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Post, J.A.B.[1*], Pothof, I.W.M.[1,2], Dirksen, J.[3], Baars, E.J.[3], Langeveld, J.G.[1,4], Clemens, F.H.L.R.[1,2]

[1]Section Sanitary Engineering, Faculty of Civil Engineering and Geosciences, Delft University of Technology, PO Box 5048, 2600 GA, Delft, The Netherlands

[2]Deltares, PO Box 177, 2600 MH, Delft, The Netherlands

[3]Waternet Foundation, PO Box 94370, 1090 GJ, Amsterdam, The Netherlands

[4]Partners4urbanwater, Javastraat 104A, 6524 MJ, Nijmegen, The Netherlands

Abstract

Gully pots are essential assets designed to relief the downstream system by trapping solids and attached pollutants suspended in runoff. This study applied a methodology to develop a quantitative gully pot sedimentation and blockage model. To this end, sediment bed level time series from 300 gully pots, spanning 15 months, were collected. A generalised linear mixed modelling (GLMM) approach was applied to model and quantify the accumulation of solids in gully pots and to identify relevant physical and catchment properties that influence the complex trapping processes. Results show that the retaining efficiency decreases as sediment bed levels increase. Two typical silting evolutions were identified. Approximately 5% of all gully pots experienced progressive silting, eventually resulting in a blockage. The other gully pots show stabilising sediment bed levels. The depth of the sand trap, elapsed time since cleaning and the road type were identified to be the main properties discriminating progressive accumulation from stabilising sediment bed levels. Furthermore, sediment bed levels exhibit no residual spatial correlation, indicating that the vulnerability to a blockage is reduced as adjacent gully pots provide a form of redundancy. The

* Corresponding author e-mail: j.a.b.post@tudelft.nl

findings may aid to improve maintenance strategies in order to safeguard the performance of gully pots.

Keywords: sediment accumulation; gully pot blockage; Bayesian inference; generalised linear mixed modelling

Nomenclature

t	observation number
i	gully pot identity
p	the probability of 'success'
ε	random part of the generalised linear model
η	Linear predictor containing the deterministic part of the generalised linear model
d	available sump depth
y	measured sediment bed level
v	normalised sediment bed level with respect to the sump depth
x	quantitative explanatory variable
β	model weight assigned to explanatory variable x
ϕ	autocorrelation strength
ω	noise term
a	shape parameter for the beta distribution
b	shape parameter for the beta distribution
θ	over-dispersion parameter
$\mathbf{z}$	row incidence vector for the random effects

1 Introduction

Street inlets are essential sewer assets responsible for collecting and conveying excess water from the urban surface. These structures are commonly designed as gully pots, referring to the presence of a sand trap. By capturing suspended particles in runoff, silting and wear of downstream sewer components are reduced. In addition, the impact on the pollutant wash-off to the sewer system is considerable (Ashley et al. 2004, Butler et al. 1995). Therefore, gully pots decrease the pollution load to receiving water bodies, especially for storm sewers. Depending on the retaining efficiency of the sand trap, the supply of solids induces progressive silting over time. When the trap capacity of is exceeded, the hydraulic performance of the gully pot is impaired. In the absence of alternative flow routes, water will pond and spread over adjacent areas causing potential health risks (De Man et al. 2014, Ten Veldhuis et al. 2010) and tangible damage (Arthur et al. 2009). The role of gully pot blockages as main contributor to sewer flooding events has been recognised by several studies (e.g. Ten Veldhuis et al. (2011) and Caradot et al. (2011)).

Unlike most sewer system components, gully pots are generally maintained with a proactive preventive approach (Butler and Davies 2004, Karlsson and Viklander 2008). It comprises of cleaning activities that are undertaken after a fixed period of time. Currently, the cleaning frequency is based on either the available budget (Fenner 2000), expert judgment, or vulnerability of the urban environment. The effectiveness of this type of management depends on the number of a blockages in a system within the specified interval (Swanson 2001). Yet, authorities lack quantitative data to support observed blockages. If data on the operational condition of gully pots are utilised to determine the maintenance interval, it is possible to balance the effectiveness of strategies and the associated resources to provide cost-effective service provision.

Adopting a condition-based approach for maintenance requires prediction tools and field data (Van Riel et al. 2014). Prediction models for solids transport in gully pots are described by e.g. Fulcher (1994) Butler and Karunaratne (1995) and Deletic et al. (2000). These models are based on dense time series with a duration varying from one to several storm events or artificial events for a limited (1 – 60) number of gully pots. Although this duration is adequate to simulate transport processes during individual events, the characteristic time scale of the solids induced blockage process in gully pots calls for time series covering a period of at least one year. Considering the complex transport processes and the corresponding parameter uncertainty, Rodríguez et al. (2012) and Pratt et al. (1987) opted for a probabilistic approach. This study modelled the long term accumulation of solids that leads to blockages by applying a generalised linear mixed modelling (GLMM) approach to time series of multiple gully pots. This approach allows for the identification of catchment and physical properties of gully pots that affect the accumulation of solids. Sufficient monitoring locations are essential for probabilistic modelling, as the potential correlation between successive measurements over time results in less unique information. To this end, sediment bed levels of 300 gully pots were measured monthly for over a year. Findings from this study may support overall maintenance strategies on a system scale and improve gully pot design. Furthermore, this work complements previous research on sediment accumulation and water quality aspects (e.g. Ellis and Harrop (1984), Memon and Butler (2002) and Butler and Karunaratne (1995)). This paper first presents an overview of literature on the relevant processes to identify the main explanatory variables that influence the occurrence of gully pot blockages. Second, the collection of sediment bed level data is discussed. Subsequently, a procedure for modelling is introduced and applied to these data.

2 Relevant transport processes and parameters

Various processes govern sediment accumulation. The following review identifies properties that are relevant for modelling sedimentation in gully pots.

2.1 Supply to gully pots

Particles present in the urban environment are predominately inorganic, comparable to sand and silt (Lager 1977, Sartor and Boyd 1972). These particles originate from different sources, such as local traffic (Deletic et al. 2000), construction activities (Ashley and Crabtree 1992), weathering of buildings (Jartun et al. 2008), animal wastes, litter, and de-icing materials (Brinkmann 1985). Particles that are transported to gully pots during storm events are generally not well removed by street sweeping (Brinkmann 1985, Sartor and Boyd 1972). Material available for wash-off to gully pots may vary spatially, as the presence of potential sources is subject to local circumstances. Pratt and Adams (1984) reported a relation between characteristics of the contributing area (e.g. size, drainage path length) and the mean mass of the measured sediment wash-off in the field. These data did, however, originate from the same gully pots, indicating a potential dependence between successive measurements over time. In addition to spatial variation, the supply to gully pots may also vary temporally. Grottker (1990b) analysed the organic content of sediment samples and found a higher organic loading (5 – 10%) in autumn. Peaks in the material supply in June, autumn and after snowmelt were mentioned by Pratt et al. (1987), indicating seasonal variation. On a shorter timescale, flow characteristics dominate the temporal variation. Ellis and Harrop (1984) found that the antecedent dry period was only weakly correlated with the sediment loading to gully pots. Rainfall intensity was, however, strongly correlated. Similar results lead Pratt and Adams (1984) to the conclusion that the shear force required to suspend material is limiting, rather than the availability of material. The overall variation in particle loading results in models that typically calls for several site specific calibration parameters (Memon and Butler 2002).

2.2 Retaining efficiency

The fraction of solids captured by gully pots has been studied extensively. Field studies reported retaining efficiencies ranging from 20 – 50% (Deletic et al. 2000, Pitt and Field 2004). Both Butler and Karunaratne (1995) and Grottker (1990a) conducted lab experiments where the solids supply to gully pots was varied. They found that the retaining efficiency was independent from the solids concentration, which support model results from Butler and Memon (1999). Butler and Clark (1995) found the build-up rate to vary between 14 – 24 mm / month for urban areas. This variation may well be related to the substantial variation in grain size distributions of samples from different gully pots (Jartun et al. 2008), as solids with a smaller diameter are captured less efficiently (Butler and Karunaratne 1995, Lager 1977).

Laboratory tests by Butler and Karunaratne (1995) with varying sediment bed levels up to the level of the outlet pipe of a gully pot show a marginal increase in the retaining efficiency with increasing sediment depths. This is contradictory with experimental results reported by Lager (1977), who found that solids removal efficiencies decreased when a threshold of 40% of the gully pot storage was exceeded. The latter is supported by the increase in the retaining efficiency with an increasing cleaning frequency (Memon and Butler 2002, Mineart and Singh 2000). Field measurements from Butler and Clark (1995) indicate that equilibrium sediment bed levels were reached at the level of the outlet pipe. Conradin (1990) reported similar results for 63 gully pots monitored for 16 months; sediment bed levels did not exceed the level of the outlet pipes and equilibrium depths were generally reached in 6 months.

2.3 Re-suspension of sediments

There is a general consensus that the sedimentation rate is inversely proportional to the rainfall intensity (e.g. Morrison et al. (1988), Deletic et al. (2000) and Ciccarello et al. (2012)). Depending on the particle size, the jetting effect induces erosion of the gully pot sediment bed (Butler and Memon 1999). Sartor and Boyd (1972) applied flushing tests equivalent to heavy storms and found only 1% of the sediment bed to be re-suspended. This confirms earlier results reported by Fletcher and Pratt (1981), who mentioned that the majority of solids discharged from gully pots are due to a lack of sedimentation rather than re-suspension. As the top layer of the sediment bed is more unstable, these solids may be eroded (Pitt and Field 2004). However, bed erosion decreases substantially as these particles are depleted and the bed becomes graded (Butler and Karunaratne 1995).

2.4 Summary of relevant transport parameters

A statistical approach calls for data on gully pots properties that may influence solids accumulation in a sand trap. Gully pots are subject to successive storm events over time, where sediment bed levels increase or decrease depending on the rainfall regime. As the height of the bed increases over time the trapping efficiency reduces, indicating the relevance of the gully pot sump depth as an explanatory variable. In addition, the transient trapping efficiency implies interaction terms between the physical properties and the elapsed time since last maintenance. Catchment properties govern both the flow rate and the supply of solids. As such, these properties are potential explanatory variables. An overview of the explanatory variables included in the model is presented in Table 4-1. Model residuals are potentially correlated, as the availability of particles from the urban surface varies both spatially and temporally.

3 Materials

Sediment bed levels of gully pots in a residential urban area in Amsterdam, the Netherlands were been monitored. The catchment area has 10.5 ha of surfaces that contribute to the runoff into the separate sewer system.

Figure 3.1: Schematisation of a roadside gully pot, with the outlet pipe positioned at the back

A sample size of 300 gully pots was selected from the catchment with 801 gully pots to allow for valid inferences given the spatial variation of the process measured. Data on the properties of gully pots in the study area was inventoried prior to the measurements. This includes geometrical data describing the physical properties of each gully pot (depth of the sand trap, surface area, manufacturer, presence of a water seal, position of the outlet pipe with respect to the grating) and catchment properties (contributing area, slope, road type). Based on the spatial distribution of the physical properties of the gully pots (see Figure 3.1), a stratified sampling design was applied. This sampling technique improves estimates of both the population and the sub-groups by taking a proportional sample from each sub-group. Stratification distinguished between the presence of a water seal, the position of the outlet pipe and the depth of the sand trap. Table 3-1 shows the frequency distribution over the different strata.

Table 3-1: Frequency distribution of the different strata

Water seal	Depth sand trap (cm)	Position outlet pipe		
		Back	Front	Side
No	[0 - 20]	11	23	14

	(20 - 40]	5	9	12
Yes	[0 - 20]	13	37	75
	(20 - 40]	11	21	79

The associated costs and spatial spread render continuous monitoring for this sample size impractical. Instead, an apparatus able to rapidly measure the height of the bed has been constructed. The principle is illustrated in Figure 3.2. It consists of a punctured disk attached to a shaft, with a retractable rod in the middle. The disk rests on the sediment bed, while the rod is driven through until the bottom of the gully pot is reached. The rod is equipped with a sequence of marks at $5 \cdot 10^{-3}$ m intervals enabling the operator to determine the height of the bed. Tests with repeated measurements from the same gully pot indicate the error to be smaller than the increment of the instrument scale.

Figure 3.2: Schematisation of the device used to measure sediment bed levels in gully pots.

Three weeks prior to the first measurement, all gully pots were emptied and lateral connections cleaned. In addition, the hydraulic capacity of the lateral connections was tested by means of a vehicle mounted sewer jetting installation capable of providing a flow of 100 l/min, equivalent to 60 mm/hr on 100 m^2, assuming the design standard applied in the Netherlands (Ganzevles and Oomens 2008). In case of a defect, the gully pot was removed from the dataset. This excluded the influence of external failure mechanisms not related to the sedimentation mechanism, such as collapse or deformation of the geometry. Gully pots were removed from the monitoring set when more than one measurement was missing, e.g. due to accessibility, or in case of signs of tampering. In addition, gully pots presumed blocked due to the accumulation of sediment during the monitoring period were tested by means of a vehicle mounted sewer jetting installation to validate this observation. The duration of the campaign was chosen to be longer than the standard preventive cleaning interval of once or twice per year and to include all four seasons.

3.1 Catchment properties

The contributing area and average slope for each gully pot was determined by means of the eight-direction flow approach described in Jenson and Domingue (1988). The digital elevation model (DEM) used to deduct these flow patterns is based on high-resolution altimetry data obtained by airborne laser scanning (Van der Zon 2011) and has a spatial resolution of 0.5 · 0.5 m. The vertical stochastic error for the grid is $2.5 \cdot 10^{-3}$ m. Confounding objects (e.g. cars and trees) were filtered from the DEM and were interpolated from the surrounding data. Both Kriging with an external drift (KED) based on land use and Ordinary Kriging (OK) were considered as interpolation methods. However, analysis of the variogram of the regression residuals showed no substantial improvement (1.5%) of the semivariance. Hence, Ordinary Kriging was applied to interpolate the DEM.

The area has two road types, being main roads and local roads (see preview photos in Figure 3.3). The former has a continuous traffic flow (2000 – 6000 vehicles/day) and a road surface consisting of asphalt pavement. The latter is characterized by brick paving (< 2000 vehicles/day) and parking lots. The area is considered to be a dense urban environment, developed as a residential area with some commercial properties concentrated around the main roads. An overview of the monitoring area is given in Figure 3.3.

Figure 3.3: Measurement area in Amsterdam, the Netherlands. Gully pots are marked by circles.

4 Methods for data analysis

As the processes associated with the transport and subsequent sedimentation of solids are complex and not fully understood, deterministic storm water quality modelling is associated with various difficulties (Deletic et al. 2000, Freni et al. 2009). Moreover, a deterministic approach requires the estimation of various site specific parameters, which are subject to uncertainty (David and Matos 2002). Based on these considerations, this study applies a probabilistic approach. Sediment bed level data were analysed by applying a Generalised Linear Mixed Model (GLMM) from a Bayesian perspective. The four components that compose this model are discussed in chapter's 4.1 - 4.4.

Selection of the structure of these components follows the protocol suggested by (Zuur et al. 2009), which is summarised in Figure 4.1. First, the data exploration procedure outlined in chapter 4.5 was applied. Subsequently, the random part and the distribution of the response variable were determined with the complete deterministic part including interactions between the physical properties and the elapsed time since cleaning. After validation, model selection was applied to identify relevant explanatory variables in the deterministic part.

Figure 4.1: procedure for the selection of the components of a GLMM. References to the corresponding paragraphs where the results are presented have been added.

4.1 Structure of the deterministic part

The linear predictor η contains the deterministic part of the model, which is a linear function of *k* explanatory variables and is given by

$$\eta_{t,i} = \beta_0 + \beta_1 x_{t,i,1} + \ldots + \beta_k x_{t,i,k} \qquad \textbf{(4.1)}$$

where *t* represents the observation number and *i* the gully pot. β refers to the weights assigned to the respective explanatory variables *x*, summarised in Table 4-1. β_0 is the intercept.

Table 4-1: Explanatory variables and their characteristics

Variable	Index	Type	Unit	Range
Depth sand trap	x_1	continuous	(cm)	[9 - 44]
Catchment slope	x_2	continuous	(%)	[1.3 - 4.3]
Time since cleaning	x_3	continuous	(days)	[21 - 420]
Contributing area	x_4	continuous	(m^2)	[5 - 1380]
Cum. Rainfall depth	x_5	continuous	(mm)	[115 - 1160]
Water seal	x_6	categorical	-	yes / no
Position outlet pipe	x_7	categorical	-	front / back
Position outlet pipe	x_8	categorical	-	side / back
Road type	x_9	categorical	-	main / local

4.2 Structure of the random part

The model assumption of independence is not guaranteed, as successive observations from the same gully pot can be expected to be more similar compared to observations from other gully pots. This violation of independence was resolved by extending the deterministic part η with a correlation structure to model inter-gully pot variation and the correlation caused by this variation. Two extensions were considered. The first candidate was a random intercept, which implies that all pairs of observations from the same subject gully pot are equally correlated (i.e. compound symmetry correlation) and defines the random part as

$$\varepsilon_{t,i} = N\left(0, \sigma_i^2\right) \quad \textbf{(4.2)}$$

Alternatively, an auto-regressive process of order 1 (AR-1) model was considered. It is a special case of the autoregressive–moving-average model family. This structure has correlations, between observations from the same gully pot, that decline exponentially with time and is given by

$$\begin{aligned} \varepsilon_{t,i} &= \phi\varepsilon_{t-1,i} + \omega_{t,i} \\ \omega_{t,i} &= N\left(0, \sigma^2\right) \end{aligned} \quad \textbf{(4.3)}$$

where the estimated parameter ϕ is the strength of the autocorrelation and ω the noise term.

4.3 Distribution of the response variable

Each outcome of the response variable is assumed to be generated from a particular distribution. This study analyses the normalised sediment bed level *v*, which is defined as the sediment bed level *y* normalised with respect to the available sump depth *d*. Two distributions were considered, the first being the binomial distribution, with probability *p*, specified by

$$\begin{aligned} & y_{t,i} \sim Binomial\left(p_{t,i}, d_{t,i}\right) \\ & E\left(y_{t,i}\right) = p_{t,i} \cdot d_{t,i} \text{ and } \operatorname{var}\left(y_{t,i}\right) = p_{t,i} \cdot d_{t,i} \cdot \left(1 - p_{t,i}\right) \end{aligned} \quad \textbf{(4.4)}$$

However, when the variation of the data is inflated compared to the theoretical expected variance according to the binomial model (i.e. over-dispersion), a more general model is required. Alternatively the response variable can be described by a beta-binomial distribution. This mixed distribution permits heterogeneity by modelling the probability of success as a beta distribution. Parameters *a* and *b* describe the beta distribution. The expected value of the beta-binomial is similar to the expected value of the binomial distribution in eq. 4.4. Yet, the variance is given by

$$\operatorname{var}\left(y_{t,i}\right) = p_{t,i} \cdot d_{t,i} \cdot \left(1 - p_{t,i}\right) \cdot \left(1 + \frac{d_{t,i}}{\theta + 1}\right) \quad \textbf{(4.5)}$$

Where the parameter $\theta = a + b$ accounts for over-dispersion. For large values of theta, the variance converges to that of the binomial distribution.

4.4 Link function

Subsequently, the link function describes the relationship between the expectation of the response variable and the extended deterministic part. The logistic link is such a function and is given by

$$p_{t,i} = \frac{e^{\eta_{t,i}+\varepsilon_{t,i}}}{1+e^{\eta_{t,i}+\varepsilon_{t,i}}} \tag{4.6}$$

Introduced by (Berkson 1944), it approximates the inverse cumulative distribution function of the Gaussian distribution and is able to model binomial data effectively (Hardin and Hilbe 2007).

4.5 Data exploration and model validation

The process of exploration and validation provides information about eligible model structures and explanatory variables. Outliers may influence the statistical analysis and cause over-dispersion (Hilbe 2007). In addition, an abundance of zero measurements may result in biased parameter estimates and incorrect standard errors (Zuur et al. 2010). Graphical exploration of the explanatory variables and the response variable allowed for the identification of both zero abundances and outliers.

Strong collinearity between explanatory variables may result in unreliable parameter estimates, as the estimates may respond erratically to small changes in the data (Zuur et al. 2013). Collinearity was assessed by inspecting pair-plots and computing Variance Inflation Factors (VIF) for high-dimension relations.

Following the model specification, the influence of individual observations was analysed by computing Cook's distance (Cook 1977). This statistic represents the normalised change in fitted values when one observation is removed. Pearson residuals were extracted from the model to verify the assumptions inherent to GLMM's. Homogeneity of variance was verified by graphical techniques, as statistical tests are sensitive to non-normality (Sokal and Rohlf 1995). Non-linear patterns in the residuals may indicate that the model needs to be extended with quadratic terms (Zuur et al. 2013). Mantel correlograms of the residuals were analysed to determine whether there is any inherent spatial or temporal dependency.

4.6 Bayesian Inference

In recent years, Bayesian inference has gained an increasing amount of attention in the field of environmental engineering (e.g. Kanso et al. (2006), Liu et al. (2008), Korving et al. (2006) and Egger et al. (2013)). The Bayesian framework considers unknown parameters as random variables. The uncertainty about these parameters is expressed by the posterior density function. This approach is not hindered by the potential inaccurate penalized quasi-likelihood generally applied to GLMM's in a frequentist framework (Zhao et al. 2006). Bayes' theorem evaluates the posterior density by updating prior information when new observations are available and is given by,

$$P(\boldsymbol{\beta} \mid \mathbf{y}) = \frac{P(\mathbf{y} \mid \boldsymbol{\beta}) P(\boldsymbol{\beta})}{P(\mathbf{y})} = \frac{P(\mathbf{y} \mid \boldsymbol{\beta}) P(\boldsymbol{\beta})}{\int P(\mathbf{y} \mid \boldsymbol{\beta}) P(\boldsymbol{\beta}) d\boldsymbol{\beta}} \tag{4.7}$$

where *P*(**β** | **y**) is the joint posterior density of parameter vector **β** based on prior information and observations **y** ($y_{1,1}, y_{1,2},..,y_{n,t}$) from *n* different gully pots on *t* occasions. The prior probability density *P*(**β**) represents expert information or historical observations before new data are involved. The marginal likelihood is denoted by *P*(**y**) and is a fixed normalising factor, scaling the sum of the posterior likelihood to one. *P*(**y**|**β**) is referred to as the likelihood function, which for a binomial generalised linear mixed model can be expressed as,

$$P(\mathbf{y} \mid \boldsymbol{\beta}, \varepsilon) = \prod_{n=1}^{N} \prod_{t=1}^{T} \binom{d_{n,t}}{y_{n,t}} \left[p_{n,t}\left(\boldsymbol{\beta}_{n,t}, \varepsilon_n\right) \right]^{y_{n,t}} \left[1 - p_{n,t}\left(\boldsymbol{\beta}_{n,t}, \varepsilon_n\right) \right]^{d_{n,t} - y_{n,t}} \tag{4.8}$$

where,

$$p_{n,t}\left(\boldsymbol{\beta}_{n,t}, \varepsilon\right) = \left[1 + e^{\mathbf{x}_{n,t}^{\mathrm{T}} \boldsymbol{\beta}_{n,t} + \mathbf{z}_n^{\mathrm{T}} \varepsilon} \right]^{-1} \tag{4.9}$$

includes both the deterministic and random part. **z** is a row incidence vector for the random part. Non-informative priors were used for the regression parameters, representing the lack of knowledge about the parameters. These distributions have a negligible influence on the posterior distribution. A half-Cauchy(25) prior was used for the standard deviation parameter, as recommended by Gelman (2006) and Marley and Wand (2010). This prior expresses the belief that the random intercepts are concentrated close to the common intercept.

Integration over the denominator of eq. 4.7 is considered to be infeasible for most practical applications due to high-dimensionality of $\boldsymbol{\beta}$ (Qian et al. 2003). Markov Chain Monte Carlo (MCMC) algorithms do not require evaluation of the marginal likelihood, since the posterior distribution is sampled directly. This study applied the Gibbs sampler (Geman and Geman 1984) as MCMC algorithm. It is referred to as an alternating conditional sampler, as it samples from the conditional distribution of each parameter with respect to the remaining parameters. The Gibbs sampler has been found to be particular suited for multidimensional problems (Gelman et al. 2003) and is implemented in the open source software JAGS (Plummer 2003), which was called from the R software environment (R Core Team 2014).

Convergence of the MCMC algorithm is essential for a correct estimation of the posterior distribution for the parameters of interest. To this end, the Gelman-Rubin diagnostic (Gelman and Rubin 1992) was used. This diagnostic compares the variance of the independent Markov chains to the variance between the chains.

5 Results and discussion

4500 sediment bed level measurements spanning 15 months (Sept. 2013 – Nov. 2014) were available at the end of the monitoring campaign introduced in chapter 3. 2% of the locations were removed from the set due to missing measurements or suspected tampering. A total rainfall depth of 1160 mm was recorded. Section 5.1 presents the results of this campaign. The remainder of this chapter is dedicated to applying the procedures introduced in chapter 4. This involves applying a generalised linear mixed modelling (GLMM) approach to the field data in order determine how the properties of gully pots affect their operational condition over time.

5.1 Field measurements

The distribution of measured sediment bed levels for each measurement day are presented in the respective violin plots in Figure 5.1. This figure shows a main cluster, consisting of a majority of the gully pots, which experienced stable bed levels several months after cleaning. In contrast, a fraction of all measured gully pots experienced progressive accumulation, eventually resulting in a blockage. The latter group covers approximately 5% of all gully pots at the end of the campaign. Based on the measured sediment levels, gully pots in this group were distinctly separated from the main cluster.

Analysis of the median sediment bed levels over time indicates that more sediment was retained in the first weeks after cleaning, compared to subsequent measurements. Since the measurement campaign lasted more than one year the increased retention of sediments cannot be attributed to seasonal variation, as later measurements in the same season do not display similar patterns. This implies a reduction in the retaining efficiency over time, under the assumption of a stationary solids load from the urban surface. Increased skewness of the distribution over time indicates dispersion of the main cluster, characterising the long term accumulation of solids.

Figure 5.1: Box-violin plot of the measured sediment bed levels over time. The symmetrical density plot shows the distribution of sediment bed levels for each day of measurement. The box plot presents quartiles and individual points representing outliers. Vertical jitter was added to the outliers to aid visual interpretation.

5.2 Data exploration

Graphical exploration of the data revealed no clear signs of outliers or zero-inflation. Analysis of the Cook's distance statistic discussed in section 4.5 showed no particular influential observation. A pair-plot of the normalised sediment bed levels v, and all explanatory variables is depicted in Figure 5.2. All explanatory variables were standardised to improving mixing of the MCMC chains. This pair-plot shows that the elapsed time since cleaning x_3 and the cumulative rainfall depth x_5 are strongly correlated, demonstrating that these variables cannot be identified separately. This is confirmed by the corresponding variance inflation factor of 64.16, which is larger than the cut-off range of 5 - 10 suggested by Montgomery and Peck (1992). Therefore it was decided to exclude the cumulative rainfall x_5 as explanatory variable.

Figure 5.2: Pair-plot of the response variable and all continuous standardised (dimensionless) explanatory variables *x*. The lower left part contains pair-wise correlations, whereas the upper right part contains scatterplots with a locally weighted polynomial (LOESS) added to reveal patterns in the scatter.

Subsequently, the Bayesian approach presented in section 4.6 was applied to the collected sediment bed data in order to determine which physical and catchment properties distinguish progressive accumulation from stabilizing sediment bed levels.

5.3 Random part and probability distribution of the response variable

Estimations of the relative quality of the proposed probability distributions and random parts in section 4.2 - 4.3 was obtained by means of the Akaike information criterion (AIC) (Akaike 1973), which is a penalized likelihood method. Each model included the complete set of explanatory variables and interactions for the physical properties. The AIC values given in Table 5-1 reveal that the models with an autoregressive component outperform their counterparts. The binomial GLMM with AR-1 correlation structure has the best relative performance. The Akaike weights (*wi*) in this table represents the probability that this model has the best performance, given the data and the other proposed models.

Table 5-1: AIC analysis for four competing model structures

Model	AIC	*wi* AIC
Binomial GLMM with AR-1	19416.24	1.00E+00
Binomial GLMM	30597.16	0.00E+00
Beta-binomial GLMM with AR-1	19474.30	2.47E-13
Beta-binomial GLMM	20566.96	1.33E-250

Analysis of the Pearson residuals revealed that the binomial GLMM is subject to an over-dispersion of 2.92. The beta-binomial GLMM allows for this extra dispersion through θ in eq. 4.5. A comparison of the mean values for θ derived from the beta-binomial GLMM with and without an AR-1 correlation structure, $4.32\cdot10^4$ versus 20.03 respectively, demonstrates the effectiveness of this component to capture the over-dispersion. Since $4.32\cdot10^4 \gg d_{t,i}$ (available sump depth), the variance of the beta-binomial distribution in eq. 4.5 converges to the variance of the binomial distribution.

5.4 Deterministic structure

The optimal deterministic structure was obtained by applying backwards selection based on the 95% highest probability density interval (HPDI). None of the interaction terms for the physical properties were significant. In addition, the explanatory variables: x_6 "presence of a water seal" and x_2 "catchment slope" are not significant from 0 at a 5% level and were excluded from the model. Exclusion of the interaction terms implies that the effect of the physical properties on the retaining efficiency does not change as the sand trap progressively silts. Figure 5.3 presents the marginal posterior distributions of the weights β_k for each explanatory variable x_k of the optimal model.

Figure 5.3: Marginal posterior distributions of the weights β_k for each explanatory variable x_k. The horizontal line shows the 95% credible interval for 800 MCMC samples. The vertical line depicts the intersection with the y-axis, indicating whether the credible interval contains zero.

The variables x_8 "*position of the outflow pipe (side)*" and x_4 "*contributing area*" have the largest p-values, 0.001 and 0.005 respectively. The deterministic component of the estimated GLMM with standardised (dimensionless) covariates and mean weight values from Figure 5.3 can be written as:

$$\eta_{t,i} = -2.490 - 0.415\cdot Depth_{t,I} + 0.261\cdot Time_{t,I} + 0.084\cdot Area_{t,I} + 0.710\cdot PipeOut_{t,i}\,\text{(front)} + 0.503\cdot PipeOut_{t,i}\,\text{(side)} + 0.481\cdot Road_{t,i}\,\text{(main)} \quad \textbf{(5.1)}$$

The predicted mean values for the normalised sediment bed level v, without the random component, for the different levels of the categorical explanatory variables are visualised in Figure 5.4. Credible intervals provide a region that contains the mean fitted values with a 95% probability, based on the marginal posterior distribution of the explanatory variables. The positive weight for β_9 *"road type (Main Road)"* compared to the baseline, corresponds to a higher sediment bed level for the gully pots located in main roads. Similar inferences hold for the weights β_7 and β_8 corresponding to the side of the outlet pipe. The higher sediment bed levels for main roads are in accordance with the statements in chapter 2, which ascribe the difference to the increased solids supply associated with the traffic intensity. It is possible that the position of the outlet pipe influences the rolling motion of flows in the sump reported by Faram and Harwood (2003), which results in high velocities near the sediment–water interface.

Figure 5.4: Fitted normalised sediment bed levels v for the entire population (without the random component) based on the marginal posterior distribution of categorical explanatory variables x_9 "road type" and **$x_7 - x_8$ "position of the outlet pipe", with 95% credible intervals**

Memon and Butler (2002) found that the depth of the sand trap is an important parameter, having a considerable impact on the reduction of the suspended solids load to downstream sewer components. The negative weight β_9 in eq. (5.1) corresponding to the depth of the sand trap demonstrates that in addition to improving the water quality, increasing the depth of the sand trap also reduces the probability of a blockage. Evidently, a reduction in the ability to retain sediment does not compensate for the smaller volume of the sand trap under similar solids loading conditions.

The contributing area to each gully pot x_4 is positively correlated with the normalised sediment bed level. Therefore it seems that, for the range of values for the contributing area in this study (5 – 1380 m^2), the impact of a higher solids supply associated with a larger contributing area predominates the scouring effect of an increased flow rate.

Figure 5.5: Model results of the Binomial GLMM with AR-1 correlation for the normalised sediment bed level v over time, including a prediction interval containing 95% of the observed data. Horizontal jitter was added to visualise overlaying points.

Estimated normalised sediment bed levels including the random part are presented in Figure 5.5. This figure illustrates that the proposed modelling approach is able to reproduce the dense cluster of gully pots in a near equilibrium state perceived in Figure 5.1, as well as the blocked gully pots. Figure 5.6 shows the propagation of the estimated blockage rate for the area, given the parameter uncertainty. The threshold where the monitored gully pots become susceptible to blockages was found to be 100 days.

Figure 5.6: The mean estimated cumulative blockage probability over time, including 95% credible intervals.

Further analysis of the model estimates for the last day of measurement is presented in Figure 5.7. The measured normalised sediment bed levels are within the 95% credible intervals for each bin, suggesting agreement between model estimates and field observations over the entire range. This confirms that the model is able to discriminate progressive accumulation from stabilizing sediment bed levels, given the estimated model parameters.

Figure 5.7: Kernel density plot of the distribution of the measured sediment bed levels for the final day of measurement, expressing the variability of the sediment bed levels over a gully pot population of 298 individuals. In addition, a histogram of the corresponding model estimate including 95% credible intervals is added.

5.5 Model validation

Analysis of the model residuals is provided in Appendix B. The Mantel correlogram in Figure 5.8 shows that there is no significant spatial correlation present in the model residuals at distances of more than 5 meters. The corresponding density graph presents the distribution of the Euclidean distances between each gully pot. This graph reveals that although there was some spatial dependence present at small distances, this concerns only a small fraction ($2 \cdot 10^{-4}$) of the total sample of gully pots. As such, this figure demonstrates that there are no spatially correlated variables (e.g. trees, local construction activities) missing in the model. The absence of a residual spatial dependence demonstrates that there are no clusters of gully pots with higher normalised sediment bed levels. This implies that maintenance strategies can be optimised when taking into account the explanatory variables x_k of the deterministic structure. Moreover, in the presence of a gully pot blockage there is no evidence of an increased blockage probability for adjacent gully pots. Therefore, the vulnerability to an event is reduced, as alternative flow routes may compensate for the occurrence of a blockage. With respect to the design of the public space, this entails that increasing the gully pot density directly adds to redundancy.

Figure 5.8: Spatial correlation of the model residuals, including 95% confidence bounds, plotted together with the empirical density function of gully pots interdistances.

Figure 5.9: Autocorrelation of the rejected binomial GLMM with compound correlation and the chosen binomial GLMM with AR-1 correlation structure. 95% confidence bounds were added.

The effectiveness of the AR-1 model to catch the temporal dependence in the residuals was illustrated in Figure 5.9. This figure shows the difference between the rejected binomial GLMM with a compound correlation structure and the selected binomial GLMM with AR-1 correlation structure. The former model structure was positively autocorrelated for several orders, as successive residual values tend to persist on one side of the mean. It exhibits a slow meandering pattern, in which residuals were consistently overestimated at the start of the time series and underestimated at the end. A clear seasonal pattern was, however, not present. Furthermore, the low-lag positive autocorrelation confirms that the sampling density of the monitoring campaign was sufficient to reconstruct the long term sedimentation process in gully pots.

5.6 Generalisation

The results presented in Figure 5.5 - Figure 5.7 are case specific due to the set of properties for gully pots in the study area. Under the assumption of sample representativeness, the marginal posterior distributions of the model parameters in Figure 5.3 can be generalised and applied to similar designed gully pots beyond the frame of the study area, e.g. to improve gully pot design. Results found in this study are generally consistent with the literature in Chapter 2. In addition, the proposed method for modelling sedimentation in gully pots can be applied to measurements from other study areas.

6 Conclusions

This study provides a procedure to model the long term accumulation of solids that leads to blockages. To this end, field measurements from 300 gully pots were analysed by means of a generalised linear mixed model (GLMM). Analysis of the measurements revealed a majority of the gully pots to have stable sediment bed levels after several months. However, a fraction (5%) experienced a blockage due to the progressive accumulation of sediment.

From the model results it can be concluded that the depth of the sand trap and the position of the outlet pipe are physical properties that distinguish progressive accumulation from stabilising sediment levels. The latter was believed to influence the velocity profile at the sediment-water interface. The former demonstrates that requirements concerning hydraulic efficiency and pollutant retention for water quality purposes are not necessarily conflicting; both benefit from deeper sand traps. No interaction between the physical properties and the elapsed time since cleaning was found to be significant. This entails that the effect of these physical properties do not change as the sediment bed level increases. The road type and the area contributing to runoff were found to be relevant catchment properties. As the parameter estimate for the latter is positive, this indicates that the higher solids supply predominates the scouring effect associated with an increased flowrate.

The absence of residual spatial correlation indicates that there are no clusters of gully pots with higher normalised sediment bed levels. Since the blockage probability is spatially independent, alternative drainage paths through adjacent gully pots may be available. As this limits the exposure to flood events, the vulnerability of the public space to blockages reduces.

Findings from this study may aid to support maintenance strategies on a system scale and to improve gully pot design. Knowledge of properties that contribute to progressive accumulation and eventually blockages, may justify investments during the design phase in order to minimise future maintenance and blockages. That is, decision makers should consider the physical and catchment properties that prevent progressive accumulation of solids, when aiming to prevent gully pot blockages. In addition, the absence of a residual spatial dependence allows for directing preventive maintenance, taking these properties into account.

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RIONED, STOWA, Tauw, vandervalk+degroot, Waterboard De Dommel, Waternet and Witteveen+Bos.

Appendix A. Supplementary data

Appendix B

Fitted values from the Binomial GLMM model with AR-1 correlation structure versus the Pearson residuals are depicted in Figure B.1. Values on the right side of this graph represent gully pots which are blocked according to the model. The change in variation for larger fitted values is not substantial, taking into consideration the increase in point density for lower fitted values. The model does, however, seem to underestimate values for nearly blocked gully pots to some extent. This is attributed to the delineation of the upper asymptote of the applied link function, which cannot return a probability of 1. Therefore, model estimations can only approximate the top full sand traps associated with perceived blockages.

Figure B.1: Fitted values from the model versus the Pearson residuals

8 References

Akaike, H. (1973) Information theory and an extension of the maximum likelihood principle, pp. 267 - 281, Akadémia Kiado, Budapest, Hungary.

Arthur, S., Crow, H., Pedezert, L. and Karikas, N. (2009) The holistic prioritisation of proactive sewer maintenance. Water Science & Technology 59(7), 1385 - 1396,http://dx.doi.org/10.2166/wst.2009.134.

Ashley, R.M., Bertrand-Krajewski, J.-L., Hvitved-Jacobsen, T. and Verbanck, M. (2004) Solids in Sewers: characteristics, effects and control of sewer solids and associated pollutants., IWA Publishing Company.

Ashley, R.M. and Crabtree, R.W. (1992) Sediment origins, deposition and build-up in combined sewer systems. Water Science & Technology 25(8), 1-12

Berkson, J. (1944) Application of the logistic function to bio-assay. Journal of the American Statistical Association 39(227), 357-365,http://dx.doi.org/10.1080/01621459.1944.10500699.

Brinkmann, W.L.F. (1985) Urban stormwater pollutants: sources and loadings. GeoJournal 11(3), 277-283

Butler, D. and Clark, P. (1995) Sediment management in urban drainage catchments, p. 93.

Butler, D. and Davies, J. (2004) Urban drainage, CRC Press.

Butler, D. and Karunaratne, S.H.P.G. (1995) The suspended solids trap efficiency of the roadside gully pot. Water research 29(2), 719-729,http://dx.doi.org/10.1016/0043-1354(94)00149-2

Butler, D. and Memon, F.A. (1999) Dynamic modelling of roadside gully pots during wet weather. Water research 33(15), 3364-3372,http://dx.doi.org/10.1016/S0043-1354(99)00050-0

Butler, D., Xiao, Y., Karunaratne, S.H.P.G. and Thedchanamoorthy, S. (1995) The gully pot as a physical, chemical and biological reactor. Water Science and Technology 31(7), 219-228,http://dx.doi.org/10.1016/0273-1223(95)00339-O.

Caradot, N., Granger, D., Chapgier, J., Cherqui, F. and Chocat, B. (2011) Urban flood risk assessment using sewer flooding databases. Water Science & Technology 64(4), 832-840,http://dx.doi.org/10.2166/wst.2011.611

Ciccarello, A., Bolognesi, A., Maglionico, M. and Artina, S. (2012) The role of settling velocity formulation in the determination of gully pot trapping efficiency: Comparison between analytical and experimental data. Water Science and Technology 65(1), 15-21,http://dx.doi.org/10.2166/wst.2011.775.

Conradin, F. (1990) Study on catch basins in Switzerland, pp. 199-214, ASCE.

Cook, R.D. (1977) Detection of influential observation in linear regression. Technometrics 19, 15-18

David, L.M. and Matos, R.S. (2002) Wet weather water quality modelling of a Portuguese urban catchment: difficulties and benefits. Water Science & Technology 45(3), 131-140

De Man, H., van den Berg, H.H.J.L., Leenen, E.J.T.M., Schijven, J.F., Schets, F.M., Van der Vliet, J.C., van Knapen, F. and de Roda Husman, A.M. (2014) Quantitative assessment of infection risk from exposure to waterborne pathogens in urban floodwater. Water research 48, 90-99,http://dx.doi.org/10.1016/j.watres.2013.09.022.

Deletic, A., Ashley, R.M. and Rest, D. (2000) Modelling input of fine granular sediment into drainage systems via gully-pots. Water research 34(15), 3836-3844,http://dx.doi.org/10.1016/S0043-1354(00)00133-0.

Egger, C., Scheidegger, A., Reichert, P. and Maurer, M. (2013) Sewer deterioration modeling with condition data lacking historical records. Water research 47(17), 6762-6779,http://dx.doi.org/10.1016/j.watres.2013.09.010.

Ellis, J.B. and Harrop, D.O. (1984) Variations in solids loadings to roadside gully pots. Science of the total environment 33(1), 203-211,http://dx.doi.org/10.1016/0048-9697(84)90394-2.

Faram, M.G. and Harwood, R. (2003) A method for the numerical assessment of sediment interceptors. Water Science & Technology 47(4), 167-174

Fenner, R.A. (2000) Approaches to sewer maintenance: a review. Urban water 2(4), 343-356,http://dx.doi.org/10.1016/S1462-0758(00)00065-0.

Fletcher, I.J. and Pratt, C.J. (1981) Urban Stormwater Quality, Management and Planning, pp. 116-124, Water Resources Publications Colo.

Freni, G., Mannina, G. and Viviani, G. (2009) Urban runoff modelling uncertainty: Comparison among Bayesian and pseudo-Bayesian methods. Environmental modelling & software 24(9), 1100-1111,http://dx.doi.org/10.1016/j.envsoft.2009.03.003

Fulcher, G.A. (1994) Urban stormwater quality from a residential catchment. Science of the total environment 146, 535-542,http://dx.doi.org/10.1016/0048-9697(94)90279-8

Ganzevles, P. and Oomens, A. (2008) Leidraad B3000: Detaillering en aanleg van stelselonderdelen, Rioned Foundation.

Gelman, A. (2006) Prior distributions for variance parameters in hierarchical models (comment on article by Browne and Draper). Bayesian analysis 1(3), 515-534,http://dx.doi.org/10.1214/06-ba117a.

Gelman, A., Carlin, J.B., Stern, H.S. and Rubin, D.B. (2003) Bayesian Data Analysis, Chapman and Hall/CRC.

Gelman, A. and Rubin, D.B. (1992) Inference from iterative simulation using multiple sequences. Statistical science, 457-472,http://dx.doi.org/10.1214/ss%2F1177011136

Geman, S. and Geman, D. (1984) Stochastic relaxation, Gibbs distributions, and the Bayesian restoration of images. IEEE Transactions on Pattern Analysis and Machine Intelligence (6), 721-741,http://dx.doi.org/10.1109/TPAMI.1984.4767596

Grottker, M. (1990a) Pollutant Removal by Catch Basins in West Germany State of the Art—New Design. Torno, H.C. (ed), pp. 215-244, ASCE, Davos Platz, Switzerland.

Grottker, M. (1990b) Pollutant removal by gully pots in different catchment areas. Science of the total environment 93, 515-522,http://dx.doi.org/10.1016/0048-9697(90)90142-H

Hardin, J.W. and Hilbe, J.M. (2007) Generalized linear models and extensions, Stata Press.

Hilbe, J.M. (2007) Negative binomial regression, Cambridge University Press.

Jartun, M., Ottesen, R.T., Steinnes, E. and Volden, T. (2008) Runoff of particle bound pollutants from urban impervious surfaces studied by analysis of sediments from stormwater traps. Science of the total environment 396(2), 147-163,http://dx.doi.org/10.1016/j.scitotenv.2008.02.002.

Jenson, S.K. and Domingue, J.O. (1988) Extracting topographic structure from digital elevation data for geographic information system analysis. Photogrammetric engineering and remote sensing 54(11), 1593-1600

Kanso, A., Chebbo, G. and Tassin, B. (2006) Application of MCMC–GSA model calibration method to urban runoff quality modeling. Reliability engineering & system safety 91(10), 1398-1405,http://dx.doi.org/10.1016/j.ress.2005.11.051.

Karlsson, K. and Viklander, M. (2008) Trace metal composition in water and sediment from catch basins. Journal of Environmental Engineering 134(10), 870-878,http://dx.doi.org/10.1061/(ASCE)0733-9372(2008)134:10(870).

Korving, J.L., Clemens, F.H.L.R. and van Noortwijk, J.M. (2006) Statistical modeling of the serviceability of sewage pumps. Journal of Hydraulic Engineering 132(10), 1076-1085,http://dx.doi.org/10.1061/(ASCE)0733-9429(2006)132:10(1076).

Lager, J. (1977) Catchbasin technology overview and assessment, U.S. Environmental Protection Agency, USA.

Liu, Y., Yang, P., Hu, C. and Guo, H. (2008) Water quality modeling for load reduction under uncertainty: a Bayesian approach. Water research 42(13), 3305-3314,http://dx.doi.org/10.1016/j.watres.2008.04.007.

Marley, J. and Wand, M. (2010) Non-standard semiparametric regression via BRugs. Journal of Statistical Software 37(5), 1 - 30

Memon, F.A. and Butler, D. (2002) Assessment of gully pot management strategies for runoff quality control using a dynamic model. Science of the total environment 295(1), 115-129,http://dx.doi.org/10.1016/S0048-9697(02)00056-6.

Mineart, P. and Singh, S. (2000) The value of more frequent cleanouts of storm drain inlets. Watershed Protection Techniques 1(3), 129 - 130

Montgomery, D.C. and Peck, E.A. (1992) Introduction to linear regression analysis, Wiley-Interscience.

Morrison, G.M., Revitt, D.M., Ellis, J.B., Svensson, G. and Balmer, P. (1988) Transport mechanisms and processes for metal species in a gullypot system. Water research 22(11), 1417-1427,http://dx.doi.org/10.1016/0043-1354(88)90099-1.

Pitt, R. and Field, R. (2004) Catchbasins and Inserts for the Control of Gross Solids and Conventional Stormwater Pollutants, pp. 1-21.

Plummer, M. (2003) JAGS: A program for analysis of Bayesian graphical models using Gibbs sampling, p. 125, Vienna.

Pratt, C.J. and Adams, J.R.W. (1984) Sediment supply and transmission via roadside gully pots. Science of the total environment 33(1), 213-224,http://dx.doi.org/10.1016/0048-9697(84)90395-4.

Pratt, C.J., Elliott, G.E.P. and Fulcher, G.A. (1987) Suspended solids discharge from highway gully pots in a residential catchment. Science of the total environment 59, 355-364,http://dx.doi.org/10.1016/0048-9697(87)90459-1

Qian, S.S., Stow, C.A. and Borsuk, M.E. (2003) On monte carlo methods for Bayesian inference. Ecological Modelling 159(2), 269-277,http://dx.doi.org/10.1016/S0304-3800(02)00299-5.

R Core Team (2014) R: A language and environment for statistical computing., R Foundation for Statistical Computing, Vienna, Austria.

Rodríguez, J.P., McIntyre, N., Díaz-Granados, M. and Maksimović, Č. (2012) A database and model to support proactive management of sediment-related sewer blockages. Water research 46(15), 4571-4586,http://dx.doi.org/10.1016/j.watres.2012.06.037.

Sartor, J.D. and Boyd, G.B. (1972) Water pollution aspects of street surface contaminants,, U.S. Environmental Protection Agency, USA.

Sokal, R.R. and Rohlf, F.J. (1995) Biometry: The Principles and Practices of Statistics in Biological Research, W. H. Freeman.

Swanson, L. (2001) Linking maintenance strategies to performance. International Journal of Production Economics 70(3), 237-244,http://dx.doi.org/10.1016/S0925-5273(00)00067-0.

Ten Veldhuis, J.A.E., Clemens, F.H.L.R., Sterk, G. and Berends, B.R. (2010) Microbial risks associated with exposure to pathogens in contaminated urban flood water. Water research 44(9), 2910-2918,http://dx.doi.org/10.1016/j.watres.2010.02.009.

Ten Veldhuis, J.A.E., Clemens, F.H.L.R. and Van Gelder, P.H.A.J.M. (2011) Quantitative fault tree analysis for urban water infrastructure flooding. Structure and Infrastructure Engineering 7(11), 809-821,http://dx.doi.org/10.1080/15732470902985876.

Van der Zon, N. (2011) Kwaliteitsdocument AHN-2, p. 31, Rijkswaterstaat & Waterschappen.

Van Riel, W., Langeveld, J.G., Herder, P.M. and Clemens, F.H.L.R. (2014) Intuition and information in decision-making for sewer asset management. Urban Water Journal 11(6), 506-518,http://dx.doi.org/10.1080/1573062X.2014.904903.

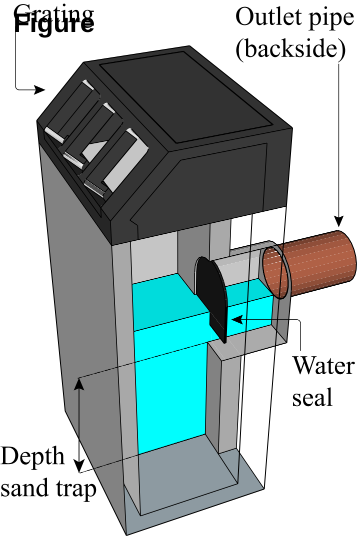
Zhao, Y., Staudenmayer, J., Coull, B.A. and Wand, M.P. (2006) General design Bayesian generalized linear mixed models. Statistical science, 35-51,http://dx.doi.org/10.1214/088342306000000015.

Zuur, A.F., Hilbe, J.M. and Ieno, E.N. (2013) A Beginner's Guide to GLM and GLMM with R: A Frequentist and Bayesian Perspective for Ecologists, Highland Statistics.

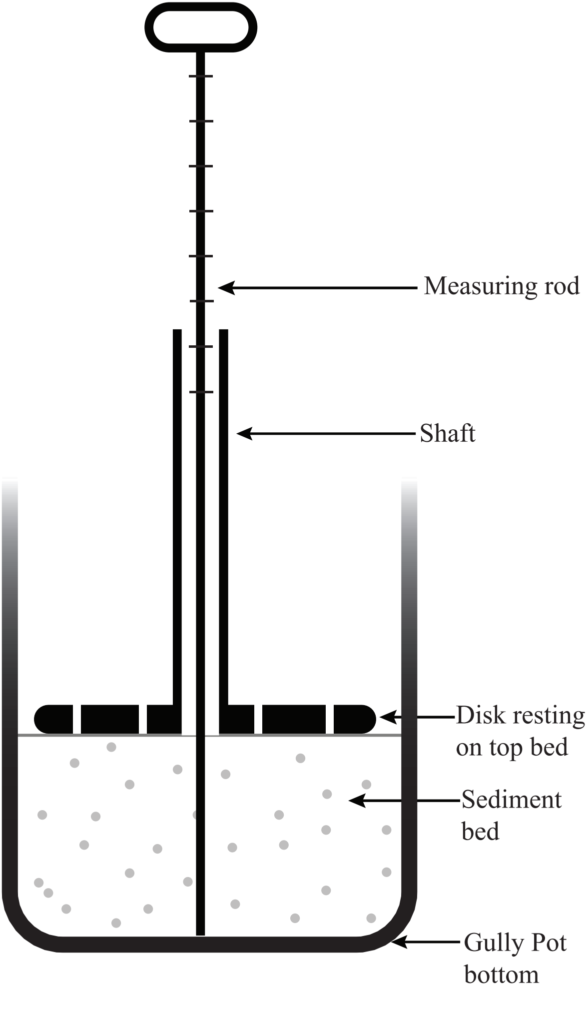
Zuur, A.F., Ieno, E.N. and Elphick, C.S. (2010) A protocol for data exploration to avoid common statistical problems. Methods in Ecology and Evolution 1(1), 3-14,http://dx.doi.org/10.1111/j.2041-210X.2009.00001.x.

Zuur, A.F., Ieno, E.N., Walker, N., Saveliev, A.A. and Smith, G.M. (2009) Mixed effects models and extensions in ecology with R, Springer Science & Business Media.

Figure

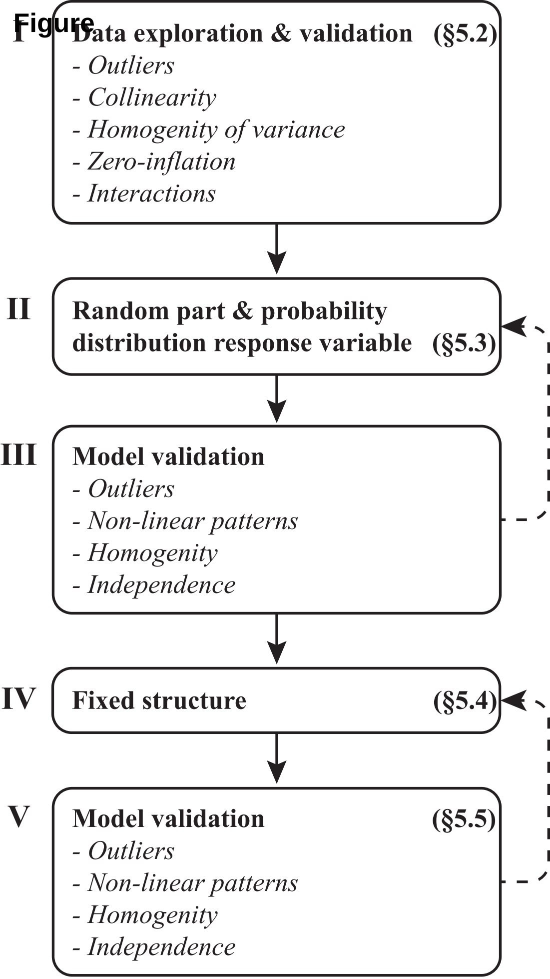


Figure


Measuring rod
Shaft
Disk resting
on top bed
Sediment
bed
Gully Pot
bottom

Figure

Figure


I
Data exploration & validation
(§5.2)
- Outliers
- Collinearity
- Homogenity of variance
- Zero-inflation
- Interactions
II
Random part & probability distribution response variable
(§5.3)
III
Model validation
- Outliers
- Non-linear patterns
- Homogenity
- Independence
IV
Fixed structure
(§5.4)
V
Model validation
(§5.5)
- Outliers
- Non-linear patterns
- Homogenity
- Independence

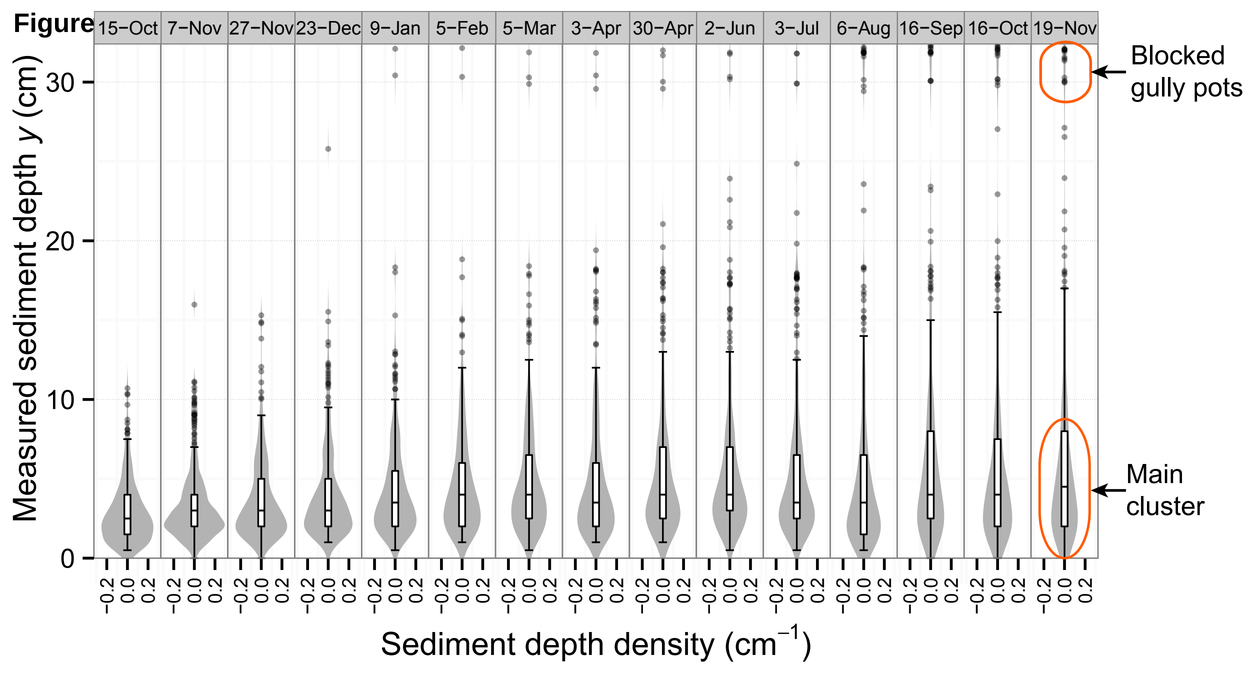
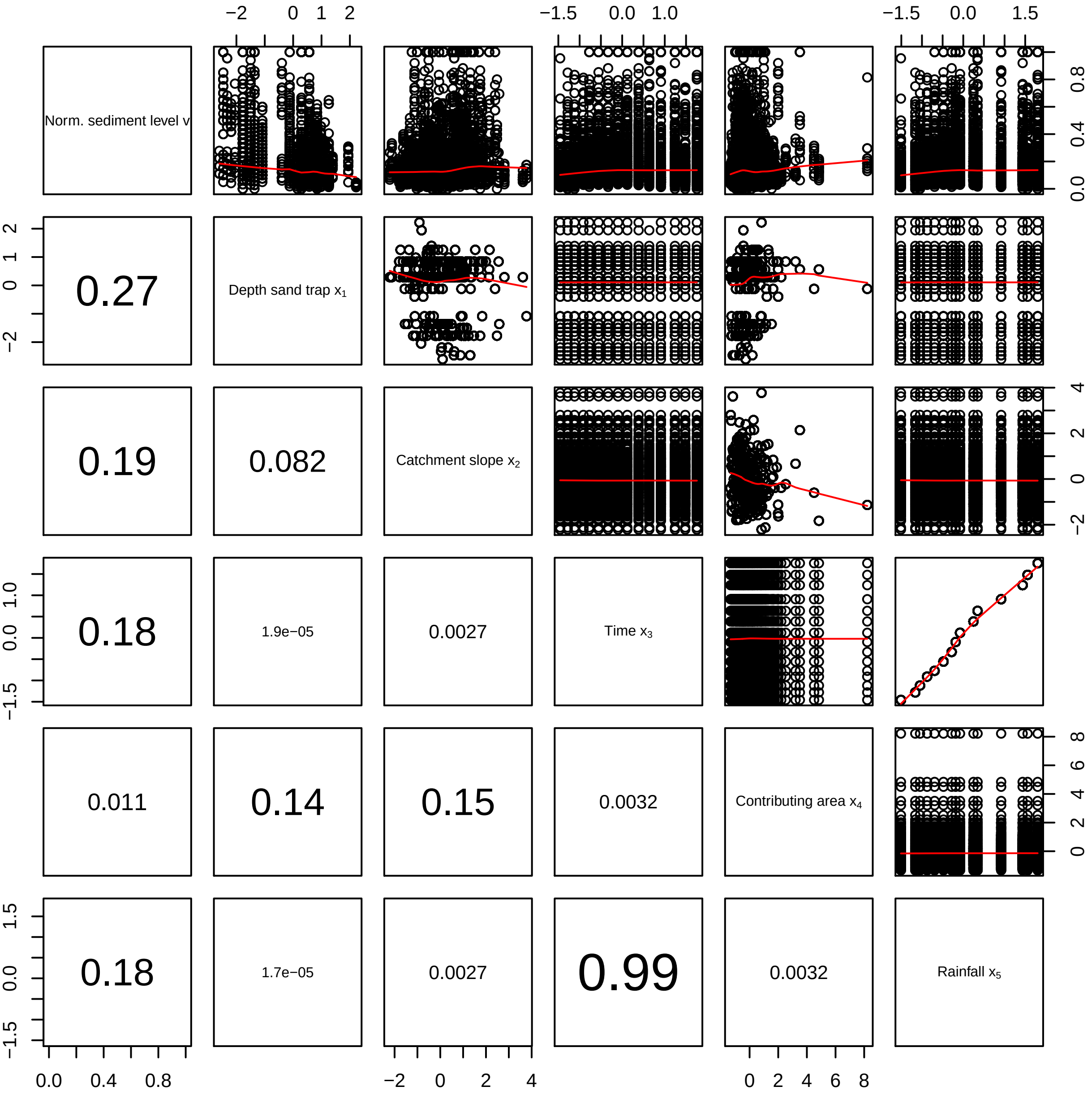


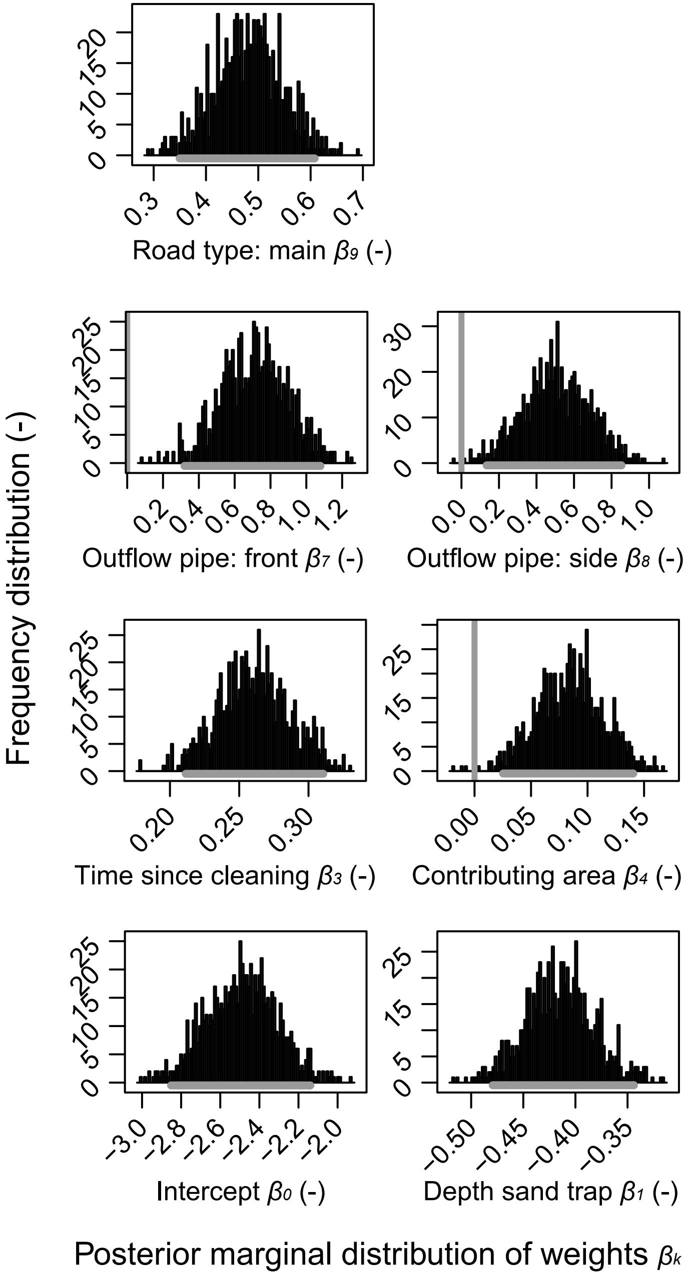
Figure
15−Oct
7−Nov
27−Nov
23−Dec
9−Jan
5−Feb
5−Mar
3−Apr
30−Apr
2−Jun
3−Jul
6−Aug
16−Sep
16−Oct
19−Nov
Blocked gully pots
Main cluster
Measured sediment depth y (cm)
0
10
20
30
−0.2
0.0
0.2
Sediment depth density (cm−1)

Figure



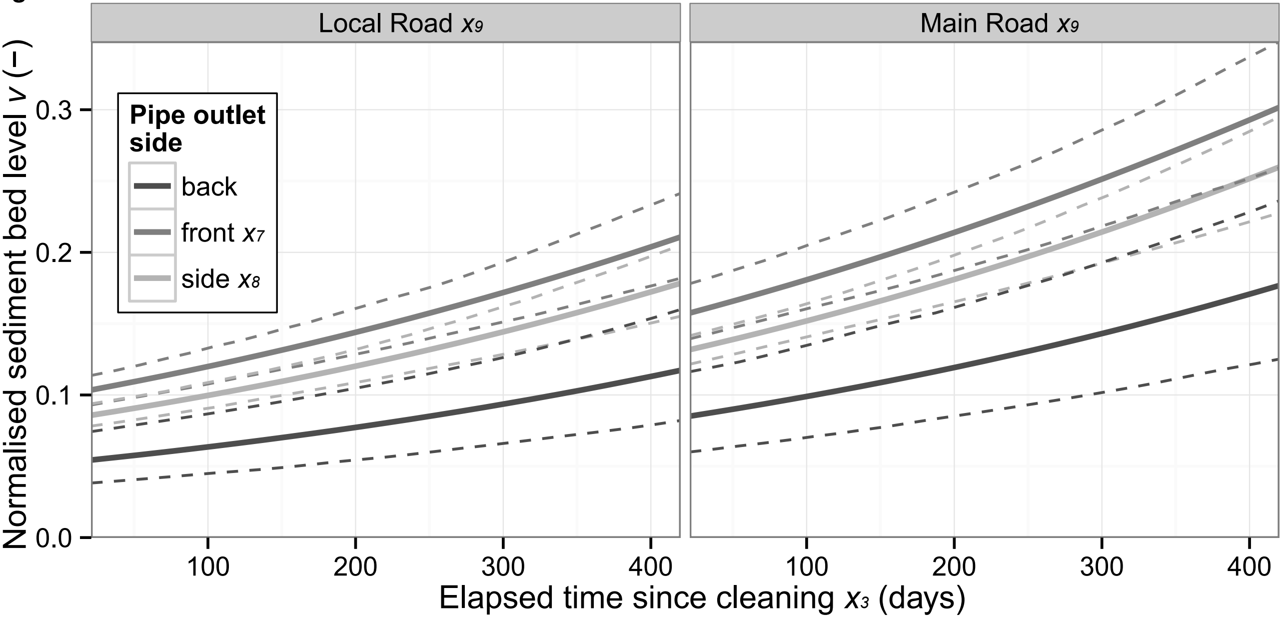
Norm. sediment level v
Depth sand trap x_1
Catchment slope x_2
Time x_3
Contributing area x_4
Rainfall x_5
0.27
0.19
0.082
0.18
1.9e−05
0.0027
0.011
0.14
0.15
0.0032
0.18
1.7e−05
0.0027
0.99
0.0032

Figure



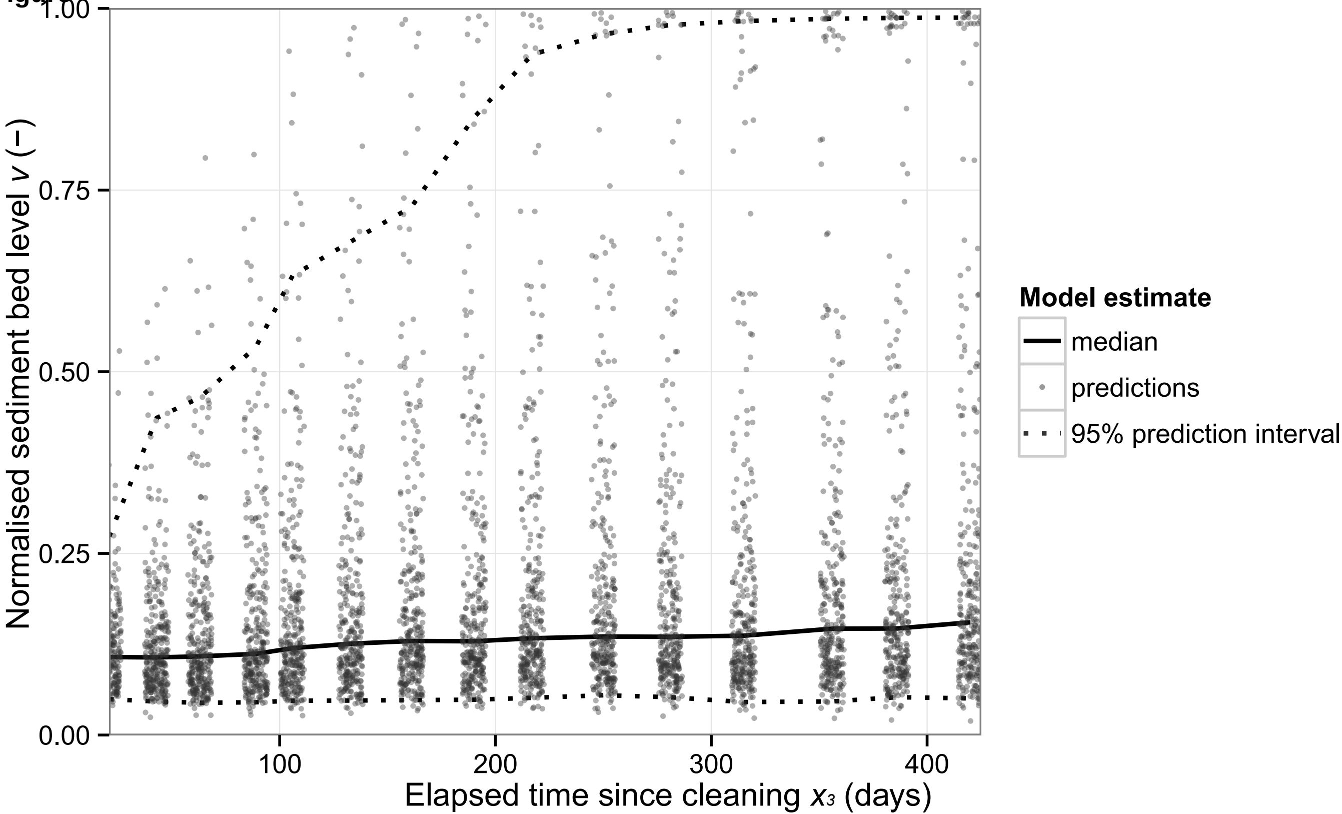
Road type: main β9 (-)
0.3 0.4 0.5 0.6 0.7
0 5 10 15 20
Outflow pipe: front β7 (-)
0.2 0.4 0.6 0.8 1.0 1.2
0 5 10 15 20 25
Outflow pipe: side β8 (-)
0.0 0.2 0.4 0.6 0.8 1.0
0 10 20 30
Time since cleaning β3 (-)
0.20 0.25 0.30
0 5 10 15 20 25
Contributing area β4 (-)
0.00 0.05 0.10 0.15
0 5 15 25
Intercept β0 (-)
−3.0 −2.8 −2.6 −2.4 −2.2 −2.0
0 5 10 15 20 25
Depth sand trap β1 (-)
−0.50 −0.45 −0.40 −0.35
0 5 15 25
Frequency distribution (-)
Posterior marginal distribution of weights βk

Figure

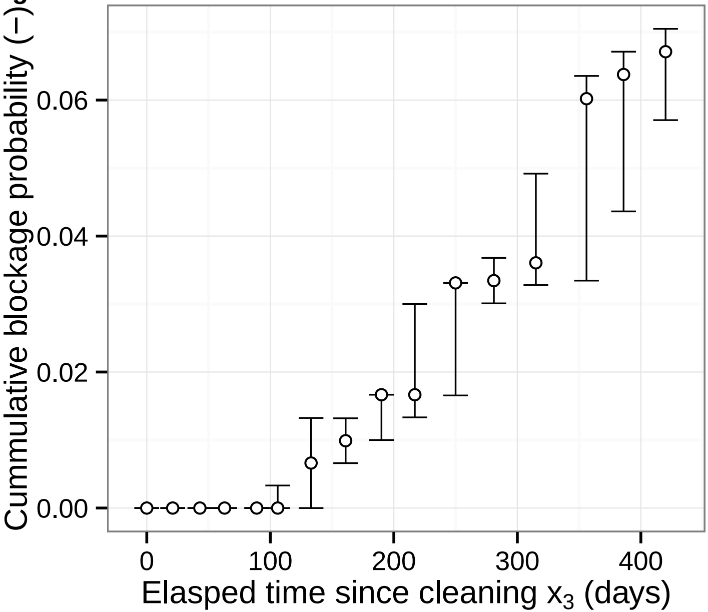


Local Road x9
Main Road x9
Pipe outlet side
back
front x7
side x8
Normalised sediment bed level v (−)
0.0
0.1
0.2
0.3
100
200
300
400
100
200
300
400
Elapsed time since cleaning x3 (days)

Figure

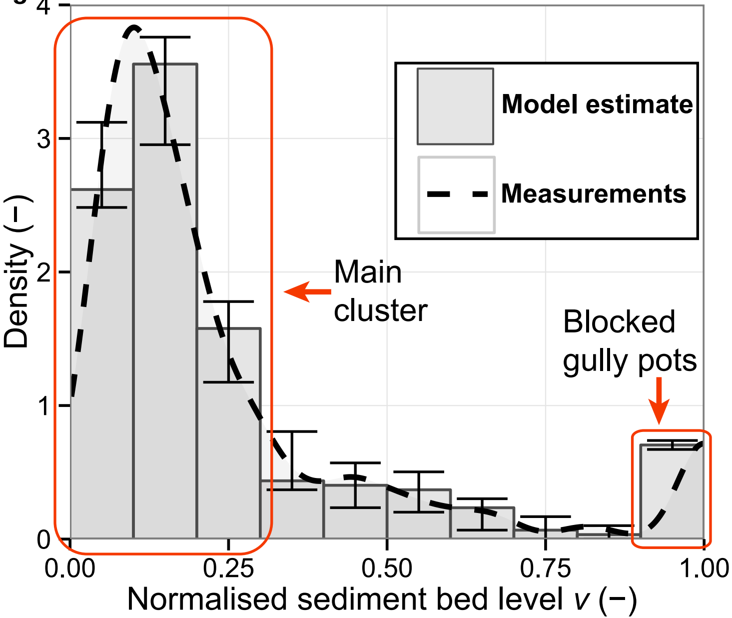

1.00
0.75
0.50
0.25
0.00
Normalised sediment bed level v (−)
100
200
300
400
Elapsed time since cleaning x3 (days)
Model estimate
median
predictions
95% prediction interval

Figure



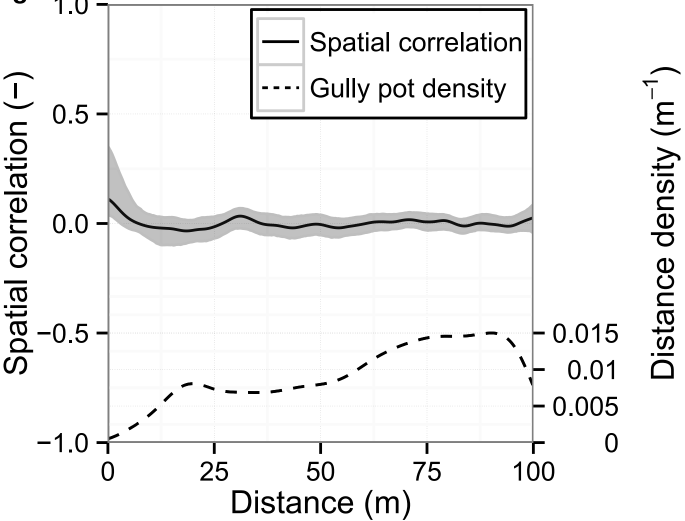
Cummulative blockage probability (–)
0.06
0.04
0.02
0.00
0
100
200
300
400
Elasped time since cleaning x_3 (days)

Figure



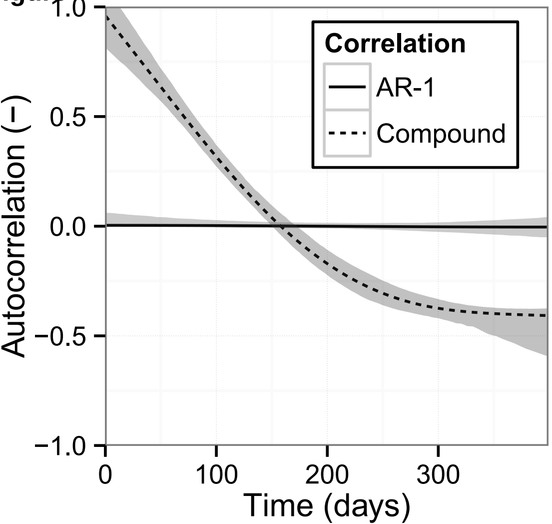
4
3
2
1
0
Density (−)
0.00
0.25
0.50
0.75
1.00
Normalised sediment bed level v (−)
Model estimate
Measurements
Main
cluster
Blocked
gully pots

Figure



Spatial correlation
Gully pot density
Spatial correlation (–)
Distance density (m^{-1})
1.0
0.5
0.0
−0.5
−1.0
0.015
0.01
0.005
0
0
25
50
75
100
Distance (m)

Figure



1.0
0.5
0.0
−0.5
−1.0
0
100
200
300
Time (days)
Autocorrelation (−)
Correlation
AR-1
Compound

Figure