.1	9.4	6	2	11	8	0	0	2.2	11.1	3.8	7.1
Commercial	6	0	1.9	0.3	10	17	1	1	0	0.9	2.4	5.6	2.3	11.8
Industrial	0	0	0	0.2	4	0	0	0	0	7.3	5.3	0	0	4.7
Institutional	2	2.6	6.4	1	2	23	15	4	2.1	11	0.2	5.5	20.6	12.2
Transportation	0	0	1.2	0	3	0	0	0	0	0	0	0	0	0
Bare ground	0	0	0	0	0	0	0	0	0	2.3	0.8	0	0	0.8
Extractive[21]	0	0	0	0	0	0	0	0	0	7.3	0	0	0	0
Water	0	0	0	0	0	0	0	0	0	0	0	0	0.3	0.7
Highway	0	0	0	0	0	0	0	0	0	0	0	0.3	1.8	3.6
Agriculture	0	0	0	0	0	0	0	0	14.1	2.3	0	0	0	0
Brush	0	0	0	0	0	0	1	1	0	0	0	0	0	0

[21] Extractive has been converted to medium to high density residential areas.

Table 42 shows hydrological soil group data for all 14 Jones Falls sub watersheds [119] [136] [137]. The values are given as a percentage of the total area.

Table 42 Land use data for all 14 Jones Falls sub watersheds.

Soil Group	Percentage of total area of sub watershed belonging to corresponding soil group [%]													
	Upper Jones Falls				North East JF				Lower JF					
	U1	U2	U3	U4	NE1	NE2	NE3	NE4	L1	L2	L3	L4	L5	L6
A	2.3	0	2.9	0	9.8	0	0	0	0	0	0	0	1.3	1.7
B	70.1	63.3	70.1	69	63.7	60.5	75.2	43	82.9	74.5	61.8	22.4	14.6	19
C	22.2	35.8	17	21.9	16.2	32.5	16.7	46.6	7.7	9.8	5.1	14.5	5	5.5
D	4.7	0.7	7.3	8.6	10.3	7	8.2	10.5	9.3	15.7	33.1	63.2	79.1	73.8

Table 43 shows how land use as given in the reports, was matched with land uses as defined in literature [128]. The land uses defined in literature are listed with corresponding empirically obtained CN values.

Table 43 Corresponding land uses as given in literature with known CN values for specific soil group and land use combination.

Land use defined by reports	Matching land use as defined for corresponding CN values	CN value for specific soil group and land use combination			
		Soil group A	Soil group B	Soil group C	Soil group D
Agricultural facilities	Farmsteads Page 327	59	74	82	86
Cropland	Agricultural land general, average	(77+51)/2	(86+67)/2	(91+76)/2	(94+80)/2
Orchards	Orchard or treefarm, fair	43	65	76	82
Pasture	Pasture, fair	49	69	79	84
Ultra low residential (agriculture)	Residential, lot size: 2 acres	46	65	77	82
Ultra low residential (forested)	Residential, lot size: 2 acres	46	65	77	82
Low density residential	Residential, lot size: 1 acres	51	68	79	84
Medium density residential	Residential, lot size: ¼ acres	61	75	83	87
High density residential	Residential, lot size: 1/8 acres	77	85	90	92
Forest	Forest, fair	36	60	73	79
Decidious forest	Forest, fair	36	60	73	79
Evergreen forest	Forest, fair	36	60	73	79
Large lot forest	Forest, fair	36	60	73	79
Wetlands	-	100	100	100	100
Open urban land	Open space, fair	49	69	79	84
Commercial	Urban districts: commercial and business	89	92	94	95
Industrial	Urban districts: Industrial	81	88	91	93
Institutional	Residential, lot size: 1/8 acres	77	85	90	92
Transportation	Impervious areas: Paved; Open ditches	83	89	92	93
Bare ground	Fallow: Bare soil	77	86	91	94
Extractive	Average of medium and high density residential	(77+61)/2	(85+75)/2	(90+83)/2	(92+87)/2
Water	-	100	100	100	100

Highway	Impervious areas: Paved driveways	98	98	98	98
Agriculture	Agricultural land general, avg	(77+51)/2	(86+67)/2	(91+76)/2	(94+80)/2
Brush	Brush, fair	35	56	70	77

Table 44 shows latitudinal and longitudinal coordinates of the 14 sub watersheds present in the JFW. Column three and four show population and area respectively [119] [136] [137].

Table 44. Geographical coordinates, population and area of the sub watersheds within the JFW.

	Longitude	Latitude	Population	Area [km^2]
Deep Run Jones Falls	39.43179	-76.66764	1374	5.8145
Dipping Pond Run	39.42967	-76.68961	1045	7.1160
Jones Falls	39.41435	-76.70755	7253	22.0449
Jones Falls North Branch	39.43371	-76.72343	2914	18.3922
Roland Run	39.42085	-76.64385	15025	15.4687
Towson Run	39.39229	-76.62893	13726	7.4713
Ruxton Run	39.40032	-76.63573	1248	1.9089
Lake Roland Direct Drainage	39.37767	-76.63388	2216	3.0784
Slaughterhouse Run	39.40009	-76.68125	1967	5.1476
Moores branch	39.38728	-76.68348	4515	5.6454
Jones Falls A	39.38467	-76.66318	4244	3.4884
Western Run	39.36546	-76.67247	31745	14.1155
Stony Run	39.34185	-76.62617	23087	9.0731
Lower Jones Falls	39.3366	-76.63183	110663	29.4895

Appendix J: Modelling Framework

The modelling process used in this report is based on the waterfall model, as depicted in figure 84, which means it is generally a linear design process although iteration may be involved. The curved arrows show the sequential waterfall process while the rectangular feedback arrows indicate an iteration step may take place.

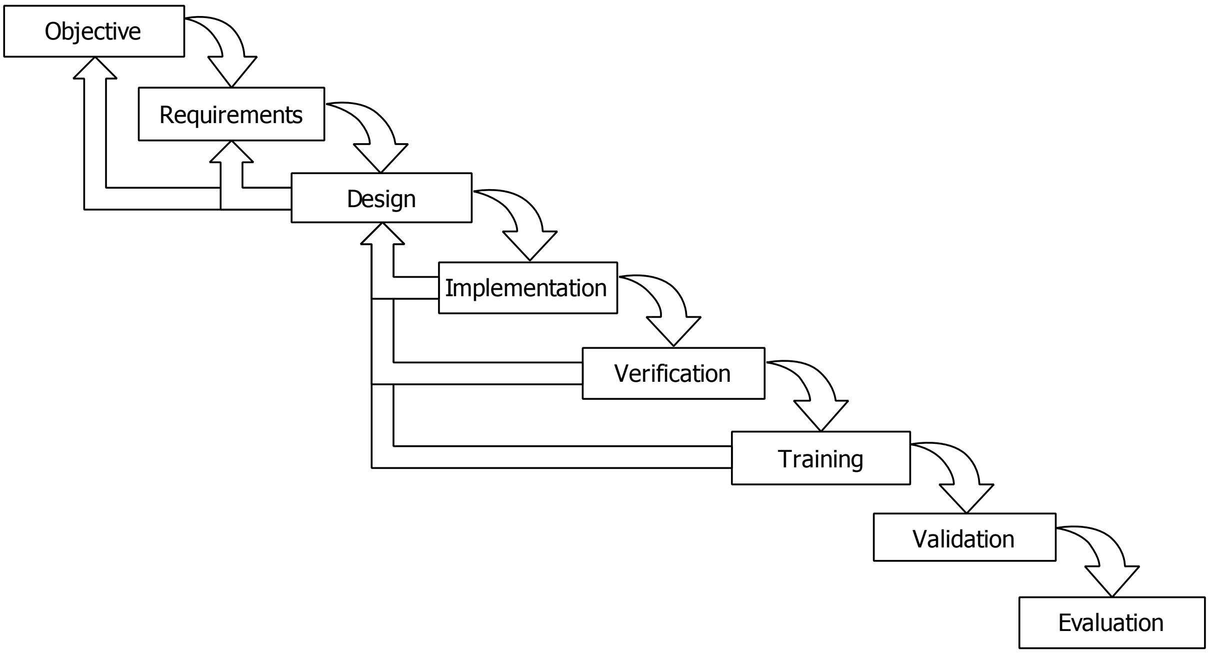


Fig. 84. Framework for the modelling process.

Appendix K: Weather data

Figure 85 shows screenshots of the weather data files in excel which are used as an input to the Matlab model. The grey columns with bold text are output columns which are used as an input to the Matlab model. The columns with orange text are used to process the data. The other columns contain the raw data as retrieved from the historic weather database used by the website *'weather underground'* [138].

A	B	C	D	E	F	G	H	I	J	K	L
Date_gmt		**Day**		**Month**		**Year**	Time_gmt		**Hour**		**Min**
31-5-2014	31	**31**	5	**5**	14	**2014**	6:15	06	**6**	06:15	**15**
31-5-2014	31	**31**	5	**5**	14	**2014**	6:35	06	**6**	06:35	**35**
31-5-2014	31	**31**	5	**5**	14	**2014**	6:55	06	**6**	06:55	**55**

M	N	O	P
precip_hrly [inch]	**Hourly Rainfall [mm]**	Windspeed [mph]	**Windspeed [m/s]**
0	**0**	3	**1,3**
0	**0**	5	**2,2**
0	**0**	0	**0,0**

Figure 85. Excel data file for one weather station.

Appendix L: Verification equations and verification parameters

The mass conservation equations described in subsection 6.4 can be defined as follows, first for verification test 1:

$$M_{D,I} \leq M_{AD,A} \quad (64) \quad and \quad M_{D,I} = 0 \quad (65)$$

$$O = \sum_{subwatersheds} M_{D,I} \quad (66) \quad and \quad O = 0 \quad (67)$$

$$M_{AD,G} = M_{D,I} + M_{D,R} + M_{AD,A} \quad (68) \quad and \quad \sum_{subwater.} M_{AD,G} = O + \sum_{subwater.} M_{D,R} + \sum_{subwater.} M_{AD,A} \quad (69)$$

For verification test 2:

$$M_{D,I} \leq M_{AD,A} \quad and \quad M_{D,I} \leq M_{D,W} \quad (70) \quad and \quad M_{D,I} \geq 0 \quad (71)$$

$$O = \sum_{subwatersheds} M_{D,I} \quad and \quad O \geq 0 \quad (72)$$

$$M_{AD,G} = M_{D,I} + M_{D,R} + M_{AD,A} \quad and \quad \sum_{subwater.} M_{AD,G} = O + \sum_{subwater.} M_{D,R} + \sum_{subwater.} M_{AD,A}$$

For verification test 3:

$$M_{D,I} \leq M_{AD,A} \quad and \quad M_{D,I} \leq M_{D,P} \quad (73) \quad and \quad M_{D,I} \geq 0$$

$$O = \sum_{subwatersheds} M_{D,I} \quad and \quad O \geq 0$$

$$M_{AD,G} = M_{D,I} + M_{D,R} + M_{AD,A} \quad and \quad \sum_{subwater.} M_{AD,G} = O + \sum_{subwater.} M_{D,R} + \sum_{subwater.} M_{AD,A}$$

Finally, for verification test 4:

$$M_{D,I} \leq M_{AD,A} \; and \; M_{D,I} \leq M_{D,P} + M_{D,W} \quad (74) \quad and \; M_{D,I} \geq 0$$

$$O = \sum_{subwatersheds} M_{D,I} \quad and \quad O \geq 0 \quad and \quad O \geq O \; of \; test \; 2 \; and \; 3 \quad (75)$$

$$M_{AD,G} = M_{D,I} + M_{D,R} + M_{AD,A} \quad and \quad \sum_{subwater.} M_{AD,G} = O + \sum_{subwater.} M_{D,R} + \sum_{subwater.} M_{AD,A}$$

The verification is performed for four versions of the model, which are discussed in sub section 7.2. Experimental plan'. For the models which do not use the available debris on land $M_{AD,A}$ nor the removal of debris by street sweeping $M_{D,R}$, i.e. the approach adopted by Wan et al. (2018) [29], some equations are different:

Equation 46 becomes: $M_{D,I} \leq M_{AD,G} \quad (76)$

Equation 50 becomes: $M_{AD,G} = M_{D,I} + M_{AD,remaining\ on\ land} \quad (77)$

Equation 51 becomes: $\sum_{\text{subwater.}} \mathrm{M}_{\text{AD,G}} = 0 + \sum_{\text{subwater.}} \mathrm{M}_{\text{AD,remaining on land}} \quad (78)$

For the verification, the following configuration parameters will be used:

Table 45. Parameter values for verification.

Parameter[22]	Value
m_{adg} **[kg]**	$\mathbf{1 \cdot Pop}$
Number of sub watersheds	3
Population of sub watersheds	10000
k_p **[kg/m^3]**	1
k_w **[kg· s^2/m^2]**	1
Q_b **[mm]**	1
V_0 **[m/s]**	1
$m_{D,R}$ **[kg]**[23]	$0.009 \cdot Pop$
$\alpha\_perc/\alpha\_perc15$ **(% of area with slope <15% and >15%)**	50%
α **(Average slope <15%)**	1
$\alpha 15$ **(Average slope >15%)**	20
Area of sub watershed [m^2]	10^6
Distance sub watershed to any of the weather stations [m]	10^3
Percentage of area allocated to each of the four soil groups	100/4 = 25%
Percentage of area allocated to each of the 18 land use groups	100/18 = 5.6%

Note that each parameter applies to every sub watershed.

[22] Note that for the model calibration and validation, the units are different, [kg] = [#debris].
[23] For the calibration of the model parameters and the model validation, $M_{D,R}$ has not been separately estimated but included as part of M_{adg}.

Appendix M: Verification data and verification sheets

Verification is performed for T = 6 days. The verification data for debris accumulation and the weather data can be found below. All weather stations use the same weather measurements.

Table 46. Verification data for debris accumulation.

Date	Day	Month	Year	Aggregated totals for PB, PS, GrB and ChB	Cumulative totals for PB, PS, GrB and ChB
3-1-2019	3	1	2019	5000	10000
3-1-2019	3	1	2019	5000	0
6-1-2019	6	1	2019	5000	25000
6-1-2019	6	1	2019	5000	0
6-1-2019	6	1	2019	5000	0
6-1-2019	6	1	2019	5000	0
6-1-2019	6	1	2019	5000	0

Table 47. Verification data for the weather stations.

Day	Month	Year	Hour	Min	P_0 [mm]	V_0 [m/s]	P_max [mm]	Vmax [m/s]
1	1	2019	0	30	0	0	10	25
1	1	2019	1	30	0	0	10	25
1	1	2019	2	30	0	0	10	25
1	1	2019	3	30	0	0	10	25
1	1	2019	4	30	0	0	10	25
1	1	2019	5	30	0	0	10	25
1	1	2019	6	30	0	0	10	25
1	1	2019	7	30	0	0	10	25
1	1	2019	8	30	0	0	10	25
1	1	2019	9	30	0	0	10	25
1	1	2019	10	30	0	0	10	25
1	1	2019	11	30	0	0	10	25
1	1	2019	12	30	0	0	10	25

The verification sheets of model M1, M2, M3 and M4 are shown on the next subsequent pages.

Table 48. Verification sheet parameters M1.

	Type	Possible/ Pausible value ranges	Matrix dimensions	Tests 1	Tests 3
MAD test 1 [kg]	INT	35000			
MAD test 3 [kg]	INT	26600			
DN, DS, DW	IV	1, 2, 3, 4, 5, 6	144x1		
ME test 1 [kg]	INT	-35000			
ME test 3 [kg]	INT	-26600			
HN, HS, HW	IV	{0,1,....,23}	144x1		
Madg [kg]	INT	100	14x1		
Mdi [kg] test 1	INT	0	6x14		
Mdi [kg] test 3	INT	[0, 100]	6x14		
Mdp [kg] test 1	INT	0	6x14		
Mdp [kg] test 3	INT	0, 2390000	6x14		
MmN, MmS, MmW	INT	30	144x1		
MN, MS, MW	IV	1	144x1		
n1	INT	144	1x1		
n0	INT	121	1x1		
normdist	INT	1/3	14x3		
O test 1 [kg]	OV	0	6x1		
O test 3 [kg]	OV	1400	6x1		
Outputmodel test 1 [kg]	OV	0	2x1		
Outputmodel test 2 [kg]	OV	4200	2x1		
P [mm] test 1	INT	0	6x14		
P [mm] test 3	INT	10·24 = 240	6x14		
Pn, Ps, Pw [mm] test 1	INT	0	6x1		
Pn, Ps, Pw [mm] test 3	INT	10·24 = 240	6x1		
PN, PS, PW [mm] test 1	IV	0	144x1		
PN, PS, PW [mm] test 3	IV	10	144x1		
Realdata [number of debris]	IV	10000, 25000	2x1		
tspanN, tspanS, tspanW [min]	INT	60	144x1		
YN, YS, YW	IV	2019	144x1		

Table 49. Verification sheet balance equations M1.

Equation	Tests	Test 1	Test 3
$M_{D,I} \le M_{AD,G}$	all		
$M_{D,I} \le M_{D,P}$	Test 3		
$M_{AD,G} = M_{D,I} + M_{AD,remaining\ on\ land}$	all		
$\sum_{subwater.} M_{AD,G} = O + \sum_{subwater.} M_{AD,remaining\ on\ land}$	all		

Table 50. Verification sheet parameters M2.

	Type	Possible/ Pausible value ranges	Matrix dimensions	Tests 1	Tests 3
Absolute error test 1 [kg]	INT	35000	2x1		
Absolute error test 3 [kg]	INT	26600	2x1		
CN values	INT	[30, 100]			
DN, DS, DW	IV	1, 2, 3, 4, 5, 6	144x1		
Error test 1 [kg]	INT	-35000			
Error test 3 [kg]	INT	-26600			
HN, HS, HW	IV	{0,1,....,23}	144x1		
Ia [mm]	INT	[0, 30)	-		
Madg [kg]	INT	100	14x1		
Mdi [kg] test 1	INT	0	6x14		
Mdi [kg] test 3	INT	[0, 100]	6x14		
Mdp [kg] test 1	INT	0	6x14		
Mdp [kg] test 3	INT	0, 2390000	6x14		
MmN, MmS, MmW	INT	30	144x1		
MN, MS, MW	IV	1	144x1		
n1	INT	144	1x1		
n0	INT	121	1x1		
normdist	INT	1/3	14x3		
O test 1 [kg]	OV	0	6x1		
O test 3 [kg]	OV	1400	6x1		
Outputmodel test 1 [kg]	OV	0	2x1		
Outputmodel test 2 [kg]	OV	4200	2x1		
P [mm] test 1	INT	0	6x14		
P [mm] test 3	INT	$10 \cdot 24 = 240$	6x14		
P5 [mm] test 1	INT	0	-		
P5 [mm] test 3	INT	1200	-		
Pn, Ps, Pw [mm] test 1	INT	0	6x1		
Pn, Ps, Pw [mm] test 3	INT	$10 \cdot 24 = 240$	6x1		
PN, PS, PW [mm] test 1	IV	0	144x1		
PN, PS, PW [mm] test 3	IV	10	144x1		
Q [m^3] test 1	INT	$(0, 7.08 \cdot 10^6)$	6x14		
Q [m^3] test 3	INT	$(0, 7.08 \cdot 10^6)$	6x14		
Realdata [number of debris]	IV	10000, 25000	2x1		
S [mm]	INT	[0, 593)	-		
S [mm]	INT	[0, 593)	-		
tspanN, tspanS, tspanW [min]	INT	60	144x1		
YN, YS, YW	IV	2019	144x1		

Table 51. Verification sheet balance equations M2.

Equation	Tests	Test 1	Test 3
$M_{D,I} \leq M_{AD,G}$	all		
$M_{D,I} \leq M_{D,P}$	Test 3		
$M_{AD,G} = M_{D,I} + M_{AD,remaining\ on\ land}$	all		
$\sum_{subwater.} M_{AD,G} = O + \sum_{subwater.} M_{AD,remaining\ on\ land}$	all		

Table 52. Verification sheet parameters M3.

	Type	Possible/ Pausible value ranges	Matrix dimensions	Tests 1	Tests 3
Absolute error test 1 [kg]	INT	35000			
Absolute error test 3 [kg]	INT	27440			
DN, DS, DW	IV	1, 2, 3, 4, 5, 6	144x1		
Error test 1 [kg]	INT	-35000			
Error test 3 [kg]	INT	-26600			
HN, HS, HW	IV	{0,1,....,23}	144x1		
Madg [kg]	INT	100	14x1		
Mda [kg] test 1	INT	90, 540	6x14		
Mda [kg] test 3	INT	90, 180	6x14		
Mdi [kg] test 1	INT	0	6x14		
Mdi [kg] test 3	INT	0, 90, 180	6x14		
Mdp [kg] test 1	INT	0	6x14		
Mdp [kg] test 3	INT	0, 2390000	6x14		
Mdr [kg] test 1	INT	10	6x14		
MmN, MmS, MmW	INT	30	144x1		
MN, MS, MW	IV	1	144x1		
n1	INT	144	1x1		
n0	INT	121	1x1		
normdist	INT	1/3	14x3		
O test 1 [kg]	OV	0	6x1		
O test 3 [kg]	OV	1260, 2520	6x1		
Outputmodel test 1 [kg]	OV	0	2x1		
Outputmodel test 3[kg]	OV	3780	2x1		
P [mm] test 1	INT	0	6x14		
P [mm] test 3	INT	10·24 = 240	6x14		
Pn, Ps, Pw [mm] test 1	INT	0	6x1		
Pn, Ps, Pw [mm] test 3	INT	10·24 = 240	6x1		
PN, PS, PW [mm] test 1	IV	0	144x1		
PN, PS, PW [mm] test 3	IV	10	144x1		
Realdata [number of debris]	IV	10000, 25000	2x1		
tspanN, tspanS, tspanW [min]	INT	60	144x1		
YN, YS, YW	IV	2019	144x1		

Table 53. Verification sheet balance equations M3.

Equation	Tests	Test 1	Test 3
$M_{D,I} \leq M_{AD,A}$	all		
$M_{D,I} \leq M_{D,P}$	Test 3		
$M_{AD,G} = M_{D,I} + M_{D,R} + M_{AD,A}$	all		
$\sum_{subwater.} M_{AD,G} = O + \sum_{subwater.} M_{D,R} + \sum_{subwater.} M_{AD,A}$	all		

Table 54. Verification sheet balance equations M4.

	Type	Possible/Pausible value ranges	Matrix dimensions	Experiment			
				1	2	3	4
Absolute error test 1 [kg]	INT	35000	2x1				
Absolute error test 2 [kg]	INT	27440	2x1				
Absolute error test 3 [kg]	INT	27440	2x1				
Absolute error test 4 [kg]	INT	27440	2x1				
DN, DS, DW	IV	1, 2, 3, 4, 5, 6	144x1				
Error test 1 [kg]	INT	-35000	2x1				
Error test 2 [kg]	INT	-27440	2x1				
Error test 3 [kg]	INT	-27440	2x1				
Error test 4 [kg]	INT	-27440	2x1				
HN, HS, HW [hour]	IV	{0,1,....,23}	144x1				
Madg [kg]	INT	100	14x1				
Mda [kg]	INT	[90, 540]	6x14				
Mda [kg]	INT	90, 180	6x14				
Mda [kg]	INT	90, 180	6x14				
Mda [kg]	INT	90, 180	6x14				
Mdi [kg] test 1	INT	0	6x14				
Mdi [kg] test 2	INT	0,90,180	6x14				
Mdi [kg] test 3	INT	0,90,180	6x14				
Mdi [kg] test 4	INT	0,90,180	6x14				
Mdp [kg] test 1	INT	0	6x14				
Mdp [kg] test 2	INT	0	6x14				
Mdp [kg] test 3	INT	0, 2390000	6x14				
Mdp [kg] test 4	INT	0, 2390000	6x14				
Mdr [kg]	INT	10	14x1				
Mdw [kg] test 1	INT	0	6x14				
Mdw [kg] test 2	INT	0, $6.24 \cdot 10^6$	6x14				
Mdw [kg] test 3	INT	0	6x14				
Mdw [kg] test 4	INT	0, $6.24 \cdot 10^6$	6x14				
MmN, MmS, MmW	INT	30	144x1				
MN, MS, MW	IV	1	144x1				
n1	INT	144	1x1				
n0	INT	121	1x1				
normdist	INT	1/3	14x3				
O test 1 [kg]	OV	0	6x1				
O test 2 [kg]	OV	1260, 2520	6x1				
O test 3 [kg]	OV	1260, 2520	6x1				
O test 4 [kg]	OV	1260, 2520	6x1				
Outputmodel test 1 [kg]	OV	0	2x1				
Outputmodel test 2 [kg]	OV	3780	2x1				
Outputmodel test 3 [kg]	OV	3780	2x1				
Outputmodel test 4 [kg]	OV	3780	2x1				
P [mm] test 1	INT	0	6x14				
P [mm] test 2	INT	0	6x14				
P [mm] test 3	INT	$10 \cdot 24 = 240$	6x14				
P [mm] test 4	INT	$10 \cdot 24 = 240$	6x14				

Pop	CP	10000	14x1				
Pn, Ps, Pw [mm] test 1	INT	0	6x1				
Pn, Ps, Pw [mm] test 2	INT	0	6x1				
Pn, Ps, Pw [mm] test 3	INT	10·24 = 240	6x1				
Pn, Ps, Pw [mm] test 4	INT	10·24 = 240	6x1				
PN, PS, PW [mm] test 1	IV	0	144x1				
PN, PS, PW [mm] test 2	IV	0	144x1				
PN, PS, PW [mm] test 3	IV	10	144x1				
PN, PS, PW [mm] test 4	IV	10	144x1				
Realdata [number of debris]	IV	10000, 25000	2x1				
tspanN, tspanS, tspanW [min]	INT	60	144x1				
Vn, Vs, Vw [m/s] test 1	INT	0	6x1				
Vn, Vs, Vw [m/s] test 2	INT	25^2 = 625	6x1				
Vn, Vs, Vw [m/s] test 3	INT	0	6x1				
Vn, Vs, Vw [m/s] test 4	INT	25^2 = 625	6x1				
Vsq [m/s] test 1	INT	0	6x14				
Vsq [m/s] test 2	INT	25^2 = 625	6x14				
Vsq [m/s] test 3	INT	0	6x14				
Vsq [m/s] test 4	INT	25^2 = 625	6x14				
WN, WNraw, WS, WSraw, WWraw, WWraw test 1	IV	0	144x1				
WN, WNraw, WS, WSraw, WWraw, WWraw test 2	IV	25	144x1				
WN, WNraw, WS, WSraw, WWraw, WWraw test 3	IV	0	144x1				
WN, WNraw, WS, WSraw, WWraw, WWraw test 4	IV	25	144x1				
YN, YS, YW	IV	2019	-				

Table 55. Verification sheet balance equations M3.

Equation	Tests	Test 1	Test 2	Test 3	Test 4
$M_{D,I} \leq M_{AD,A}$	all				
$M_{D,I} \leq M_{D,W}$	Test 2				
$M_{D,I} \leq M_{D,P}$	Test 3				
$M_{D,I} \leq M_{D,P} + M_{D,W}$	Test 4				
$M_{AD,G} = M_{D,I} + M_{D,R} + M_{AD,A}$	all				
$\sum_{subwater.} M_{AD,G} = O + \sum_{subwater.} M_{D,R} + \sum_{subwater.} M_{AD,A}$	all				
O (test 4) ≥ O (test 3) and ≥ O (test 2)	Test 4				

Appendix N: Calibration of model parameters

N.1. Simulated annealing

The following parameters, cooling schedule and neighborhood function were applied after tuning the algorithm:

Table 56. Simulated annealing parameters, cooling schedule and neighborhood function.

SA parameters	**Value/definition**
Starting temperature T_0	1,000,000
Cooling schedule	Geometric, $T = T_0 \cdot \alpha^t$
Cooling factor α	0.99998
Total iterations	1E6
Neighborhood function	Binary numbers

The solution space was determined separately for each parameter. For k_p, it was determined by calculating a first estimate, dividing the average total accumulation of debris by the average precipitation over the same period and the total watershed population:

$$k_p = \frac{m_I}{Pop \cdot P} \quad (79)$$

This is because the population of each sub watershed was used as a weight factor in the debris input equation:

$$m_I = m_{D,P} = k_p \cdot Pop \cdot (P - P_b) \cdot \Delta t \quad (80)$$

The obtained number is subsequently divided by 10 and multiplied by 10 to obtain the lower and upper bound of the solution space. It is assumed k_p will operate between these numbers. Subsequently, once the step size was chosen, the quantity of steps determined the amount of bits required, in this case 13. For M_{adg}, the lower and upper bound were obtained by using the maximum daily accumulation registered, namely 55980 debris items. The maximum and 1% of the maximum determined the lower and upper bound. A similar approach was used to acquire the number of bits, namely 16. For the precipitation threshold P_b, 100 steps were selected, ranging from 0 to 9.9 mm. This requires 7 bits. An overview of all the lower, upper bounds, step sizes, bits and parameter functions can be found below in table 57 below. The upper bound has been adjusted upwards for the number of steps available by the number of bits.

Table 57. Lower, upper bounds, step sizes, bits and parameter functions used for simulated annealing.

	M_{adg}	k_p	P_b
Lower bound desired	560	0.000567	0
Upper bound desired	55980	0.0567	9.9
Step size	1	0.00001	0.1
Steps	55421	5618	100
Minimum bits needed	16	13	7
Steps available	65536	8192	128
Upper bound with selected bits	66096	0.08759	12.7
Parameter function	560+ step	0.000567 + 0.00001·step	0 + 0.1·(step-1)

The simulated annealing algorithm as defined for model two (M2) is defined as follows:

Objective function $M2(x_1, x_2, x_3)$, *with* $x_1 = M_{adg}, x_2 = k_p \ and \ x_3 = Q_b$
Initialize initial temperature T_0 *and initial guess* $x_1^{(0)}, x_2^{(0)}, x_3^{(0)}$
Set maximum number of iterations N
Define cooling constant α

for n = 1: N

Move to new location:

Choose randomly one parameter to change, parameter x_i, $i \in \{1,2,3\}$
Choose randomly one bit to change
Change parameter x_i

Calculate difference in performance $\Delta M2 = M2\left(x_i^{(n)}, x_{ii}^{(n)}, x_{ii}^{(n)}\right) - M2\left(x_i^{(n-1)}, x_{ii}^{(n-1)}, x_{ii}^{(n-1)}\right)$,

with $x_i^{(n)} \neq x_i^{(n)} \ and \ x_{ii}^{(n)} \neq x_{ii}^{(n)}, with \ ii \in \{1,2,3\} \cup ii \neq i$

if $\Delta M2 > 0$, *accept new solution*

else

Generate a random number

Accept if $exp\left(-\frac{\Delta M2}{T}\right) > 1$

end

Update new best x_i *if necessary*

Update temperature: $T^n = T^{n-1} \cdot \alpha$

end

N.2. Figures model training

The figures below show the actual debris accumulation and predicted debris accumulation for the calibrated values obtained through model training.

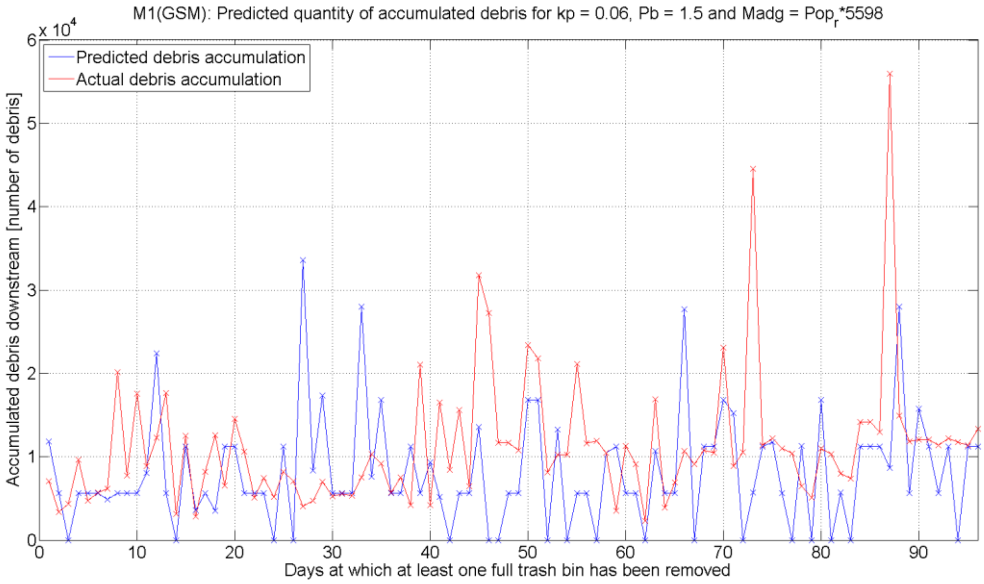


Fig. 86. Actual and predicted debris accumulation after training of model (M1).

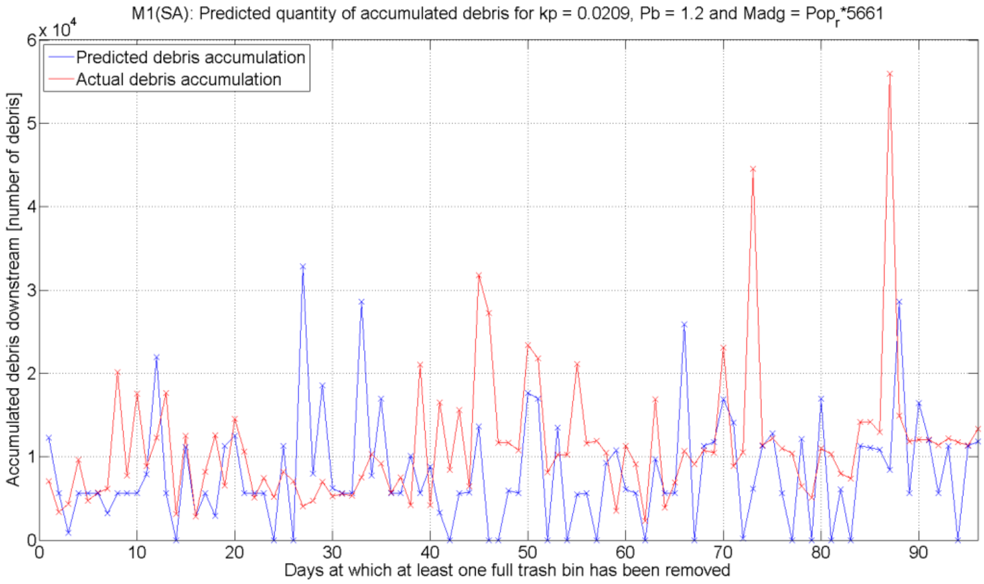


Fig. 87. Actual and predicted debris accumulation after training of model 1 (M1), SA.

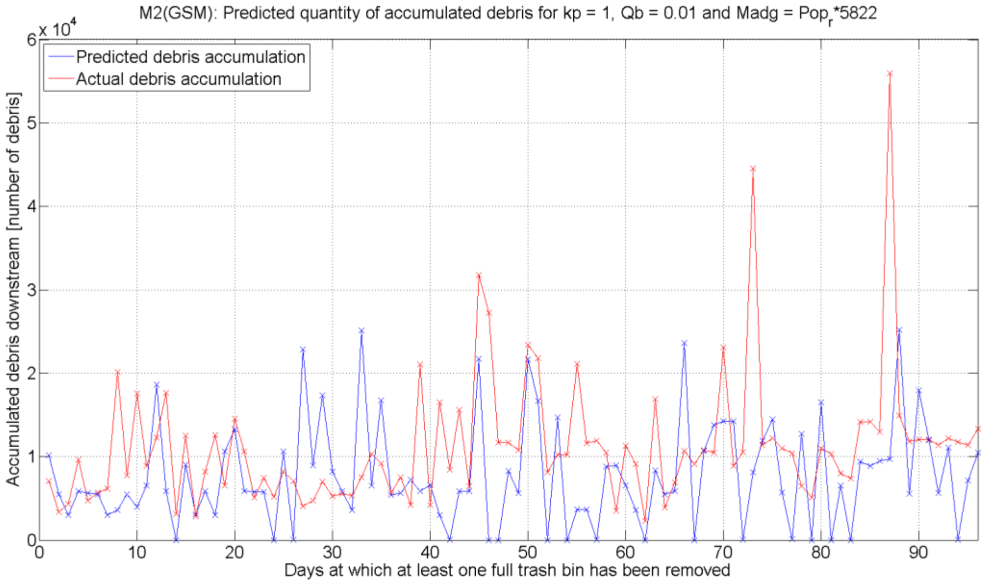


Fig. 88. Actual and predicted debris accumulation after training of model 2 (M2), GSM.

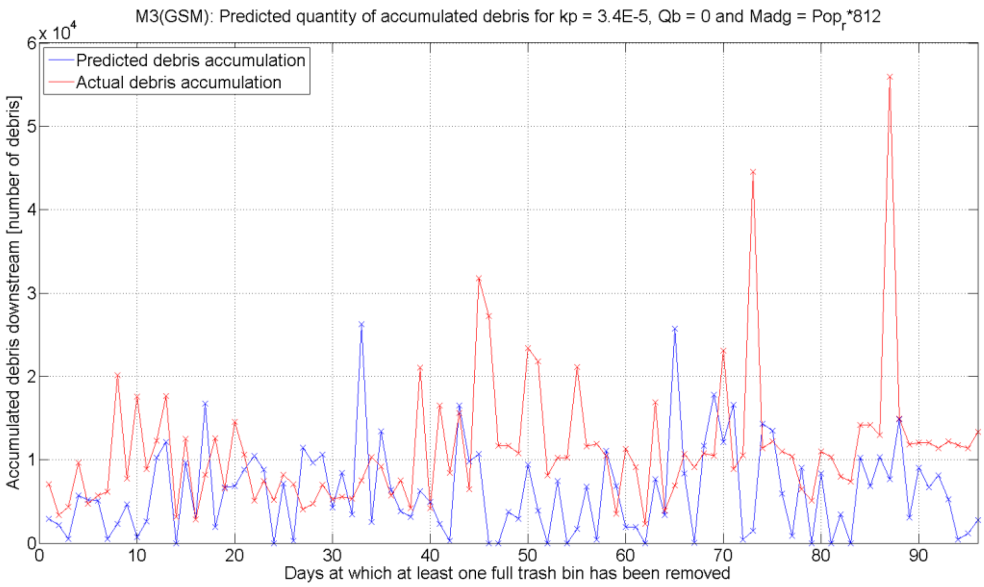


Fig. 89. Actual and predicted debris accumulation after training of model 3 (M3).

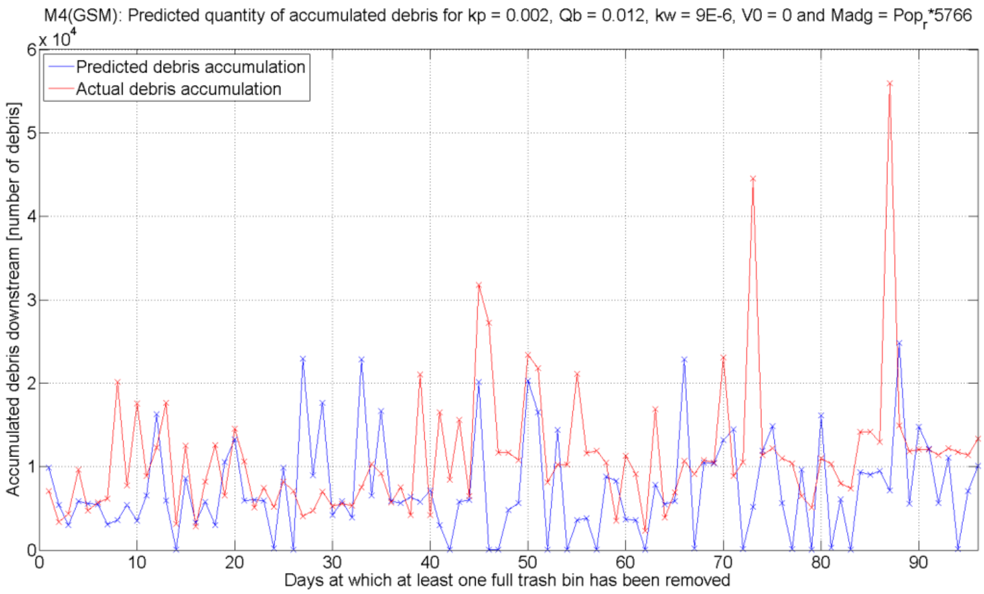


Fig. 90 Actual and predicted debris accumulation after training of model 4 (M4).

Appendix O: Graphs validation analysis

In this appendix the graphs can be found, as discussed in subsection 7.5.1.

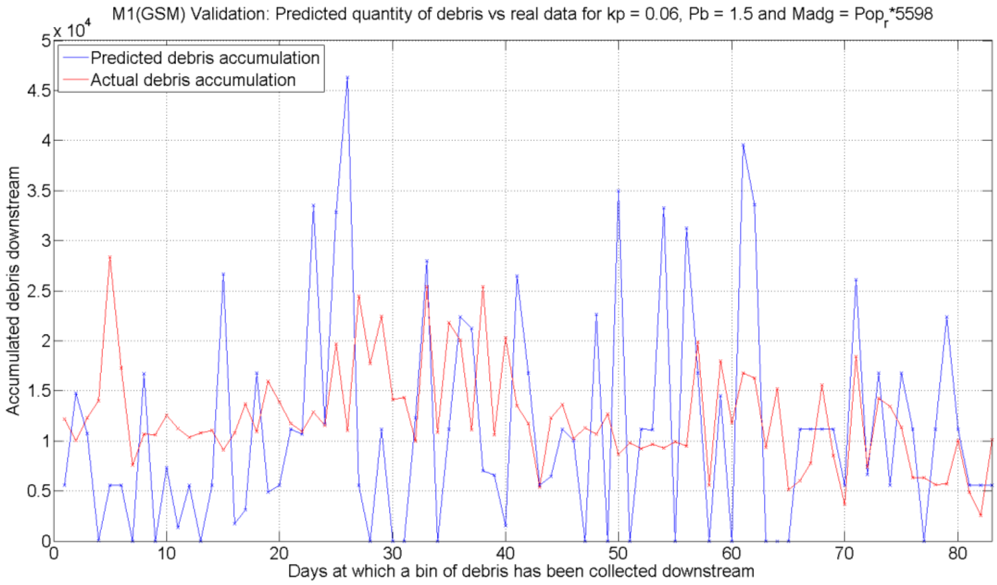


Fig. 91. A comparison between the predicted and actual accumulation of debris for M1, GSM (the dots representing the values were connected by lines to improve readability).

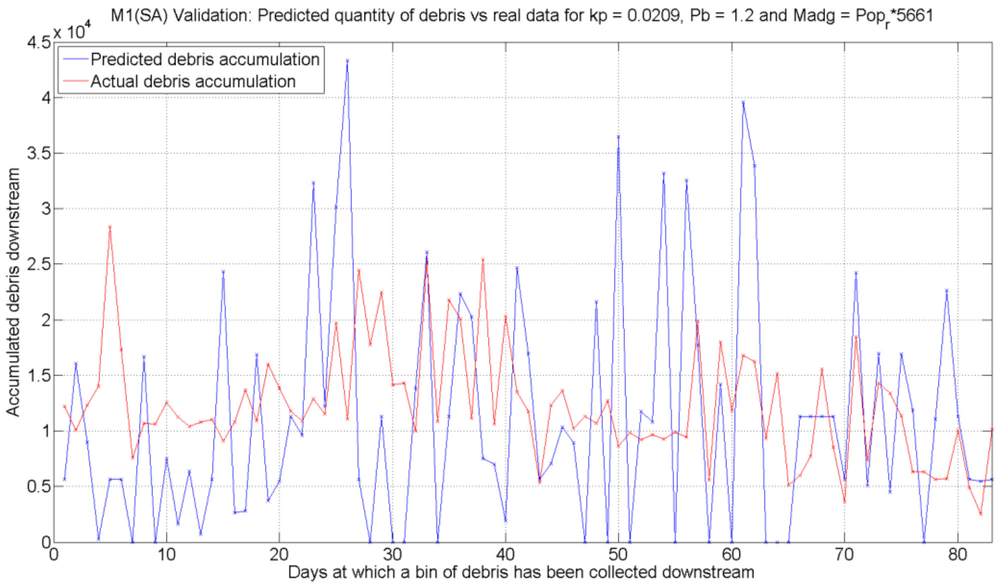


Fig. 92. A comparison between the predicted and actual accumulation of debris for M1, SA (the dots representing the values were connected by lines to improve readability).

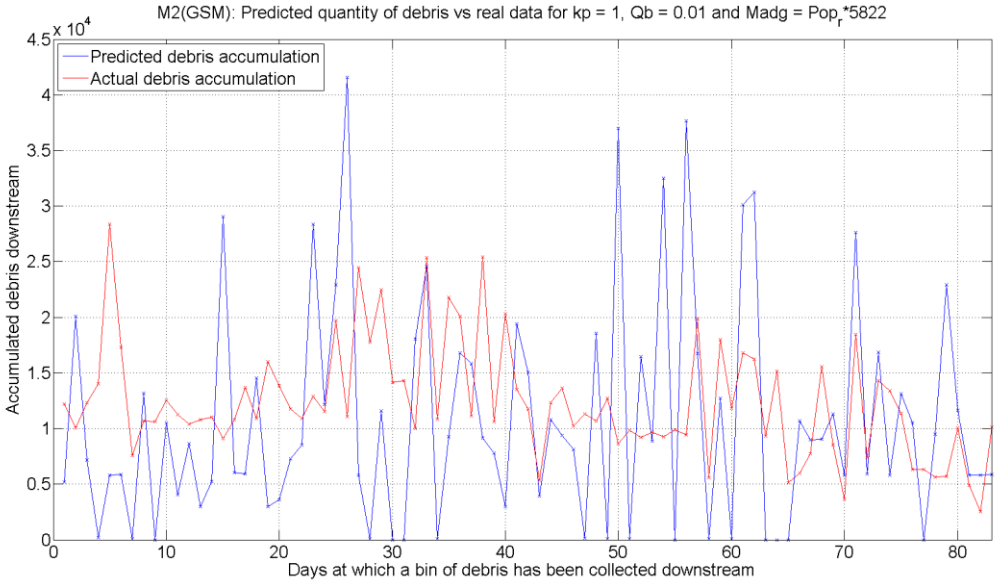


Fig. 93. A comparison between the predicted and actual accumulation of debris for M2, GSM (the dots representing the values were connected by lines to improve readability).

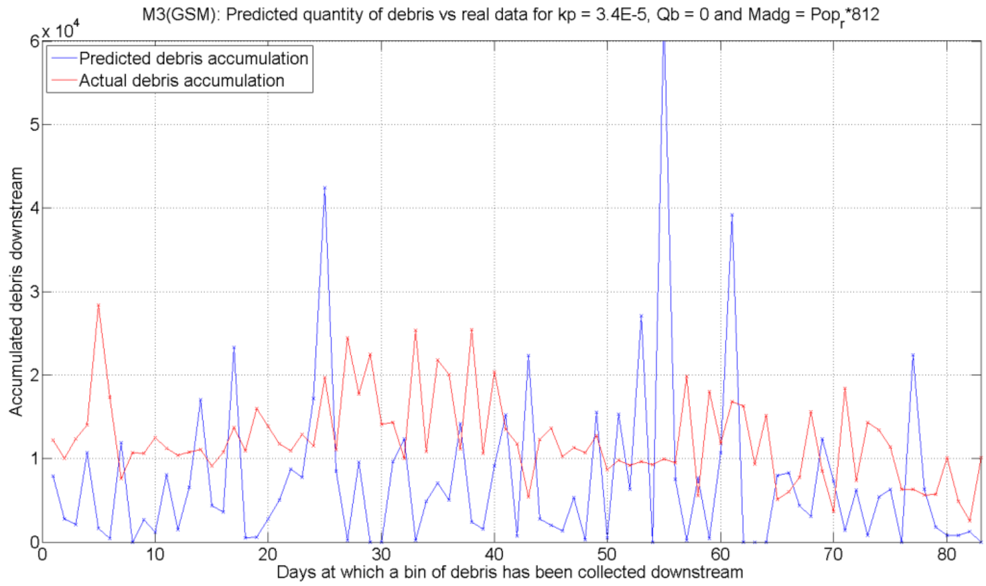


Fig. 94. A comparison between the predicted and actual accumulation of debris for M3, GSM (the dots representing the values were connected by lines to improve readability).

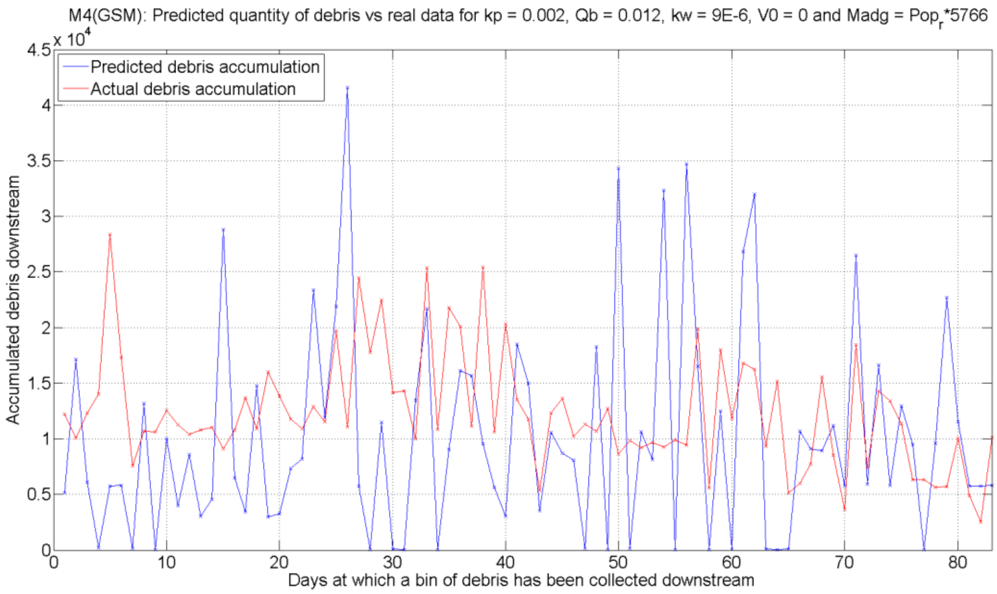


Fig. 95. A comparison between the predicted and actual accumulation of debris for M4, GSM (the dots representing the values were connected by lines to improve readability).

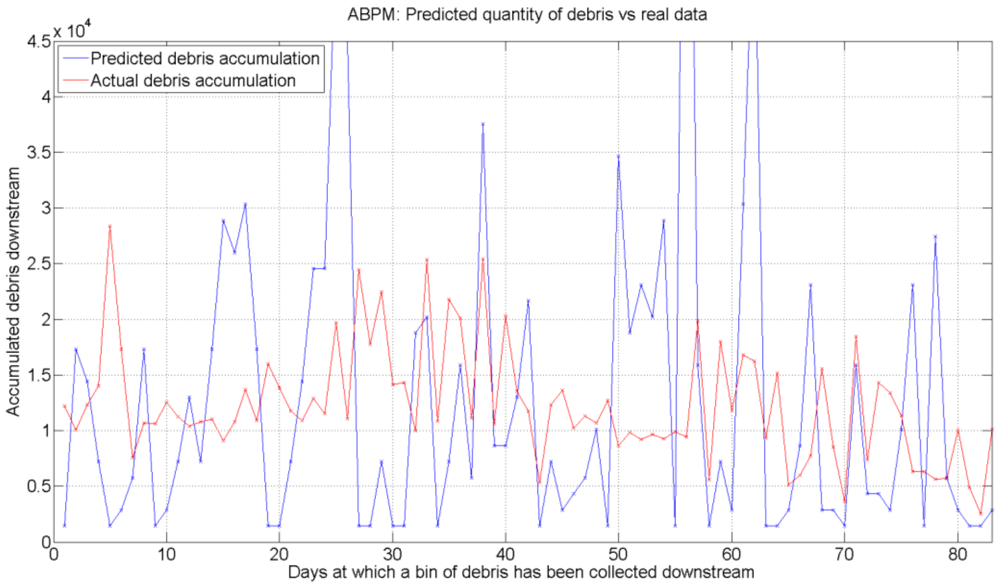


Fig. 96. A comparison between the predicted and actual accumulation of debris for ABPM (the dots representing the values were connected by lines to improve readability).

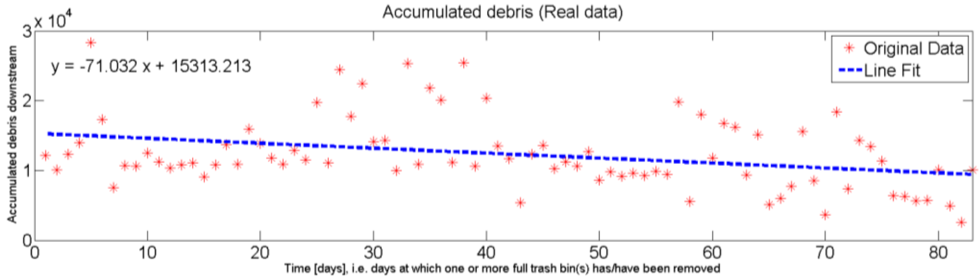


Fig. 97. Time series with line fit, actual values.

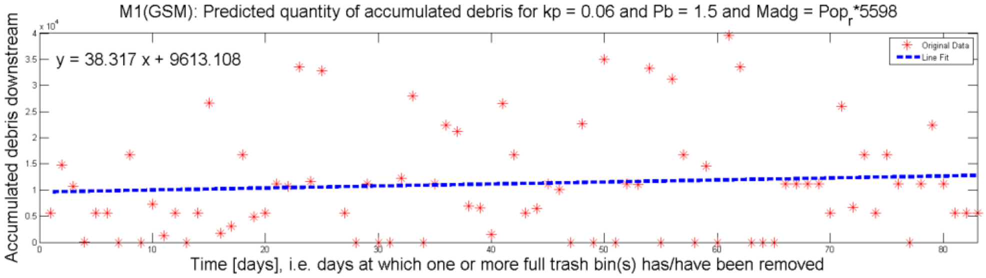


Fig. 98. Time series with line fit, M1 (GSM).

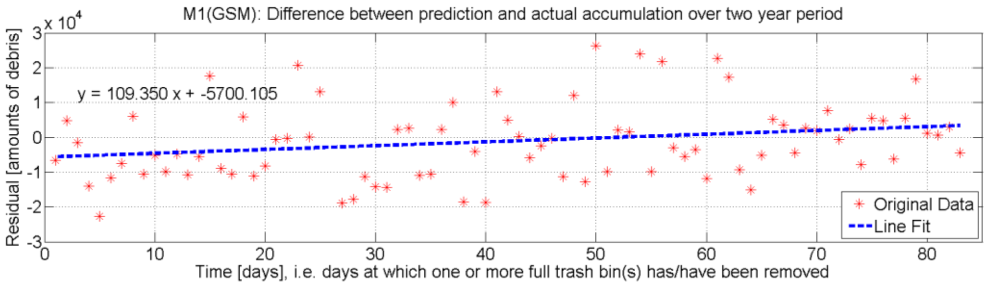


Fig. 99. Residuals, M1 (GSM).

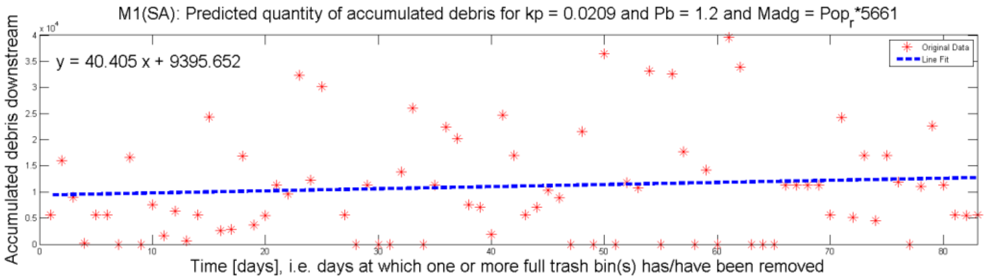


Fig. 100. Time series with line fit, M1 (SA).

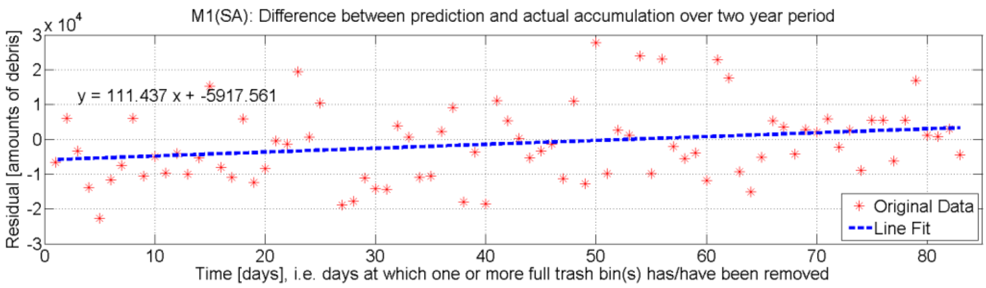


Fig. 101. Residuals, M1 (SA).

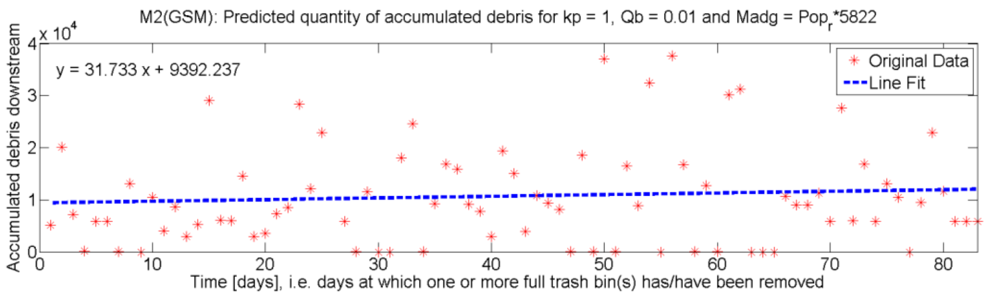


Fig. 102. Time series with line fit, M2 (GSM).

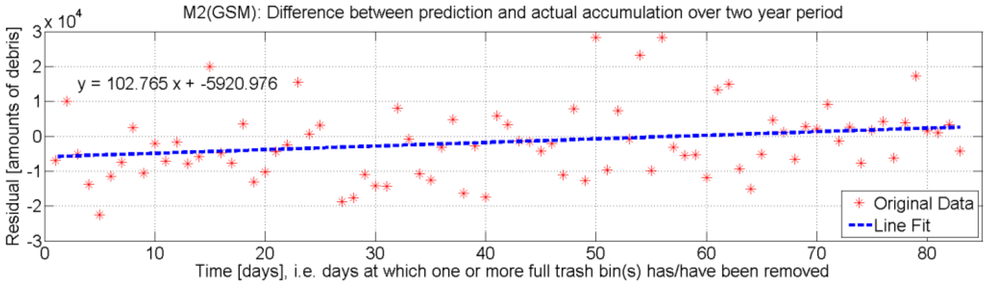


Fig. 103. Residuals, M2 (GSM).

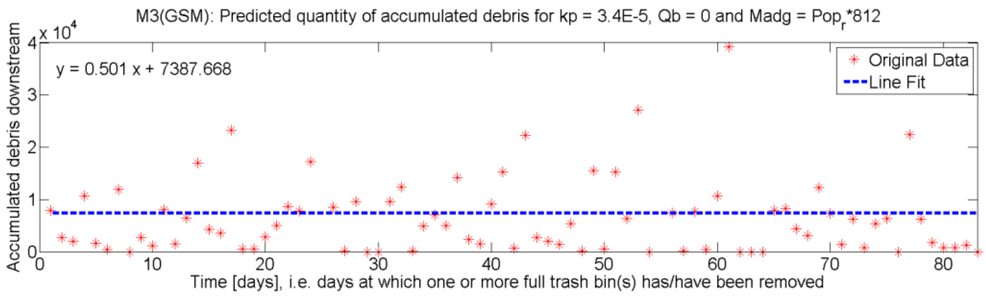


Fig. 104. Time series with line fit, M3 (GSM).

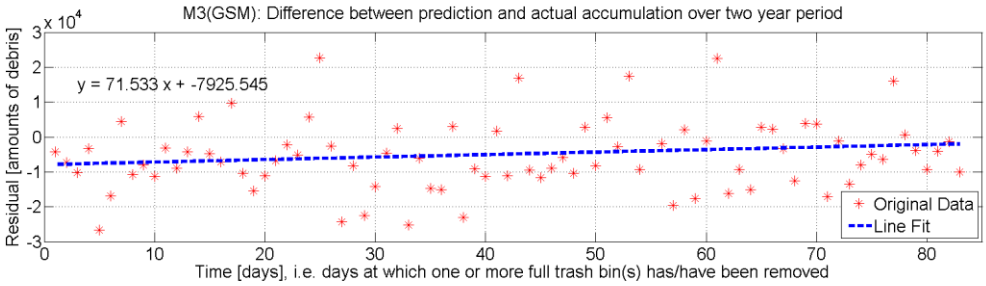


Fig. 105. Residuals, M3 (GSM).

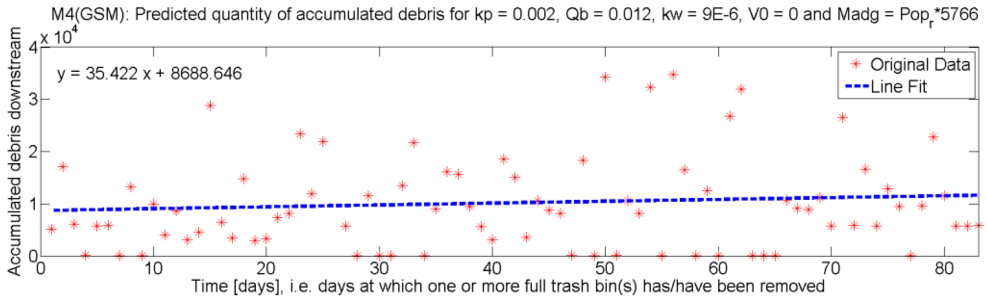


Fig. 106. Time series with line fit, M4 (GSM).

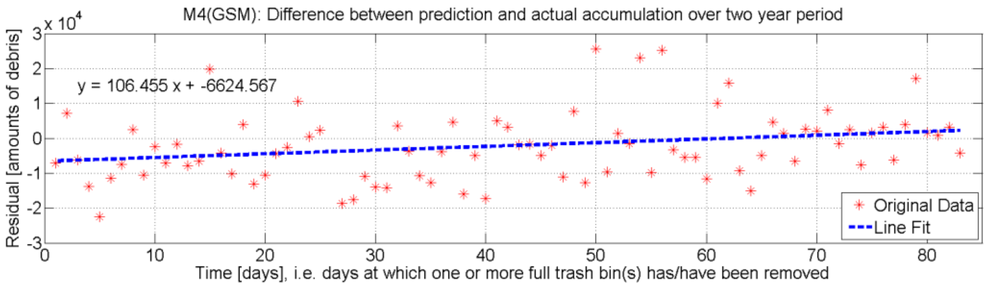


Fig. 107. Residuals, M4 (GSM).

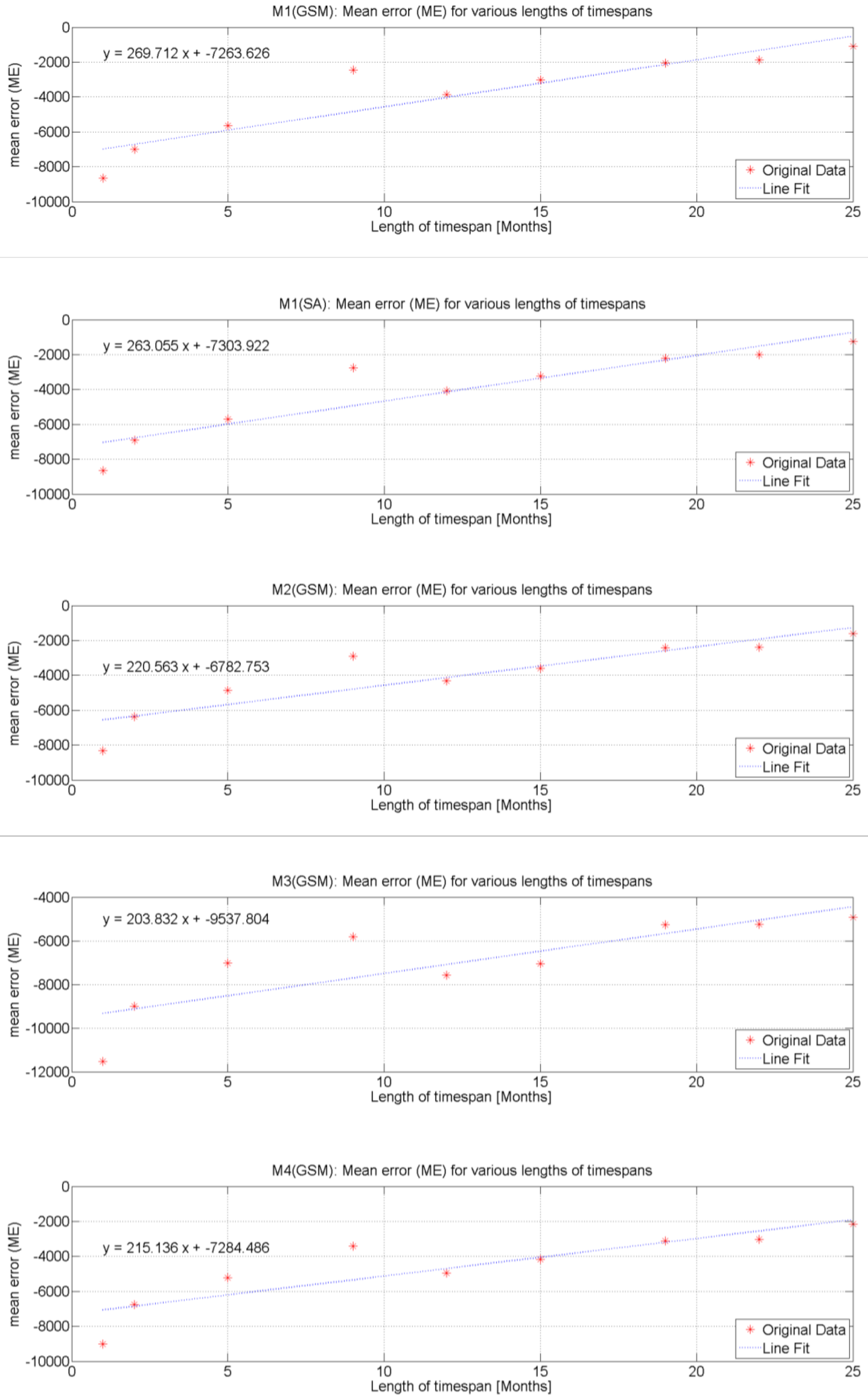


Fig. 108. Mean errors for various timespans, all models.

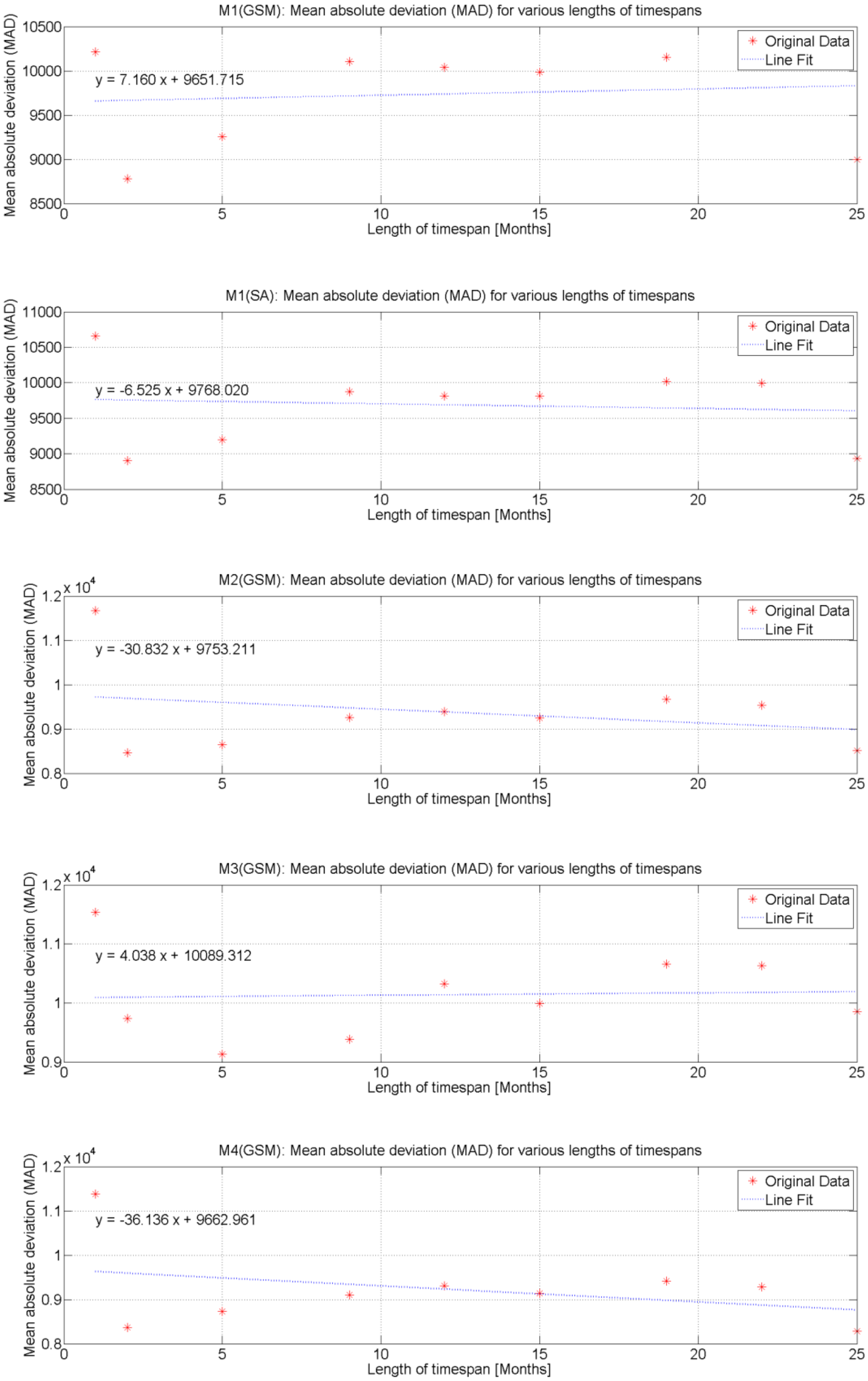


Fig. 109. Mean absolute deviation (MAD/MAE) for various timespans, all models.

Appendix P: Graphs sensitivity analysis

The results of the sensitivity analysis are given below. These results are discussed in subsection 7.5.2.

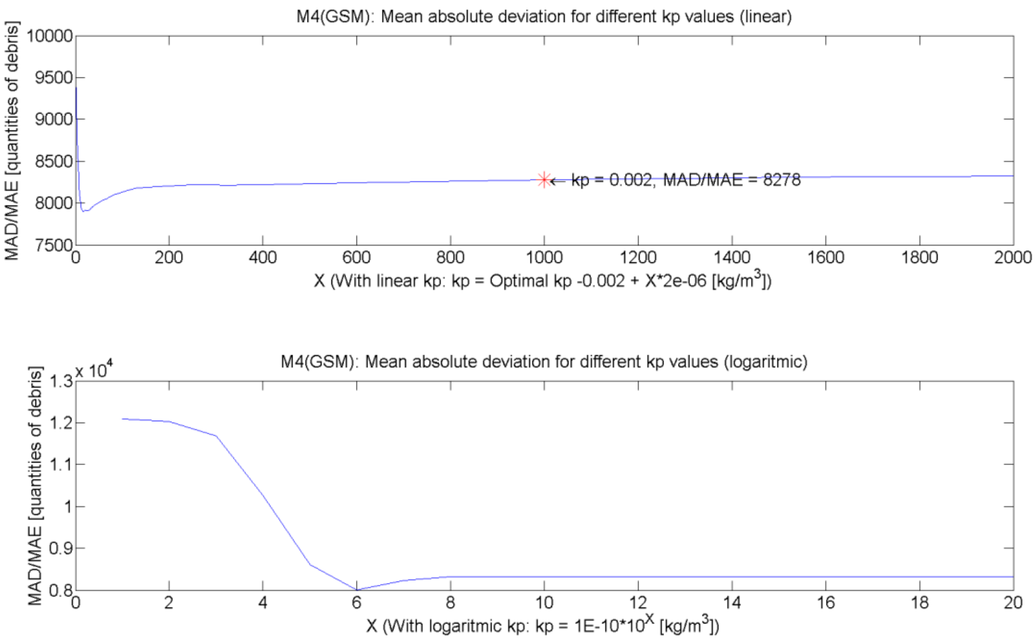


Fig. 110. Model performance (MAD) for various values of k_p.

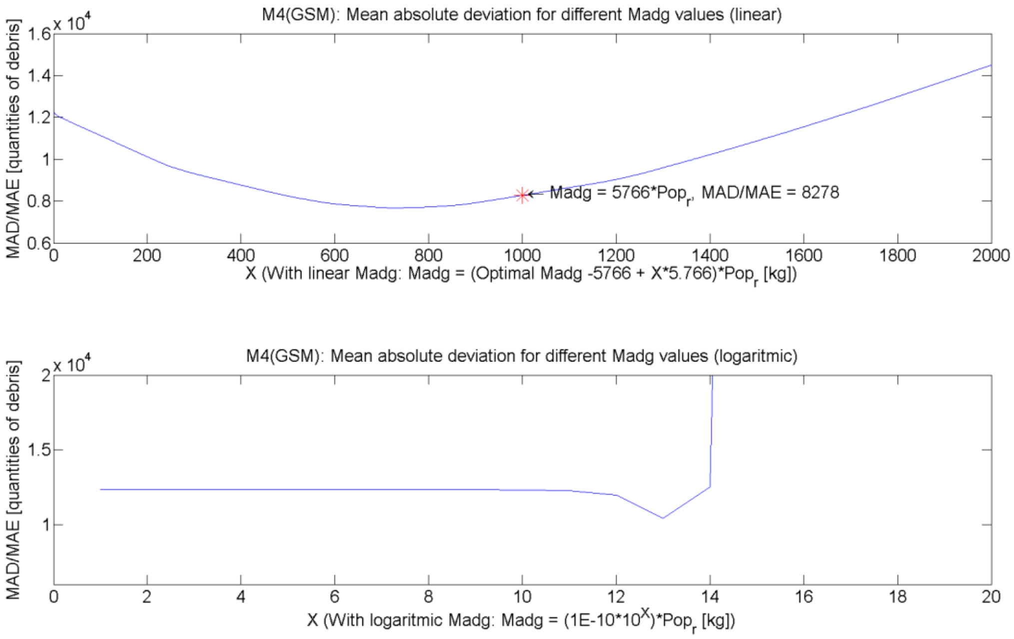
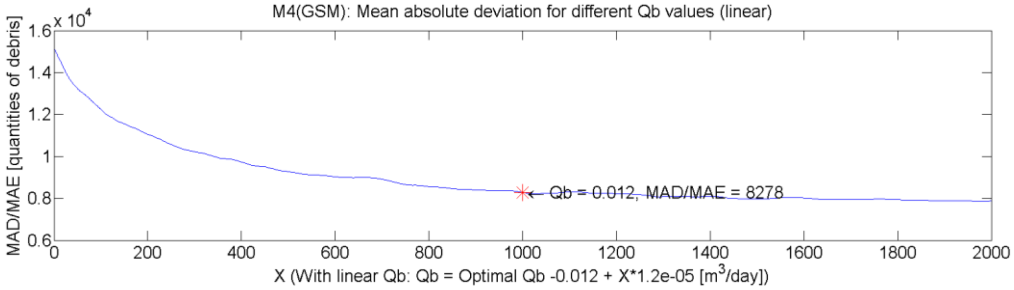


Fig. 111. Model performance (MAD) for various values of M_{adg}.



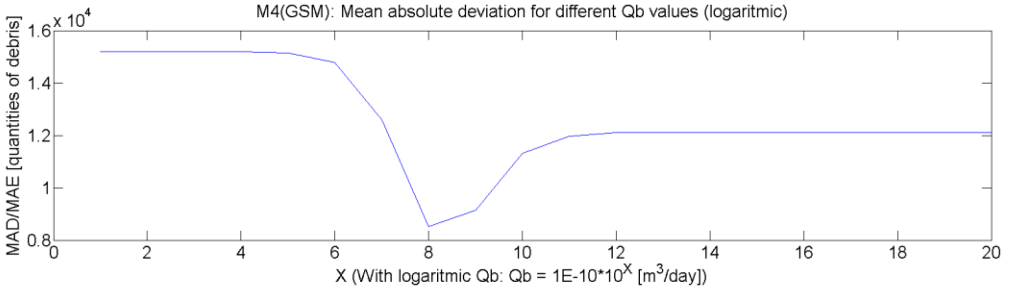
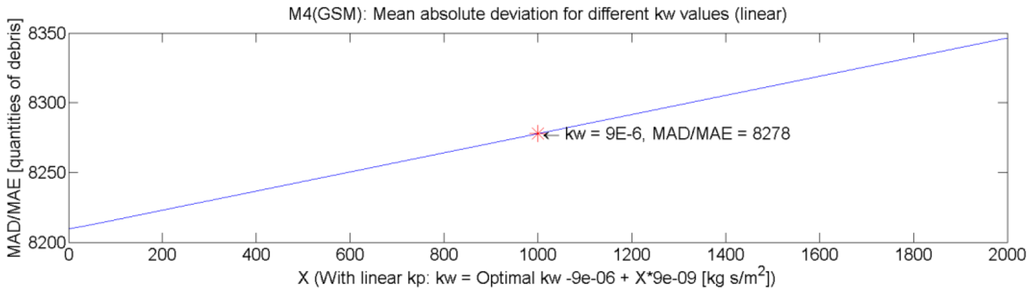


Fig. 112. Model performance (MAD) for various values of Q_b.



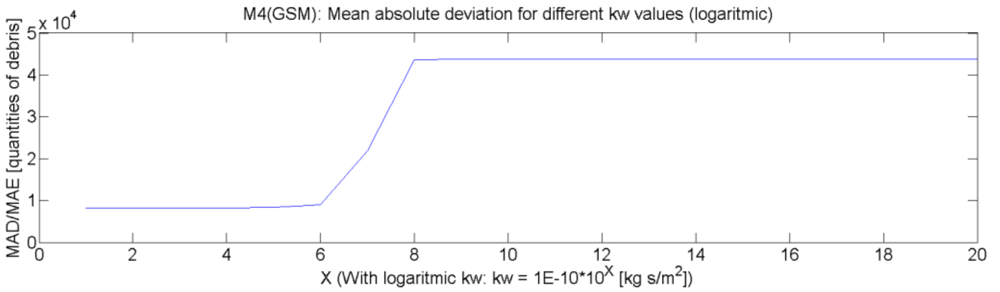


Fig. 113. Model performance (MAD) for various values of k_w.

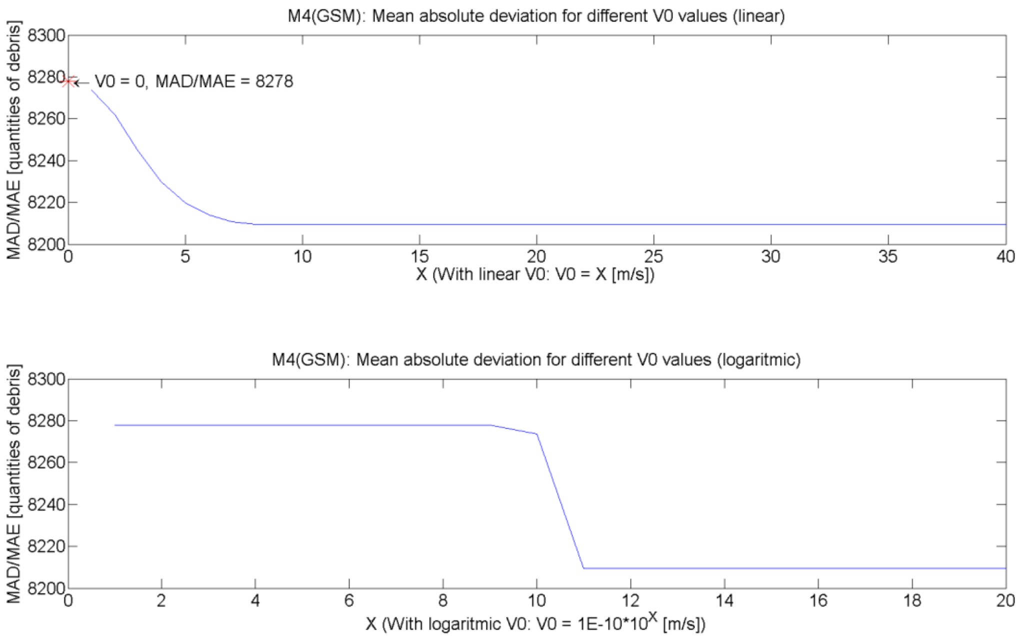


Fig. 114. Model performance (MAD) for various values of V_0.