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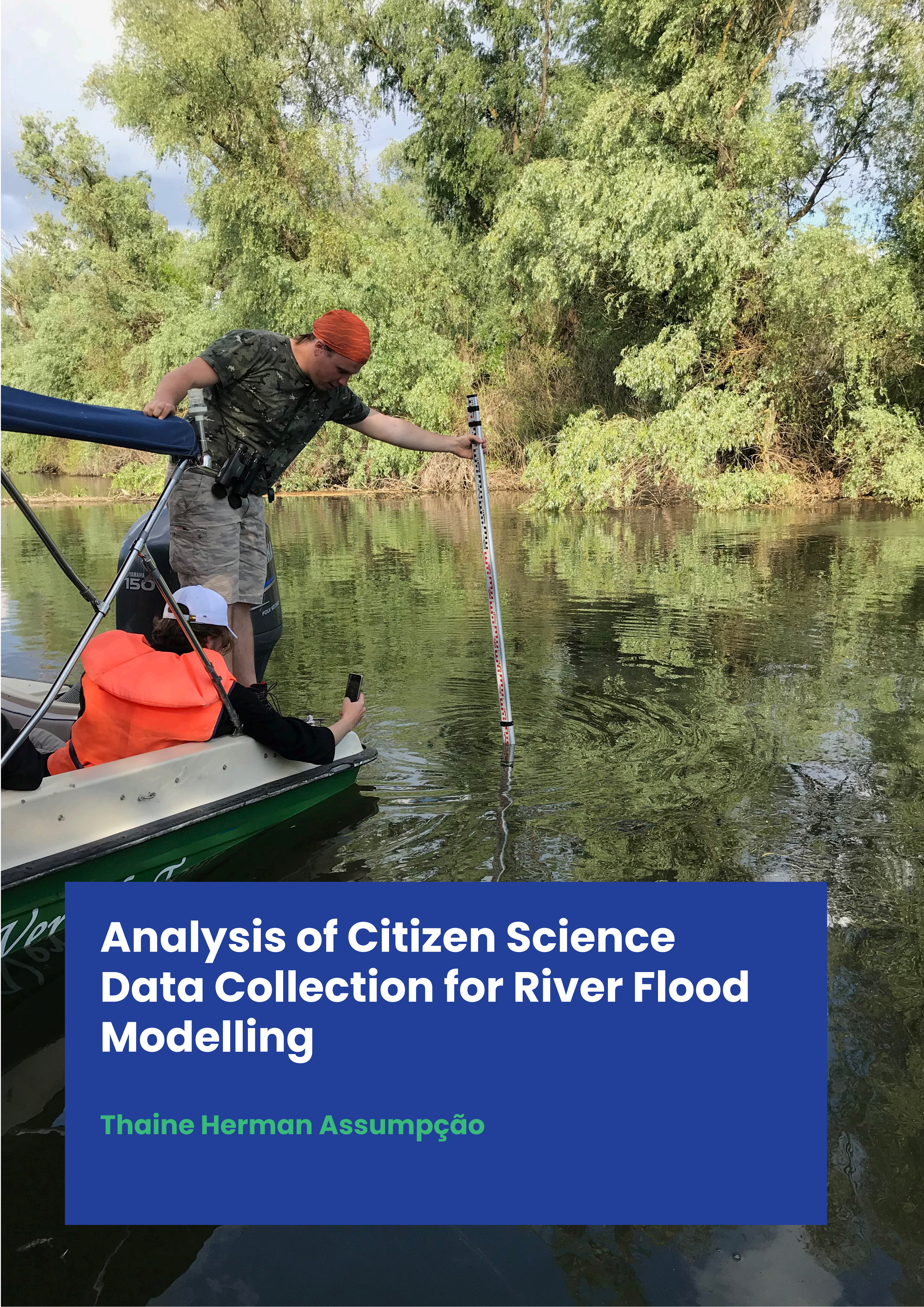

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Thaine Herman Assumpção

ANALYSIS OF CITIZEN SCIENCE DATA COLLECTION FOR RIVER FLOOD MODELLING

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DISSERTATION

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chair of the Board for Doctorates
and
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by

Thaine HERMAN ASSUMPÇÃO

This dissertation has been approved by the promotors.

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Vice Rector IHE Delft	vice-chairperson
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To my family, my friends and to the citizen scientists of now and of the future

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SUMMARY

In the context of a changing climate and increasing environmental pressures, the demand for data to understand the mechanisms of change and their interactions with the hydrological cycle has grown significantly. Further, a gap in data availability remains between the Global North and the Global South. This thesis contributes to the research into the capabilities of citizen science as a recent approach to data collection in water resources. Data obtained via citizen contributions, mainly through social media mining, has been shown to achieve accuracy comparable to authoritative sources and provide valuable inputs for hydrodynamic modelling. Nonetheless, aligning the spatial and temporal resolution of citizen-generated data with modelling requirements remains a challenge.

The primary aim of this research is to critically assess the design, efficiency and effectiveness of citizen campaigns in obtaining data to inform river flood modelling applications. It aims to assess how the design choices of citizen campaigns influence the amount of information collected, to develop methods for quality control and analysis, to validate citizen-based data against traditional measurements and lastly, to explore the usefulness of final results to flood models. Methodologically, the research spans two case studies with distinct characteristics: the Danube Delta in Romania, a complex wetland system, and the Kifissos Catchment in Greece, a small urban catchment. A theoretical framework is first established to identify gaps in the data cycle and propose tools to address them, including a novel approach to route delineation for data collection. Citizens used a mobile gaming application to collect water depth, surface velocity, and land cover data by photographing gauges, tracking floaters, and documenting land cover. The proposed quality control and analysis methods were designed to be applied in two instances: to assess the multimedia, before data extraction, and to asses the data. Following validation against traditional measurements, the data were used in modelling: in the Danube Delta, for calibrating and validating a hydrodynamic model, and in Kifissos, to produce a land cover map used in a hydrological model.

The results demonstrate that once an adaptive data collection system is in place that covers more than one element of the data cycle, large volumes of data can be obtained, where citizens appreciate being involved in the effort, although the tools and campaign duration can be improved. Even so, the amount of information collected is different from expectations. This is further corroborated by large portions of multimedia pieces being discarded before processing, due to citizen mistakes, environmental conditions and technological restrictions. While water depth estimates aligned well with traditional data, velocity estimates were less reliable. The use of citizen-based data was not much different from traditional ones for calibration and validation of the Danube Delta model, where the

model was insensitive to calibrated roughness values regardless of the calibration or validation dataset. For Kifissos, the citizen science-based land cover map performed similarly or outperformed traditional land cover maps, mainly in the gridded hydrological models, because it was able to better capture imperviousness, for which the model is sensitive.

In conclusion, this thesis underscores how citizen science campaigns can be arranged to collect data at high spatial resolution and serve modelling applications. It also demonstrates that, unlike traditional measurements, citizen-based data collection is not highly efficient and therefore efforts for data collection should be accounted for. This thesis advocates for user-focused data collection campaigns that account for the inherent inefficiencies of citizen participation, advancing citizen science as a viable approach to environmental data collection.

SAMENVATTING

In de context van een veranderend klimaat en toenemende druk van het milieu is de vraag naar gegevens om veranderingen in de mechanismen van de hydrologische cyclus te begrijpen, aanzienlijk toegenomen. Daarnaast is er een grote kloof tussen de beschikbaarheid van deze gegevens voor het mondiale noorden en het mondiale zuiden. Dit proefschrift draagt bij aan het onderzoek naar de mogelijkheden die 'citizen science' biedt bij gegevensverzameling van waterbronnen. Gegevens die via bijdragen van vrijwilligers zijn verkregen, voornamelijk via het verzamelen van informatie op sociale media, blijken een nauwkeurigheid te bereiken die vergelijkbaar is met die van officiële bronnen en leveren waardevolle input voor hydrodynamische modellering. Echter blijft het een uitdaging om de ruimtelijke en tijdsgebonden resoluties van de burgerdata af te stemmen op de eisen van modellen.

Het voornaamste doel van dit onderzoek is om het ontwerp, de efficiëntie en de effectiviteit van burgercampagnes kritisch te beoordelen in het verkrijgen van gegevens voor rivier overstromingsmodellen. Daarnaast beoogd dit onderzoek: i) Kritisch te beoordelen hoe ontwerpkeuzes tijdens de opzet van de burgercampagnes de verzamelde informatie beïnvloed. ii) Methodes te ontwikkelen voor kwaliteitscontrole en resultaatanalyse. iii) Om de verzamelde burgerdata te valideren en te vergelijken met traditionelere meetmethodes.iv) De bruikbaarheid van de resultaten voor overstromingsmodellen te evalueren. Methodologisch beslaat het onderzoek twee case study's in gebieden met verschillende kenmerken:de Donaudelta in Roemenië; een complex moerasgebied.het Kifissos-stroomgebied; in Griekenland, een klein stedelijk stroomgebied. Eerst werd een theoretisch kader opgesteld om tekortkomingen in de gegevenscyclus te identificeren, op basis daarvan zijn middelen voorgesteld om deze tekortkomingen te verkleinen. Waaronder een nieuwe aanpak voor routebepaling bij gegevensverzameling. Burgers gebruikten een mobiele game-applicatie om gegevens over waterdiepte, stroomsnelheid en landbedekking te verzamelen door watermeters te fotograferen, drijvers te volgen en landbedekking te documenteren. De voorgestelde kwaliteitscontrole- en analysemethoden werden ontworpen voor twee toepassingen: voor beoordeling van de multimedia vóór gegevensverwerking, en voor beoordeling van de gegevens zelf. Na validatie met traditionele metingen werden de gegevens gebruikt in modellering: in de Donaudelta voor het kalibreren en valideren van een hydrodynamisch model, en in Kifissos om een landbedekkingskaart te maken die werd gebruikt in een hydrologisch model.

De resultaten tonen aan dat wanneer een systeem voor gegevensverzameling wordt opgezet dat meerdere elementen van de gegevenscyclus dekt, grote hoeveelheden gegevens kunnen worden verzameld, waarbij burgers het waarderen om bij te dragen aan de inspanning, hoewel de gebruikte tools en de duur van de campagnes voor verbetering vatbaar zijn. Toch bleef de hoeveelheid verzamelde informatie naar verwachting ver achter. Dit wordt verder bevestigd door het feit dat een groot deel van de multimediabestanden werden geëxcludeerd vanwege meetfouten door burgers. Daarna waren omgevingsomstandigheden en technologische beperkingen de grootste factoren die invloed hadden op de bruikbaarheid van burgerdata. Waar schattingen van waterdiepte goed overeenkomen met traditionele gegevens, bleken de snelheidsmetingen minder betrouwbaar. Het gebruik van burgergegevens week niet veel af van traditionele gegevens bij de kalibratie en validatie van het Donaudelta-model, waar het model minder gevoelig bleek voor gekalibreerde ruwheidswaarden, ongeacht de gebruikte dataset. Voor Kifissos presteerde de landbedekkingskaart op basis van citizen science vergelijkbaar met of zelfs beter dan traditionele kaarten, vooral in gerasterde hydrologische modellen, omdat deze beter in staat was om ondoorlaatbaarheid vast te leggen, een parameter waar het model gevoelig voor is.

Concluderend benadrukt dit proefschrift hoe 'citizen science' campagnes kunnen worden opgezet om gegevens te verzamelen met een hoge ruimtelijke resolutie en nuttig te zijn om toe te passen in modellen. Tevens wordt aangetoond dat, in tegenstelling tot traditionele metingen, gegevensverzameling door burgers niet altijd efficiënt is en dat deze inspanningen in de planningsfase van campagnes moeten worden meegenomen. Deze scriptie pleit voor op de eindgebruiker gerichte gegevensverzamelingscampagnes die rekening houden met de inherente inefficiënties van burgerparticipatie, en draagt zo bij aan de ontwikkeling van citizen science als een vatbare methode voor het verzamelen van milieugegevens.

CONTENTS

1

INTRODUCTION

1.1 BACKGROUND

Climate change is intensifying the frequency, severity, and spatial variability of hydrometeorological extremes, including floods and droughts, with far-reaching consequences for both human and natural systems (de Brito, 2021; Gaitán et al., 2019; Guerreiro et al., 2018; UNDRR, 2021). These extremes are increasingly linked to the degradation of ecosystems (Sun et al., 2025), the disruption of critical infrastructure such as roads, bridges, and water supply (Neumann et al., 2015; Stahl et al., 2016), and rising mortality rates, particularly in vulnerable regions (Jonkman et al., 2024; Stanke et al., 2013). Further, the impact of floods and droughts can be significantly amplified when they occur in a compound manner (Zhang et al., 2021).

Across the globe, monitoring can be sparse or biased to perennial rivers (Krabbenhoft et al., 2022), and in some instances, gauging stations are being deactivated (Andrews and Grantham, 2024; Ruhi et al., 2018). Current monitoring systems can be insufficient to capture extreme events' increased local and temporal variability (Xiong and Yang, 2025). Traditional hydrological data collection has relied on centralized approaches, using expensive, high-maintenance equipment and expert-driven protocols (Luo et al., 2024). These systems often exclude local knowledge and are slow to adapt to emerging needs or technologies (Pecora and Lins, 2020). As a result, many areas—especially in the Global South—remain under-monitored, leaving communities vulnerable to water-related hazards and limiting the ability of governments to make informed decisions (Dalu et al., 2025; Xiong and Yang, 2025). The need to diversify and investigate the value of new data sources has been raised as one of the main problems in hydrology (Blöschl et al., 2019).

In response, citizen science has emerged as a complementary approach to traditional hydrological monitoring (Njue et al., 2019a). Enabled by advances in low-cost sensors, mobile technologies, and open data platforms, citizen science allows non-experts to contribute to data collection, interpretation, and even co-design of monitoring systems (Haklay, 2013). This approach has been successfully applied in fields such as biodiversity conservation and astronomy (Strasser et al., 2023; Zinger et al., 2023), and is increasingly being explored in hydrology (Njue et al., 2019a).

Beyond its technical contributions, citizen science is also recognized for its social and political value (Raap et al., 2024). It can democratize knowledge production, increase transparency, and foster community engagement in environmental governance (Buytaert et al., 2016). However, the integration of citizen-generated data into formal decision-making processes remains limited, in part due to concerns about data quality, standardization, and legitimacy (Nardi et al., 2022). These concerns are particularly acute in hydrology, where data at specific and often high spatio-temporal resolution is critical.

1.2 Motivation

Citizen science in hydrology, particularly for monitoring water quantity, is a relatively recent development but is steadily expanding in scope and ambition (Assumpção et al., 2018; Njue et al., 2019b). Unlike discrete or categorical observations—such as counting species or identifying land cover types—measuring continuous variables like water depth and discharges presents greater technical and methodological challenges (Strobl et al., 2019). This complexity has likely contributed to the slower uptake of citizen-based approaches in this domain.

In some scientific fields, for instance, ecology and astronomy, projects have engaged hundreds of thousands of participants globally (Strasser et al., 2023; Zinger et al., 2023). Hydrology, by contrast, has seen more modest efforts. Most water-related citizen science projects—especially those focused on water quality—operate at fewer than 100 sites and typically span one to five years (Njue et al., 2019b). Still, there are exceptions: the iWetland project, for example, collected over 2,600 water table measurements across 24 locations (North et al., 2023). Despite their smaller scale, hydrology-focused initiatives have demonstrated that citizen-generated data can match the quality of conventional measurements (Kebede Mengistie et al., 2024). This supports the effectiveness (accuracy) and efficacy (ability to achieve intended outcomes) of citizen science in water monitoring. However, the design of these projects—how sites are selected, how volunteers are trained, and how protocols are tested—remains underreported. While some studies have validated the legitimacy of the data, few have critically examined the experimental setup or justified design decisions.

Another underexplored dimension is efficiency—the cost, effort, and data loss associated with citizen participation. In image-based flood monitoring, for example, high rates of rejected images and quantification of error margins are common (Dasgupta et al., 2022; Drews et al., 2023; Kebede Mengistie et al., 2024; Rollason et al., 2018; Songchon et al., 2023). Active citizen science projects, where volunteers collect data directly, rarely report on these aspects, though a few have quantified data quality (Seibert et al., 2019).

Data quality in citizen science is influenced by multiple factors, including the complexity of the task, the level of training, and the participants' prior experience and background knowledge (Crown et al., 2018; Katrak-Adefowora et al., 2020). Training strategies such as Just-In-Time Training (JITT), which provides guidance during data collection, have shown promise in improving outcomes with minimal preparation time (Katrak-Adefowora et al., 2020; Kosmala et al., 2016). Environmental conditions—such as lighting, distance to the target, and background interference—also affect the reliability of water level observations (Shrestha et al., 2024; Strobl et al., 2019).

To address these challenges, researchers are adapting streamflow measurement techniques to work in uncontrolled, real-world settings. This includes the use of Unoccupied Aerial Systems (UAS) for citizen science, and increasingly, deep learning algorithms to process visual data (Eltner et al., 2020; Rozos et al., 2022; Tauro et al., 2018, p.201; Tlhomole et al., 2025). However, aside from a few notable efforts (Seibert et al., 2019; Strobl et al., 2019), systematic evaluations of data quality and influencing factors remain scarce. Some progress has been made, for instance, the development of quality indicators for citizen-collected precipitation data (Eisma et al., 2023; Tedla et al., 2022). But overall, reporting on data quality remains inconsistent (Balázs et al., 2021).

Long-term citizen science programs with large datasets are beginning to show how to determine the minimum data volume needed to meet accuracy thresholds. These studies advocate for more quantitative, design-driven approaches that optimize volunteer contributions while ensuring data reliability (Rivera et al., 2024).

1.3 Research objectives

The main objective of this thesis is to critically assess the design, efficiency and accuracy of citizen campaigns in obtaining data to inform flood modelling applications. Data refers to water depths, velocities and land cover.

The specific objectives are:

1. To assess how the design choices of citizen campaigns, including the routes taken for data collection, influence the amount of multimedia pieces collected by citizens
2. To develop methods for the quality control and quality analysis of multimedia pieces, extracted data and merged estimates
3. To validate estimates obtained via citizen contributions against traditional measurements
4. To explore the usefulness of estimates derived from citizen campaigns for flood models, in calibration, validation and as input

1.4 METHODOLOGY

The methodological approach followed in this thesis is summarised in Figure 1.1. It is composed of three steps, each oriented towards addressing specific research objectives. Two case studies support this research, to a different extent in each step: the Danube Delta, in Romania, and the Kifissos Catchment, in Greece.

In the first step, we situate this study within existing citizen science frameworks and propose one for analyzing our citizen campaigns. Its innovative component was establishing a campaign design based on data needs from local authorities. Further, innovative tools were created to integrate the process: a campaign manager to establish points of interest; a smartphone app for gamified multimedia collection; and tools to extract data (water depths, surface velocities and land cover maps) from the multimedia collected. It is also proposed an approach for the selection of routes for data collection, taking the same principles of local interests into account. The execution of four field campaigns was assessed qualitatively and quantitatively. Questionnaires are used to evaluate citizens' experiences. A comparative analysis investigates the expected versus realized number of points of interest and the number of multimedia items collected. The campaigns are designed and executed for the two case studies of this thesis.

The second step focuses on assessing the effectiveness and efficiency of the campaigns. We built a visual-inspection method for multimedia quality control and analysis. It is a method to evaluate multimedia pieces' rejection rates, provide quality scores and diagnose the root causes for rejection or bad quality data. After data extraction, data points also go through quality analysis (geotag, timestamp and data point value). Clustering and averaging are used to aggregate multiple data points into citizen-based estimates, which in turn are validated against traditional estimates. Assessing the efficiency of the citizen science campaign process is one of the innovative components of this research. The in-depth analysis of this step is carried out for two campaigns in the Danube Delta case study.

In the third and last step, citizen-based estimates are applied to modelling. In the Danube Delta case study, a 1D/2D hydrodynamic model was developed, calibrated and validated with limited data in the area of interest. The model is further calibrated for roughness with traditional and citizen-based estimates of water depth and surface velocity. Validation is performed similarly. For the Kifissos catchment case study, continuous hydrological models were developed, both lumped and distributed. Three different land cover maps were used to parameterize the models, including a map generated from citizen multimedia on land cover. The novelty of these applications lies in applying a still not very common citizen science dataset in modelling (citizen-based land cover map) and in applying citizen science water depth and velocity datasets in a remote and complex delta context.

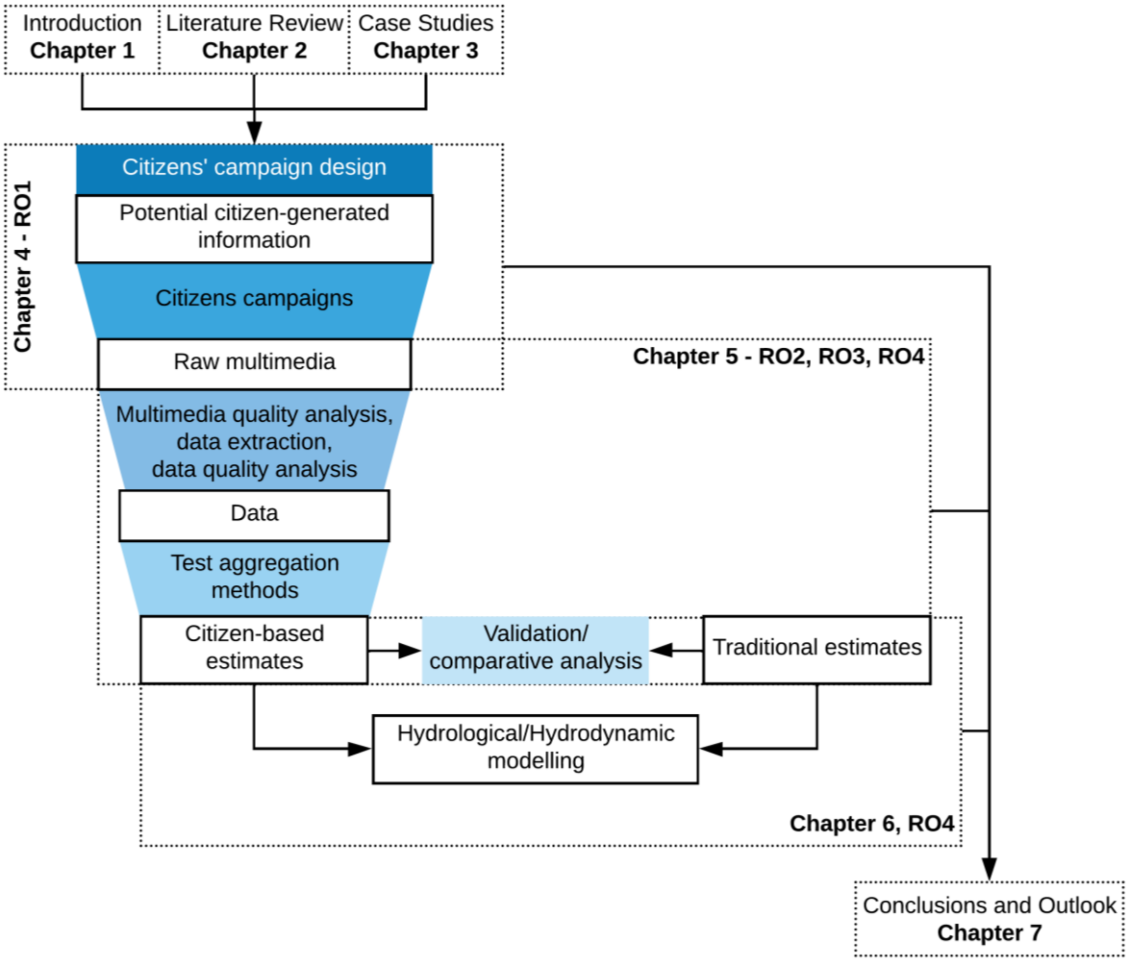

Figure 1.1. Research methodology, research objectives and outline of the thesis

1.5 Thesis outline

The thesis is structured in seven chapters, as presented in Figure 1.1. The figure presents how the different chapters interconnect and how they address the research objectives delineated in Section 1.3.

Chapter 1 introduces the context in which citizen science has emerged in water resources management, delineating the motivation for this research and the consequent research objectives, together with an overview of the thesis structure.

Chapter 2 provides a state-of-the-art review of citizen science for data collection and application to flood models, in particular hydrodynamic ones. It highlights the knowledge gaps addressed in the following chapters.

Chapter 3 describes the two case studies in which the research approach was applied: the Danube Delta in Romania, a deltaic wetland system, and the Kifissos catchment in Greece, a small urban basin.

Chapter 4 introduces the details of how the campaigns for data collection were designed; the goals that were set, the route selection framework applied, the results expected and lastly, the results obtained.

Chapter 5 is a deep dive into the results from the campaigns, starting from the image and video quality assessments, moving towards extracting data from them, aggregating the data and the final step of validation against traditional data.

Chapter 6 tests the citizen-based estimates' applicability in calibrating and validating a hydrodynamic model, and as input for a hydrological model.

Chapter 7 finishes the thesis with a reflection on the research objectives, on how they were met and what outlook can be derived from their conclusions.

2

CITIZEN SCIENCE CONTRIBUTIONS TO FLOOD MODELLING - REVIEW AND ANALYSIS

This chapter provides a literature review on how citizens have collected information that is useful to inundation modelling[1]. It first analysed the type of information collected through citizen science (e.g. water levels, topography), their collection methods (e.g. data mined from social media) and purpose (i.e. monitoring, mapping or modelling). The literature on modelling was then further analysed to characterize in which part of the modelling process the contributed information was being used and how it is compared to ideal model needs (e.g. time series as upstream input). It was observed that contributions from citizens are able to inform the monitoring, mapping and modelling and that there are multiple ready-to-use tools available to monitor varied data types. However, it is yet unclear what the uncertainties of these contributions are, their uncertainty sources, and how to leverage contributed information to volumes that are useful in operational contexts.

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[1]This chapter is adapted from: Assumpção, T. H., Popescu, I., Jonoski, A., & Solomatine, D. P. (2018). Citizen observations contributing to flood modelling: opportunities and challenges. Hydrology and Earth System Sciences, 22(2), 1473–1489. https://doi.org/10.5194/hess-22-1473-2018

2.1 INTRODUCTION

2.1.1 Background

The necessity to understand and predict the behaviour of floods has been present in societies around the world. This comes from the fact that floods impact their surroundings - in negative or in positive ways. The most common way used nowadays to better understand and often predict flood behaviour is through modelling and, depending on the system at hand, a variety of models can be used (Teng et al., 2017).

In order to have adequate representation of floods, most models require large amounts of data, both for model building and model usage. This is especially true for pluvial flood modelling, where flooding may not occur in gauged rivers and hence, flow gauging stations outside of flooded zones may be of little use. Remote sensing technologies are a part of the solution, as they offer spatially distributed information. However, their availability may be limited, also in terms of space and time, and their uncertainties often are not quantifiable (Di Baldassarre et al., 2011; Grimaldi et al., 2016; Jiang et al., 2014; Li et al., 2017). Thus, acquiring the necessary data for simulations and predictions can still be expensive, particularly for rapidly changing systems that require frequent model updates.

In this context, sources of data coming in abundance and at low costs are needed, together with modified modelling approaches that can use these data and can adapt to changes as fast as they occur. Citizen Observatory (CO) is an emerging concept in which citizens monitor the environment around them (Montargil and Santos, 2017). It is often considered under the umbrella of Citizen Science (including citizen participation up to the scientist level) and it is also related to the concept of crowdsourcing (distributing a task among many agents). With technology at hand, it is possible to empower citizens to not only participate in the acquisition of data but also in the process of scientific analysis and even in the consequent decision-making process (Evers et al., 2016). Citizen Observatories have been researched in several EU-funded projects. Finished projects (CITI-SENSE, Citclops, COBWEB, OMNISCIENTIS and WeSenseIt) already resulted in valuable contributions to the field (Alfonso et al., 2015; Aspuru et al., 2016; Friedrichs et al., 2014; Higgins et al., 2016; Uhrner et al., 2013). For example, the CITI-SENSE project managed to simultaneously collect perception data and acoustic measurements in an approach that can be used to develop citizen empowerment initiatives in case of noise management (Aspuru et al., 2016); while in COBWEB project processes of quality assurance, data conflation and data fusion were studied and recommendations were made (Friedrichs et al., 2014). The currently running CO projects (Ground Truth 2.0, LANDSENSE, Scent and GROW Observatory) propose to investigate this concept further.

Citizen science concepts have been researched and applied in various fields such as ecology and galaxy inspection (Lintott et al., 2008; Miller-Rushing et al., 2012). Volunteer Geographic Information (VGI), as one of the most active citizen science areas, has developed over the past decade and several researchers reviewed the state of the art of citizen science in the field of geosciences (Heipke, 2010; Klonner et al., 2016). There is also a part of the scientific community dedicated to investigating damage data crowdsourced after flood emergencies (Dashti et al., 2014; Oxendine et al., 2014) and evaluating the cycle of disaster management (Horita et al., 2013). In the context of water resources, Buytaert et al. (2014) reviewed and discussed the contribution of citizen science to hydrology and water resources, addressing the level of engagement, the type of data collected (e.g. precipitation, water level) and case studies where more participatory approaches are being implemented. Le Coz et al. (2016) provided examples and reflections from three projects related to flood hydrology and crowdsourcing, which involve the derivation of hydraulic information from pictures and videos in Argentina, France and New Zealand.

The present review aims to look at studies that had citizen science connected to floods. Specifically, it focuses on the data collected by citizens that are relevant in a flood modelling context, benchmarking difficulties and benefits of their collection and integration into models. Integration is considered for the purposes of model setup, calibration, validation, simulation and forecasting.

The review process involved defining web platforms, keywords and criteria for searching and selecting publications. The main platforms used were Scopus and Google Scholar. The keywords are a combination of words related to citizen science (e.g. "citizen science" and crowdsourcing) and to flood-related variables (e.g. "water level" and "flood extent"). The obtained articles were scanned for their content. Articles were selected mainly if crowdsourced data was obtained for quantitative use in monitoring, mapping or modelling. Some studies were not selected because they just mention the use of crowdsourced data and do not provide more relevant information on collection, analysis, use and quantity of data, such as Merkuryeva et al. (2015). The same is the case of studies that evaluate variables qualitatively, in ways that cannot be directly associated with modelling (Kim et al., 2011). This review included articles published up to April 2017.

Further in this section, we introduce the citizen science concept and related classification systems. In Section 2.2, we overview studies on citizen contributions for flood modelling, classifying them according to the flood-related variable the contributions were made, followed by a summary of the pros and cons of measurement and analysis methods. Section 2.3 aggregates the studies that involve flood modelling and analyzes the contributions considering the component of the modelling process where they were used, also including a discussion of the factors that affect flood modelling. Section 2.4 describes the challenges and opportunities of using data contributed by citizens in flood modelling, and finally, Section 2.5 presents the conclusions and recommendations.

2.1.2 Citizen science

Buytaert et al. (2014) defined citizen science as "the participation of the general public (i.e. non-scientists) in the generation of new knowledge". In the same manner that the involvement of citizens can be diverse, such is the way their participation is found in the scientific literature:

- Citizen Science (Buytaert et al., 2014)
- Citizen Observatory (Degrossi et al., 2014)
- Citizen Sensing (Foody et al., 2013)
- Trained volunteers (Gallart et al., 2016)
- Participatory data collection methods (Michelsen et al., 2016)
- Crowdsourcing (Leibovici et al., 2015)
- Participatory sensing (Kotovirta et al., 2014)
- Community-based monitoring (Conrad and Hilchey, 2011)
- Volunteered Geographic Information (Klonner et al., 2016)
- Eyewitnesses (Poser and Dransch, 2010)
- Non-authoritative sources (Schnebele et al., 2014)
- Human Sensor Network (Aulov et al., 2014)
- Crowdsourced Geographic Information (See et al., 2016)

Some of the terms used by the above-mentioned articles have specific definitions that are used to delineate debates on the social mechanisms of citizen participation. Others are just the best form the researcher found to characterise the contribution or the citizen (e.g. eye witnesses). Citizen Science and adjacent areas have become fields of research in themselves that, for instance, focus on understanding the motivation of citizens or their interaction with public institutions (Gharesifard and Wehn, 2016).

In this field, one of the classifications of citizen science is by level of engagement. Haklay (2013) built a model that has four levels (Figure 2.1), in which the first one refers to the participation of citizens only as data collectors, passing through a second level in which citizens are asked to act as interpreters of data, going towards the participation in definition of the problem in the third level and finally, being fully involved in the scientific enterprise at hand. The review presented in this current chapter is focused on the contribution towards flood modelling only, coming most prominently from the two lowest levels of engagement. We do not discuss topics related to engagement for the generation of (quantitative) data. Further in this article, for readability, only the term crowdsourced data is used to refer to data from these two levels of engagement.

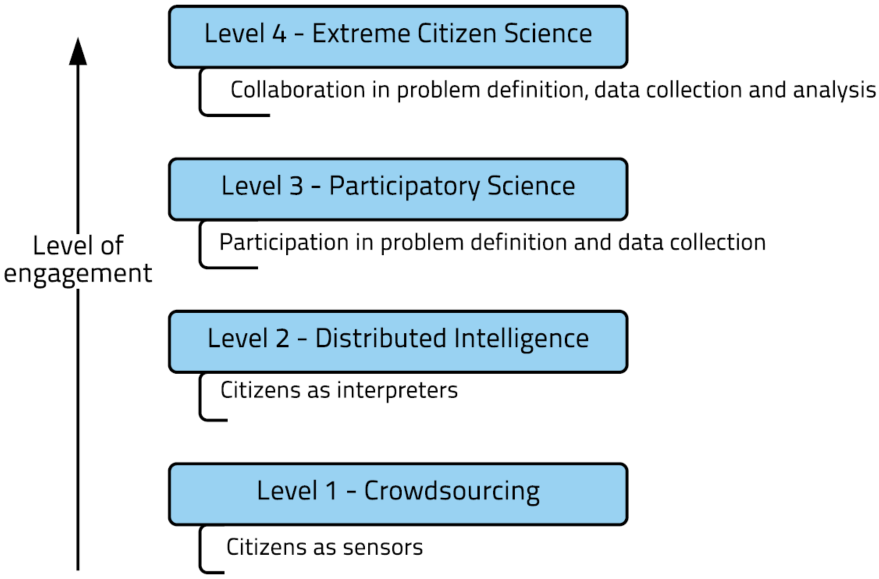

Figure 2.1. Levels of participation and engagement in citizen science projects. Adapted from Haklay (2013)

Another way to classify citizen science initiatives (within the context of VGI) is by setting them as implicitly/explicitly volunteered and implicitly/explicitly geographic (Craglia et al., 2012). In this classification system, geographic refers to the main information conveyed through the contributed data; therefore, geo-tagged data is not necessarily geographic. For example, in the Degree Confluence Project (Iwao et al., 2006), citizens were oriented to go to certain locations, take pictures, make notes and deliberately make available their material on the project's website. In this case, the information is explicitly volunteered and geographic. Most land use/cover projects related to citizen science collect geographic information. Differently, in the study conducted by Lowry and Fienen (2013), citizens would also willingly send text messages to the researchers, in this case providing water level readings from installed water level gauges. Although explicitly volunteered, the message was non-geographic (just geo-tagged). Another type of implicitly geographic information was derived from Twitter by Smith et al. (2015) to obtain flood water level, flow rate and flood inundation estimates. As the citizens did not make the information public with the specific purpose of providing estimates, it is implicitly volunteered.

The concepts defined by Craglia et al. (2012) can be graphically represented as in Figure 2.2. The Scent project[2] (Smart Toolbox for Engaging Citizens in a People-Centric Observation Web) is one of the four Horizon 2020-funded projects focusing on citizen observatories. It lies in the middle of this quadrant as it encourages citizens to participate in gaming to collect land cover/use data, in field campaigns to collect other implicitly geographic information (e.g. water level), and also aims to obtain implicitly volunteered contributions through a CAPTCHA[3] plugin, in which citizens tag, for instance, images of certain land cover/use or water level gauges, in order to access online content. Tagging images is uncorrelated to the CAPTCHA, it is a task performed after the test, on the same platform. More information on the Scent campaigns is provided in Chapter 4.

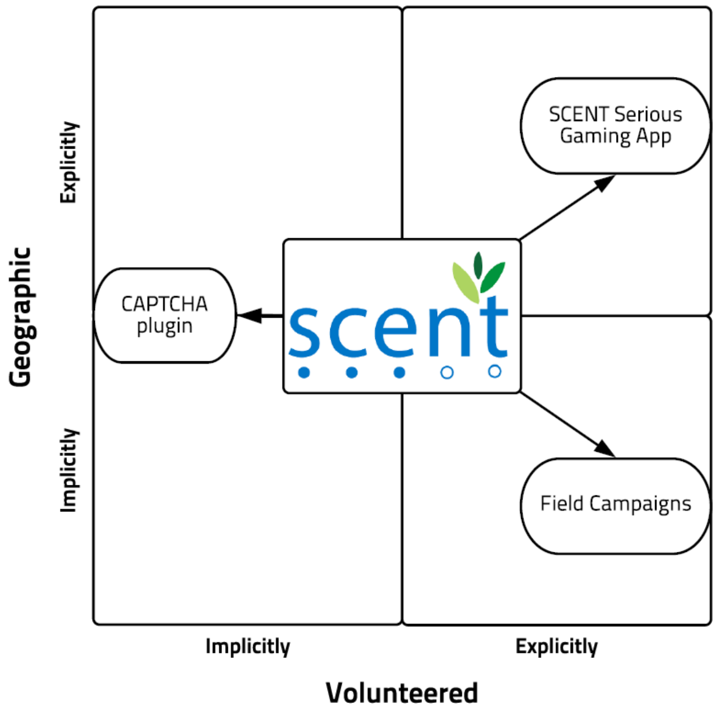

Figure 2.2. Scent project represented in the typology of VGI (volunteered geographic information)

[2] https://scent-project.eu/

[3] CAPTCHA stands for 'Completely Automated Public Turing test to tell Computers and Humans Apart'. It is a test evaluating if the subject is human, which is used in websites to provide security. After the test is done the user can be asked to perform extra tasks, for example, tag images.

2.2 Flood-related crowdsourced data

There are many types of data that relate to floods that can be collected by citizens. Likewise, there are many ways to collect, analyse and use them (for monitoring, mapping and modelling). In the next sub-sections, we address how these aspects were explored in the scientific literature. Each sub-section discusses a data type corresponding to a flood modelling variable: water level, velocity, flood extent, land cover and topography. Depending on the type of flooding, other variables are relevant, such as precipitation. The scientific literature already shows that citizens' contributions could be useful for observing this variable (De Vos et al., 2017; Muller et al., 2015). However, rainfall is not included in this section because it was already covered by the review of Muller et al. (2015). Moreover, in general, it is a variable of greater importance for hydrological models, whilst the present review is focused on a hydrodynamic representation of floods. Regarding the presented articles, there are some mentioned and reviewed in more than one section because they evaluated more than one variable, as is, for example, the case of Smith et al. (2015).

2.2.1 Water level

Table 2.1 gives an overview of the articles about the collection of water level data. The studies presented started to involve citizens in data collection with the explicit goal of improving flood management. This is due to the ease of collecting such data, which mostly consists of comparing the water level with a clearly defined reference. In some cases, the reference is a water level gauge, the comparison is made by the citizen, and readings are submitted to the researchers (Alfonso et al., 2010; Degrossi et al., 2014; Fava et al., 2014; Lowry and Fienen, 2013; Walker et al., 2016). Such kind of readings practically do not require further analysis, although they entail the installation of water level gauges.

Table 2.1. Scientific literature on citizen contributions to the measurement and analysis of water level

Study	**Measurement/analysis methods**	**Type**	**Purpose**	**Flood type**	**Location**
Alfonso et al. (2010)	Citizen's reading of water level gauges sent by text message	1D	Monitoring	No flooding	The Netherlands
Lowry and Fienen (2013)	Citizen's reading of water level gauges sent by text message	1D	Monitoring	No flooding	USA
Degrossi et al. (2014)	Citizen's reading of water level gauge sent through app/webpage	1D	Monitoring	No flooding	Brazil
Walker et al. (2016)	Citizen's reading of water level gauge collected and provided by the community	1D	Monitoring	No flooding	Ethiopia
Fava et al. (2014)	Citizen's reading of water level gauge sent through app/webpage	1D	Modelling	Flood forecasting	Brazil
Le Boursicaud et al. (2016)	LSPIV analysis of video collected from social media (YouTube)	1D	Monitoring	Flash flood	France
Le Coz et al. (2016)	LSPIV analysis of video sent through webpage	2D	Modelling	Fluvial flood	Argentina
Michelsen et al. (2016)	Analysis of images extracted from videos collected from social media (YouTube) and own photographs	Neither	Monitoring	No flooding	Saudi Arabia
Li et al. (2017)	Analysis of texts and pictures collected from social media (Twitter)	2D	Monitoring	Flood map	USA
Starkey et al. (2017)	Citizen's reading of water level gauge and analysis of pictures and videos collected from social media (Twitter) and crowdsourced (email, webpage and mobile app)	2D	Monitoring	Flood	UK
McDougall, (2011); McDougall and Temple-Watts (2012)	Analysis of texts and pictures collected from social media (Twitter, Facebook) and crowdsourced (email, text message, Ushahidi, Flickr and Picasa)	2D	Mapping	Flood map	Australia

Kutija et al. (2014)	Analysis of pictures collected by the University and City Council	2D	Modelling	Pluvial and drainage flood	UK
Aulov et al. (2014)	Visual analysis of texts and pictures collected from social media (Twitter and Instagram)	2D	Modelling	Coastal flood	USA
Fohringer et al. (2015)	Visual analysis of pictures collected from social media (Twitter) and crowdsourced (Flickr)	2D	Mapping	Flood	Germany
Smith et al. (2015)	Analysis of texts and pictures collected from social media (Twitter)	2D	Modelling	Pluvial and drainage flood	UK

In other cases, the citizen provides qualitative data that will be compared to references by researchers. Mostly during flooding situations, citizens provide pictures (Fohringer et al., 2015; Kutija et al., 2014; Li et al., 2017; McDougall, 2011; McDougall and Temple-Watts, 2012; Smith et al., 2015; Starkey et al., 2017) or videos (Le Boursicaud et al., 2016; Le Coz et al., 2016; Michelsen et al., 2016). In the case of pictures/images, the water level is compared with objects in the images that have known or approximately known dimensions. For videos, although the water level was estimated, the main goal was to obtain discharge values by combining the water level estimates with estimates of flow velocity. In two cases, texts from citizens (e.g. water over the knee) were used to calculate water level values or to assume a certain value when no value was provided (Li et al., 2017; Smith et al., 2015). This sort of data (text, pictures and videos) was mostly collected through social media and public image repositories. Gathering data from such sources requires mining of the relevant material (i.e. extraction of specific data from a dataset) and dealing with uncertainties in the spatio-temporal characterization of the data of interest.

One aspect that varies across the studies is the level of detail in the comparison method used for determining the water level measurement. For example, McDougall (2011) and McDougall and Temple-Watts (2012) explicitly state that field visits to the selected photo locations are required in order to properly analyse the image and extract water level values. In contrast, Fohringer et al. (2015), Smith et al. (2015) and Starkey et al. (2017) do not mention any comparison method.

In most cases, crowdsourcing has been used to monitor water level, followed by the use of such data for modelling and lastly for mapping. In the case of Starkey et al. (2017), although hydrological modelling was done and water levels were converted into discharge to allow for comparisons, only qualitative comparisons were made.

2.2.2 Velocity

As velocities and discharges traditionally require more complex measuring methods, the collection of this type of data by citizens has not been explored on a scientific basis. However, it is common to include direct measurements of velocity in protocols to monitor the environment and water quality, as is the case with Hoosier Riverwatch (IDEM, 2015). In these cases, the citizens perform measurements that involve more processing on their side (e.g. definition of transects to measure flow, use of formulas).

To the best of the authors' knowledge, only three studies were found that make use of velocity data collected by citizens, all for the study of floods, as presented in Table 2.2. Le Boursicaud et al. (2016) evaluated the surface velocity field in a channel from a YouTube video, using the LSPIV methodology (Large Scale Particle Image Velocimetry), an established method to obtain velocity from a sequence of images. For enabling this analysis, information about the camera (model and lens type) is needed. Further, visible, fixed elements need to be used as reference points and it is also required that both river banks are visible. Although the method calculates the velocity in two dimensions, in Table 2.2 we referred to it as 1D because it was carried out in a channel, which in the context of flood modelling is considered a 1D domain. A complementary project was discussed by Le Coz et al. (2016), in which the same technique is applied to a video crowdsourced by a citizen, this time using the result to estimate discharge and the latter to calibrate a 1D hydraulic model. For this, a visit to the location was needed to extract cross-sectional data. In this context, Yang and Kang (2017) developed a method for crowd-based velocimetry of surface flows, in which citizens mark features in the picture. The method has not been tested with citizen-collected data yet.

Table 2.2. Scientific literature on citizen contributions to the measurement and analysis of velocity

Study	Measurement/analysis methods	Type	Purpose	Flood type	Location
Le Boursicaud et al. (2016)	LSPIV analysis of video collected from social media (YouTube)	1D	Monitoring	Flash flood	France
Le Coz et al. (2016)	LSPIV analysis of video sent through a webpage	2D	Modelling	Fluvial flood	Argentina
Smith et al. (2015)	Analysis of texts and pictures collected from social media (Twitter)	2D	Modelling	Pluvial & drainage flood	UK

The third study, conducted by Smith et al. (2015), selected Twitter messages that include terms of semantic value related to the citizen's location, water depth (e.g. knee-deep) and velocity. The terms were then associated with quantitative values/ranges. The authors did not go into detail on discussing the reliability and uncertainty in such data, even though the issue is recognized.

2.2.3 Flood extent

Flood extent, similarly to water level, is a variable that is simple to measure as it consists of binary values: flooded or non-flooded area. As a 2D variable, it needs a lot of spatial information and it is the main reason related studies gather flood extent estimates in data-rich environments, through social media/photo sharing services mining, as shown in Table 2.3. In some cases, the citizens act only as sensors, providing pictures to be analysed by the research team, while in other cases, they also act as interpreters by providing the flooded/non-flooded information. As can be expected, all studies found were carried out in urban areas.

In some of the studies, the text and images indicate the location of their origin as being flooded (georeferenced or inferred) (Aulov et al., 2014; Smith et al., 2015; Yu et al., 2016), whilst in others (Cervone et al., 2016; Li et al., 2017; Rosser et al., 2017; Schnebele et al., 2014; Schnebele and Cervone, 2013) there is processing of the information to infer the surrounding inundated areas. Additionally, the last group of studies mentioned fused flood extent data from citizens with satellite data or with gauge data.

Table 2.3. Scientific literature on citizen contributions to the measurement and analysis of flood extent

Study	Measurement/analysis methods	Purpose	Flood type	Location
Cervone et al. (2016); Schnebele et al. (2014); Schnebele and Cervone (2013)	Analysis of pictures and videos collected from social media (Facebook and YouTube) and crowdsourced (Flickr)	Mapping	Flood map	USA and Canada
Li et al. (2017)	Analysis of texts and pictures collected from social media (Twitter)	Mapping	Flood map	USA
Rosser et al. (2017)	Analysis of crowdsourced pictures (Flickr)	Mapping[a]	Flood map	UK
Aulov et al. (2014)	Visual analysis of texts and pictures collected from social media (Twitter and Instagram)	Modelling	Coastal flood	USA
Smith et al. (2015)	Analysis of texts and pictures collected from social media (Twitter)	Modelling	Pluvial and drainage flood	UK
Yu et al. (2016)	Citizen's visual identification of flooded location collected by governmental Chinese website	Modelling	Pluvial and drainage flood	China
Padawangi et al. (2016)	Citizen information	Monitoring	Flood	Indonesia

[a] An statistical model is created, but in this study, we consider only physical models in the modelling category

2.2.4 Land cover/Land use

Land cover is not a variable in flood-related models, but we include it in this review for its importance in inferring roughness (i.e. the parameter representing momentum loss due to friction, to the ground resistance encountered by the flow). Other valuable aspects of land use data are the information on roads and structures that can be obstacles to floods, which can be incorporated in the model structure; and the information on vulnerability (e.g. hospitals, dense residential areas, industrial zones), which can be used to obtain flood risk maps. According to Klonner et al. (2016), when reviewing the literature on VGI for natural hazard analysis, there are few studies on vulnerability analysis. The aspects of land use related to vulnerability and risk are complex and study topics on themselves, so these aspects are not discussed further in this chapter.

Table 2.4 presents the articles considered for this review. Compared to previously discussed variables, the contribution of citizens to land cover maps generation has already been proved as a concept (Albrecht et al., 2014; Fritz et al., 2012), nowadays being researched further for the quality of data (Salk et al., 2016) and fusion of maps (Karagiannopoulou et al., 2022; Lesiv et al., 2016).

Table 2.4. Scientific literature on citizen contributions to measurement and analysis of land cover/land use

Study	Measurement/analysis methods	Purpose	Flood type	Location
Iwao et al. (2006)	Visual interpretation of crowdsourced tagged pictures sent through app/webpage (Degree Confluence Project website)	Mapping	No flooding	Global land cover map
See et al. (2015b) [a]	Visual interpretation of Google Earth and pictures sent through app/webpage (GeoWiki)	Mapping	No flooding	Global land cover map
Dong et al. (2012)	Analysis of tagged pictures from Global Geo-Referenced Field Photo Library (DCP citizen pictures + field trip pictures)	Mapping	No flooding	Forest cover map in Asia
Dorn et al. (2014)	Use of Open Street Maps	Modelling	Fluvial flood	Austria

[a] Many other articles related to crowdsourcing through GeoWiki

One of the first publications on the subject was from Iwao et al. (2006), in which they describe the Degree Confluence Project. The objective was to generate a global land cover map, which implies obtaining ground truth data from around the globe. For obvious reasons, it is unfeasible to centrally organize sufficient field campaigns or analyse sufficient low-resolution images. Thus, they launched a webpage that invited citizens to visit integer coordinates (e.g. 25° W, 25°) locations, take photos from the four cardinal directions and provide comments on the region. They discovered that citizen-generated data had quality similar to that provided by specialists.

Another significant project is GeoWiki. It started in 2009 as a platform for people to validate global land cover maps by comparing their classification to high-resolution images (Fritz et al., 2009). The project has grown since and has recently achieved its main goal: to generate a hybrid global land cover map by fusing existing maps and performing calibration and validation using the analyses made by citizens (See et al., 2015a). Current initiatives in the GeoWiki project include gamification and analysis of pictures uploaded onto the platform (See et al., 2015c). Many studies stemmed from the data collected, generally focused on specific land cover types. A similar approach is taken by Dong et al. (2012), who analyze pictures uploaded by citizens using a different web application. The research conducted by Dorn et al. (2014) goes one step further, as it attributes roughness values to multiple land cover maps, including Open Street Maps (a website where citizens can modify the current street and land cover map).

2.2.5 Topography

The Digital Elevation Model (DEM) is one of the most important components in flood modelling, as it generally heavily influences flood propagation. It is particularly important in urban settings, where spatial variability in refined scales has a considerable effect on the direction of water flows. Unfortunately, this is a complex variable to measure that so far relies either on fully trained professionals to go to the field, or on expensive airborne technologies. The usage of drones, also called Unmanned Aerial Vehicles (UAVs), is a potential low-cost alternative that is increasingly being more studied (Hamshaw et al., 2017), but so far studies on citizen generated drone data are limited to evaluating the spatial distribution of contributions (Hochmair and Zielstra, 2015) or to the analysis of repositories for image sharing (Johnson et al., 2017). However, recently, Shaad et al. (2016) studied a terrain capturing low-cost alternative to LiDAR remote sensing images and other expensive methods. The low-cost technique is a ground-based close-range photogrammetry that consists of collecting images/videos from the ground, post-processing them and obtaining terrain information. Volunteers made the videos in a designated location, where even UAVs would not be able to collect data. After comparing the results to other methods, they concluded that the result has an acceptable quality.

2.2.6 Summary analysis

By classifying the discussed studies according to Craglia et al. (2012), there is an overall similarity in the number of studies that crowdsource data implicitly and explicitly (Figure 2.3). It is visible though that this aspect does not translate into homogeneous distribution per flood-related variables, with most implicitly volunteered contributions being related to flood extent and most explicit being related to water level. There is a slightly higher concentration of modelling studies that are explicitly volunteered, but not enough to be able to draw any conclusions.

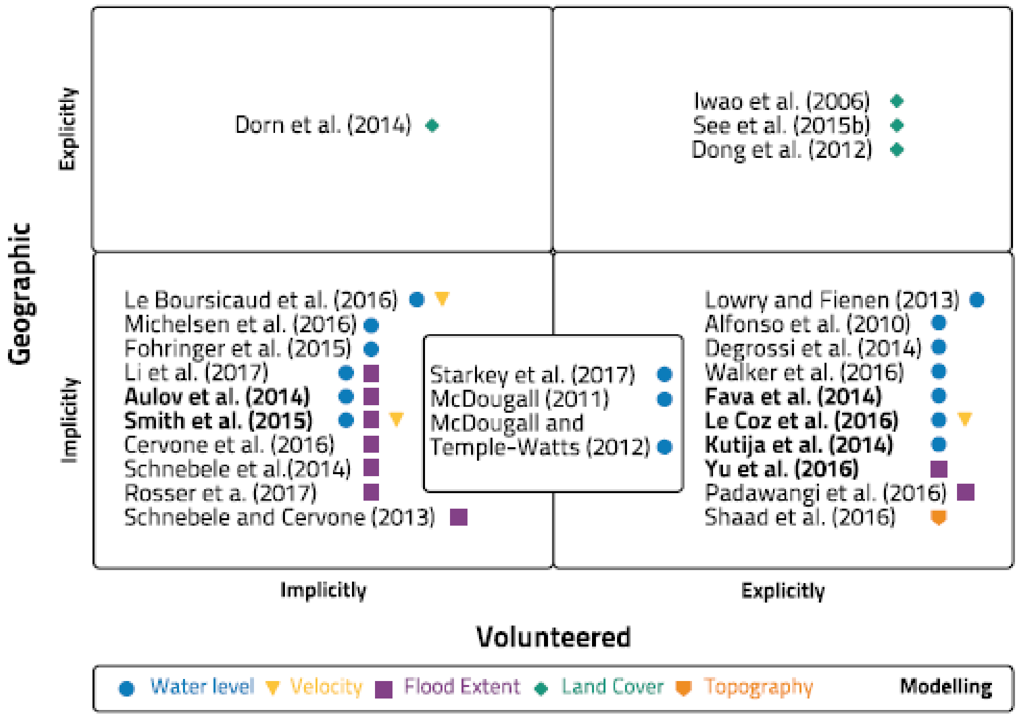

Figure 2.3. Selected studies represented in the typology of VGI

Considering the temporal distribution of studies evaluated in this review, it is evident that there is a trend: the rise in the number of studies from 2014 onwards (Figure 2.4). This relates to the initial barrier in acknowledging citizen data as having a quality that is high enough for scientific studies (Buytaert et al., 2014). This resistance is reducing over time as such data is being proven useful, protocols are being designed and the data uncertainty is being better understood and quantified.

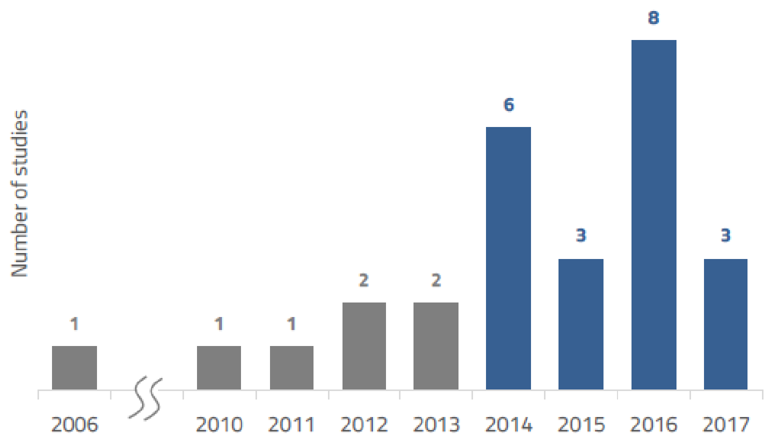

Figure 2.4. Number of studies analysed per year

If the analysed studies are aggregated into categories (Figure 2.5), it can be seen that modelling studies amount to approximately the same quantity as monitoring ones, but they are only about a third of all studies reviewed. This is expected because, to use data in models, it is necessary to monitor them first. Also, monitoring and mapping applications attend to more general end uses. Specifically for land cover, there is an unexplored field in modelling (there are more mapping studies than the ones in the graph, see Section 2.2.4). The reason behind may be that modellers do not tend to validate their own land cover maps and thus will not do it with citizen science data. What can be noted though, is the lack of exploration of velocity and topography variables, which, as mentioned, can be due to the complexity in analysing and setting up the experiment.

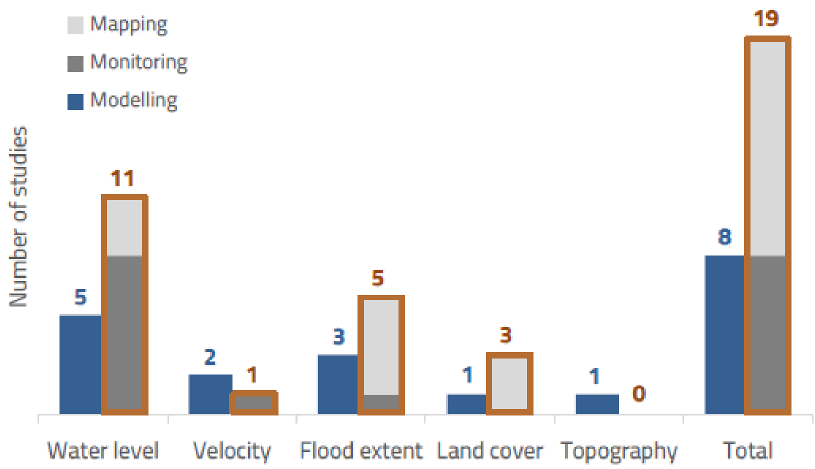

Figure 2.5. Number of studies analysed per flood-related variable per category: mapping, monitoring and modelling

Related to that, previous sub-sections discussed in detail the methods for the collection and analysis of flood-related data obtained through crowdsourcing. For example, water level data obtained from reading a water level gauge is easy to collect and easy to analyse. On the other hand, it requires the installation of gauges (Figure 2.6). In summary, whenever data is collected from the Internet, there is the disadvantage of needing social media/photo sharing services mining, entailing computational efforts and dealing with a high percentage of data that is not georeferenced or time-stamped. Further, in the case of water level and velocity, some studies suggest that field visits are necessary and the methods to analyse data are complex. Considering crowdsourced data on land cover and topography, it is straightforward to measure and analyse them, although their delivery to the interested parties may require a smartphone app or a website to be set up and maintained (except for Open Street Maps).

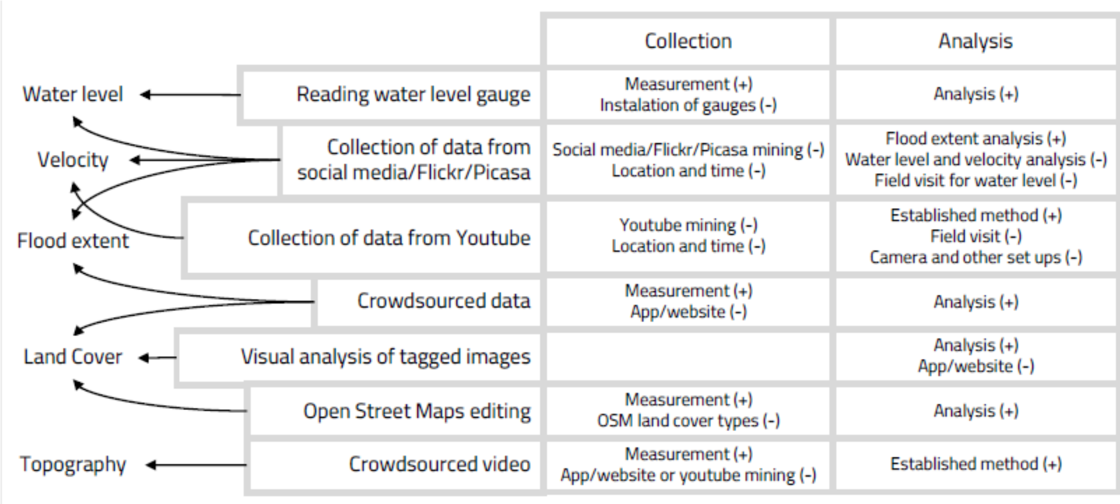

Figure 2.6. Pros and cons of the collection and analysis methods used to collect flood-related data by citizens

2.3 CROWDSOURCED DATA IN FLOOD MODELLING

2.3.1 Integration per flood model component

By concentrating on the studies in which modelling was performed, we explore in detail how crowdsourced data was integrated into each component of flood models.

There is a variety of flood models developed to deal with different types of flood, including: fluvial, pluvial, coastal and drainage floods. The main driver of fluvial floods is upstream river discharge, of pluvial floods is precipitation and of coastal floods is storm surges. In urban drainage floods, the flows inside, through and outside of drainage systems are pivotal for flood representation. Moreover, there are complex cases where more than one flood process needs to be represented. Although in physically-based flood models water flow is computed by the same principles, different sets of data are needed for different types of flood models. We focus on a general hydrodynamic model definition and its common inputs, but present what was the flood type evaluated in the scientific literature (Table 2.5).

Table 2.5. Scientific literature on crowdsourced data used in flood modelling

Use in modelling	Study	Measurement method	Type	Variable	Flood type	Location
Model setup	Dorn et al. (2014)	Use of Open Street Maps	2D	Land cover	Fluvial flood	Austria
	Shaad et al. (2016)	Analysis of pictures captured by volunteers at a selected location	2D	Topography	Fluvial flood	Indonesia
Calibration	Smith et al. (2015)[a]	Analysis of pictures and tweets collected from social media (Twitter)	2D	Water level and velocity	Pluvial and drainage flood	UK
	Le Coz et al. (2016)	LSPIV analysis of videos sent through a webpage	1D	Velocity	Fluvial flood	Argentina
	Yu et al. (2016)	Citizens' visual identification of flooded locations provided through a Chinese website	2D	Flood extent	Pluvial and drainage flood	China
Validation	Kutija et al. (2014)	Analysis of pictures collected from the University and the City Council	2D	Water level	Pluvial and drainage flood	UK
	Yu et al. (2016)	Citizens' visual identification of flooded locations provided through a Chinese website	2D	Flood extent	Pluvial and drainage flood	China
Data assimilation	Aulov et al. (2014)	Visual analysis of texts and pictures collected from social media (Twitter and Instagram)	2D	Water level and flood extent	Coastal flood	USA

Mazzoleni et al. (2015, 2017)	Simulated citizen reading of the water level gauge sent through an app	1D	Water level	Flood forecasting without a flood model	Italy and the USA
Fava et al. (2014)	Citizens' reading of a water level gauge sent through an app or webpage	1D	Water level	Flood forecasting without a flood model	Brazil

[a] It is classified as calibration because, in the classical sense, it improves the model according to observations. However, what is actually done is the fine-tuning selection of the precipitation field that fits the observations better.

The flood modelling process typically has two parts: model building and model usage. (Figure 2.7). Model building starts by defining the model setup (boundary conditions, parameters, schematization, input data), followed by calibration and validation of the water level and velocity fields (dependent variables) with observed values. Calibration and validation can be performed for both simulation and forecasting models. Once the model is ready, simulations can be run by using different boundary conditions or introducing designed measures for better flood management, or forecasts can be made by using forecasted water levels or discharges as boundaries. In a simulation setting, model parameters are assumed to be constant in time, while in a forecasting setting, the parameters, inputs or states (water levels) can be updated while the model is in use, using data assimilation.

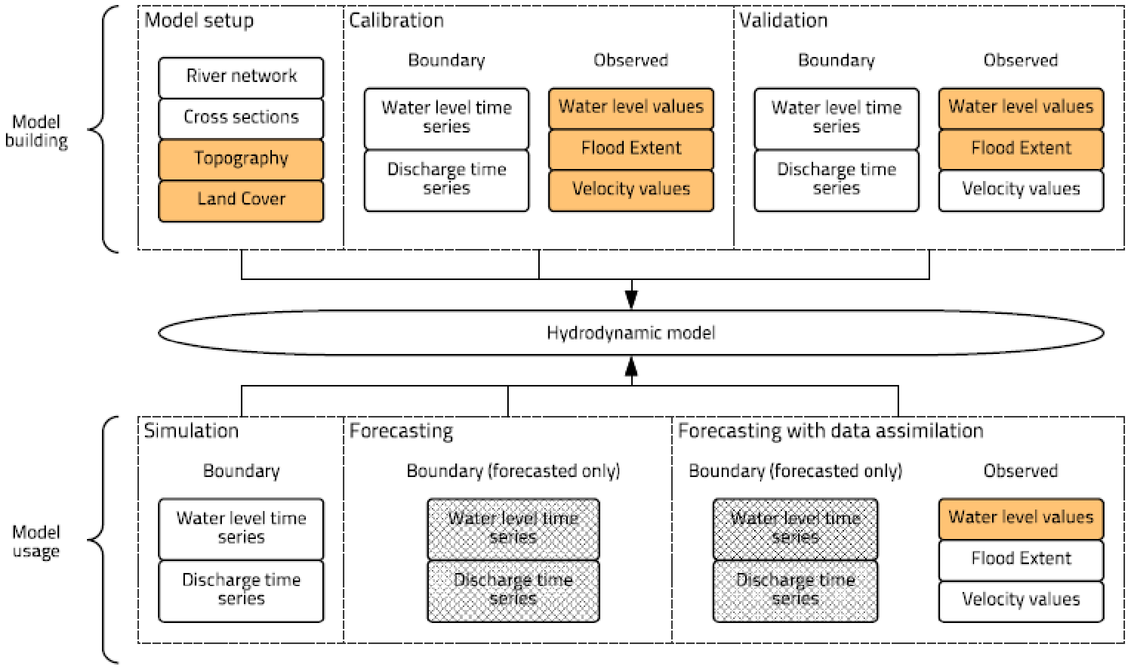

Figure 2.7. Flood models' data requirements. Orange-coloured tiles correspond to data that citizens have contributed to in a flood modelling context and gridded tiles correspond to data that citizens cannot contribute to (forecasted water levels and discharges)

From the studies analysed (Table 2.5), three consider 1D channels and the others worked in a 2D setting. Most of them analyse only one variable, except Smith et al. (2015), who evaluate water level and velocity. Moreover, most of them model urban floods, some in a pluvial and others in a fluvial context.

Considering model building, specifically the model setup, citizens contributed to improving/updating land cover (and consequently roughness) and topography information. (Dorn et al., 2014) used the land cover information contained in Open Street Maps[4] for modelling a fluvial flood. They do not analyse how much contribution was made by the citizens and data processing is restricted to attributing land cover classes to the features displayed in the maps. In the study of Shaad et al. (2016), which addresses topography, there is only one citizen contribution (low-cost alternative) in one selected location that is merged with an existing DEM and then used in the model. In both cases,

[4] Open Street Maps (OSM) is an online platform that provides street maps and other information. The maps provided can be edited by the users at any time

the objective was to compare the performance of this low-cost alternative against the performance of consolidated technologies when used for hydrodynamic simulations.

Crowdsourced data has also been used to calibrate and validate flood models in four studies. One study gathered such data through social media and public image repositories mining and the others through data uploaded by citizens on specific platforms. Smith et al. (2015) identified storm events through social media, triggering shock-capturing hydrodynamic model runs with various rainfall intensities. The results were compared with social media data on water level/velocity. The comparison consisted of defining a buffer zone around the crowdsourced observation location, building a histogram of simulated cell values within it, and evaluating the overlap of crowdsourced value/range and the histogram 70-95th percentile range. As most citizen contributions did not have a water level/velocity value, they received a minimum water level value. Because of that, the selected simulation was the one with more ‘overlaps’ and that would not perform better than a simulation with slightly higher rainfall. Yu et al. (2016) collected flood data through a Chinese website and divided it into calibration and validation data sets for a pluvial flood model verification. There is no mention of how this data is provided (e.g. text or image). Le Coz et al. (2016) obtained a discharge value for calibration of a hydraulic model based on the surface velocity data obtained by a video uploaded to a specific website. Kutija et al. (2014) collected pictures uploaded by citizens and extracted water levels from them by comparison with reference objects, such as cars (no further detailing on the method of extraction is made). Water level data is then used to validate a pluvial flood model.

The described approaches so far consider citizen data for model building and its possible extension for recalibration and revalidation. Four studies went one step further, integrating crowdsourced data into model usage. Mazzoleni et al. (2015, 2017) used synthetically generated data to represent citizen observations, which were incorporated in the model through data assimilation algorithms, adapted to deal with the intermittent nature of crowdsourced data. Aulov et al. (2014) and Fava et al. (2014) also used the data for simulation/data assimilation, but the methods used are not detailed in the studies. However, the studies of Fava et al. (2014) and Mazzoleni et al. (2015, 2017) were made for flood forecasting through hydrological models and not using hydrodynamic models.

2.3.2 Crowdsourced data information content

If we aim at integrating data into a model, data accuracy, volume and temporal and spatial coverage should be at a certain level. When these data properties are inadequate, data integration would not provide useful results (i.e. the model performance can be low). Although most modelling variables vary in time and space, the data does not need to cover all dimensions in all parts of the modelling process. For instance, in model setup, topographic data is not needed every 15 minutes, hourly or daily; it can be provided in a discrete time coverage, from months to years. We analyse four data properties: temporal coverage, spatial coverage, volume and uncertainty (Table 2.6). Although same for all parts, the last two properties vary significantly when analysing the information content of crowdsourced data and that is why these properties are included (Table 2.6).

Table 2.6. Data properties currently required in the modelling process

	Setup	**Calibration & Validation**[a]	**Simulation**	**Data assimilation**	**Data assimilation**
	Topography *Land Cover*	*Water Level* *Velocity* *Flood Extent*	*Water Level* *Velocity*	*Water Level* *Velocity*	*Flood Extent*
Temporal coverage	Discrete	Discrete/Continuous	Continuous	Variable	Variable
Spatial coverage	Distributed	Discrete/Distributed	Discrete	Discrete	Unknown
Uncertainty	The lower the better				
Volume	The higher the better				

[a] Dependent on purpose of the model

Analysing crowdsourcing studies by their information content, it is possible to draw the following conclusions:

- Model setup: for integration of topographic and land cover data, it is necessary to have spatially distributed data. While this has been achieved within land cover studies, there is only one study involving topography and the data obtained so far have discrete spatial coverage.
- Calibration and validation: through mining and crowdsourcing of water level and flood extent estimates, spatially distributed crowdsourced data have already been obtained for calibration/validation of simulation models. The accuracy of the time stamp was considered vital (Kutija et al., 2014) and results in time have a preliminary good level of agreement with citizen observations (Yu et al., 2016). However, even though these studies compare the results with citizen observations in time, this is done qualitatively and there is no focus on reporting and evaluating the temporal coverage.
- Simulation: traditional modelling efforts require time series of data at specific frequencies, which has only been achieved through crowdsourcing in the realm of community-based approaches, in which water levels are measured at 6 a.m. and 6

p.m. in agreement with the community (Walker et al., 2016). However, this type of data has been only monitored and not used in a modelling context so far.

- Data assimilation: it generally assimilates data provided with a fixed time frequency, but there are a few studies that consider intermittent data to be assimilated (Mazzoleni et al., 2015, 2017). However, similarly to simulation, the temporal coverage of crowdsourced data is insufficient for data assimilation efforts.

Considering uncertainty, this is highly dependent on the collection/analysis method. For example, obtaining water level values from pictures of flooded areas (2D) is uncertain, as it mostly involves the selection of what constitutes a good reference point to be made by the citizen. Flood extent, on the other hand, tends to be less uncertain to measure, due to its binary nature. The collection through data mining (and sometimes crowdsourcing) has, in general, more sources of uncertainty: from geotagging, timestamping and the observed value. To deal with the first two, Aulov et al. (2014) used only data that contained proper geotags and timestamps. Kutija et al. (2014) classified non-timestamped data as during or after the event, based on picture visual inspection, defining an observation time range. Smith et al. (2015) dealt with uncertainty in location by generating a histogram of simulated values around the observed point. Yu et al. (2016) acknowledged these sources of uncertainty. Regarding uncertainty in value, which exists in all sources of crowdsourced data, most studies used the (processed) observations as they were, without indication of uncertainty. Smith et al. (2015) defined ranges, although these are not discussed. Mazzoleni et al. (2015, 2017) used uncertain synthetic crowdsourced data with variable uncertainty.

Regarding the volume of data collected, this is an issue for all modelling processes, although data mining has again been able to provide a better coverage. Besides the challenge of uncertainty, data mining also has the challenge of providing data in conditions that are not extreme, as most of the contributions are done in flood situations and it is limited to certain variables (water level, flood extent and velocity). Some of the studies were proof of concepts and integrated up to 3 crowdsourced observations each (Fava et al., 2014; Le Coz et al., 2016; Shaad et al., 2016). Others ranged from 12 to 298 observations (Kutija et al., 2014; Smith et al., 2015; Yu et al., 2016), and in some cases, it was not possible to define the exact number of observations (Aulov et al., 2014; Dorn et al., 2014).

2.4 OPPORTUNITIES AND CHALLENGES

In recent years, the interest in citizen science and the number of citizen science studies in the water resources context have risen considerably. The main factors affecting its use in flood modelling are the degree of how difficult it is to acquire and evaluate these data and their integration into the models. Our analysis of the existing literature allows for pointing out a number of positive experiences from which we can derive opportunities to:

- Explore and improve the existing methods to obtain water velocity and topography from videos
- Explore calibration and validation employing data collected through social media in urban environments
- Explore the possibilities of setting up the models with the use of land cover maps validated with citizen science
- Make use of apps/websites already developed for citizen science

The first one is based on small-scale but successful studies related to using well-developed techniques in a citizen science scenario. The relevant experience in data gathering and analysis can be updated to fit the needs of flood modelling. Also, social media and public image repositories mining has proved to be successful in calibration and validation in modelling studies, proving the concept and opening the opportunity to investigate how large this contribution is. As mentioned previously, in the field of land cover map generation, citizen data has been used to validate maps and this successful example could be used to obtain new roughness maps in a modelling context. Lastly, technological development of apps, websites and techniques could be shared and put to public use, to be tested further and to avoid duplicated work.

There are aspects of the integration of crowdsourced data into flood modelling that are still challenging. These are:

- Explore the use of citizens as data interpreters
- Improve methods to estimate water level from pictures
- Harmonise the time frequency and spatial distribution of models with the ones of crowdsourced data
- Quantification of uncertainty
- Increase the volume of data gathered, mainly in non-urban environments

Most of the analysed studies regard the citizen as a sensor, except for studies about land cover-related data, in which the citizen also acts as an interpreter. For other variables, some studies have already started evaluating the ability of citizens to provide interpreted information (Degrossi et al., 2014), but these are few. Regarding water levels, readings from rulers and extraction from pictures are described differently in the literature, with varying degrees of thoroughness, indicating a need for development and testing of water level measurement methodologies in the context of citizens' contributions. The third point brings up a challenge that concerns not only citizen science but also modelling: what is the necessary temporal and spatial distribution for data collection? Is the traditional modelling approach definitive in terms of data requirements, and citizen science approaches should adapt to it, or, the modelling process can be adapted to receive citizen science data? Recent research has found that yes, it is possible for hydrological models to work with, and hydrological knowledge to be derived by, lower frequency contributions than traditional measurements, and even by contributions made in terms of classes, rather than values (Davids et al., 2017; Etter et al., 2020). The characteristics of the catchment and how severe are errors in the citizen data influence how much such contributions are applicable.

The fourth challenge relates to the quality of data and, again, in the area of global land cover maps some articles have already discussed the subject (Foody et al., 2013), but still, when modelling is concerned, the crowdsourced data are treated as traditional data and the issue of quality is hardly addressed (albeit recognized as an issue). To what extent does this assumption hold? What is the uncertainty in citizen science data? Lastly, there is a challenge mentioned by many studies but not really addressed in itself and it is the volume of data. Although the volume of data necessary depends on the objective of the modelling effort, the volume of crowdsourced data tends to be low, lacking temporal/spatial coverage for integration into models. This leads to the question: How to increase the volume of data? Considering this limitation, it is also natural to move towards the question: How much data is needed to improve the model significantly?

Application of citizen science in modelling brings an extra challenge of an interdisciplinary. Among similar technical fields (e.g. geosciences and hydrodynamic modelling), there is an issue of technology transfer to be addressed, and there are discussions on underlying assumptions and uncertainties that need to be considered. Additionally, hard and soft sciences are also very linked, as the quality and value of the citizens' observations and their temporal/spatial coverage are intrinsically related to social drivers such as why citizens engage, for how long, with which frequency and what is the role of various stakeholders.

2.5 CONCLUSIONS AND RECOMMENDATIONS

Citizen science has successfully made its way in many scientific domains and it is only fair that the contribution of citizens to modelling floods is also investigated, due to the related intensive data needs. Analysis of literature clearly shows an increasing number of scientific studies in this area. Successful examples of using existing measurement and analysis methods (e.g. velocity and land cover) and of modelling floods with citizen science data (e.g. social media mining) have been published and are seen as a good basis for further exploration. There is a clear need to standardise and consolidate methodologies and there are challenges involving the temporal and spatial distribution of data, uncertainty and volume.

It can be observed that the role of citizen contributions is not only in providing information about the current state of the environment, in monitoring and mapping studies, but also in providing data that can be used in its modelling and forecasting. Studies reviewed in this article showed that crowdsourced data can be integrated: in model building, to improve their overall performance; and directly into models (by data assimilation), to improve immediate forecasts. These are promising studies, however, still too few, and they highlight the need for further work in this direction. The integration of crowdsourced data into flood models is a viable way to help solve issues of data scarcity, with a higher potential in ungauged catchments and systems subject to change (e.g. climate change).

One of the challenges worth mentioning is the integration of citizen data with other more traditional data sources, like gauging and remote sensing. It is also necessary to analyse cases in which citizens are involved at higher levels of engagement (e.g. participating in the problem definition, analysis of results and even in the decision-making process) and to evaluate the trade-off between model data needs and levels of engagement. The active involvement of citizens may lead to more data collected, which in turn, may lead to more involvement and subsequently, to improved modelling of floods.

Finally, there is the challenge to make citizen contributions valuable in a time when automation is gaining increasing space. One may say that citizens are not needed because of automated sensors. At the same time, there are situations where crowdsourced data are very valuable. One of the non-technical challenges that we see here is to demonstrate such situations and increase acceptance of crowdsourced data by water managers.

3

CASE STUDIES

This chapter presents the case studies used to critically assess the design, efficiency and accuracy of citizen campaigns in obtaining data to inform flood modelling applications. Two case studies were selected: Sontea-Fortuna (Romania) and Kifissos catchment (Greece). The case studies' characteristics, their relevance and the specific area in which the research is applied are delineated in detail.

3.1 INTRODUCTION

Data collection campaigns of riverine and catchment conditions vary significantly depending on the purpose of data collection and the local context. To assess data gathering via citizen science in a plural manner, case studies with distinct characteristics were selected: the Danube Delta and the Kifissos catchment.

On one hand, the Danube Delta is a predominantly natural and flat wetland system, formed by a large network of canals and lakes (Oosterberg et al., 2000). Floods in the Danube Delta are a benefit for the local, unique ecosystem in the region (Navodaru et al., 2002). The understanding of water levels and velocities within the region allows for assessing the resilience of the ecosystem under competing water uses (Giosan et al., 2013; Oosterberg et al., 2000). Hydrometric information is also important for planning climate change adaptation measures (Bănăduc et al., 2023). In this thesis, the case study area is a subset of the Danube Delta, the Sontea-Fortuna area.

On the other hand, the Kifissos catchment is predominantly urban with steep slopes, and it is dry for most of the year, until flash floods occur, putting the society and economy at risk. The catchment is small and under a fast urbanization process, undermining the capacity of forecast and early warning systems. The sub-basin of Kifissos upstream of the location where the river goes underground is selected as a case study.

The research in this thesis is applied to case studies as presented in Table 3.1. The following sub-sections provide further information on case studies.

Table 3.1. Research application to case studies

Research	Chapter	Case study
Citizen science campaign design	4	Danube Delta, Kifissos catchment
Citizen-contributed river data quality analysis	5	Danube Delta
Modelling application – Hydrodynamic modelling	6.2	Danube Delta
Modelling application – Hydrological modelling	6.3	Kifissos catchment

3.2 Danube Delta

As the Danube River nears the Black Sea, it branches out to form the Danube Delta, a transboundary wetland system spanning parts of Romania and Ukraine (Figure 3.1). It covers an area of 4,455 km^2, with 79% lying within Romanian territory, and it is the second largest wetland in Europe (Baboianu, 2018). The river fans out into a delta by splitting into three main distributaries: Chilia, Sulina, and Sfântu Gheorghe. The delta's hydrographic network is extensive, comprising nearly 3,500 km of waterways, including both natural streams and man-made canals, and contains close to 500 lakes, which collectively cover 258 km^2 (Oosterberg et al., 2000).

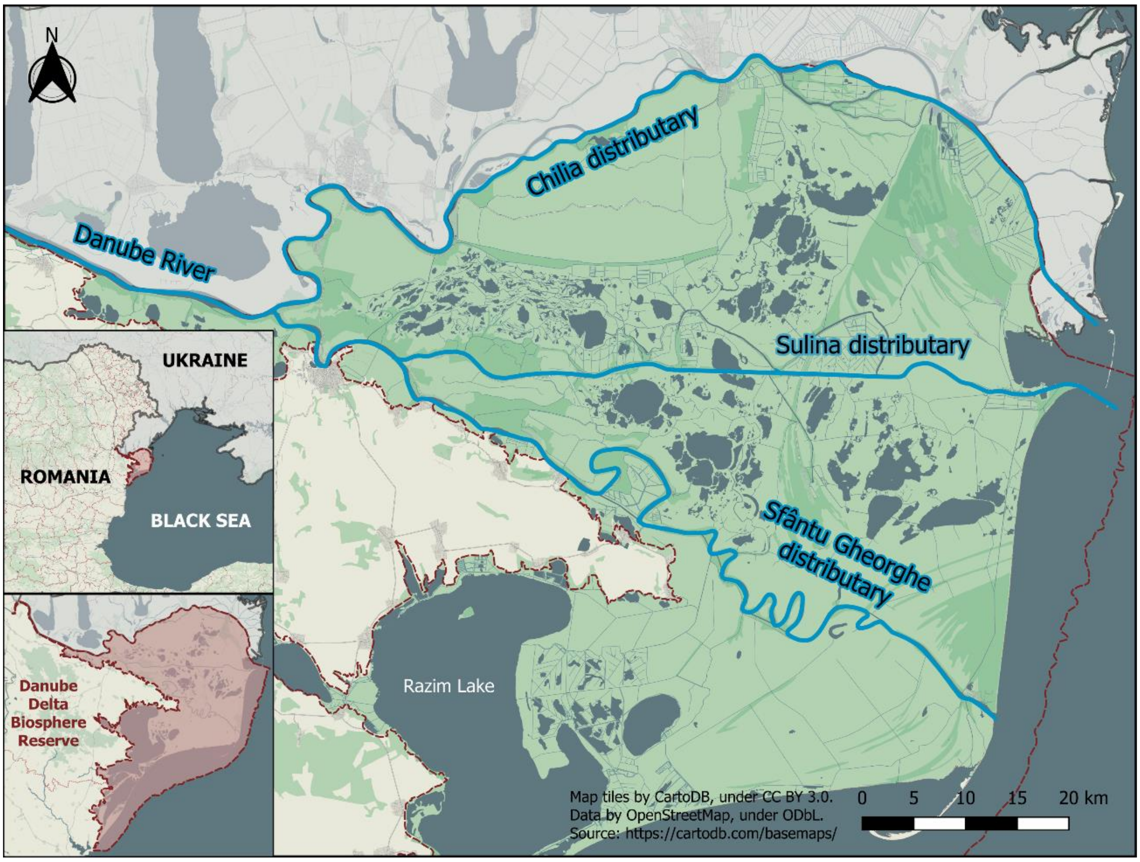

Figure 3.1. The Danube Delta and the main distributaries of the Danube River

During the 20th century, in efforts to enhance navigation, to manage floods, and ultimately to support economic activities such as agriculture, fishing, reed harvesting, and forestry, the Danube Delta was heavily modified (Tiron Duţu et al., 2022). Natural waterways were dredged and new channels and polders were created, reshaping the delta's connectivity (Figure 3.2). For instance, between 1948 and 1992, the area of polders expanded eightfold (up to 976 km^2), whilst in the 1950s, the river network was extended by approximately

700 km (Bondar and Panin, 2001). Further engineering works were carried out in the 1980s to shorten and deepen the Sulina and Sfântu Gheorghe distributaries, and embankments were also constructed along major distributaries (Bondar and Panin, 2001).

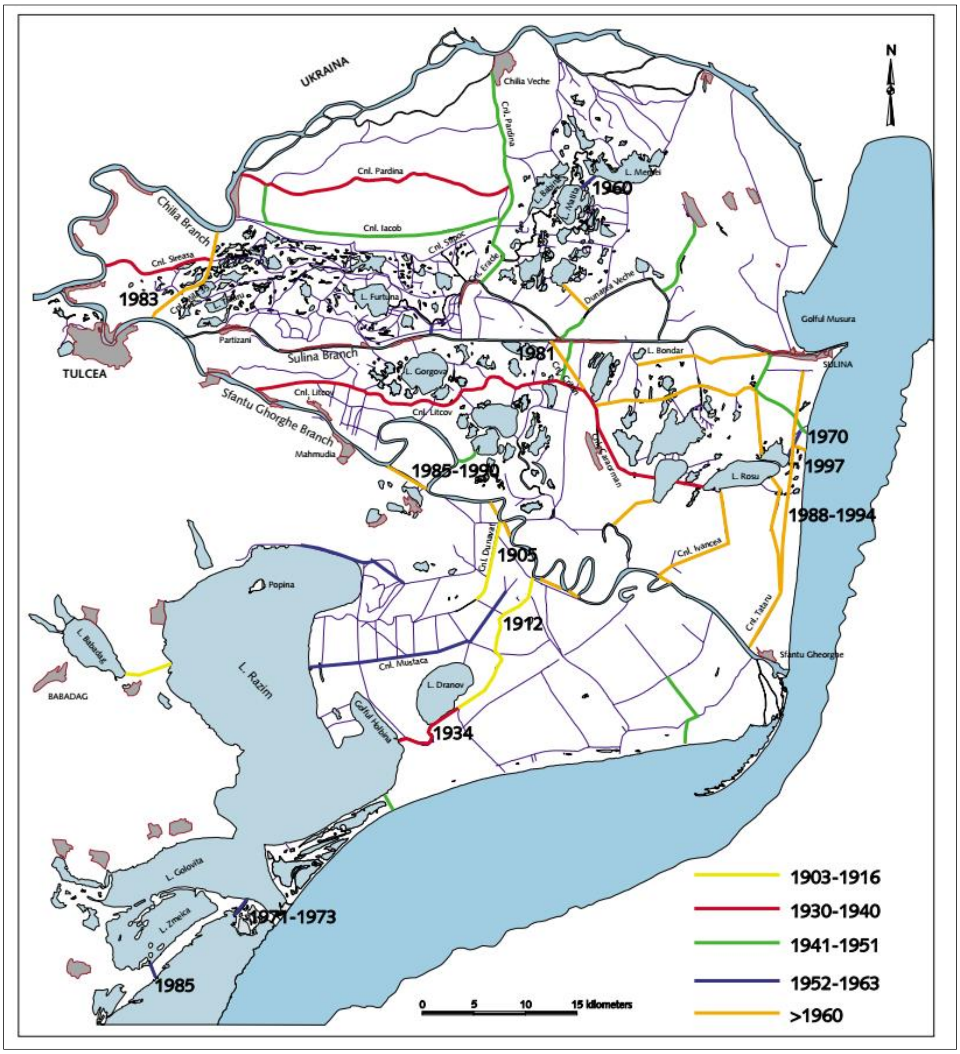

Figure 3.2. Hydrotechnical history of the Danube Delta.
Source: Oosterberg et al. (2000)

Topographically, the delta is situated at an average elevation of 0.52 m, with an average terrain slope of 0.043%. Over half of the delta (54.5%) lies between 0 and 1 meter above sea level, and about 21% is below sea level (Figure 3.3). Beyond water surface areas, inland marshes, non-irrigated arable land and broad-leaved forests dominate the land cover (Figure 3.4). In terms of precipitation, the Danube Delta experiences a relatively low annual average of approximately 350 mm, while potential evapotranspiration almost triples this amount, reaching around 1,000 mm per year (Oosterberg et al., 2000). Wind is persistent in the area, occurring roughly 80% of the time throughout the year. Although wind directions vary, there is a slight predominance from the northwest, with the strongest winds typically observed near the coastal areas (Oosterberg et al., 2000). In terms of soil, interactions with groundwater are considered minimal or negligible, once the delta's soils are generally saturated for most of the year (Oosterberg et al., 2000).

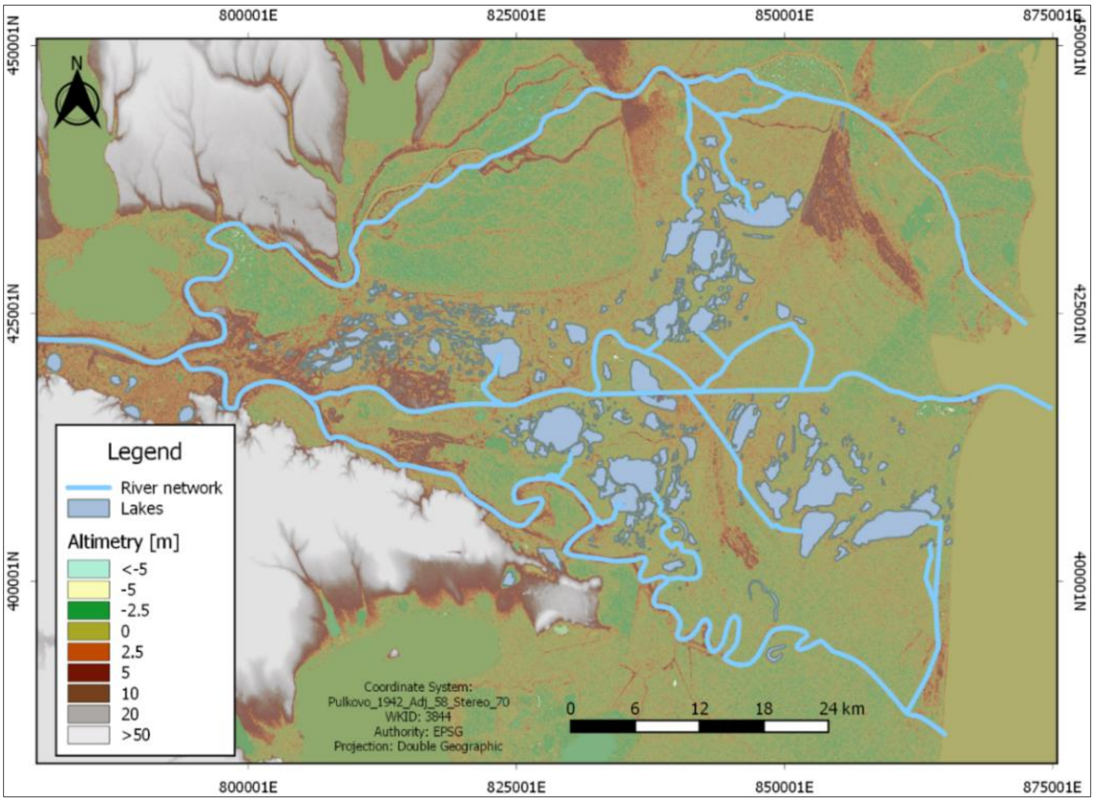

Figure 3.3. Digital Elevation Map (DEM) of the Danube Delta. Data source: NASA Shuttle Radar Topography Mission (SRTM, 2013)

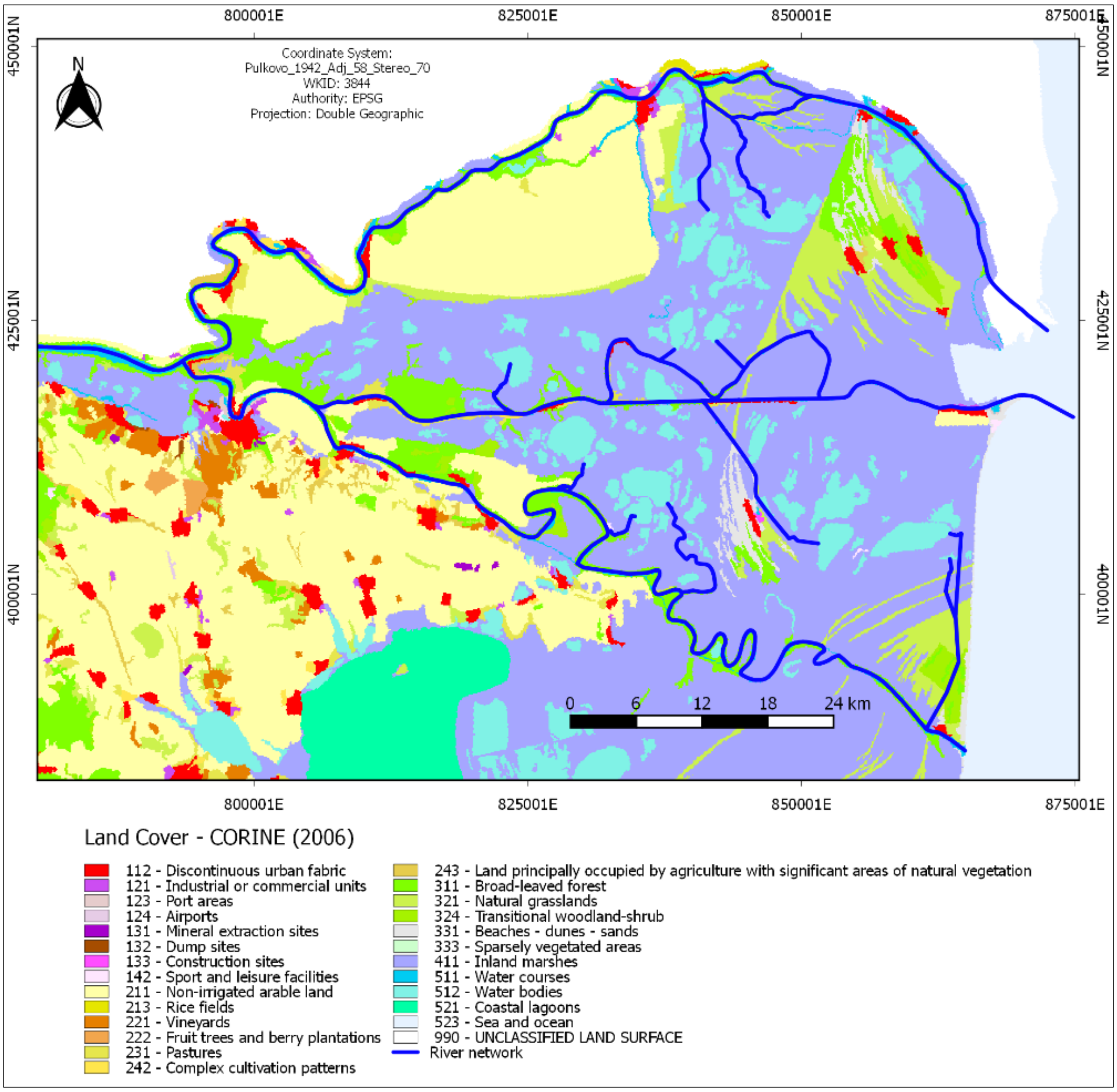

Figure 3.4. CORINE Land Cover classification of the Danube Delta for the year 2006. Data source: European Environment Agency (EEA, 2006)

Considering flows in the Danube Delta, the Danube River has an average discharge of 6,283 m^3/s, based on data from 1840 to 1990 (Bondar and Panin, 2001). Before the intense period of interventions in the delta, over 70% of this discharge reached the sea via the Chilia distributary. After, the flow became more distributed: 57% through Chilia, 18% through Sulina, and 25% through Sfântu Gheorghe. Of the Danube's total discharge, around 5% is diverted into the interior of the delta (Popescu et al., 2015). This proportion varies seasonally; during low-flow periods, more water exits the inner delta than enters it, while the opposite occurs during high-flow conditions (Bondar and Panin, 2001). Increased inflow to the inner delta is linked to the overtopping of natural levees when the Danube discharge exceeds 9,100 m^3/s (Bondar and Panin, 2001). Seasonal water level variations, based on measurements at Tulcea (Figure 3.1), indicate high flow conditions from March to June (Figure 3.5), during which water levels rise by 1 m on average, though an increase by 3 or 4 meters can occur (Niculescu et al., 2010). At the distributaries' outlets, a 0.6 meter above sea level (m.a.s.l) can be assumed, as tidal effects in the Black Sea are insignificant (Popescu et al., 2015).

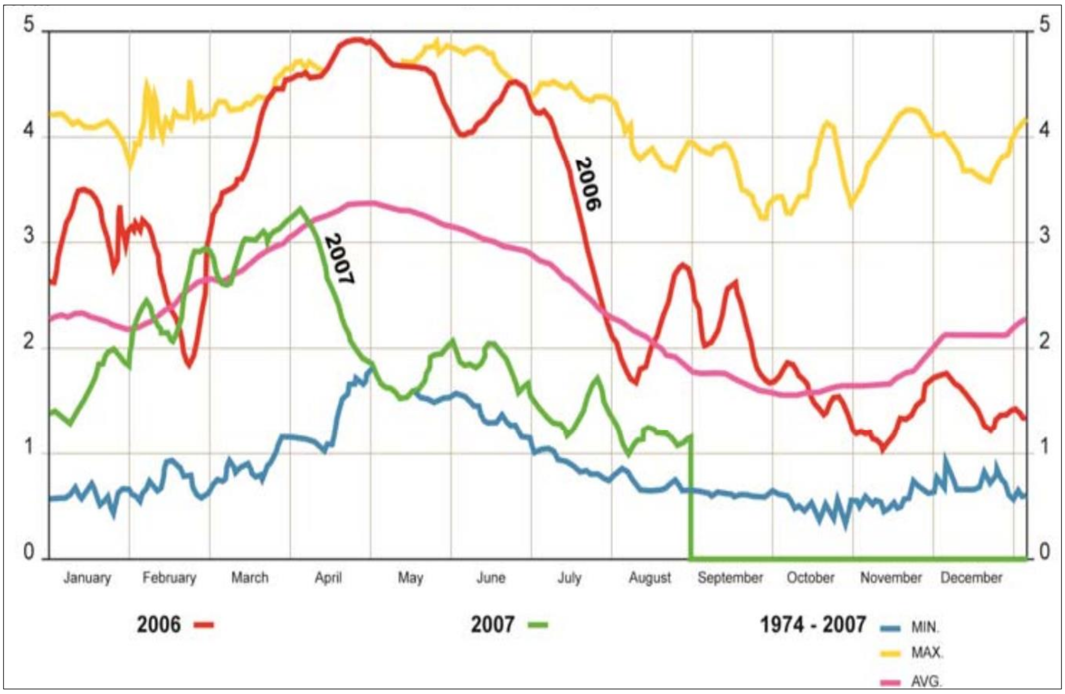

Figure 3.5. Danube water levels (in meters) at Tulcea (1947-2007). Source: Niculescu et al. (2010)

The importance of the Danube Delta's biodiversity and ecology is recognized at national, European and international levels. In 1990, the Government of Romania designated the Danube Delta, in conjunction with the Razim-Sinoe lake complex, as a Biosphere Reserve (Figure 3.1, Gâștescu, 2021). Several strictly protected zones are listed as UNESCO World Heritage sites. Under the Ramsar Convention, the Danube Delta is documented as a wetland of international importance, mostly due to its significance as a waterfowl habitat (Oosterberg et al., 2000). The delta contains a very high biodiversity, comprising 2,383 plant species and 4,029 animal species. Among these, 13 fauna species have been classified as Nature's Monuments, indicating their conservation priority (Danube Delta Biosphere Reserve, 2017).

Despite its protected status, the delta faces ecological pressures linked to hydrological changes. Seasonal flooding plays a vital role in recycling nutrients and supporting a rich and balanced fish community in the Danube Delta (Navodaru et al., 2002). Hence, increased river discharge, reduced sediment transport, and shifts in nutrient dynamics have affected ecosystem functioning (Constantinescu et al., 2023). Rising temperatures and sea levels due to climate change could affect around one-third of the Danube Delta's fish species (Bănăduc et al., 2023). These changes highlight the need for improved river basin management, including monitoring systems and flood modelling tools to support adaptive decision-making (Giosan et al., 2013; Oosterberg et al., 2000). In response to degradation, restoration efforts have targeted areas with low economic productivity or abandoned. Three polders were converted into ecological restoration zones between 1994 and 2000, to reintroduce natural processes and improve habitat conditions (Hein et al., 2016). Recent efforts to understand water quality problems made use of machine learning and satellite data to estimate water physico-chemical parameters across the delta, an approach that yielded fairly good results for most parameters (Necula et al., 2022).

The Sontea–Fortuna hydrographic complex, located within the Danube Delta Biosphere Reserve (DDBR), was selected as the case study area for this research (Figure 3.6). It is one of the seven major hydrographic units in the DDBR and spans approximately 267 km². The largest water body within this complex is Lake Fortuna. This area was chosen due to several key characteristics that were delineated as important to local stakeholders (in consultation, see Chapter 4). First, it is among the first regions in the delta to be affected by flooding events. Second, it includes the Nebunu protected area, and approximately half of its surface lies within a designated buffer protection zone (Gâştescu, 2009). These conservation features coexist with fishing and with active economic areas, including agricultural land in surrounding polders and commercial activity in the city of Tulcea. In more practical terms, there is enough data from the Sontea-Fortuna area to build a hydrodynamic model and it is close to population centers, which facilitates the design of campaigns, data collection and citizen engagement.

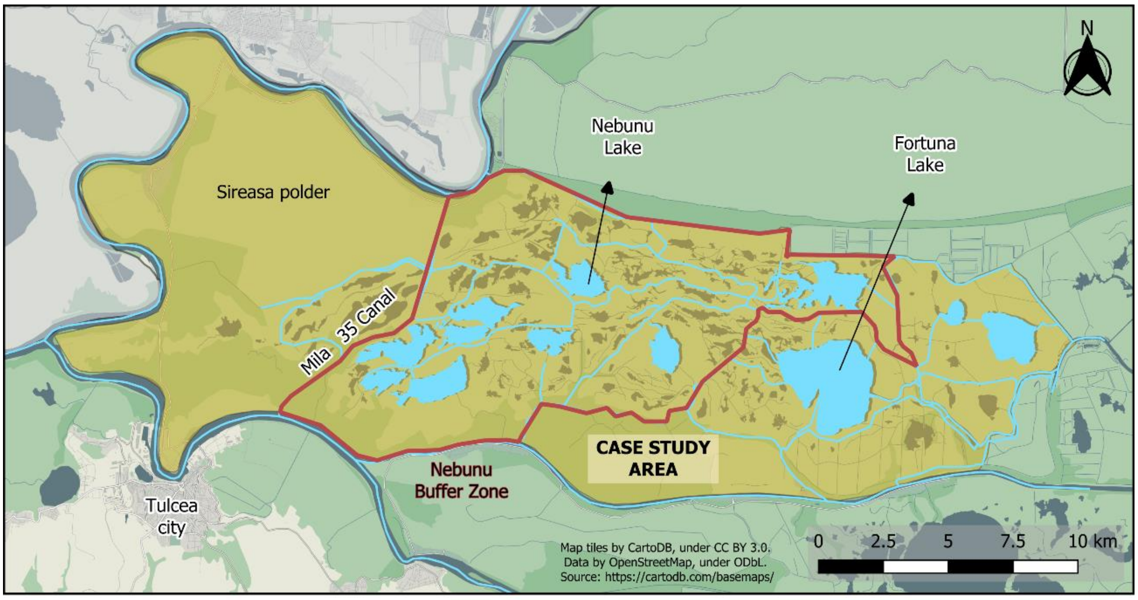

Figure 3.6. The case study area. It is composed of the Sontea-Fortuna hydrographic area and the Sireasa Polder

3.3 KIFISSOS CATCHMENT

Kifissos and Ilissos are the two largest catchments that compose the Athens Basin, located in the Attica region, in Greece, which is surrounded by mountains (Figure 3.7). Athens Basin has an area of 534 km^2, out of which around 379 km^2 (71%) belongs to the Kifissos catchment (Diakakis, 2014; Koussis et al., 2003). The Athens basin is 68% urbanized and has an approximate population of 4 million residents. The Kifissos catchment encompasses the city of Athens and more than 31 municipalities.

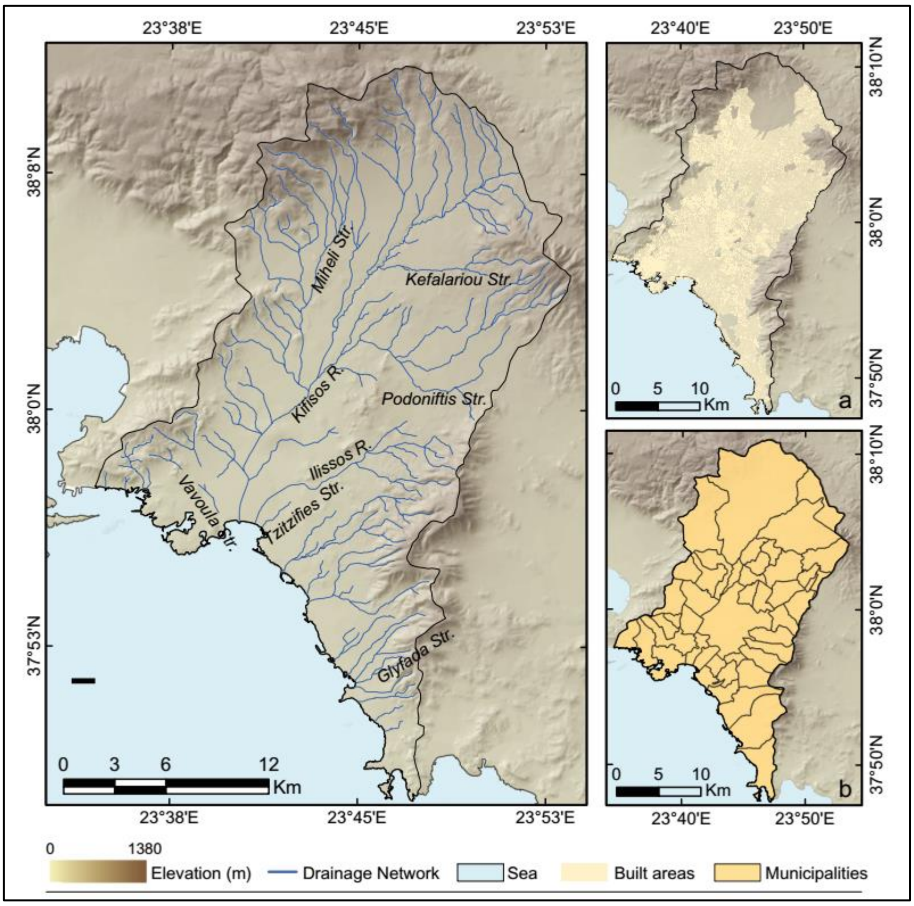

Figure 3.7. Map illustrating the extent of Athens basin, the drainage network, the built areas (a) and the local administrational entities (b). Source: Diakakis (2014)

The main channel of Kifissos River has a total length of about 40 km, crossing Athens (for 25 km) and discharging into the Saronic Gulf (Bathrellos et al., 2016). Kifissos River had around 42% of its length altered: 6.2 km channelized and 8 km transformed into underground waterways (Figure 3.8). Additionally, artificial stone embankments were made along open stretches of the river and its cross-section enlarged in downstream reaches (Bathrellos et al., 2016). In the upper parts of the catchment, pervious areas were substituted by impervious ones and rivers are turned into streets or built upon, due to the urbanization process (Baltas and Mimikou, 2002).

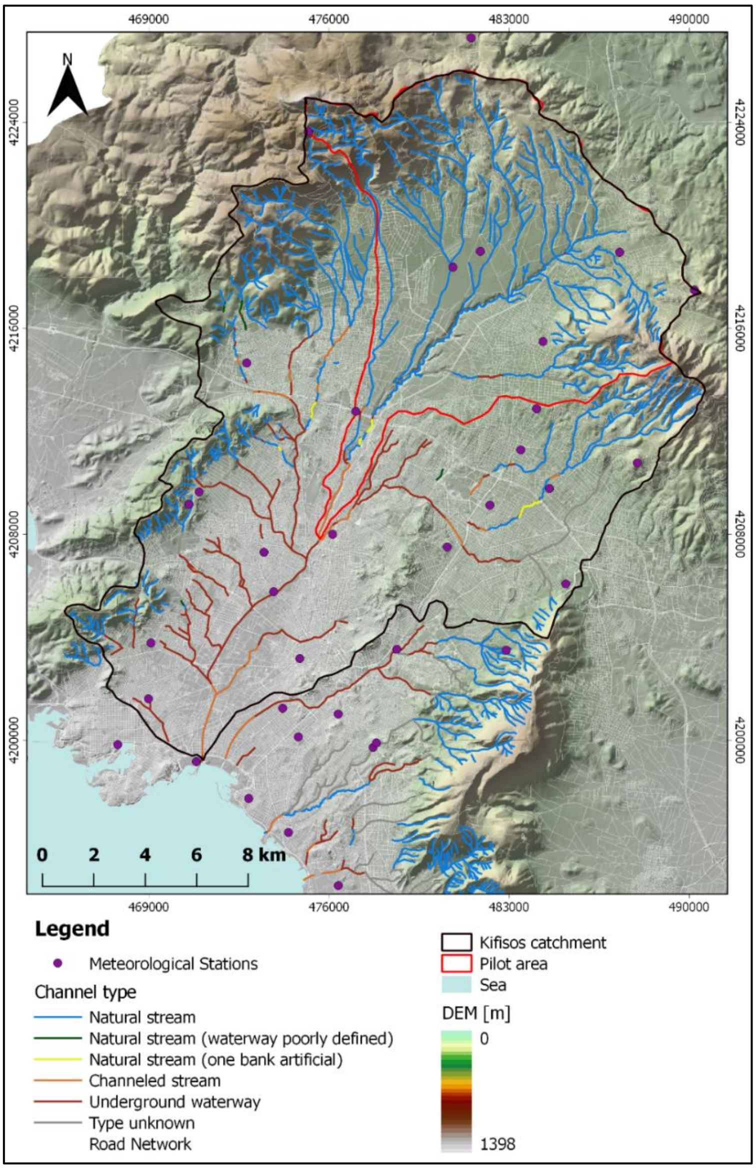

Figure 3.8. Kifissos catchment map, with channel type, location of meteorological stations and the elevation map (DEM). Delineated in red, the study area for this thesis

Unfortunately, flow information is scarce due to a lack of discharge and water level data at the time of this study. Most time of the year, there is little or no flow through the river network. The Kifissos River was partially modified to handle 1 in 50 years floods, mainly by enlarging the downstream cross section to accommodate discharges of 1,400 m^3/s (Diakakis, 2014; Evelpidou et al., 2009).

The topography of the area has two main characteristics: steep slopes in the upstream part, with a change in elevation from around 200 m to 1,412 m; and a flatter terrain, varying approximately from 0 m to 400 m, in the downstream part of the basin (Figure 3.8). The soil from the Kifissos catchment is predominantly semi-permeable (Figure 3.9a).

However, the land cover (Figure 3.9b) is mostly urban, creating an extensive impervious layer above the soil. Other important land cover categories are vegetated and agricultural areas.

According to Bathrellos et al. (2016), the climate in the Athens Basin is Mediterranean, which means that it tends to have dry summers and mild, moist winters. Considering the period from 1973 to 2003, the coldest and hottest months of the year are January and August, respectively. The mean annual air temperature is 18.8 °C and the mean annual precipitation is approximately 332 mm (Bathrellos et al., 2016). Although the annual precipitation is low, the maximum daily rainfall value for a return period of 1 in 50 years is comparable to the value encountered in western Greece, where the mean annual precipitation exceeds 1800 mm (Baltas and Mimikou, 2002). Koutsoyiannis and Baloutsos (2000) estimated that the potential evaporation in the area is more than three times the amount of precipitation.

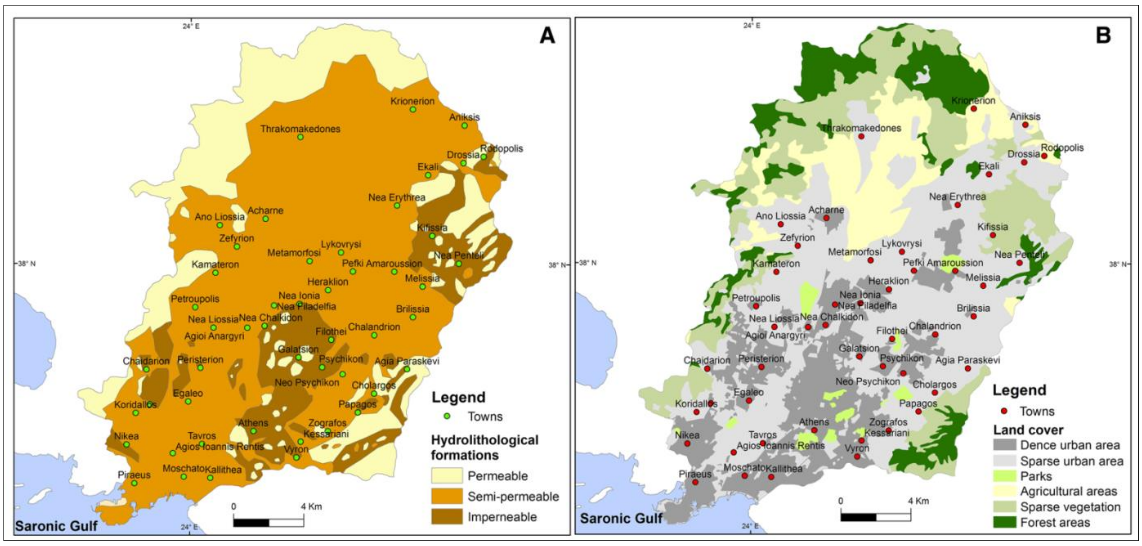

Figure 3.9. (a) Map showing the spatial distribution of hydrolitological formations. (b) The land cover in the basin of Athens. Source: Bathrellos et al. (2016)

Kifissos catchment is a flash flood-prone area once, as a consequence of the steep slope upstream, intense rainfall events are translated into high velocity flows. These flows are restricted to a low-density river network with small cross sections, often overflowing the channels. Diakakis (2014) made a complete inventory of flood events in the Athens Basin for a period of 130 years (1880-2010), utilizing all available sources of information about floods, estimating an occurrence of 52 flood events with 182 casualties. The author concluded that there is a positive trend in flood events, although not in casualties, and that most incidents occurred in the Kifissos catchment in autumn. The incidents are spread over the river network, with higher occurrences closer to the rivers’ mouths.

The study area for the Kifissos case study is situated in the upper part of the Kifissos catchment and covers 136.5 km^2 (the basin highlighted in red in Figure 3.8). It is a region where the drainage network has not been heavily modified, and where hydrological processes are dominant. It is also the area where urbanization processes are transforming the land cover the most.

4

DESIGN OF CAMPAIGNS FOR CITIZEN OBSERVATORIES

This chapter explores this issue of assessing the entire citizen data collection cycle: from the inception of campaigns to the final amount of multimedia collected by citizens[5]. The chapter briefly points out the relevance of defining purposes for data collection connected to the local context and delineates an empirical framework for data collection that is adapted to the goals of local stakeholders. It includes a description of campaign organization details (e.g. number of campaigns) and design choices related to points of interest and routes. The campaigns were carried out in the context of the Scent project for the case studies of Sontea-Fortuna and Kifissos catchment. Data collected included pictures of water depth gauges, pictures of land cover and videos of tennis balls in the river. A parallel was drawn between the expected and final amount of multimedia collected. Overall, the amount of multimedia collected to obtain water depth and velocity estimates greatly exceeds amounts previously reported in the literature, demonstrating the potential of campaigns, mainly in natural environments. It is clear that the campaign design choices affect the amount of data collected and, as such, should be reported and analysed when discussing the value of contributions made by citizens.

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[5]This chapter is adapted from:

Assumpção, T. H., Jonoski, A., Theona, I., Tsiakos, C., Krommyda, M., Tamascelli, S., … Popescu, I. (2019). Citizens' campaigns for environmental water monitoring: lessons from field experiments. IEEE Access, XX, 1–18. https://doi.org/10.1109/ACCESS.2019.2939471

Venturini, A. B., Assumpção, T. H., Popescu, I., Jonoski, A., & Solomatine, D. P. (2019). Modelling support to citizen observatories for strategic Danube Delta planning: Sontea-Fortuna case study. Journal of Environmental Planning and Management, 62(11), 1972–1989. https://doi.org/10.1080/09640568.2018.1523787

4.1 INTRODUCTION

Advancements in the Internet of Things (IoT) technologies, including smart sensors and wireless networks, are recently enabling much more efficient in-situ sensing, especially in urban water systems within the overall concept of smart cities development (Rashid and Rehmani, 2016). Further, environmental monitoring in general, including water resources, has greatly benefited from remote sensing (Bozza et al., 2016). Another source of information is 'citizen science' or 'citizen observatories', in which citizens contribute with data, with their ability to interpret information or through distributed computing (Haklay, 2013; Yadav et al., 2018).

With the emergence of all these new sources of data, there is a lack of guidelines on their application to different local and regional contexts. For example, in water quantity estimation in urban water distribution networks, new devices and network technologies are presented as part of the overall water supply system with clearly identified data needs for their area (Hsia et al., 2013; Lubega and Farid, 2016). In general, all urban water systems have these characteristics, due to the rather centralized management of the system by water utility organizations. However, when monitoring environmental water resources, the connection to the local decision-making context is more difficult, due to the diverse number of involved stakeholders and overlapping management responsibilities of the involved institutions. Also, environmental water resources are much more affected by the challenges that are still present in using IoT technologies for monitoring. These include the inherent cost for each sensor device, which increases exponentially in relation to the technological features provided (sensor type, resolution, energy bank, transfer speed, transmission power, etc), as well as the associated costs of deployment and long-term maintenance. Therefore, it is still difficult to take advantage of such sensor networks and their autonomous operation in collecting quantitative measurements, in communicating to each other (local routing/relaying) or directly to a central hub and, eventually, enriching a global measurements map for a specific spatiotemporal domain (Tiwari and Chatterjee, 2010). With these aspects in mind, scaling up the current wireless sensor networks in the realm of big data applications is still problematic, if not unfeasible altogether for many domains, including monitoring environmental water resources (Bhattacharyya et al., 2010; Carlos-Mancilla et al., 2016).

Similar challenges also appear in citizen science and citizen observatories for water monitoring, for which contributions from volunteers are either opportunistic (i.e. citizens contribute at random locations and/or at random times) or are restricted to small-scale experiments (i.e. at very specific and limited locations and moments in time) (Assumpção et al., 2018). There are community-based monitoring efforts with clear data collection objectives, for which collection protocols and citizen science research are more consolidated, although these tend to concentrate on collecting water quality data (Carlson and Cohen, 2018). For monitoring water quantity in the environment, the link between emerging data sources and collection strategies and actual data collection needs is poorly described in the scientific literature.

In view of this background, the overall objective of this research is to tackle a common challenge to citizen science, IoT and new sensor technologies: the lack of connection with a local context. In other words, how to adapt citizen science and new sensing technologies to collect data that is useful to local authorities? More specifically, we aim to evaluate the feasibility of implementing such an author-centric approach in citizens' campaigns. By author-centric, it is meant adapted to data needs identified by the managing water authorities and diverse stakeholders. Further, we also present technologies adapted to dealing with identified needs, although the main focus is on discussing the practical aspects of field experiments. We gauge its success in terms of citizen experience and efficiency of data collection through the data cycle. We also present a method to select points of interest to fulfill stakeholders' interests and to define routes that maximize data collection.

The approach both requires and supports a stronger partnership among the authorities, stakeholders and citizens, leading to clear identification of data needs, with shared understanding and purpose by all involved parties. Actual data collection takes place with targeted campaigns, in which supporting web and mobile phone applications allow authorities to set parameters of the campaign (type of data to be collected, duration, points of interest), while the citizens carry out the campaigns using an entertaining game-like mobile phone app. The approach has been developed within the framework of a European research project from the H2020 programme, entitled Smart Toolbox for Engaging Citizens into a People-Centric Observation Web (Scent). The project aims to develop a strategy to engage citizens in environmental monitoring (Tserstou et al., 2017). Several field campaigns have taken place within this project. This chapter presents the experiences and lessons learned from some of the field campaigns conducted in both project case studies, the Danube Delta in Romania and the Kifissos catchment in Greece.

This chapter is structured as follows: Section 4.2 discusses the conceptual framework within which the citizens' campaigns are organized; Section 4.3 describes the tools developed to overcome the challenges delineated in Section 4.2, and a novel approach for the selection of routes for data collection. Section 4.4 presents the results and discussion on the effectiveness of the proposed adaptive methods, including the lessons learned from campaigns organized within the Scent project; Section 4.5 closes the chapter with conclusions and recommendations.

4.2 Conceptual framework for environmental water resources data collection with citizens' campaigns

Citizens' participation in data collection for science can be traced back to the 17th century, followed by the uprising of citizen science and citizen observatories projects in diverse fields (Bonney et al., 2009; Miller-Rushing et al., 2012). As a result, frameworks have been created to classify and understand them. In the following sub-sections, we situate this study within existing frameworks and propose one for analyzing citizen campaigns. The latter is aimed at better communicating the challenges involved in the data collection cycle of this study. Although suggestive, it is not intended as a generic framework for citizen science projects involving campaigns, as for that, sociological research is needed, which is outside the scope of this study.

4.2.1 Research placement within existing frameworks

As discussed in Section 2.1.2, one important distinction among citizen science initiatives is the degree of participation, from citizens as data collectors to collaborators in designing the research (Haklay, 2013). In this study, citizens contribute by collecting data and interpreting it, via the two lower levels of engagement (crowdsourcing and distributed intelligence). Considering the framework on the kind of information collected (geographic or not) and if it was contributed voluntarily or implicitly (Craglia et al., 2012), Scent is placed in the center of these two methods (see Section 2.1.2). This chapter is focused on the presential citizens' campaigns, to collect land cover, water depth and velocity information. Therefore, it can be classified as both implicitly and explicitly geographic and as explicitly volunteered.

The purpose of a citizen science campaign can also be seen as a framework in which it is inserted. As citizen science has evolved as a concept, it encompasses an increasing variety of contexts and purposes. For example, in a study conducted by Carlson and Cohen (2018), participants from community-based monitoring organizations in Canada were interviewed on the purpose of their program. Answers were grouped into five categories, with the most popular one being to deal with their concerns about ecosystems. The remaining categories were related to: incentivizing education and engagement; acting against the lack of data; providing content for managerial decisions related to the local ecosystems; and taking part in research and in building a baseline database to discuss trends. Scent has the purpose of setting up a toolbox to facilitate citizens in generating content for managerial decisions. The difficulty in establishing the link between data collection and its usage for the local management process was emphasized in the study by Carlson and Cohen (2018).

One of the main challenges of citizen science initiatives is data quality (Zheng et al., 2018). Recent research shows that in some fields, citizen data quality can surpass that of experts, while in others, it is not good enough (Kosmala et al., 2016). However, it is a consensus that there is a need for more detailed reporting and standardization of methodologies for collecting and evaluating citizen data (Kosmala et al., 2016; Zheng et al., 2018). This chapter presents the implementation of a chain of novel, untested technologies in the broader framework of setting these tools in a campaign context. As such, it presents basic raw data quality control routines and how they perform. A detailed delineation of quality control and analyses of data collected via citizen campaigns is presented in Chapter 5.

4.2.2 Citizens' campaigns framework

Several technological advances for aiding citizen science projects were made previously, composing a dense body of literature spread through many fields. For example, in the eBird project, over the years, a flexible platform was developed for collecting data in three ways (website, forms and apps), verifying it and distributing it for multiple user communities (Sullivan et al., 2013). Another example is the author-centric approach proposed by Kim et al. (2013).

As mentioned in the previous section, for environmental water resources, most current platforms are not driven by data use. Therefore, the link with the local context can be studied by conceptualizing the data collection within a cycle (Figure 4.1):

- Stakeholders' data collection needs are identified
- Information regarding the required data is communicated to the citizens' groups that are to be involved in the campaigns
- The campaign is organized: citizens are encouraged to volunteer and participate in the data collection in required locations and periods that fulfil identified needs (e.g. water levels, velocities, discharges, etc.)
- Dedicated data acquisition tools are developed and tested
- Data are collected during the execution of campaigns
- Data are shared with authorities and other stakeholders
- Data are used for identified purposes (e.g. monitoring, modelling, assessment, management actions, etc.)
- Results from the usage of data are provided together with feedback to the participating citizens/volunteers

The cycle components represented in blue boxes are considered here as complex processes that involve multiple actors and processes, while those represented with red arrows are considered support tools for moving within the cycle from one component to another. The cycle presented is a conceptual framework for discussion, rather than the architecture of the data collection framework, which is briefly discussed in Section 4.3.

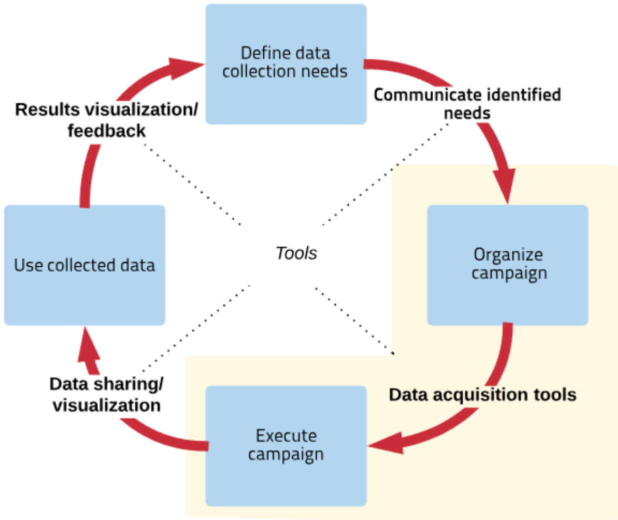

Figure 4.1. Data collection cycle for citizens' campaigns in water management. This study focuses on the lower left corner, highlighted in yellow

Using this conceptual presentation, we can now briefly describe the purpose of each component together with the current challenges for its implementation. We highlight that although we discuss the full cycle, the focus of the research is on the organization and execution of the citizens' campaigns, as mediated by technological tools (the right and bottom-right corner of Figure 4.1).

The first item of the cycle, data needs identification, is a participatory process in which stakeholders are gathered in dedicated workshops, often supported by web information platforms. Structured approaches are commonly used, in which the problems of interest to different stakeholders are mapped and scientific objectives or management goals are identified. These are then disaggregated and hierarchically organized in tree-like structures so that the low-level nodes are in fact associated with data needs. The main challenge is to engage in this process representatives of local volunteer groups (e.g. Non-Governmental Organizations - NGOs) that can, in fact, mobilize the citizens in the follow-up campaigns and link the data needs with immediate concerns within a particular location (see, for example, Newman et al., 2017). Further challenges are those of diverse knowledge needs of different stakeholders, conflicting interests, and the necessity for prioritizing data needs, given the limited availability of resources. These challenges regularly occur in water resources, given their shared nature. More focused data needs identification associated with a particular water problem (e.g. flood management, specific water quality problem, or similar) would lead to easier prioritization and well-targeted campaigns. In turn, this approach contributes to the broader goals of citizens' engagement in the co-creation of solutions to water problems.

Tools for communicating the identified data needs to a broad group of citizens and volunteers are currently lacking. Translating the data needs from the identified scientific objectives or management goals to content and form that is both easily understood and motivating for the citizens is challenging. Such tools and applications also need to develop and maintain the trust and partnership between the water management authorities and the broader stakeholder groups and citizens. In some cases, this is achieved through the use of specific tools that allow the set-up of data collection surveys/campaigns, enabling users to create new campaigns, modify existing ones, and view campaign data on a map-based interface that displays the locations where observations were made, along with observation data (Butchart et al., n.d.; Higgins et al., 2016; Kim et al., 2013). Other approaches involve the use of mobile applications towards the acquisition of environmental-related information and communication of the latter in dedicated repositories (Chacon-Hurtado et al., 2017; Kim et al., 2011). However, such cases do not support the customization and configuration of the data acquisition tools, and thus do not support the proper connection to the interested stakeholders' requirements and needs. The actual organization of citizens' campaigns would greatly benefit from innovative tools that could enable water management authorities to design and set up citizens' campaigns for a particular water-related problem. The campaigns themselves, however, require more organizational efforts in terms of logistical support. With citizen observatories still in development, these tasks are commonly carried out within particular research projects.

Not only is there the challenge of operationalizing campaigns within local institutions, but campaign organization itself is also a complex, context-dependent process for which decisions directly influence the results. It can be encapsulated in three general steps:

- Volunteer recruitment
- Dates and duration definition
- Points of Interest and routes definition.

The execution of these steps is also affected by the number of campaigns, their periodicity and the types of data being collected.

The acquisition of data for water management encompasses multiple domains: the weather, the flows and the geography. In this way, there are various types of data that can be collected, requiring different data acquisition tools. We will discuss here tools for acquiring Land Cover/Land Use (LU/LC) information, and for water quantity measurements (water level and water velocity), as these were the main target variables in our citizens' campaigns. The following discussion focuses on the tools used for data collection, while Chapter 2 provided a deeper overview of the innovations and overall literature on these variables.

LU/LC information is needed for many application areas, beyond the water domain, such as transportation, spatial planning, etc. Community mapping and web and mobile apps through which citizens can provide such information are already in place (see, for example, Olteanu-Raimond et al., 2018). The apps commonly require citizens to annotate LU/LC features from a pre-defined taxonomy, either using externally generated images (by remote sensing, or by other contributors) or images taken by their mobile phone camera. The main challenge here is the integration of the citizens' data with other sources, such as remote sensing, especially drone-generated data.

In terms of water level, one of the most basic forms of data collection is manual annotation of water levels from installed gauges (Walker et al., 2016). These records are usually given directly to the authorities/researchers or uploaded to a database. With the advancement of mobile technology and the Internet of Things, initiatives in which citizens send text messages with such water levels started to appear (Alfonso et al., 2010; Jonoski et al., 2012; Lowry and Fienen, 2013), as well as sending their readings through dedicated apps or websites (Degrossi et al., 2014; Fava et al., 2014). The process of obtaining data from gauges is limited to these actions, without any automation. While there are many methods dedicated to text extraction from images, known as Optical Character Recognition (OCR), to the best of our knowledge, there are no efforts to implement these techniques for water level extraction. On the other hand, apps and websites have been used for collecting images of floods (Starkey et al., 2017). The water level estimation is mostly manual from these images.

For water velocity measurements, due to their complexity, there are few studies that use applications with which citizens would contribute such data. Volunteers have been instructed to make direct velocity measurements and provide their values, without the use of a tool (IDEM, 2015). Citizens were also asked to upload videos to a dedicated website, which would be used to extract the velocity using the LSPIV algorithm (Le Coz et al., 2016). In the latter, only one video was uploaded. Likewise, measurements of discharge are equally or more complex. In a review about that, Davids et al. (2018) discuss that there is a lack of studies in which volunteers use existing smartphone-based video processing methods. The authors then proceed to evaluate the applicability of simple streamflow measurement methods for citizens. After selecting and testing three of them (float, salt dilution and Bernoulli run-up), they conclude that salt dilution worked better for their case study in Nepal, while the float method was the simpler one to perform. Similarly to water level, the challenge is to introduce a procedure by which water velocity estimates would be automatically provided from videos provided by citizens.

Citizen-generated data show a particular diversity in terms of their type and characteristics. This, in combination with the continuously increasing volume of citizen science data, necessitates the need for efficient and standardized management, sharing and visualization of such data. Most of the relevant applications capitalize on a variety of open source platforms and tools, focusing on the visualization of the information collected from the citizen scientists in a dynamic way. To this end, Open Geospatial Consortium (OGC) standards such as the Web Map Service (WMS), Web Feature Service (WFS) and/or Sensor Observation Service (SOS) are utilized in applications, aiming to organize and present the citizen contributions and facilitate the interpretation of the environmental parameters under investigation. As discussed previously, one challenge here is data quality, more specifically, its effect on the decision to share particular datasets generated by citizens. Even after data quality checks and improvements, these datasets often have significant uncertainties that need to be communicated in the sharing and visualization process. Further challenges are in developing standards that are both efficient for machine-to-machine processes and sufficiently expressive for sharing and visualization by human users.

Using data collected by citizens, depicted in the left-most component of Figure 4.1, can be done for different purposes, such as augmenting monitoring information, improving modelling or management of water resources. However, due to the uncertainties associated with these data, especially water level and velocity/discharge measurements, current studies on citizen science and citizen observatories focused on these data types do not report analyses of data usage. The current situation is such that crowdsourced or volunteered data are collected for scientific purposes, first as a proof of concept that such data can be obtained (Le Coz et al., 2016), and, secondly, to study how informative these data can be, due to their uncertainties (Starkey et al., 2017). The complexity of obtaining such data from citizens may be too high for the desired accuracy and coverage. For example, as discussed in sub-section 2.3.2, water models generally require data in certain standards (e.g. time series for upstream boundary conditions) and therefore there is a need to reconcile the temporal and spatial availability of citizen data with the needs of models. This can be contrasted with the comparatively easier acquisition of flood extent data that have been collected by volunteers, communities and stakeholders for flood risk management, meeting specific data needs (Tellman et al., 2016).

Finally, regardless of the purpose for which the data have been collected and used, it is very important that the actual results are visualized and feedback is provided back to the community that participated in data collection. Such feedback needs to be connected back to the issues raised during the data needs identification, especially to those that are of local concern of the involved citizens. This approach strengthens the ownership of the whole process by all involved partners, which in turn ensures its long term sustainability.

4.3 ADAPTIVE DATA COLLECTION FOR WATER RESOURCES MANAGEMENT

Based on the challenges identified in Section 4.2, there is a clear need to develop technologies that integrate the data cycle presented in the conceptual framework, enabling the transfer of identified data collection needs through the subsequent steps in the process. Moreover, these tools need to be adaptive; be able to handle new data needs.

As mentioned previously, this research is part of the Scent project, which aims to make the citizens the eyes of the decision makers. The project implements a range of technologies to achieve this goal, encapsulated within a so-called Scent Toolbox. It includes three tools that are featured in the data cycle (Figure 4.2): the Campaign Manager, a platform for communicating identified data needs (sub-section 4.3.1); the Scent Explore, an application for collecting data (sub-section 4.3.2); and tools to extract data from images (sub-section 4.3.3). Sub-section 4.3.4 describes the pathway selection approach, created for the case study where it is needed (the Danube Delta).

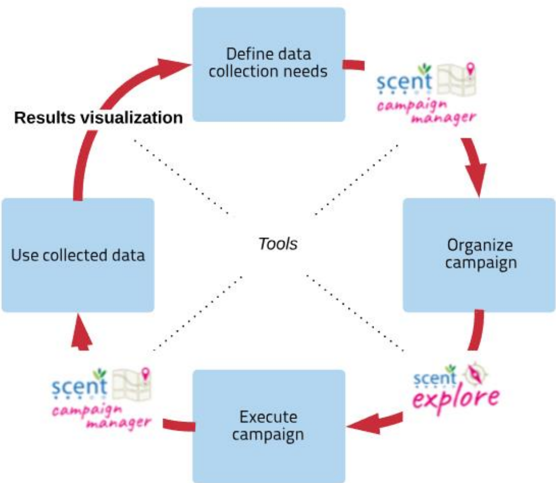

Figure 4.2. Data collection cycle for citizens' campaigns in water management with adaptive tools

In terms of architecture, the Scent toolbox includes a crowdsourcing platform, acting as a central data broker. It links the Scent frontend applications used by citizens to provide images, annotations, sensory data, event reports and videos to all the other toolbox components. It also ensures the quality of the citizens' image annotations through a data quality control module, and some control routines were also implemented to assess the quality of images/videos for water-related data extraction (sub-section 4.3.3). Due to the novelty of the extraction tools, the quality of the final extracted measurement is not controlled automatically. After being treated in varied toolbox components, the data are converted to international data sharing standards and stored, together with drone data, satellite imagery and other information acquired within the project. The full toolbox architecture includes more elements and is very complex. As the focus of this study is on the feasibility of field experiments, the full toolbox architecture and benchmarks with similar solutions are not presented.

4.3.1 Campaign manager

Scent Campaign Manager constitutes a web-based application that enables policymakers and local, regional or national authorities to monitor and streamline the collection of environmental information. More specifically, users are able to design citizen-science campaigns and define points of interest in locations where data on land cover/land use (LC/LU), soil conditions and river parameters are needed, mobilizing the use of the relevant components of Scent Toolbox. The tool is also responsible for managing the policymakers' user accounts, their personal settings, as well as for notifying them of any relevant reported events. In addition, it supports the visualization of the citizen-generated data (i.e. images, sensor measurements, etc) as well as maps of the areas of interest with information regarding LC/LU and flood hazards maps.

4.3.2 Scent Explore

Scent Explore[6] is a gaming app for crowdsourcing. It was specifically designed to gather multiple types of environmental data and to be connected to the Scent Campaign Manager. Therefore, there are not very similar applications available for smartphones, mainly considering the augmented reality strategy applied.

Citizens can select a campaign and display the Points of Interest (PoI) on a map (Figure 4.3a). When approaching a PoI within a range of 75 meters, the application activates the camera. For pictures, augmented reality is also activated and the citizen can see an animal, to be captured by taking a picture of it (Figure 4.3b). Based on the amount and type of animals captured, the citizen increases their score. By capturing an animal, a picture is taken, for which the citizen chooses a tag: either land cover-related tags or the tag 'Water level indicator' for images of water gauges (Figure 4.3c). When floaters were used, a particular functionality without the animal was triggered.

[6] The app is no longer available in app stores. For further information contact XTeam Software Solutions (https://www.xteamsoftware.com/new/).

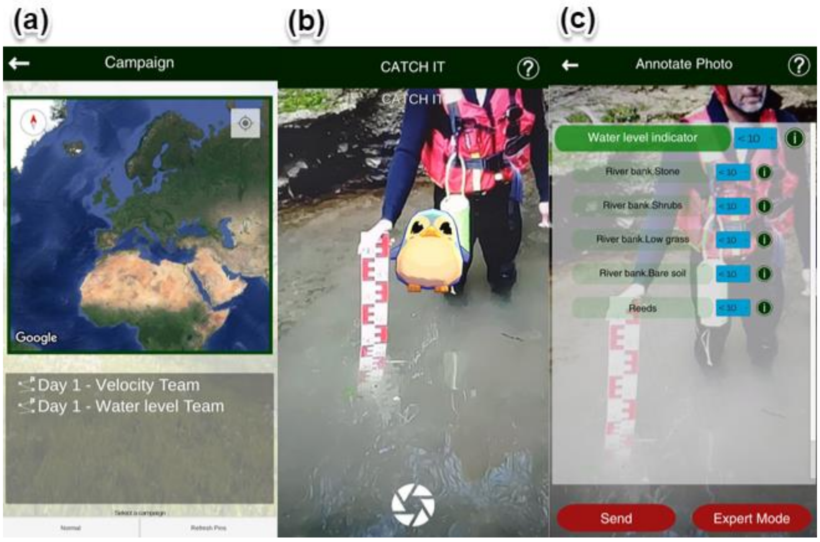

Figure 4.3. Scent Explore functionalities

To improve the user experience, Scent Explore can generate PoIs itself, so the citizen has no long breaks between 2 PoIs and can have fun with the game. To accurately define the position of the PoI with respect to the citizen, in addition to using the position by GPS, the application uses the gyroscope (if available) for direction, thus integrating the values with the compass data. Both pictures and videos are supported by the app functionalities. Pictures are used for land cover and water level estimation, whereas videos are the raw material for velocity detection. All pictures receive tags from volunteers, either related to land cover or water level.

The app connects to the Scent Crowdsourcing Backend, which sends images to the Scent Intelligence Engine (SIE), where tags are attributed to the received images, with a confidence score. Tags from SIE are independent of citizen tags. From SIE, images are moved back to the backend towards the Data Quality Engine, in which the citizen tags and the attributed tags are compared, as a validation process. If the SIE has a confidence score higher than a certain threshold, the SIE tag is validated; if not, human confirmation is required, weighing more as the tool loses confidence. Human confirmation comes from tags provided by volunteers in the field and can also be achieved through Scent Collaborate, a web-based platform in which citizens annotate images online. Tags provided by field volunteers are valued at double the tags from online annotation. If a tag provided by a field volunteer is not found by SIE, it should pass through Scent Collaborate and will be considered valid if about 70% of evaluators agree with the presence of the tag. This procedure does not go on forever though: if the threshold is not reached after a maximum number of annotations, the tag is considered invalid.

Validated images of water gauges are sent to the Water Level Extraction Tool (WLET). For videos, Explore automatically connects to the Water Velocity Extraction Tool

(WVET). The app also provides support for the acquisition of improved data for the WLET and WVET tools. The app stabilizes images by directly accessing the smartphone camera's Charge-Coupled Device (i.e. sensors that record still and moving images), instead of using picture interpolation. Image stabilization is improved by taking 3 photos at close range and choosing the photo with less variation of the mobile accelerometer. The resulting photos have sharper colours and better definition, despite being small in size (about 2M pixels). The video stabilization is obtained with the accelerometer to compensate for the movement of the phone, which is relevant if citizens are aboard a boat. It detects the roll and up-down movements at each frame. Since the first tests, stabilization of videos has been improved by 15% to 20% using this technique.

Beyond improving the content through stabilization, the app improves positional data quality by attempting to get GPS data with an implementation of Position (3D) Dilution of Precision (PDOP). This means that whilst the GPS best-expected accuracy is in the order of 3-5 meters or 10-20 meters in isolated environments, with PDOP, the position accuracy can be less than 2 meters or 3-5 meters, respectively. To allow the use of the app in conditions where there is no good internet connection, Scent Explore can work online and offline.

4.3.3 Estimation Methods

As discussed in Section 4.2, it is challenging to balance the accuracy of the measurement method, the ease in data collection and the level of involvement expected by the citizen. In order to balance these aspects, it was defined that the methods to estimate LC/LU, water levels and velocities would be based on pictures and videos, once these could be easily obtained by citizens and handled by the Scent Explore app.

Specifically for the water level and velocity tools, as discussed in Section 4.2, the methods described in the current literature are not automated and thus, in this study, new methods with automatic data extraction are proposed. For these tools, object detection was chosen, and it is implemented in Python, using the OpenCV 3.0 library[7].

Map Segmentation Tool

The map segmentation tool is a technology developed to obtain land cover maps from tagged images taken by citizens. The images are tagged according to a tailored taxonomy developed to address identified data needs. The images that passed through quality control are then used in a deep learning classification method. Considering the complexity of the

[7] https://www.opencv.org/releases.html

tool and the current focus on the campaigns, this chapter does not discuss the inner workings of the tool.

Water Level Extraction Tool (WLET)

The Water Level Extraction Tool detects the water depth based on the picture of a gauge, graded according to international standards. The gauge can be fixed or painted to the riverbank or it can be a portable one.

A histogram of oriented gradients (HOG) classifier is trained to recognize digits. HOG is a feature descriptor used in computer vision and image processing for the purpose of object detection. The technique counts occurrences of gradient orientation in localized portions of an image (Tian, 2013). This method is similar to that of edge orientation histograms, scale-invariant feature transform descriptors, and shape contexts, but differs in that it is computed on a dense grid of uniformly spaced cells and uses overlapping local contrast normalization for improved accuracy. A visual explanation of the algorithm can be found on the "Learn OpenCV" platform[8].

The procedure for extraction is described below:

- The trained classifier is used to detect digits in the image captured by the volunteers.
- The identified digits are processed to remove overlapping identifications.
- Based on the very distinct and uniform pattern of the hydrological gauges, the digits are formed into pairs.
- The pair that is located at the lower part of the image is chosen as the identified measurement.

By following this procedure, data is measured with an accuracy of 10 cm. While initially the "E" grading (distinct pattern of the hydrological rods) was to be taken into consideration to improve the accuracy of the estimation to 2 cm, the different models of rods used during the pilot activities did not enable its use (Figure 4.4).

[8] https://www.learnopencv.com/histogram-of-oriented-gradients/

Figure 4.4. Portable water gauges in different colours

The extraction procedure is triggered for each image captured by Scent Explore that contained the ‘water level indicator’ tag and was validated in the Data Quality Engine. As described, the SIE validation only checks if the image is indeed the image of a water gauge. Within WLET, a quality control routine is used to detect problems and invalidate images. These include that no numbers are recognized, the image is of too low quality to confidently extract the measurement and if the image is corrupted/not available. In this study, we visually extract the water depth value from the pictures, to check the efficiency of the control mechanism.

Water Velocity Extraction Tool (WVET)

For the extraction of velocity, a specific object is the target of detection in the frames of the video. The object selected was a tennis ball. The algorithm combines two distinct characteristics of the object, the round shape and the yellow colour. The procedure for the extraction of velocity is listed beneath:

- The tool examines the videos captured by volunteers frame by frame. In each frame, the pre-defined floating object, a tennis ball, is located.
- The start and end of the video are determined, the start being the first frame that contains the object while the end is the first frame after this one that does not contain the object.
- The valid part of the video is processed again. For each pair of successive frames:
    - o The optical flow between two successive frames is calculated. Optical flow is the pattern of apparent motion of image objects between two consecutive frames caused by the movement of the object or camera. It is a 2D vector field where each vector is a displacement vector showing the movement of points from the first frame to the second.

  - The average displacement of the area identified as the object is calculated.
  - The average displacement of the rest frame is calculated.
  - The two values are subtracted. In this manner, the result is devoided of any noise that might have been caused by the movement of the camera.

It should be noted that the resultant displacement of each vector (i.e. the combination of its y and x directions) is used. Some more information on this and other sensing methods applied during the Scent project can be found at Krommyda et al. (2020).

Differently from images, videos are not validated by the Data Quality Engine. There is a quality control routine that invalidates videos in which:

- The pre-defined object is not found;
- The tennis ball detected was less than 5 pixels in size or if the displacement was smaller than the tennis ball;
- Video is not long enough (i.e. the object is present in fewer frames than the video frame rate, meaning less than one second of useful material); and
- Video is corrupted/not available.

4.3.4 Pathway selection approach

This approach was developed to support citizen observatories in delta areas, in the context of delta planning, to define which boat routes to follow when citizens participate in data collection organised campaigns. The approach is not specific to the Danube Delta case study, therefore is presented in generic terms. Its applicability is tested and demonstrated on the Sontea-Fortuna area.

The main principle of the proposed approach is to combine the interest of local stakeholders and the characteristics of the study area (Figure 4.5). Based on analysis of these two aspects, possible pathways can be identified and prioritized. Then, the data collected by citizens using the selected pathway(s) can be used (e.g. in flood modelling) and the knowledge gained can indicate new data needs. There is also experience gained that helps adjusting pathway parameters (e.g. time needed to make an observation). Such feedback mechanisms, although indirect, enable the creation of new campaigns, which in turn can create more sustained citizens engagement in the process. In other words, we propose to cyclically re-evaluate actor coalition interests and redesign campaigns, not only to continually gather data but to sustain participation.

Figure 4.5 shows the application steps. The first step of the approach is to define purposes for data collection based on delta planning needs. Based on these purposes, it was necessary to identify the location in space (points of interest) where data can be collected. To prioritize pathways, each group of points of interest related to a specific purpose (named “location set”) was attributed with a score, depending on its importance. Thus, each point of interest (in this case reach of interest) accumulates a score (reach score), according to the purposes it serves.

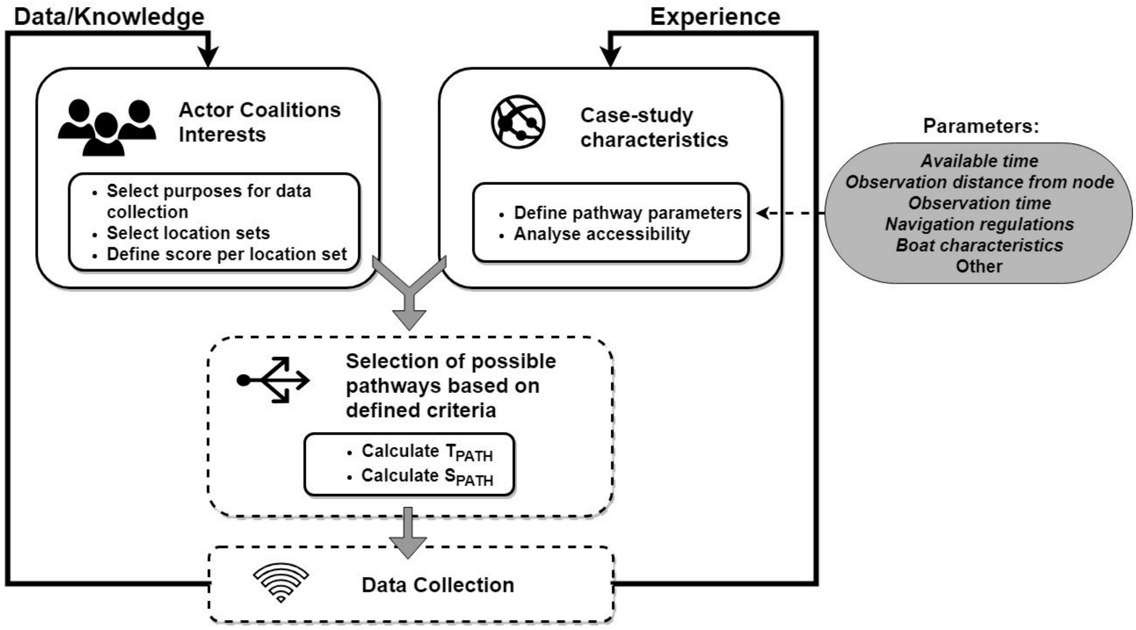

Figure 4.5. Pathway selection approach concept

Three purposes for data collection were identified based on workshops with local stakeholders (Section 4.4): to investigate water stagnation; support hydrodynamic modelling of the area; and investigate engineering modifications. A hydrodynamic model was developed (Chapter 6). However, because of the limited data available for calibration and validation, the confidence in the model results is also limited. This means that the second purpose is to improve model accuracy. Still, the model was already useful to have a first definition of stagnation points and accessibility.

Investigation of stagnant water was set as a purpose, hence, a “location set” with all canals where stagnant water is expected was defined. Canal scores were selected to vary from 0 to 4, from the least stagnant to the most stagnant canal. The canals that were mostly affected by water stagnation are presented in Figure 4.6. To improve model accuracy, two locations sets were defined. One set is composed of the canals located in the downstream section, in order to enable the model to be limited to the Sontea-Fortuna area. To these canals, a score of 2 was given. The second location set included observations in all canals, also with a score of 2, because they provide data for model calibration. To investigate engineering modifications, the canal Mila 35 was selected and a score of 2 was attributed to it. All the scores were set according to the ranking as discussed by stakeholders during user requirement meetings. A summary of the scoring approach is presented in Table 4.1.

By summing up scores, the overall score for each canal, according to data collection purposes, is presented in Figure 4.7.

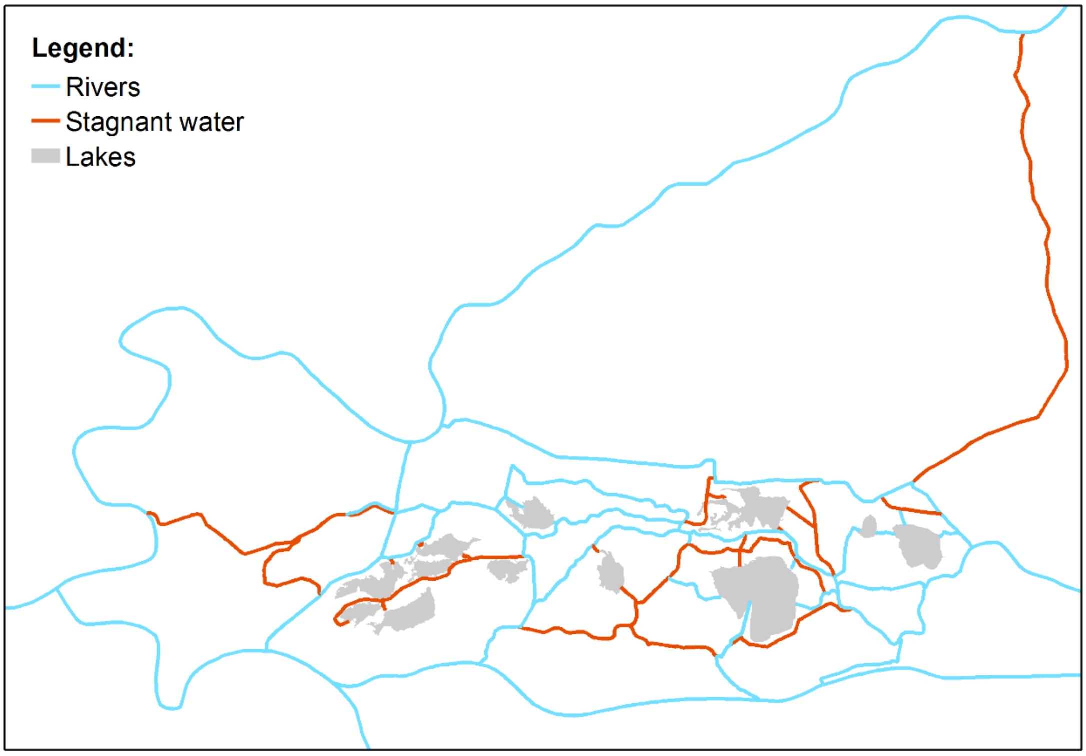

Figure 4.6. Rivers and canals experiencing water stagnation in Sontea-Fortuna. Lakes are not considered stagnant water

Table 4.1. Scoring of selected purposes of data collection in the case study

	Purposes			
	Investigate water stagnation	*Improve model accuracy*		*Investigate engineering modifications*
Location Sets	Stagnant canals	Downstream BC canals	All canals (model calibration)	Canal Mila 35
Scores	0-4	2	2	2

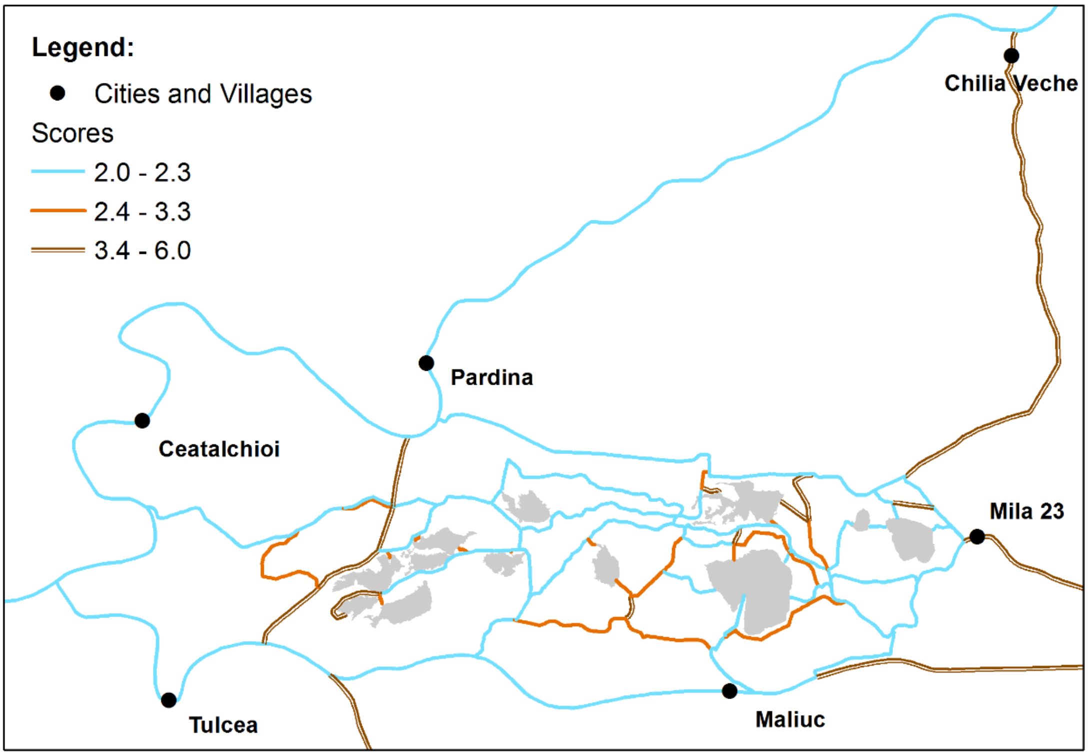

Figure 4.7. Final scores for data collection and start points for pathways

In the following step, parameters for the pathways design are defined and an accessibility analysis is conducted, both depending on the case study characteristics. The parameters are: the maximum available time for a boat trip (T_{max}); time for citizens to collect data (T_o) and velocity of the boat (v). The time spent on the observation itself is dependent on the type of sensor used and the velocity of the boat depends on the boat, the flow and the navigation regulations in each canal. Apart from the three mentioned parameters, the number of observations taken along a pathway is defined as n and it comprises all the observation points along the main pathway plus a number of important points located outside the main pathway, but not too far. The minimum distance from the main pathway to the outside observation point ($Dout_{min}$) needs to be defined to ensure correctness of the collected data. For example, if velocity data is collected in an observation point that is located away from the main pathway, the boat needs to travel to a point where velocity is not affected by the velocity on the main pathway.

For the present case study, a minimum distance of 500 m was defined for $Dout_{min}$. In order to determine the maximum time possible for one trip, it was assumed that the boat travels during working hours, from 9:00 AM until 5:00 PM, hence the boat should return to the starting point of the trip within eight hours (T_{max}). Considering that observations are performed by taking pictures and videos using a smartphone, it is assumed that for each individual observation a time frame of 5 minutes is needed (T_o). Looking into the

DDBR navigation regulations[9], it was found that the maximum allowed navigation speed is 40 km/h or 15 km/h, depending on the size of the canal. Canals located near colonies of birds have a maximum speed of 5 km/h. Since the main part of the study area is located in small canals, the adopted boat speed for calculation of pathways was 15 km/h (v).

Accessibility analysis is performed to take into account all existing constraints in the area. The first constraint is the non-accessibility of boats in the canals due to low water levels for navigation. In Sontea-Fortuna, a standard boat size with a maximum capacity of 35 passengers was considered. The draft for this boat, which is the vertical distance between the waterline and the bottom of the boat, was 0.5 m. This draft was then compared to the water depth map results simulated for the dry, average and wet scenarios, resulting in different accessibility for these hydrological regimes. A second constraint took into account strictly protected areas where access is prohibited. Inside the study area, there is only one such lake, the Nebunu Lake.

The third step of the approach is the actual generation of pathways. A pathway is generated when a boat departs from a start/end point and stops for observations to be taken along the navigated canals. As the overall time varies from one pathway to another, Equation (4.1) was proposed to estimate the time covered for each generated pathway. The time to navigate the pathway was considered as the sum of the overall time spent with observations plus the boat travel time. The time of each pathway should be equal to or smaller than the predefined available time, as shown in Equation (4.2). The observation distance outside the main pathway should be equal to or greater than the minimum distance for accurate data collection, as presented in Equation (4.3).

$$T_{path} = n * T_0 + \frac{L_P}{v} \tag{4.1}$$

$$T_{path} \leq T_{max} \tag{4.2}$$

$$Dout \geq Dout_{min} \tag{4.3}$$

where;

T_{path} = pathway time [h]

n = number of observations

[9] http://gov.ro/en/news/new-traffic-rules-on-danube-delta-inland-channels-and-lakes

T_o = time of observation [h]

L_P = pathway length [km]

v = boat velocity [km/h]

T_{max} = maximum available time [h]

$Dout$ = observation distance outside the main pathway [m]

$Dout_{min}$ = minimum observation distance outside the main pathway [m]

If the maximum available time constraint is violated, that pathway is rejected and a new pathway is generated. A pathway score is obtained by summing up the scores of the canals where observations were carried out (Equation (4.4)).

$$S_{path} = \sum_{i}^{n} S_i \qquad (4.4)$$

where,

S_{path} = pathway score

S_i = total score for an individual canal where the observation is carried out

Following the above procedure, a set of possible pathways is generated, starting from different start points (Figure 4.7). Then, pathways can be prioritized by ranking them according to their scores, and field campaigns can be set up for data collection.

4.4 Applications and Results

To apply the adaptive data collection approach in the case studies selected, preliminary steps towards preparing for the field experiments included:

- Identification of end-user and stakeholder needs and requirements relevant to citizen observatories (first step of the data cycle), aided by the experience and expertise of local partners as regional authorities, as well as their strategic goals as policymakers.
- Insights on the design features of the campaign manager, aiming to enhance its relevance to the local context.

Workshops with stakeholders were performed to achieve these steps, as described in sub-section 4.2.2. Workshops revealed that in the Danube Delta, there are high concerns in terms of water quantity (in particular water stagnation) and that the Mila Canal, part of the extensive engineering modifications in the area, is of major local importance. It was also stressed that it was important to have a good hydrodynamic model. In Kifissos, on the other hand, it was discussed that it is a smaller-scale and very dynamic area, in terms of changes in land cover and land use and of the time for the passage of floods. Thus, there is interest in monitoring in such a way that these differences are captured. The workshop culminated in a list of data needs the Scent Toolbox took as a base for the data collection (Table 4.2, Table 4.3), together with the qualitative insights shared above. To keep the study focused and the results relevant, water level, velocity and land cover data needs are the focus of this chapter. Campaigns organized to collect sensor data (soil moisture and air temperature) and data on obstacles in the river were left out of the scope.

Table 4.2. Data needs identified and addressed in the Sontea-Fortuna case study.

Data need	Addressed in the Scent Toolbox?
Water level	Yes
Water temperature	No
Air temperature	No
Water surface velocity	Yes
Digital elevation	No

Table 4.3. Data needs identified and addressed in the Kifissos Catchment case study

Data need	Addressed in the Scent Toolbox?
Land cover/Land use	Yes
Digital Elevation	No[a]
Soil conductivity	No
Soil Moisture	Yes
Air temperature	Yes
Water level	Yes
Water surface velocity	No
Water temperature	No
Water flow obstacles	Yes
Hydrographic network	No
Geological and hydroleogical map	No

[a]Research on this topic was made during the project, but not incorporated into the toolbox

In the following sub-sections, the pathway selection results are presented (sub-section 4.4.1), as well as the results on how the campaigns were organized and executed (sub-section 4.4.2), what the experience of volunteers was (sub-section 4.4.3) and what the results in terms of the success of the campaign were (sub-section 4.4.4).

4.4.1 Pathway selection results

To investigate the applicability of the proposed approach, an analysis of the generated pathways for the three proposed hydrological regimes was performed. The analysis helped in better understanding the spatial distribution of the pathways (the accessible ones) and the resulting scores.

For the dry scenario, there were 27 canals with a total length of 56 km (out of 407 km) that were not accessible. Additionally, 7 out of 11 lakes located on the west side of the study area were not accessible due to the non-navigability of the access canals (Figure 4.8). On the other hand, in the average and wet scenarios, all canals were accessible, except for the protected area of Nebunu Lake. The accessibility analysis showed that there were plenty of pathways for citizen data collection, even during the dry scenario.

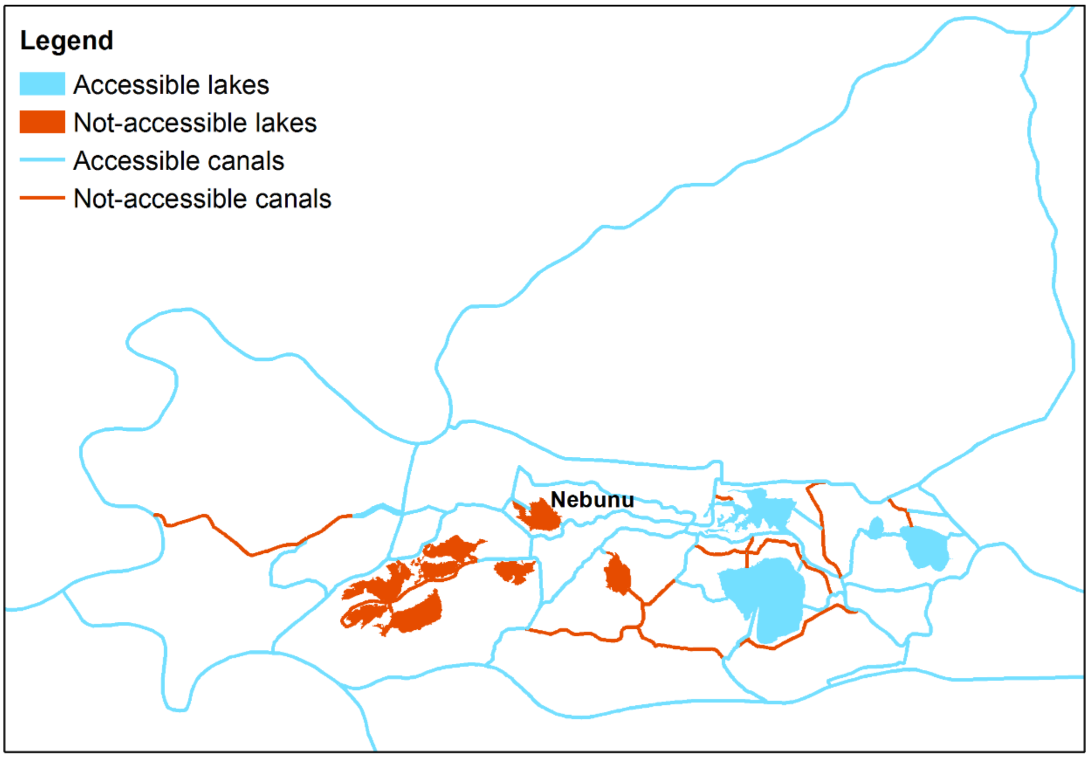

Figure 4.8. Accessibility map for dry scenario

For the boat trip starting and ending in Tulcea city, four pathways were proposed. Their characteristics are presented in Table 4.4. These scores were generated to assess the pathways' performance according to the distance to the start/end point, number of observations taken and the considered hydrological regime. In Figure 4.9, pathways 1 and 2 are shown, where the boat trajectory passed through Canal Mila 35 and the surrounding Sontea-Fortuna wetland. The difference between Pathway 1 and Pathway 2 is that the latter includes observation points that were outside of the main pathway track. For Pathway 1, the number of observations was lower than Pathway 2, and so was its score. Conversely, the time needed for the second pathway is larger than the maximum time imposed for data collection. For that reason, a balance between the maximum time constraint and the number of observations should be sought. To carry out observations in nearby canals was a good approach because it allows for the collection of more data; however, it might not fit the time constraint because it increases the time spent on observations and navigation. Pathway 1 would increase its score to at most 70 by adding 3 observations (the only ones possible within the constraint). Another aspect revealed by the analysis was that the scores of the canals play an important role in prioritizing some pathways when time is limited.

Table 4.4. Pathways summary.

Pathway	Scenario	Nº observations	T_{path}	S_{path}
1	Dry	21	7:29	52
2	Dry	39	10:17	99.5
3	Dry	32	7:57	78.6
4	Wet	33	7:57	90.7

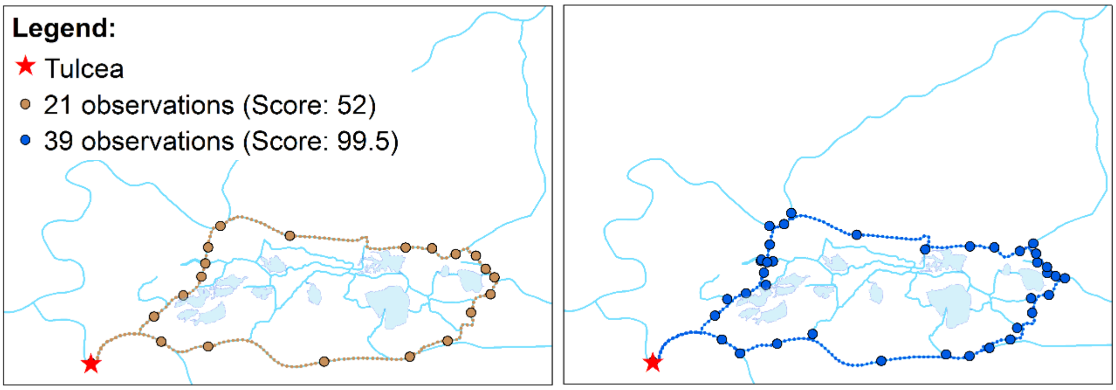

Figure 4.9. Pathway 1 (left) and 2 (right) from Tulcea for a dry hydrological regime

In Figure 4.10, the third and fourth pathways were proposed for dry, average, and wet regimes. Because the average and wet regimes show the same path, they are noted as average/wet. By comparing pathways 1 and 2 to pathways 3 and 4, it could be noticed that when the pathway is short (close to the start/end point) the number of observations will most probably increase, because, as the distance travelled decreases, the time spent in travel from one observation point to the other decreases and, consequently, there is more time to collect data. Comparing Pathway 3 to Pathway 4, the reason for a higher score for the pathways with the same amount of time was the fact that the first collects data in canals that were not accessible in the dry scenario. Therefore, a pathway that gets the best score in one scenario might not be the same for another scenario.

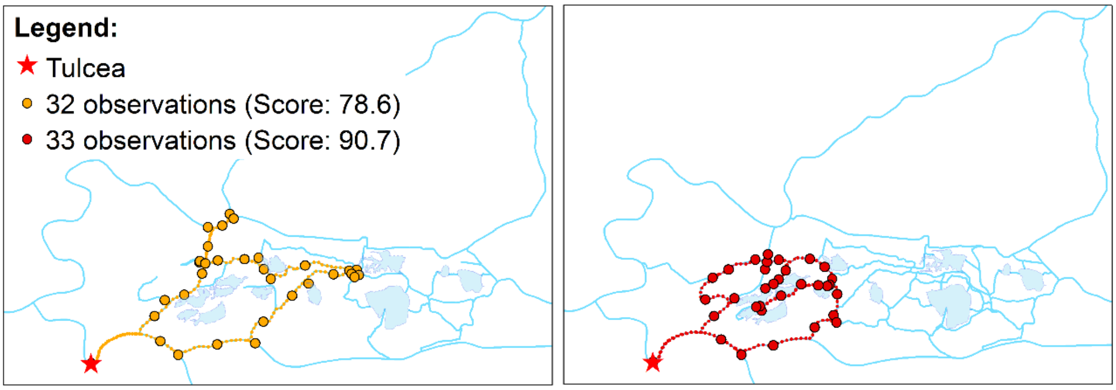

Figure 4.10. Pathway 3 (left) and 4 (right) for dry and average/wet hydrological regimes, respectively

In the interest of having an overall visualization of the pathways' distribution over the canals for different start/end points, a map including one pathway per city/village was proposed (Figure 4.11). All six pathways were determined with the aim of achieving high scores within the time constraint. It could be observed that the pathways with the highest scores had their start/end points in Tulcea and Mila 23. Both of them included 33 observations, and the reason for the high score of the Tulcea pathway was the fact that it passed through the canal Mila 35, St. Gheorghe branch (downstream BC), and four canals, which had high stagnation. The Mila 23 pathway also had a high score because it covered three downstream BC and four canals with high water stagnation. In addition, Chilia Veche was the worst-scoring start/end point because larger distances needed to be covered to reach more observation points. However, Chilia Veche is the second most populated city in the area, and this variable should be considered in further analysis.

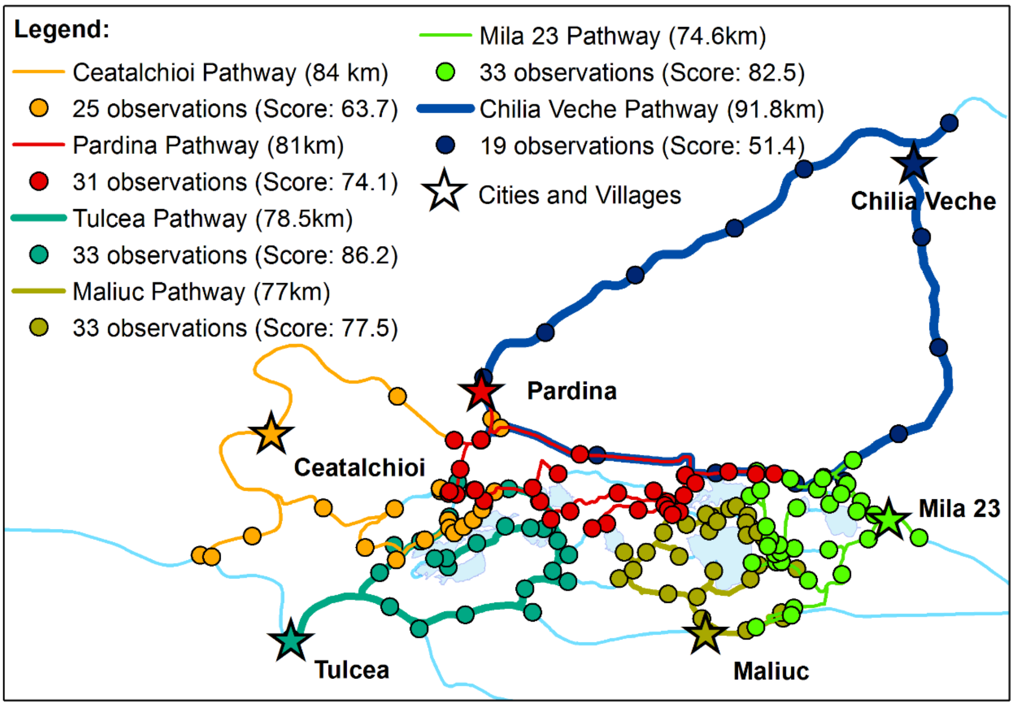

Figure 4.11. Overall view of pathways assessed for all start/end points for average/wet hydrological regime

To evaluate how sensitive the pathways were to their parameters, keeping the same observation points, we varied the boat velocity (v) and observation time (T_O) per route. While the scores remained fixed, the effect could be seen in the pathway time, checked against different maximum pathway times (T_{MAX}). At first glance, the results are not very different among pathways, except for Pathway 2, which had the longest pathway time already (Figure 4.12). It is clear that it is not feasible to move slower than 10 to 15 km/h, to be able to complete the route within a day. Changing the observation time from 1 to 10 minutes meant increasing the pathway time on average by 5 hours. Therefore, the pathways were very sensitive to the boat velocity and mildly sensitive to the observation time. We assessed the observation distance outside the main pathway ($Dout$) and it did not impact the pathways.

(a)

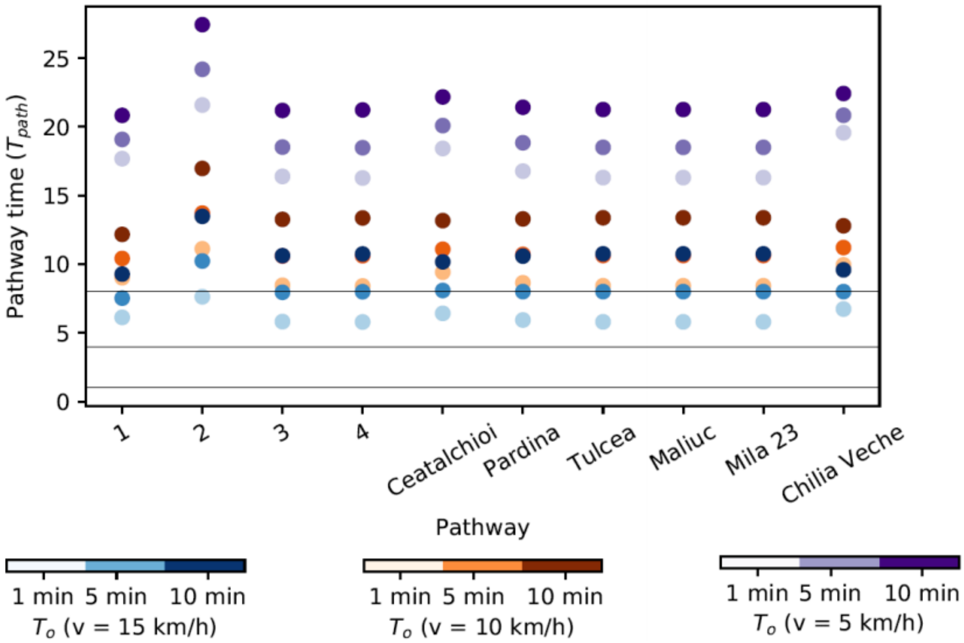

Figure 4.12. Sensitivity analysis results. The horizontal lines indicate different potential maximum pathway times (1h, 4h and 8h)

The pathway selection approach is a contribution that was missing in citizen observatories research. In other fields, such as transportation systems, there is a definition of routes to be followed by vehicles such as cars, and there are optimization algorithms to minimize costs and time (Clarke and Wright, 1964). Despite similarities, there are important differences in citizen observatories' pathways that hinder direct application, mainly in terms of such methods' objectives and level of complexity. The goal of the pathway for citizen observatories is to collect data at selected points, which in this case study includes more than 110 points, whilst in transportation problems, there are a few targeted locations.

Overall, the selection of pathways was able to prioritize pathways, being affected by the number of observations collected, which significantly impacts both the pathway's time and score, and the boat velocity, needing at least 10 to 15 km/h. The analysis showed that the best pathways are located relatively close to their start/end points and that they can be associated with different start/end points in different hydrological regimes. This information also supports that more than one start/end point needs to be considered when planning citizens' observatory campaigns in the case study area.

4.4.2 Campaign organization and execution

As mentioned previously, the organization of campaigns is generally a task within research projects. In the case of Scent, local institutions that are project partners were the campaign organizers. Danube Delta National Institute (DDNI) and the Romanian Ornithological Society (SOR) led the efforts in the Danube Delta, while the Region of

Attica (RoA)[10] was the main organizer in the Kifissos catchment, together with the Hellenic Rescue Team of Attica (HRTA).

In any citizen science initiative, engaging citizens is a complex task. Hence, for both case studies, desk research, online surveys and focus groups were organized to understand citizens' attitudes and behaviours. Based on this, for mobilizing volunteers in the Danube Delta, members from the Romanian Ornithological Society (SOR) were targeted and their involvement was fostered through direct communications and emailing. In Kifissos, RoA addressed to its broad network of stakeholders (municipalities from the regional authority of Attica, NGOs, individual citizens, citizen-led communities, walking groups, and scouts). In order to motivate and mobilize such diverse target groups, RoA disseminated the Scent brand communication material through mailing lists, via the Region's website and social media. Printed leaflets were handed out and press releases have taken place.

In general, based on the expected number of volunteers, campaigns were planned for an overall duration of 4-6 days (weekdays and weekends), including training. As the Sontea-Fortuna area is remote, with difficult access, all volunteers were present for all campaign days. Initial/conceptual training was performed on the first day for all volunteers and it covered the Scent project, the Scent toolbox and the aim of the campaign. The volunteers then received daily training on the Scent Explore app. In the Kifissos catchment, for each day of the campaign, an average of 1.5 hours was allocated for all types of training. In both cases, citizens were accompanied in the field by trained members of the Scent project, who answered questions and re-explained how to collect data if necessary. This meant that just-in-time training (Katrak-Adefowora et al., 2020) was done to a certain extent.

The campaign duration per day varied due to the volunteering profile and case study characteristics. In Sontea-Fortuna, volunteers were more open to being in the field for longer hours and therefore, the daily duration was 4.5-6 hours. On the other hand, in the Kifissos catchment, volunteers were engaged in 2-3 hours of data collection. The shorter time was chosen to include citizens who were willing to become involved but could not invest in a time-demanding activity. These values include transportation through the area.

For both case studies, Points of Interest (PoIs) were identified by the project's domain experts, considering the identified data needs. For Sontea-Fortuna, the final set of routes was defined using the results and insights from the previous sub-section, considering the selected starting points and the multi-day campaigns. Once final decisions are reached, domain experts, developers and local partners set up the campaign in the Scent Campaign Manager. In the Sontea-Fortuna area, routes are carried out by boats and in Kifissos, on

[10] RoA introduces and implements policies, including the development and application of strategic plans and the particularization of the guidelines of environmental policies at a regional level.

foot. In Kifissos, due to the unpredictability of PoIs conditions, routes were surveyed prior to campaigns by the field experts (Hellenic Rescue Team Attica - HRTA) with a special focus on accessibility, safety and guidance. Moreover, during the campaign, volunteers were escorted by safety teams at all times.

To simplify data collection by citizens, campaigns were organized thematically (land cover- or river-themed), where citizens collected data only of the assigned type. This thesis encompasses five campaigns (Figure 4.13). This chapter focuses on the execution of the first four campaigns, all performed in 2018, one for each data type per case study. The results of both Danube Delta river campaigns were studied in depth in Chapter 5.

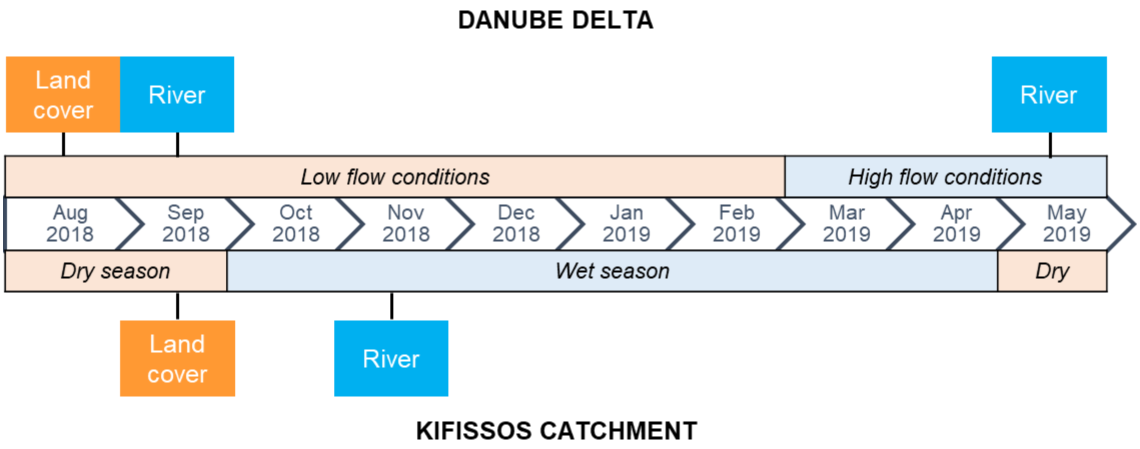

Figure 4.13. Timeline of citizen campaigns, per case study and per type of data collection. The 2018 campaigns were studied in this chapter (Chapter 4). Both Danube Delta river campaign results were studied in depth in Chapter 5

Overall, around 400 participations were recorded during the 2018 campaigns (Table 4.5), with some volunteers participating more than once. In Sontea-Fortuna, numbers were lower as the local community is smaller and was not particularly targeted; birdwatchers came from many cities in Romania. For the LC/LU campaign in Sontea-Fortuna, the main incentive for participation was its inclusion in a birdwatching summer camp. It is assumed that the decline in the number of volunteers in the river collection campaigns is due to the cold weather; volunteers were less willing to participate. In the Kifissos catchment, more significant participation was obtained, due to its urban context and broader mobilization.

Table 4.5. Number of volunteers per campaign

Campaign type	Sontea-Fortuna	Kifissos catchment
Land Cover/Land Use	62	183
River Data Collection	27	129

In the Scent Campaign Manager, a campaign was set up for each day, together with the corresponding points of interest to be visited (Figure 4.14).

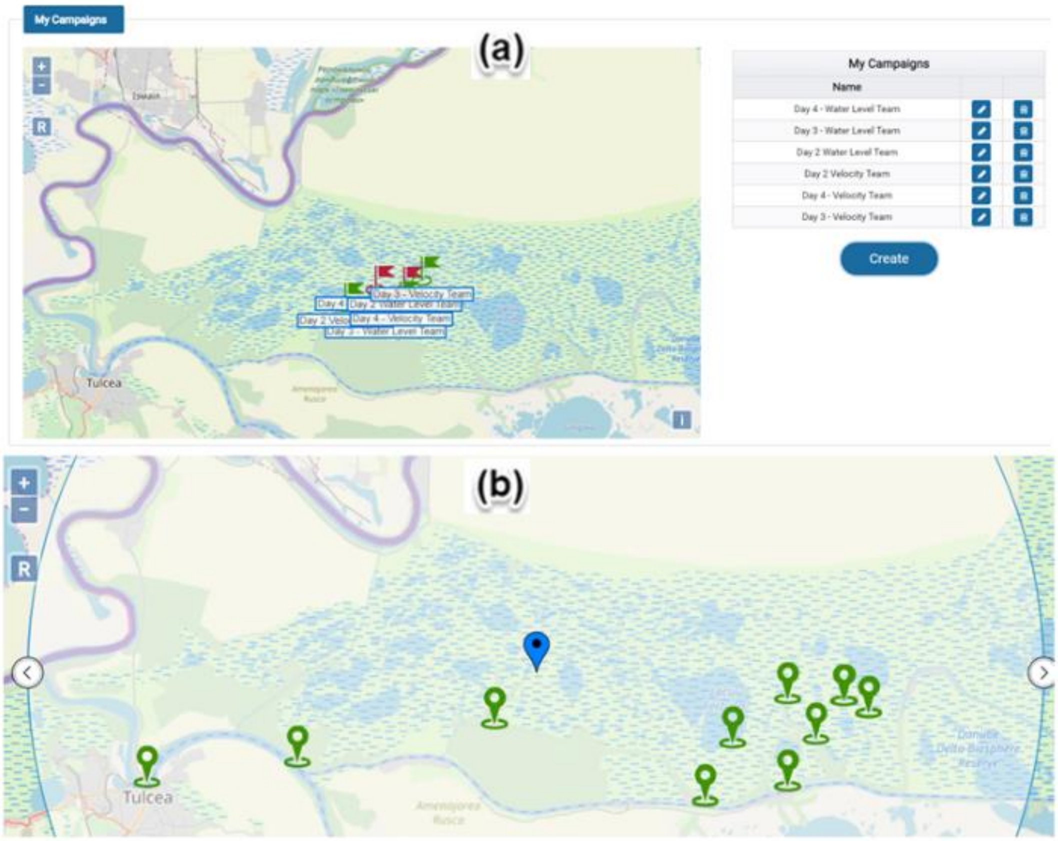

Figure 4.14. Campaign manager. (a) Setup of river data collection campaign; (b) Setup points of interest

PoIs' definition was very contrasting between the types of thematic campaigns. For LC/LU, multiple PoIs were set up along the routes to ensure a high number of pictures. For river data collection, fewer PoIs were set up and at specific locations. Due to potential impossibilities to visit PoIs in Sontea-Fortuna (e.g. dense underwater vegetation, too low water levels), extra PoIs were also set up. In Sontea-Fortuna, from all setup PoIs (including extras), 67-83% were covered, except for the last day, for which only half were visited due to a large detour (Table 4.6). In the Kifissos catchment, the choice of restricting data collection to 2-3 hours, together with traffic conditions, culminated in fewer PoIs to planned to be visited. The river data collection campaign was successful for the first two days but, due to unexpected rainfall, on day 3 the route from day 2 was revisited (no rain in that area) and on day 4 the campaign was cancelled.

Table 4.6. Planned and realized number of Points of Interest visited in the river data collection campaign

Day	**Sontea-Fortuna**		**Kifissos catchment**	
	Planned	Realized	Planned	Realized
1	15	10	11	9
2	12	10	7	6
3	22	18	5	5[a]
4	13	7	3	0
Total	62	45	26	20

[a]Not the planned PoIs

In both case studies, 1-3 routes were planned for each campaign day. For the Sontea-Fortuna case, the navigable network was covered by more than 80 percent of planned routes (Figure 4.15a). Some were altered due to a lack of or gain in accessibility (Figure 4.15b). Issues affecting the routes were diverse. For example, one day, the path through a certain channel had been purposefully blocked by locals – local representatives suppose this is when fishermen do not want their nets disturbed by traffic. In Kifissos, due to a more controlled and previously surveyed environment, all attempted routes were covered.

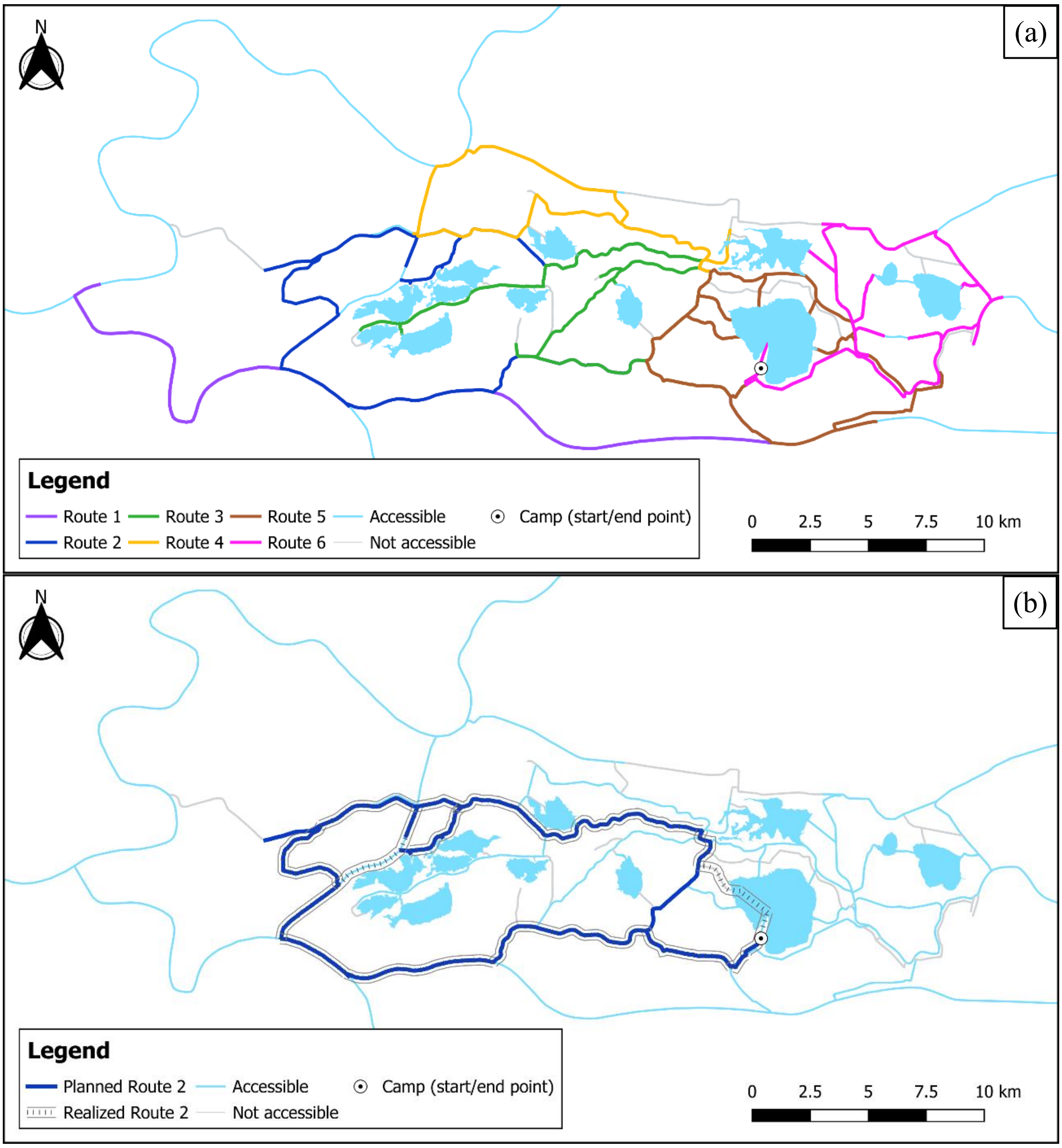

Figure 4.15. Pathway selection. (a) All routes planned for Sontea-Fortuna LC/LU campaign; (b) Example of a planned and realized route for the fifth campaign day

4.4.3 Campaign and application experience

The fieldwork carried out by volunteers was evaluated by questionnaires distributed to all the participants at the end of the campaigns. The questionnaires aimed at gauging how volunteers experienced the campaign and the app. The feedback provided is used to tailor the campaigns and the app to increase engagement.

The questionnaires were anonymous but asked about some demographics. They included both open and multiple-choice questions, nine of which were targeted to the evaluation of the field activity. Initially, four questions were designed to evaluate the training experience, but it was realized that more concrete feedback on the app experience was necessary and therefore, the former were substituted by the latter from the first river campaign onwards. Unfortunately, due to logistical problems, only 6 questionnaires were answered in the LC/LU campaign of Sontea-Fortuna, which are not statistically significant and thus are evaluated subjectively. A little over half of the questionnaires were returned answered (Table 4.7). With 95% confidence, the margin of error in the statistics shared from this point onwards ranged from 5.8 to 14.7%.

Table 4.7. Planned and realized number of questionnaires per campaign

Campaign type	**Sontea-Fortuna**		**Kifissos catchment**	
	Planned	Realized	Planned	Realized
Land Cover/Land Use	62	6	183	100
River Data Collection	27	17	129	89

In the Kifissos pilot, responses for both LC/LU and river campaigns were very similar. The response to the time spent on the activities was positive. Around 80% of the volunteers believed they had sufficient time to collect images and videos (Figure 4.16), and approximately 63% considered the two hours allocated for this task to be sufficient. In the Danube Delta (4 to 6 hours spent in the boat), 65% of the surveyed volunteers considered it a little too much and almost 90% would prefer to stay up to 4 hours.

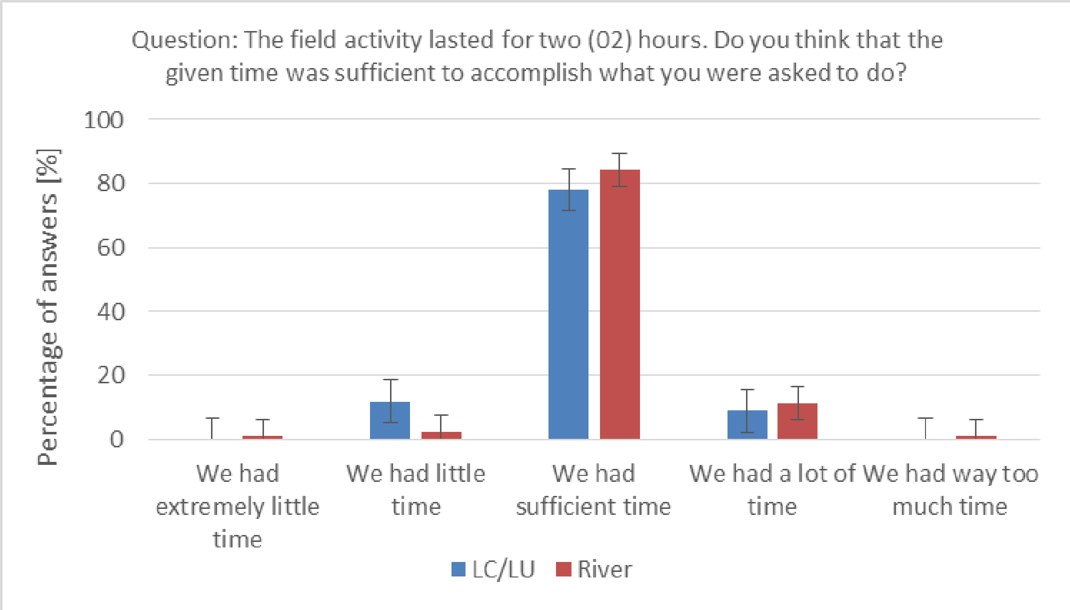

Figure 4.16. Answers about the campaign duration in Kifissos case study

The overall feeling during the field activity was also positive. In LC/LU campaign, 83 to 95% of the participants regarded it as an interesting to excellent experience; 91 to 95% in the river campaign. Up to 10% overall found it boring, tiring or disliked the weather. In Sontea-Fortuna the situation was different, in the river data collection campaign these motivations were the main reason why the timing was not perfect.

In Kifissos, questions about the gaming experience were also made, in which 90% of the volunteers judged normal to extremely easy to play the game by capturing the Augmented Intelligence animal. Three-quarters of volunteers agreed on the pace at which the group was moving to perform data collection (Figure 4.17), although considering the number of animals that appeared 60% were satisfied, about 15% thought it was too much and 20% thought it was too few. Looking at the responses in the open questions pertinent to the field activity offers useful insight. A few participants expressed their confusion regarding the location of the Scent animals, mentioning that at times the animals appeared in insignificant locations, such as in the sky, or were in a non-interesting location that they would prefer not to photograph. In what concerns the evaluation of the training session, almost 90% were satisfied with the guidelines provided and the remaining were partially satisfied.

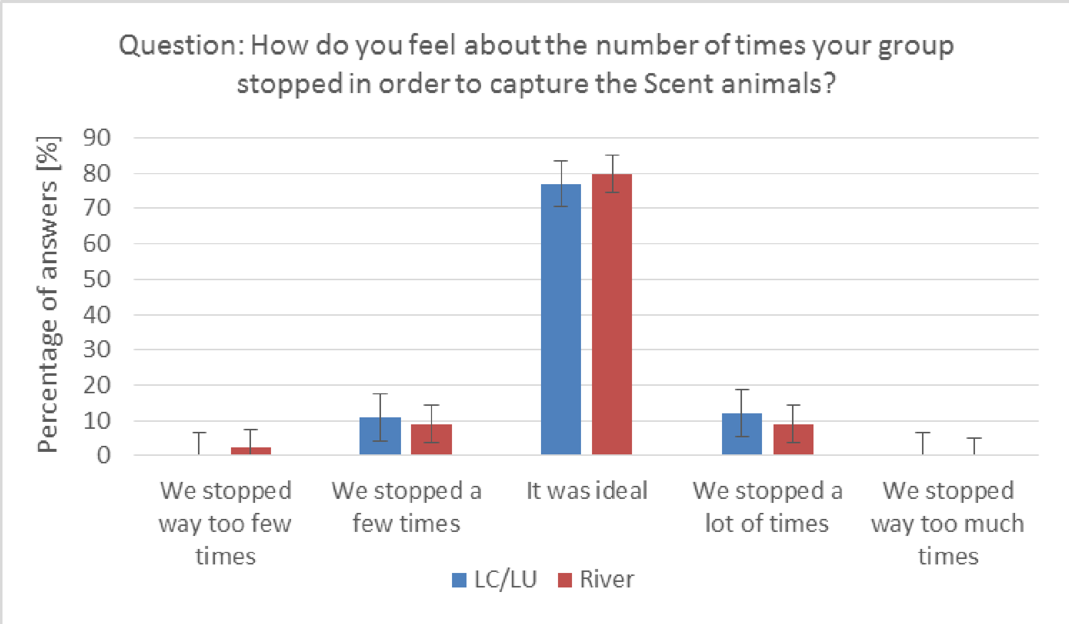

Figure 4.17. Answers to the number of stops in Kifissos case study

Issues that emerged after analyzing the open questions focused on the use of the Scent Explore app and were pertinent to energy consumption, access to Wi-Fi and compatibility with older versions of smartphones' operating systems. Regarding the design of the Scent Explore app, many participants requested more categories in order to be able to classify the captured images more accurately and asked for easier functionality and usability of the taxonomy process. Finally, a few participants wished for better accessibility, bigger letters and clearer images in the application.

In the Danube Delta, other aspects were that they wanted to see more birds, that the tasks were repetitive, boring and that there were issues with the instructions and the app. Considering the capturing of animals, opinions were divided; about half of the volunteers considered it hard to capture animals with the boat moving, and the other half considered it easy. Around 60% of the people thought the number of animals appearing was good, whilst the other 40% considered there were too many. There is also some dispersion of opinions on boat stops; half considered it was ok, about 30% thought it was too much and about 20% thought there could be more. The ones that said it was too much had more PoI in their route.

Overall, the answers to the open questions were very shallow and many participants did not answer all the boxes. We assume the reasoning is that, due to the cold wind generated by the boat's movement, the participants didn't want to stay with their hands out for too long. Three volunteers did not answer the open questions and for some questions, there were only 60% of responses. What volunteers liked the most about their boat experience was the scenery: the view, birdwatching, and the Danube Delta habitats. Many volunteers from one boat answered that the best part was spending time with nice people. The least liked aspects were the cold and the wind. Also, some thought it was too much time, that the activity was pointless and that the app was buggy. Suggestions for improvements revolved around making a shorter trip, making the trip in good weather. Some other points were to improve the app, use more professional methods and diversify the activity.

The two main aspects of the app that people liked the most in the Danube Delta case study were that it was fun to catch animals and that the app is innovative, with an interesting way of gathering data and a potential for citizen science. A few volunteers expressed that they did not like the app at all. Considering what they disliked, the most common was that the app was too slow, crashed and had bugs. Some said it was not working properly and was not user-friendly, while others said that the animal system was childish. Suggestions for improvement were mainly on improving the speed and making it more friendly and stable. Some volunteers said the app needs redeveloping or making a new one and one volunteer suggested a better explanation of usage.

A little under half of the volunteers were male and 35% female, whilst the remaining would prefer not to state their gender. Age-wise, the group was very homogeneous, with 65% in the range of 35-44 years old, about 25% a bit younger (25-34) and the remaining 10% were older (45-64).

During the campaigns in the Kifissos pilot, challenges of a technical nature emerged, as well as difficulties related to the particular characteristics of the field, in combination with the weather conditions. Technical challenges included battery-discharging issues as the apps proved energy-consuming and internet connectivity issues. Those were addressed in the second implementation of the campaign by providing portable Wi-Fi hotspots and power banks to the volunteers. Despite the app working offline, this connection with the internet was a part of the campaign to guarantee that the data, even if collected in offline mode, would be uploaded at some point (instead of never being uploaded in case the citizen did not open the app anymore). Furthermore, mobile devices were made available to the participants who did not wish to use their personal smartphones.

In what concerns a second order of difficulties, in both campaigns, participants were faced with rather challenging weather conditions ranging from extreme heat to heavy rainfall that rendered exploring the field a demanding and exhausting experience. To this end, the team decided to incorporate more flexibility in future implementations and allocate more days to future campaigns in order to be able to reach the participation numbers and the particular goals of each one.

In the Danube Delta, similar problems were encountered. The weather was also challenging in both campaigns and the time in the boat proved to be long, even when reducing from a 6h to a 5h journey. Since the area to be covered is extensive, optimization of routes is an option to be explored, as well as more engaging techniques to keep the volunteers interested for a longer period.

4.4.4 River data collection execution results

After the campaigns, the data reaches the Scent Campaign Manager, where the decision-maker can see the resulting images and videos (Figure 4.18). These data contain in their metadata the results from the WLET and WVET.

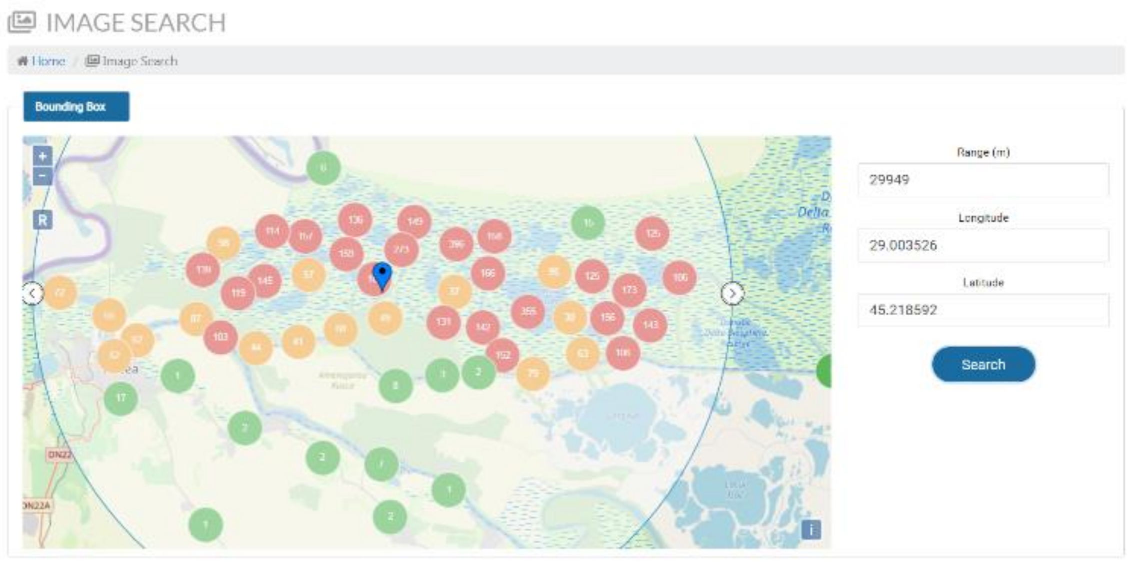

Figure 4.18. Campaign manager tool showing results for Sontea-Fortuna land cover campaign

All in all, 9568 pictures and 330 videos were collected through the four campaigns. Specifically, during river data collection campaigns, 306 pictures and 330 videos were collected. The amount of data collected during the campaigns is directly related to the number of volunteers performing the task. Volunteers were separated into water level and velocity teams to facilitate their understanding, to better adapt to the application, and thus to obtain better, more "specialized" measurements. Because velocity measurements are more complicated, two-thirds of the volunteer group would be assigned to velocity and one-third to water depth.

In view of that, the expected results for the river data collection measurements were:

- Sontea-Fortuna:
  - o Water level: for each PoI, 4 volunteers (2 per boat) were expected to take pictures, 1-2 pictures each. It was expected at least 4 pictures per PoI.
  - o Velocity: for each PoI, 10 volunteers (5 per boat) were expected to make videos. For small rivers, the ball would be thrown in the middle of the river (1-3 times) and, for large rivers, the ball would be thrown in three locations (near banks and in the middle, 1-3 times in each location). Therefore, it was expected at least 10 videos per PoI.
- Kifissos catchment:
  - o Water level: for each PoI, 5 volunteers were expected to take pictures, at least 1-2 pictures each. It was expected at least 5 pictures per PoI;
  - o Velocity: for each PoI, 10 volunteers were expected to make videos. The ball would be thrown in the middle of the river (1-3 times). Therefore, it is expected at least 10 videos per PoI.

In Table 4.8 and Table 4.9, the results in terms of the collected number of pictures/videos are provided. Due to technical issues, there was a problem with video uploading in the Sontea-Fortuna case study and no videos collected through Scent Explore were stored. Videos collected outside the app were inserted into the platform.

Table 4.8. Number of expected and collected pictures (water level)

Day	**Sontea-Fortuna**		**Kifissos catchment**	
	Expected/ Updated[a]	Collected	Expected/ Updated[a]	Collected
1	60/40	73	66/54	69
2	48/40	61	42/36	14
3	88/72	38	30/30	51
4	52/28	0	18/0	0
Total	248/180	172	156/120	134

[a]Considering the number of PoIs visited

Table 4.9. Number of expected and collected videos (velocity)

Day	**Sontea-Fortuna**		**Kifissos catchment**	
	Expected/ Updated[a]	Collected	Expected/ Updated[a]	Collected
1	150/100	3	110/90	106
2	120/100	2	70/60	99
3	220/180	8	50/50	92
4	130/70	20	30/0	0
Total	620/450	33	260/200	297

[a]Considering the number of PoIs visited

In the Sontea-Fortuna case, the number of images was very positive in the first two days of the campaign, while there was a decline on Day 3 and problems on Day 4. In Kifissos, it is clear that the minimum expected numbers were reached or surpassed. In terms of videos for Sontea-Fortuna, it is speculated that the technical issues were related to a poor internet connection, as in Kifissos the number of expected videos was easily surpassed under better connectivity conditions.

As described in Section 4.3, collected images are received by the system and sent to the image classifier and afterwards to the Data Quality Engine. Images that for technical reasons did not reach the classifier were counted as 'Unavailable'; classified images are either 'Valid' (there is a gauge in the image) or 'Undecided', being sent for further manual annotation at Scent Collaborate. These statistics are presented in Table 4.10. In Sontea-Fortuna, most of the images that reached the tools were valid, while in Kifissos, human confirmation is needed for about a third of the dataset.

Table 4.10. Number of unavailable, undecided and valid pictures collected (water level)

Day	Sontea-Fortuna			Kifissos catchment		
	Unavailable	Undecided	Valid	Unavailable	Undecided	Valid
1	10	6	57	2	18	49
2	7	4	50	2	3	11
3	5	0	33	1	23	27
4	0	0	0	0	0	0
Total	22	10	140	5	44	87

After classification validation, image quality for water depth extraction was automatically evaluated by the WLET. The automatic rejection was compared to manually rejecting images. The automatic and manual control obtained similar percentages. For Sontea-Fortuna, 82% of the images passed quality control, while for Kifissos, 51% passed (Table 4.11). If manual control is considered the ground truth, the automatic control routine performed reasonably well, with 9 to 23% of errors, mainly by missing invalid images in the Kifissos case study.

Table 4.11. Evaluation of the automatic image quality control routine

		Sontea-Fortuna		Kifissos catchment	
		Manual control		Manual control	
		Valid [%]	Invalid [%]	Valid [%]	Invalid [%]
WLET	Valid [%]	73	9	32	19
	Invalid [%]	0	18	4	45

Upon preliminary screening of the WLET results, it became clear that even using gauges that follow international standards, the gauges showed enough diversity to negatively affect automatic detections. The tool was trained to identify two digits of the same size, but in the Danube pilot, the indicator had a larger number to indicate the meter and a smaller one for the centimeters, not following the traditional pattern. This means that the automatic extraction still needs to be improved to fully integrate the Scent toolbox.

Considering the automatic quality control mechanism for videos (Table 4.12), compared to manual control, there is a significant difference. In both case studies, only around half of the data was assessed similarly between manual and automatic. In Sontea Fortuna, manual control validated half of the videos beyond the 35% in agreement with automatic control. For Kifissos, proportions of valid and invalid remained similar for both control methods (44 to 52%). Given that manual methods may fail to detect some errors (e.g. if the size of the floater is sufficient) and vice-versa (e.g. detect that the video is freezing), it is not possible to affirm that the manual control is ground truth to the automatic control. This topic is revisited in more depth in Chapter 5. Concerning the ability of the WVET to extract velocities, preliminary screenings and pilots indicate it should be evaluated further, together with the validation of extracted estimates (see Chapter 5).

Table 4.12. Evaluation of the automatic video quality control routine

		Sontea-Fortuna		**Kifissos catchment**	
		Manual control		**Manual control**	
		Valid [%]	Invalid [%]	Valid [%]	Invalid [%]
WVET	Valid [%]	36	0	19	32
	Invalid [%]	51	12	24.5	24.5

Based on results obtained so far, local authorities involved in the project were able to identify potential uses for the collected data in decision-making within their institutions. In the Danube Delta, the Danube Delta Institute for Research and Development has been working on increasing its understanding of the drivers of biodiversity loss in the region. This includes the knowledge of low flows, which can be monitored through citizen river collection campaigns. In what concerns the Region of Attica, land use/ land cover data collected during the pilots provide accurate and updated input on a small spatial scale that will facilitate a more precise recording of the conditions of the Kifissos riverfront. As the area is densely urbanized, these preliminary datasets, as well as an ongoing reporting element, will enable relevant authorities to monitor and control unauthorized uses and remove artificial obstacles both from the riverbanks as well as the riverbed that may pose further risk in case of a flooding, while addressing maintenance needs more efficiently and promptly. Furthermore, river data collection, in conjunction with meteorological data and updated land use mapping, will help the Region of Attica configure more accurate flooding trails and flood risk maps. Such data will allow for the identification of the most vulnerable areas and citizens and the preparation of appropriate evacuation plans. Thus, the RoA will enhance its capacity for risk management and response to natural disasters.

4.5 Conclusions and recommendations

In this chapter, we conceptualized the full cycle of data collection in the case of citizens' campaigns organized to fulfill stakeholders' data needs. The cycle started with the identification of data needs for data collection, in which it was identified that water quantity-related data collection is necessary for the Sontea-Fortuna pilot and that higher resolution land cover data is important for the scale and quickly changing urban conditions of the Kifissos catchment. The campaign manager tool used to link the data needs to the campaign execution has worked well, although it has not been tested single-handedly by authorities.

The developed pathway selection approach in the Sontea-Fortuna also proved useful, as it was found that the wetland is more accessible than expected, for all flow scenarios, and that there are many possible pathways for points of interest, even when only one city is involved in the campaigns. The proposed pathway approach was robust, attributing distinct scores to different pathways. It can be applied in other citizen observatories, specifically in deltas, wetland areas and other regions with an intricate network of channels, where it is challenging to know where to go. Moreover, we envisioned that the approach could be adapted to terrestrial pathways, such as hiking routes, to collect, for instance, soil moisture data from low-cost sensors.

Considering the campaign execution, fostering and sustaining engagement for the purposes of the project was shown to be a demanding and challenging task. As it was inferred from the evaluation process, for the campaigns to become more appealing, they should be organised as a holistic experience in nature that focuses more on capacity building and knowledge transfer within the context of the project, rather than an exhaustive route between PoIs. To this end, local partners consider incorporating the aforementioned ideas in the next campaigns. Despite the difficulties, the number of volunteers is still considered good overall.

In terms of the experience of the gamified application, it was stated that it consumed considerable energy and had bugs and crashes, even though part of the volunteers appreciated the gamification. Lastly, the experience of having the data channeled through the Scent Toolbox in low-connectivity environments culminated in the loss of data. It is recommended that experiments be done prior to the campaign and that monitoring of the data stream is done in real-time during the campaign. The number of images received corresponds to expectations, as well as videos for the Kifissos case study, where connectivity was not an issue.

Overall, we conclude that it is feasible to implement author-centric citizens' campaigns and that the campaigns were successful for the pilot applications. The quantitative water-related dataset (306 images and 330 videos) is in itself a valuable contribution to the citizen science and water resources community, as such a volume has been scarcely reported in the scientific literature, mainly in remote areas such as the Sontea-Fortuna area. The implemented novel technologies were pivotal to allow for such volume to be collected.

Improvements of the proposed pathways selection approach can be made in different directions. This study considered only an average boat velocity for all canals and one type of sensor (mobile phone). When the speed limit is available on each canal and more than one sensor is planned to be used, variable velocities and time for observation should be considered. The scale ranges of the proposed scores need to be further tested regarding their effectiveness, depending on the purposes of data collection. Finally, the pathway selection approach can be posed and solved formally as a mathematical optimization problem, in which the pathway score is maximized, constrained by the accessibility and maximum available time. From a scientific perspective, it is advisable that citizens participate and/or collaborate in the design and development of data collection campaigns (Wehn and Evers, 2015), and that is recommended as the next step.

Further work also lies in assessing the value of data to authorities: to evaluate if/how the land cover maps and the water level and velocity measurements were used by decision makers. By doing so, the last step in the proposed conceptual framework is completed and new, more targeted data needs can be derived. Lastly, performing a cost-benefit analysis of executing citizens' campaigns is the next step to inform local authorities on what it takes to keep the campaigns going.

5

CONVERTING MULTIMEDIA DATASETS TO HYDRAULIC VARIABLES

This chapter expands on the analysis performed in Chapter 4, by investigating the part of the data cycle from multimedia (i.e. pictures and videos) to water depth and surface velocity estimates[11]. More specifically, it looks at the data losses at each step of the way. For that, it establishes procedures to assess and control the quality of each multimedia piece. Several factors were analysed, for instance, environmental factors (e.g. contrast) and human factors (e.g. camera positioning). It is also established ways to control and assess the resultant data and metadata from the multimedia. In this chapter, we have seen that many multimedia pieces were collected concomitantly from different citizens, causing a desired redundancy in data collection. Thus, this chapter proceeds to compare methods to merge the data at each point of interest. The final estimates were validated against traditional measurements. The results show that the citizen capturing abilities and the technological restrictions were extremely influential on the quality of multimedia, resulting in more data losses than inaccuracies in location and time due to smartphone use. More water depth estimates were validated than surface velocity estimates. The research demonstrates the need to quantify rejection rates for understanding the quality versus quantity trade-off discussed in citizen science.

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[11] This chapter is adapted from: Assumpção, T. H., Teruel, D. Popescu, I., Jonoski A., Solomatine, D.P. (2025). Beyond Accuracy: Evaluating Data Rejection Rates in Citizen Science for Water Depth and Velocity Monitoring. *Hydrological Sciences Journal.* Submitted.

5.1 INTRODUCTION

The main objective of the research presented here is to study the efficiency of citizen science campaigns, which were set to collect multimedia data to inform on water depths and velocities. More specifically, to understand how much information is lost and to which factors information losses can be attributed. We discuss in terms of rejection rates instead of error rates to highlight losses occurring in the entire process of raw multimedia becoming useful estimates.

In this study, we first explain the methodology followed to obtain information losses (Section 5.2), followed by the discussion over the obtained results, separately for images and videos (Section 5.3). In Section 5.3, we also show the results of comparing the final estimates to traditional measurements and discuss the findings concomitantly. Lastly, we present our conclusions and recommendations (Section 5.4).

5.2 METHODS

This study involves the river data collection of the dry campaign in September 2018, hereafter referred to as Campaign 1; and the river data collection of the wet campaign in May 2019, hereafter Campaign 2. It regards only the collected multimedia (images and videos) to estimate water depths and velocities. During the campaigns, at each point of interest, the boat was stopped on the riverbank for citizens to collect multimedia. This study achieves its objective by breaking down the information processing and quality control steps involved in processing citizen science contributions and keeping account of the losses and the issues found along the way (Figure 5.1).

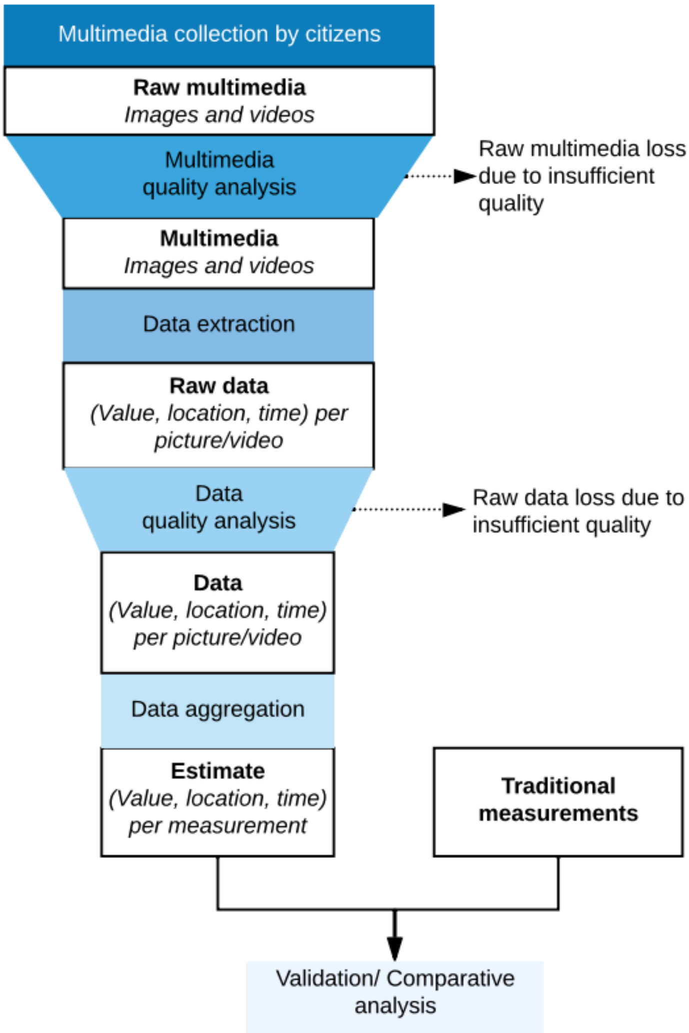

Figure 5.1. Research methodology

5.2.1 Multimedia collection by citizens

For water depth measurements, photos were taken from graded staff gauges with a precision of up to 1 cm (Figure 5.2a). Three gauges were used, and one of them was slightly damaged (considered an ill campaign design, explanation is given in sub-section 5.2.2). The gauge was placed in the water just outside of the boat, by campaign organizers or by citizens, and pictures were taken by the remaining citizens within the boat. For surface velocity, videos of a traceable object floating with the flow were recorded. In this study, a tennis ball was used (Figure 5.2b). The floater was thrown into the water close to the boat, in the middle of the channel or far from the riverbank where the boat was stationed. After several throws, the floaters were retrieved. Volunteers were instructed to face the river, with their smartphones positioned parallel to the float trajectory, with the field of view capturing the water but also the riverbank across from them. They were instructed to start recording as soon as indicated or as soon as the floater entered the camera's field of view and to stop as soon as it left the field of view. Volunteers were also instructed to keep as still as possible and not to move their phones during the recording. Per point of interest, the boats would attempt to perform depth measurements on both sides of the riverbank, and velocity measurements across the channel, also performing ball throws from both sides. Each time the depth gauge was put in the water or a tennis ball was thrown, it was considered a measurement. In this study, we have used all images tagged 'Water Level Indicator', from the citizens or the classifier, and all videos.

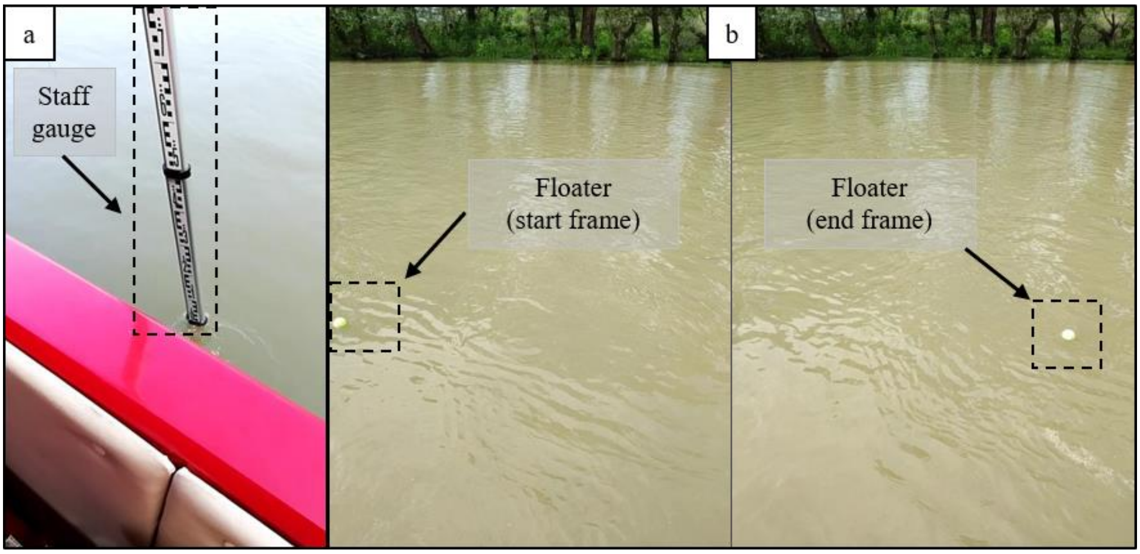

Figure 5.2. Examples of multimedia collected by citizens. (a) Example of an image taken by a citizen using a graded staff gauge, used to extract depth data. (b) Example of a start and an ending frame from a video contributed by a citizen, with the floater

5.2.2 Multimedia quality control and analysis

We consider that the quality of images and videos can be affected by four categories of criteria: environmental conditions, citizens' mistakes, ill-design of the campaigns and technology restrictions. The third category is included because citizen science campaigns are often carried out outside a strict scientific experimental context, mainly large-scale ones, such as in this case. We consider that shortcomings from poor choices perceived ad hoc should be acknowledged. The quality criteria within these categories depend on the robustness of the data extraction method used. For images, a researcher read the water depth markings from the gauge in the image; thus, the image needs to have a gauge present and to be visible enough. For videos, the algorithm used to extract the data relies, for example, on the floating object size remaining the same throughout the video (see sub-section 4.3.3). Hence, criteria regarding the camera position are important.

Criteria for images (Table 5.1) and videos (Table 5.2) were proposed, where each criterion defines an effect in the multimedia. If the effect makes it impossible to infer water depths or velocities from a multimedia item (e.g. image is too dark), the item is considered to have insufficient quality in that criterion and is rejected. If the item has sufficient quality (e.g. image is a bit dark but it is possible to see the water level in the gauge), the severity of the effect is scored according to the following rating scale:

- 0 – no negative effect detected
- 1 – mild effect detected
- 2 – medium effect detected
- 3 – strong effect detected, while still with sufficient quality

Table 5.1. Criteria for evaluation of volunteer-contributed images.

Category	Criteria	Sufficient	Score
Citizen mistake*	Gauge presence	No/Yes	-
	Water level presence	No/Yes	-
	Gauge vertical tilt	No/Yes	0-3
	Lateral capturing angle	No/Yes	0-3
	Top-down capturing angle	No/Yes	0-3
	Image focus	No/Yes	0-3
	Presence of riverbank as reference	-	0-3
Campaign design	Gauge printing	No/Yes	0-3
	Distance to gauge	No/Yes	0-3
	Image resolution	No/Yes	0-3
Environmental conditions	Brightness	No/Yes	0-3
Environmental conditions/ Campaign design	Flow velocity	-	0-3
Not applicable	Other	No/Yes	0-3

* Citizen mistakes include both accidental mistakes and negligence in following protocol.

Table 5.2. Criteria for evaluation of volunteer-contributed videos.

Category	Criteria	Sufficient	Quality score
Citizen mistake*	Floating object presence	No/Yes	-
	Multiple floating objects presence	No/Yes	-
	Floating object release present in video	No/Yes	-
	Floating object recovery present in video	No/Yes	-
	Camera follows the floating object	No/Yes	0-3
	Camera shaking	No/Yes	0-3
	Recording angle deviation	No/Yes	0-3
	Video duration	No/Yes	0-3
	Presence of riverbank as reference	-	0-3
Campaign design	Floating object contact with the riverbank	No/Yes	-
	Interference in floating object movement	No/Yes	-
	Distance to floating object	No/Yes	0-3
Environmental conditions	Floating object visibility/contrast	No/Yes	0-3
	Floating object trajectory - cross-sectional deviations	No/Yes	0-3
	Floating object trajectory – wave presence	No/Yes	0-3
	Disturbance to float movement	-	0-3
Technology restriction	Video freezing	No/Yes	0-3
Not applicable	Other	No/Yes	0-3

* Citizen mistakes include both accidental mistakes and negligence in following protocol.

Scoring was done by two researchers and images and videos were randomized at the time of evaluation and separated by case study. The quality scores were attributed based on expert knowledge, i.e. the researchers attributed the score based on their best judgment of fit according to the criteria description (Appendix A). For videos, videos were not discarded if at least a 5-second piece had sufficient quality, followed by quality scores for the whole video. The automatic quality control for images was not used because the extraction method used in this chapter is different (see section below) and the automatic control mechanism was tailored for the automatic extraction. The results for the automatic quality control for videos are revisited in sub-section 5.3.1.

5.2.3 Data extraction from multimedia

The water level estimation tool was not used in this study, as it did not reach high accuracy in preliminary tests and a better manual extraction was possible. Water depth data were read by a researcher from the gauge captured within images. The markings on the gauge image were used to obtain the value. If the gauge was in poor condition but a value could be inferred from the surrounding markings, a value was derived. If it was possible to only estimate a range of values, a range was derived. While this process was taking place, we also assessed the certainty of each reading by attributing an uncertainty band to each of them, based on the expert's perception. The uncertainty bands reflect the gauge's markings: ± 0.01 m, ± 0.02 m, ±0.05 m and within a certain range. Within a range means that no one value could be inferred, but a value within two identified values. The goal of this exercise is to later assess if uncertainty while reading is associated with specific quality criteria (e.g. if a darker image meant reduced certainty in the value extracted).

Velocity data were calculated by the water velocity extraction tool developed within the Scent project (sub-section 4.3.3).

5.2.4 Data quality control and data aggregation

Geographical data have three main properties: value, location and time. During traditional data collection efforts, it is likely to exist quality control for the value property, while space and time records tend to be so precise that their inaccuracies are considered insignificant. By collecting data with a smartphone, mainly in remote areas, the geotag and the timestamp of the measurement are less controlled. Thus, in this article, we quality control the value, location and timestamp. Per campaign, the steps taken were:

1. Control location precision: reject data points more than 15m inland and in waterways that were not navigated.
2. Control time precision: reject data points outside of the campaign hours.
3. Control value precision: negative values and outliers over five times the value expected (e.g. 3 m/s for velocities).

In Step 1, the distance of 15m was chosen conservatively, to reject data points that were unrealistic. We considered that the boats were 7m in length, the average GPS accuracy was 5m and that there was tree cover, making the edge of waterways sometimes hard to pinpoint.

After the data quality was controlled, all data points were clustered by point of interest. Two boats visited each point of interest, and measurements were performed on both riverbanks, so multiple measurements were performed per point of interest. Therefore, each cluster was sub-grouped, where each sub-cluster tried to match a measurement. Depth data points were manually sub-grouped to best match their value, time and location, in this order of importance, as this is the perceived order of decrease in accuracy. Velocity data points were sub-clustered considering the time, location and value in respective order of importance, as the accuracy of the velocity detection algorithm is not known. The clustered data points were averaged.

5.2.5 Comparative analysis

We assess how the derived estimates compare to Acoustic Doppler Current Profiler (ADCP) measurements. Profiles were collected within the same time frame of the campaign, if possible within the same day, and as close as possible to citizen measurements. 55 profiles were collected with sufficient quality and within 100 meters of citizen-contributed data. To avoid compounding the errors in geolocation with the errors in values from the citizen-based estimates, we do not use multimedia geolocation. Another reason for this is that videos of the tennis ball have the geolocation of the phone instead of the tennis ball, thus being an unreliable estimator of the measured location. Instead, we defined which zones of the river cross-section the measurements were performed in and used those zones to extract values from traditional measurements (Figure 5.3). For instance, for depth measurements, the staff gauge was inserted in the water the farthest possible from a static boat, which was oriented from parallel to perpendicular to the shoreline. Given a boat length of 7 meters, the depth zone ranges from 3 to 8 meters from the shoreline. For velocities, the zone from one meter away from the boat all the way across was used.

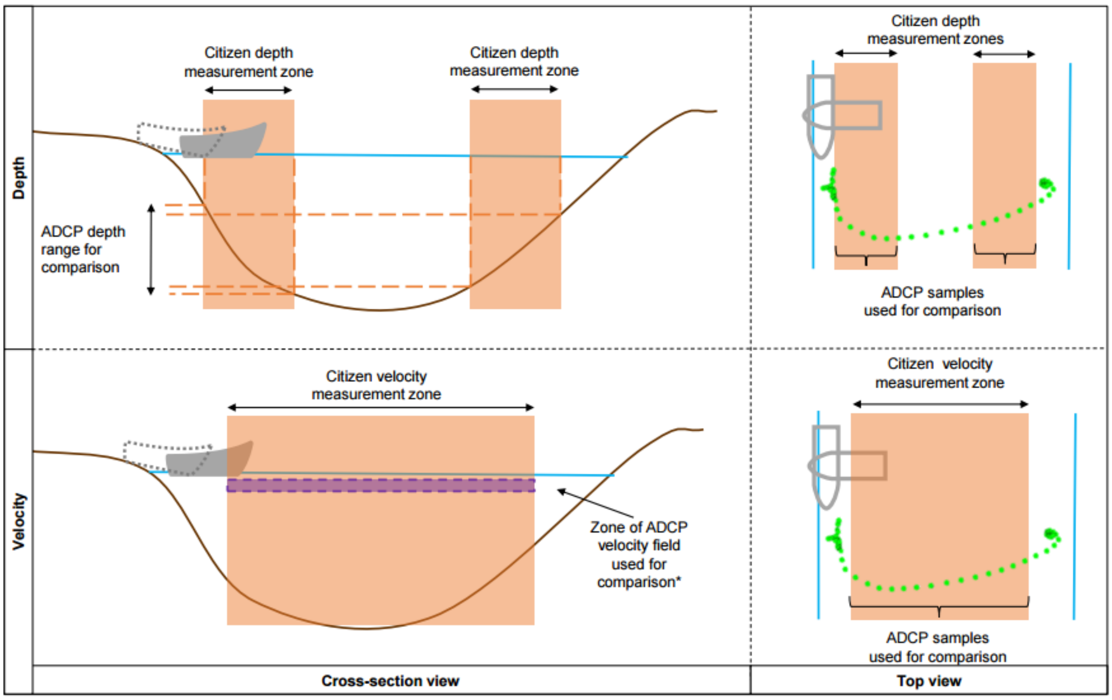

Figure 5.3. Schematic demonstrating the zones within the cross-section where citizen measurements were performed, zones that were used to define which ADCP samples are used for comparison

5.3 Results and discussion

5.3.1 Multimedia quality control and analysis

In the Danube Delta, a total of 1401 images (399 in Campaign 1[12] and 1002 in Campaign 2) were obtained. On average, 77% of the images had sufficient quality to be retained for information extraction (90% in Campaign 1 and 72% in Campaign 2). The remaining were discarded and from these, only 10 images were discarded due to more than one reason. Citizens took many pictures without the gauge, despite instructions (84% of total discarded images). In both campaigns, at least 94% of the discarded images were discarded due to citizen mistakes, and another 5% due to the campaign design. Campaign 1 showed a slightly higher variability of the reasons for discarding images, with the three

[12] The number of images differs from the result in Chapter 4 (172 images) because of improvements done the image classification and validation strategies. For research purposes, the images and their original tags were re-run through the system, generating this discrepancy.

main ones being the lack of gauge, the lack of water level and the image being unfocused (Figure 5.4).

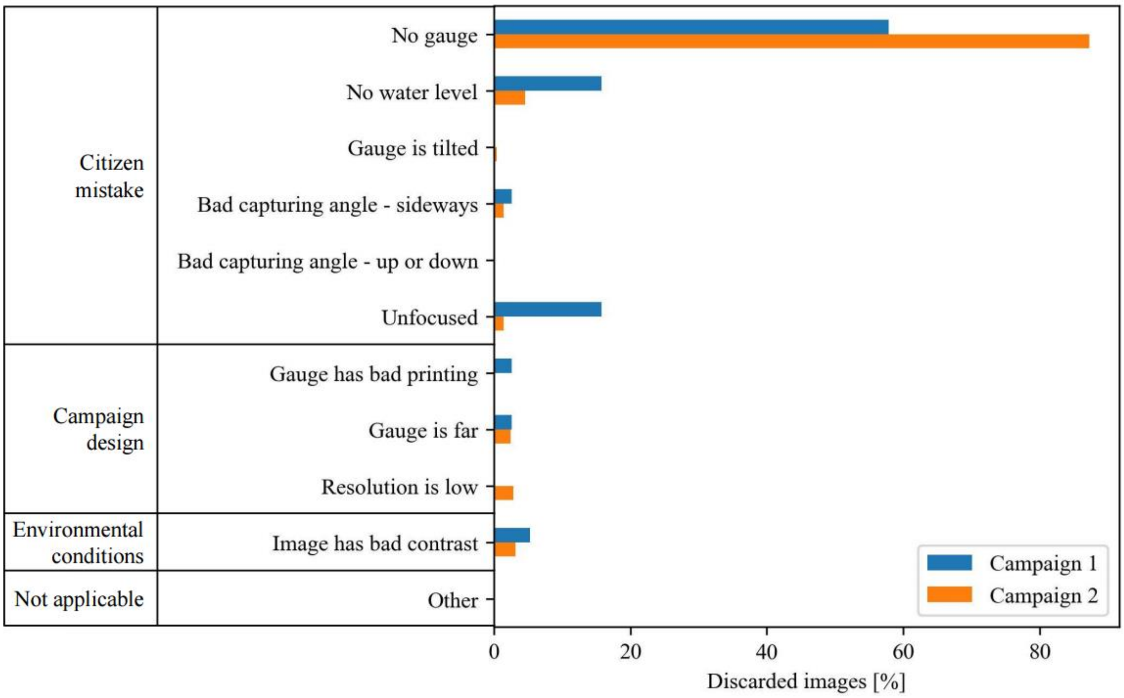

Figure 5.4. Main causes for discarding images (images could be discarded as per more than one observed effect)

From the retained images, about 49% scored in at least one quality criterion and a few images (<5%) in more than two. Considering the scores themselves, 51% of the retained images did not show any fault in quality (Score 0), i.e. they were perfect pictures from a multimedia-quality perspective. When negative effects were observed, results for the two campaigns varied (Figure 5.5). In Campaign 2, the majority of images with negative effects had very mild effects (Score 1), with the tilted gauge being the most common effect. It is also clear that the campaign design and environmental conditions played a bigger role than when rejecting images, accounting for 34% of the images with a score of 1 in that category. In Campaign 1 though, 33-77% of images scored negatively in the lack of bank reference and 6-16% in the gauge printing criteria, with a significant number of images in the three severity levels. Looking at the uncertainty bands attributed to data points when extracting the readings from the images (as described in sub-section 5.2.3), around 60% of readings were done within a centimeter of uncertainty, 32% around two centimeters and only one percent above 5 centimeters.

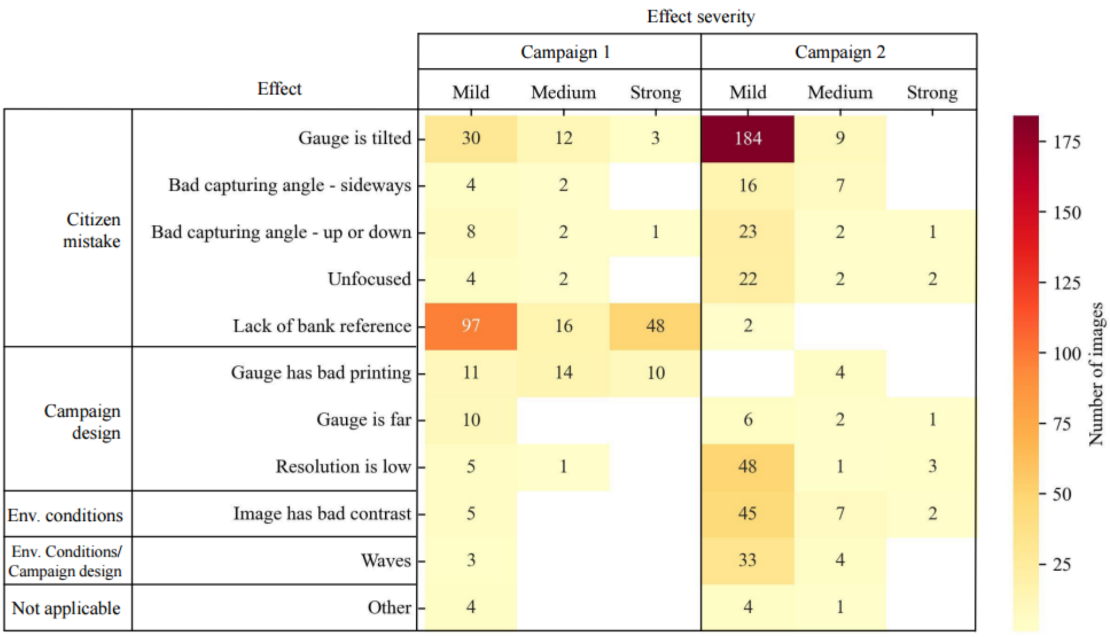

Figure 5.5. Severity of effects influencing the images' quality as per effect considered and effect category

Unfortunately, technical difficulties in the backend were experienced during the execution of the first campaign and few videos were uploaded to the database (less than 50), while 1200 videos were obtained in the second campaign. Due to this large discrepancy, only the second campaign is analyzed in this paper.

Of the videos from campaign 2, 46% showed sufficient quality to be retained and only 40 videos (3%) were discarded for more than one reason. Compared to the images, the reasons for discarding videos were much more diverse (Figure 5.6), although video freezing was the main cause by far (45%). Other relevant causes, accounting for about 11% each, were being hard to see the ball (due to color similarity with the water or because of sun reflection), camera shaking and no ball in the video. In general, the technology restriction (45%) and the citizen mistake (38%) were the categories in which most discarded videos were found. Although some videos do not have sufficient quality when processed as a whole, 8% of all videos that were discarded could be used if a part of the video was cut.

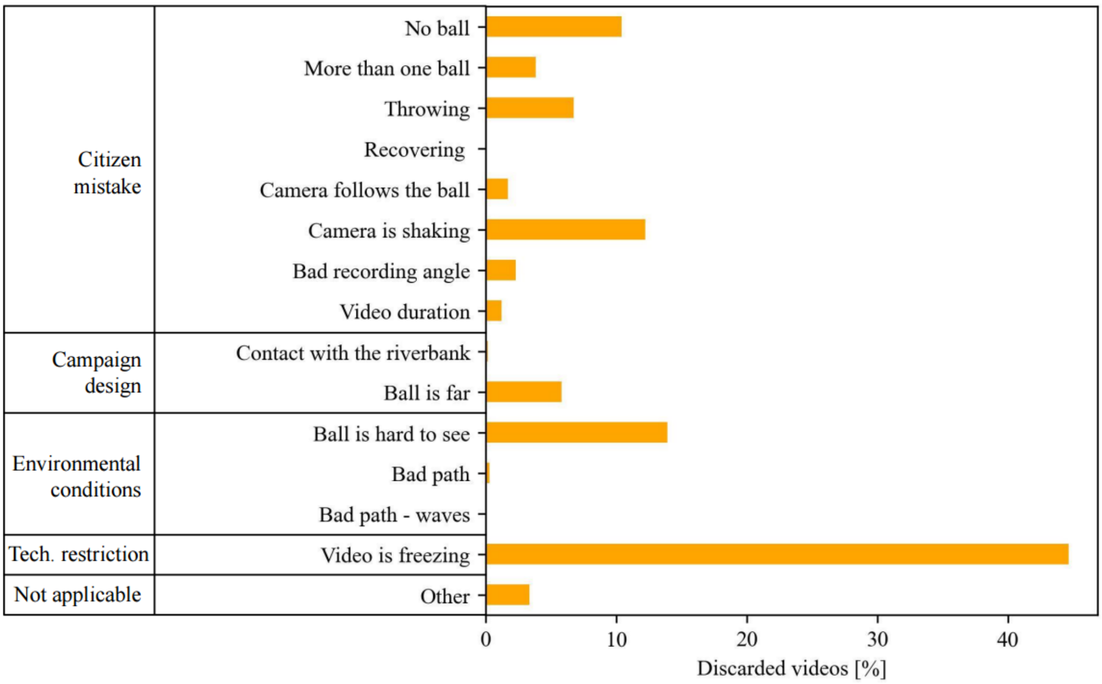

Figure 5.6. Main causes for discarding videos (videos could be discarded as per more than one observed effect)

Retained videos also counted with higher loss in quality when compared to images. Negative effects were detected in 89% of videos, while in most videos (67%) a combination of negative effects was found, from 2 up to 6 effects. Most negative effects on retained videos were of mild to medium severity (Figure 5.7). Camera shaking was the prevailing mild effect, persisting as a common medium effect together with being hard to see the ball and with the ball being far. Together these three effects compose 70% of the medium severity negative effects on retained videos. Overall, citizen mistakes (with 27 to 57%) and environmental conditions (17 to 35%) accounted for most effects.

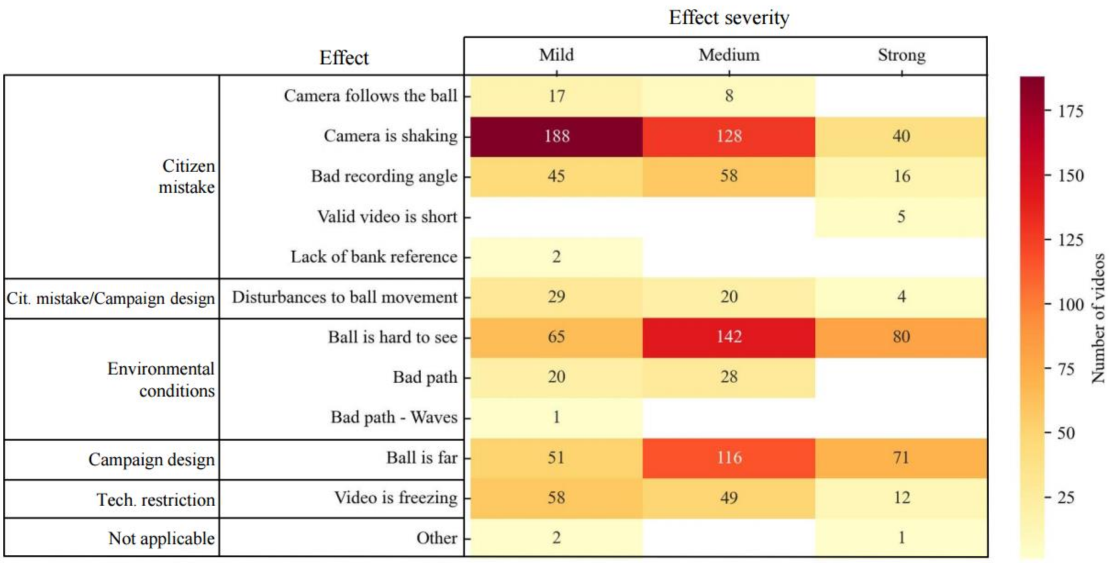

Figure 5.7. Severity of effects influencing the videos' quality as per effect considered and effect category

For videos, it is expected that the analysis above was capable of rejecting the videos that do not have sufficient quality to have their velocity extracted. However, 28% of the videos rejected in the multimedia analysis were not rejected by automatic extraction (Table 5.3). We consider that the automatic quality analysis is not robust enough to detect all defects in the videos. Further, it is not possible to extract velocity values from the videos rejected by the algorithm. Therefore, retained videos from hereon refer to videos retained in both processes (301 videos).

Table 5.3. Overlap of manual quality analysis of videos and acceptance by the video data extraction algorithm

		Automatic extraction quality control	
		Retained	Rejected
Video quality analysis	Retained	25 %	20 %
	Rejected	28 %	27 %

5.3.2 Data quality control

After controlling the quality of images and videos, we further controlled the quality of data points based on their geotags, timestamps and extracted values. Table 5.4 shows the percentage of rejected data points, based on those retained from the multimedia quality analysis. The amount of rejections is reduced greatly, down to up to 11% in total for images, but less than 5% in total for videos.

Table 5.4. Percentages of depth and velocity data points rejected based on unprecise location, time or value

Data point type	Percentage rejected based on			
	Campaign	Location [%]	Time [%]	Value [%]
Water depth	1	5.5	<1	Not applicable*
	2	9.2	1.7	Not applicable*
Surface velocity	1	Not available	Not available	Not available
	2	2	1	1

* water depth values were estimated from readings of images retained for good quality and there are no values expected to be controlled.

If asking ourselves what would the data losses be if the multimedia was not screened for their quality beforehand, the statistics are virtually the same (up to 1% difference). This indicates no clear link between removing unfit multimedia and automatically removing points with bad geotags. This is indeed the case, as we found data points with good gauge pictures but with wrong geotags (Figure 5.8a); and data points with correct geotags and time stamps but of pictures of the surroundings (Figure 5.8b) or selfies. We attribute the first to network connection issues and the latter to volunteers not following the instructions, among others (as discussed previously in sub-section 5.3.1).

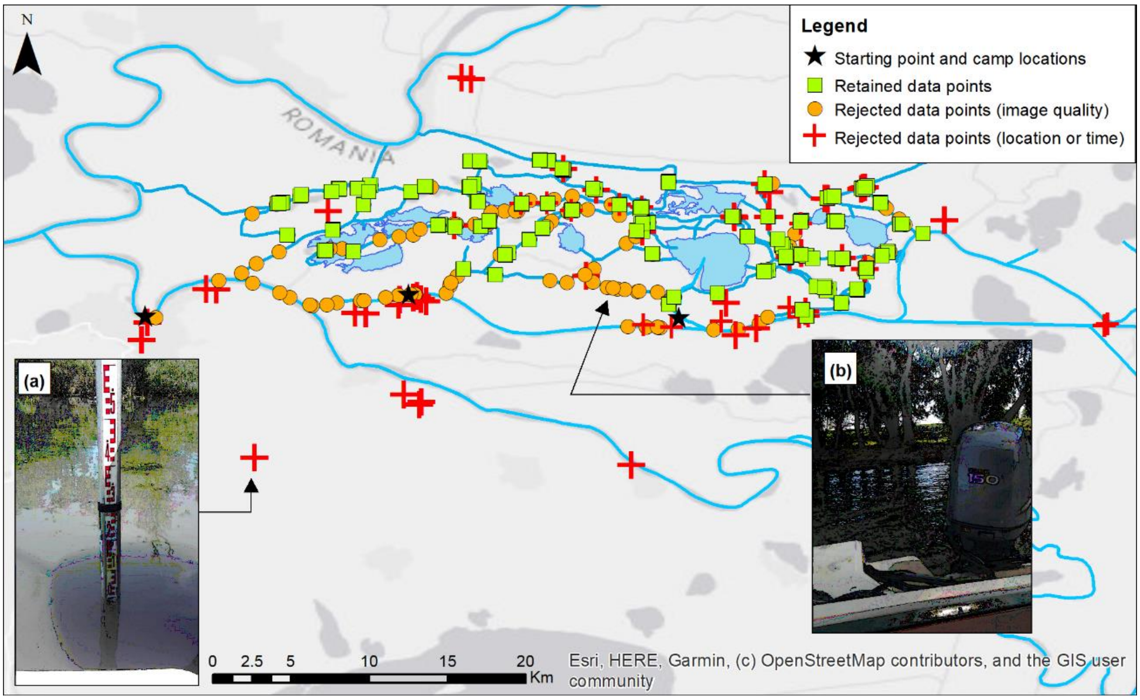

Figure 5.8. Spatial distribution of images taken and their status. (a) Picture of a gauge, with the wrong geotag; (b) Picture taken from an accepted location at an accepted time, but not of a gauge

5.3.3 Merged estimates

After controlling for the multimedia, geotag and timestamp quality, we are left with several data points per point of interest visited. Ideally, every time a measurement was performed, a distinct cloud of points formed around it. This was observed in our experiments (Figure 5.9a), but it was also observed in cases with less precise spatial spread (Figure 5.9b). Most times, it was possible to distinguish between measurements collected at different sides of the channels.

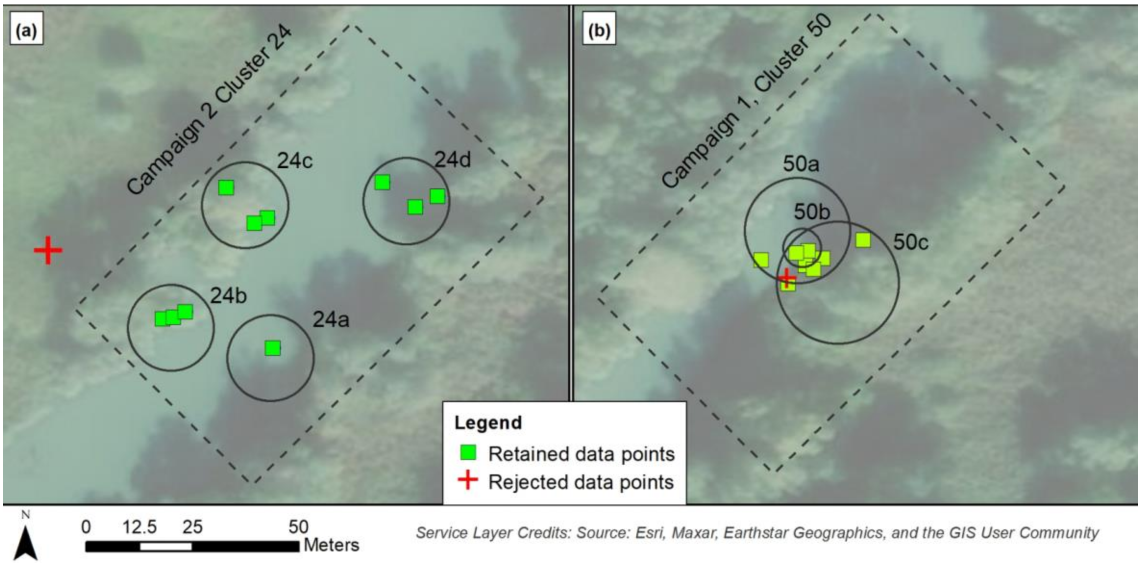

Figure 5.9. Examples of varied geospatial spread of data points. (a) Data points form defined sub-clusters. (b) Data points do not have defined sub-clusters spatially, but their values and timestamps allow for sub-clustering

In terms of the volume of images, we had already observed that Campaign 2 collected largely two times more data points than Campaign 1. This was probably achieved by taking more measurements, meaning that more sub-clusters were created and thus, more data points were added to the clusters (Table 5.5). It can also be observed that, by sub-clustering per value, very precise sub-cluster estimates were obtained, with a standard deviation lower than 5 cm. For videos, the rejection of many data points meant a reduced density of points in clusters and sub-clusters. Even the average standard deviation is balancing the few sub-clusters with many measurements whilst a majority of sub-clusters had only one item.

Table 5.5. Statistics on the clusters and sub-clusters formed based on the data points related to images collected in both campaigns.

	Water depth data points		Velocity data points
	Campaign 1	Campaign 2	Campaign 2
Clusters [#]	57	63	53*
Average sub-clusters/cluster [#]	2.5	3.5	2.5
Average data points/cluster [#]	6	10	5.5
Average data points/sub-cluster [#]	2.4	2.9	2.2
Average standard deviation/cluster [m]	0.3 m	0.5 m	0.4 m/s
Average standard deviation/sub-cluster [m]	0.02 m	0.02 m	0.2 m/s

*out of 57 when compared to the 63 visited for water depth data collection.

5.3.4 Comparison analysis

For depth, 47 comparisons were made between citizen-contributed estimates and ADCP profiles. For velocity, it was 43 comparisons. We discarded 8 ADCP profiles that were much further from citizen-based data than the selected 47. The average distance between paired comparisons was 14 m.

Depth

We can compare directly the range of estimated depth values from citizen contributions and the range of observed values from ADCP measurements, per cluster (Figure 5.10). Citizen-based depth ranges are of similar width to ADCP ones (both 0.89 m standard deviation, on average), in both cases with some variation from cluster to cluster. From a visual assessment, it is already clear that citizen-based estimates tend to capture higher values than the ADCP measurements, but still, there is quite some overlap between the two.

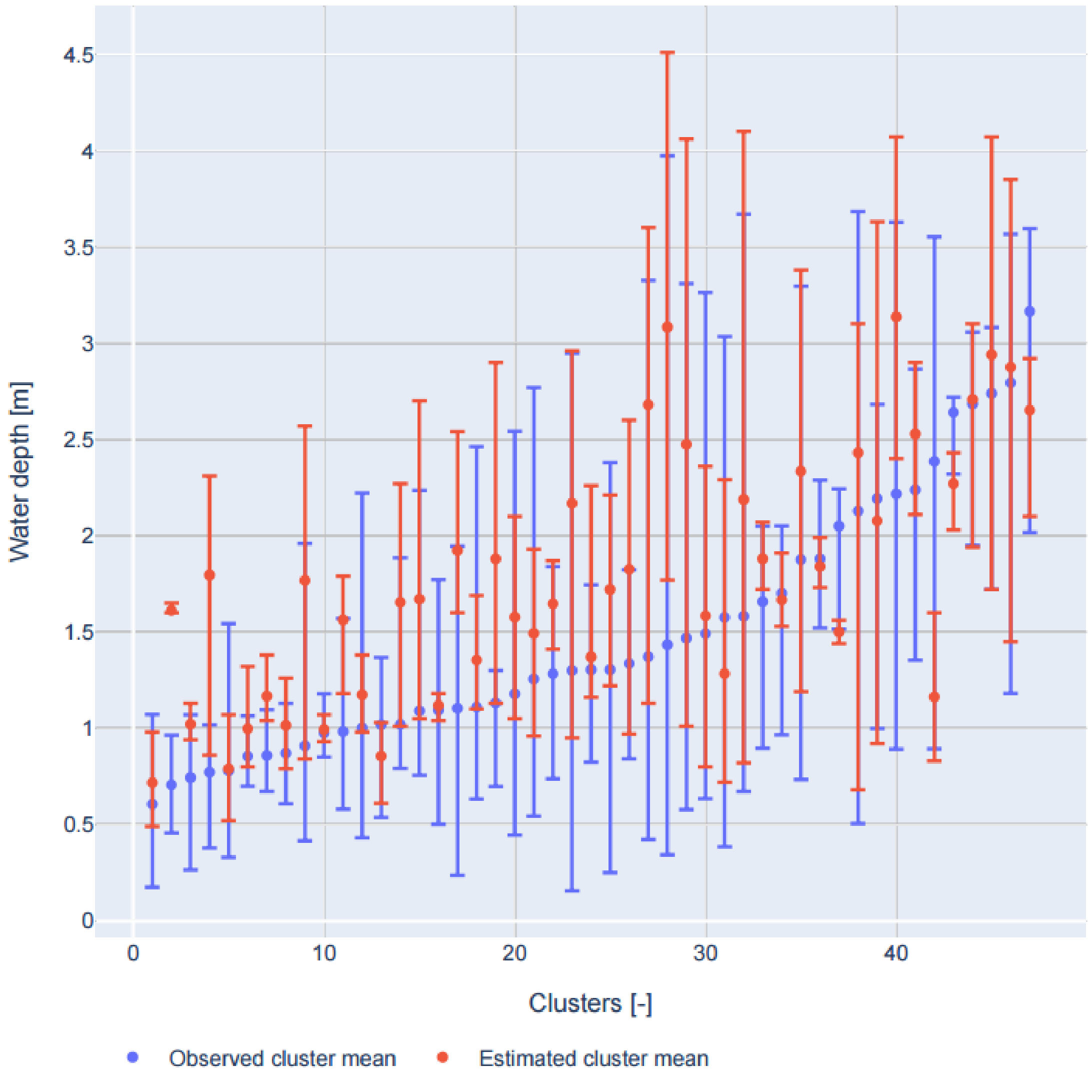

Figure 5.10. Comparison, per cluster, between the range of depths estimated from citizen-contributed data and the range of depths that could have been the correspondent observation, as measured with ADCP equipment

The comparison of the intervals can be summarized in two metrics. We can first check the Hit Rate, i.e. number of hits per total number of comparisons. A hit in this case is when a comparison pair has some overlap. The hit rate for clusters is 98% and continues to be 98% even if outliers are removed from the calculation (absolute errors above the 90% percentile). For sub-clusters, the hit rate is about 72 to 79%, if outliers are removed. We can also compute the mean Intersection over Union (mIoU), which tells us how much overlap there is between the ranges, on average. This metric only makes sense for clusters, as sub-clusters have a very small standard deviation (<5cm). These statistics tell us that whilst sub-clusters missed the observed range of values about 25% of the time, there were enough sub-clusters per cluster to guarantee an average 44% overlap with observations.

This made the clusters successful in finding the right depth value, with an almost perfect success rate.

To understand how accurate citizen-based estimates were, it is also important to look at central tendencies. When comparing mean cluster estimates and mean ADCP values, a moderate correlation is found ($R^2 = 0.47$), with a Mean Absolute Error (MAE) of 0.44 m (Figure 5.11a). If looking at the sub-clusters, the correlation is weak and the error increases ($R^2 = 0.26$, MAE=0.62 m, Figure 5.11b). The error distribution is positively skewed, with an overestimation of depth values (Figure 5.12). By removing outliers of the clusters, the skewness is reduced, a strong correlation can be found ($R^2 = 0.69$, Figure 5.11a) and the MAE is reduced to 0.35 m. Removing outliers from sub-clusters has a similar effect ($R^2 = 0.46$, MAE=0.47 m). These results indicate that arranging the data in big clusters instead of sub-clusters is positive, as it reduces the variability of the data (i.e. the influence of wrong sub-clusters), representing better the depth central tendency in the corresponding point of interest.

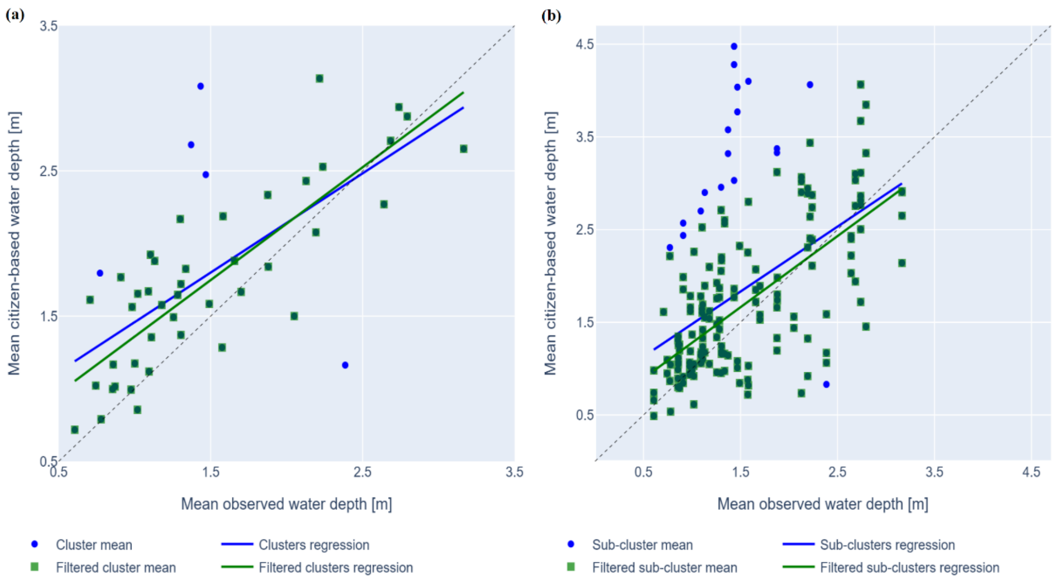

Figure 5.11. Correlation between the mean depth estimate and the mean observed depth, considering all estimates or estimates filtered for outliers (absolute errors above the 90% percentile). (a) Considering the mean of clusters; (b) considering the mean of sub-clusters

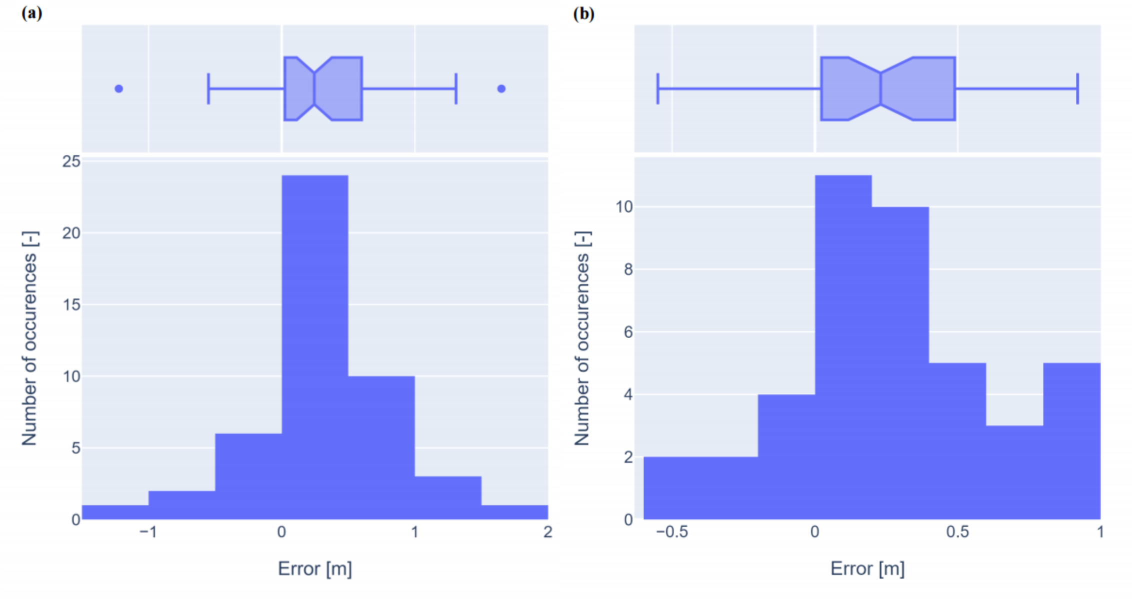

Figure 5.12. Distribution of the depth errors. (a) With all estimates, (b) removing outliers

Another factor that can influence citizen science results is the density of data points per measurement, as it is expected that with more citizen science contributions, the more reliable the data will be. By removing the less dense sub-clusters (with less than 3 data points), we eliminate about 45% of sub-clusters and 10% of clusters. Considering the metrics discussed so far (Table 5.6), despite a slight increase in correlation for filtered clusters (less than 10%), overall there is not much gain from this selection. Results get slightly worse in terms of MAE (up to 16% increase) and hit rate for clusters. In combination with the low variability within sub-clusters, this indicates that more photos in a single measurement do not produce better results. Rather, it shows that by removing less dense sub-clusters, we are removing sub-clusters with more comparable depths to observations. The variability of depth values within a point of interest (cluster) is similar to the error observed in these locations. Therefore, part of the errors in citizen-based data may not be due to the citizen-based data but rather to the natural depth variability in cross-sections and the comparison design proposed.

Lastly, it is important to consider if the quality of images, assessed in sub-section 5.3.1, impacts the accuracy of the results. Given that fewer than 50 images had medium or strong negative effects on them (less than 10% of the dataset), it is understandable that comparison metrics have not changed (Table 5.6).

Table 5.6. Comparison between estimated and observed depths for three metrics (R^2, MAE and Hit Rate) in three scenarios (direct comparison, dense sub-clusters only, good quality estimates only), considering all estimates or estimates without outliers. Bold values are the best statistics for the metric; underlined values are the second best.

			Direct comparison	**High-density estimates only***	**Good quality estimates only****
R^2 [-]	Clusters	All	0.47	0.45	0.47
		Filtered	<u>0.69</u>	**0.74**	<u>0.69</u>
	Sub-clusters	All	0.26	0.33	0.26
		Filtered	0.46	0.48	0.46
MAE [m]	Clusters	All	0.44	0.51	0.44
		Filtered	<u>0.35</u>	0.39	**0.34**
	Sub-clusters	All	0.62	0.64	0.62
		Filtered	0.47	0.49	0.46
Hit rate [%]	Clusters	All	**98**	93	**98**
		Filtered	**98**	<u>95</u>	**98**
	Sub-clusters	All	72	72	72
		Filtered	79	80	79

* Only sub-clusters of 3 or more members

**Only videos with no to mild negative effects

The results obtained by filtering high-density estimates and good-quality estimates also offer us insight into the efficiency of the campaign design. Focusing on more measurements and fewer pictures per measurement could improve the data quality of depth estimates. A more precise validation method that reduces the variability of the traditional measurement could better support the accuracy assessment. For instance, setting a few control points of interest with known hydraulic characteristics could support that. Lastly, manual data quality control proved to be very efficient in ruling out bad data points and should be considered to continue in the design. This could change if switching to automated methods.

Velocity

When comparing observed and estimated ranges of surface velocity, the most obvious difference is the ADCP measurements recording negative flows (Figure 5.13). These can most likely be attributed to some fluctuations around zero, when velocities are almost stagnant, also almost at the limit of the equipment measurement capacity; and to potential boat movements on the edge of the surveyed cross-section, causing flow in the opposite direction. Here there is a much larger difference than when comparing water depths. Overall citizen-based estimates have a much wider variability within a cluster (±0.8 m/s) than ADCP-based measurements (±0.4 m/s standard deviation), but also much more variability in standard deviation among clusters. Citizen-based estimates show higher velocity values, with a quarter of clusters ranging over 1 m/s, while almost all ADCP-based observations are contained to less than 1 m/s.

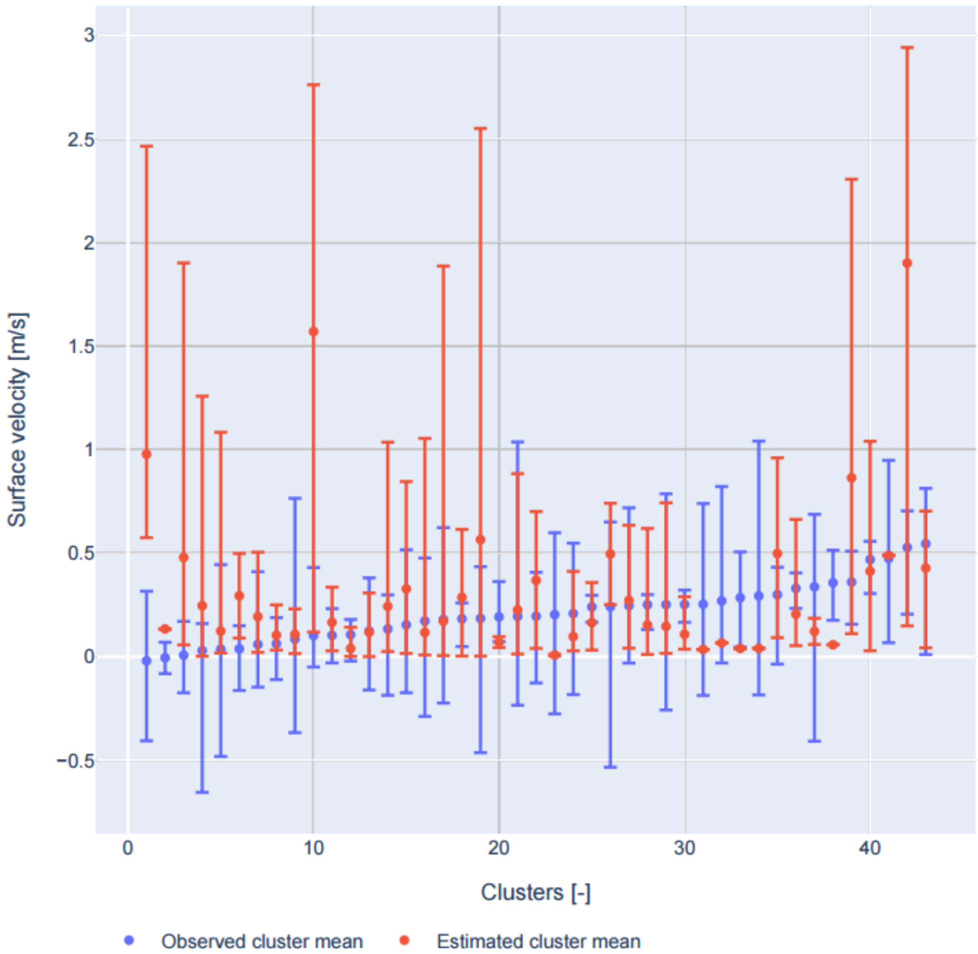

Figure 5.13. Comparison, per cluster, between the range of velocities estimated from citizen-contributed data and the range of depths that could have been the corresponding observation, as measured with ADCP equipment

There are misses (i.e. no intersection between observed and estimated ranges) visible in this comparison, resulting in a lower hit rate for velocity estimate per cluster of 91% (92% without outliers). For sub-clusters, the rate is similar to water depths (71-78%). With an average lower overlap between ranges (29-30%), most likely some good sub-cluster estimates are concentrated within some specific clusters. Alternatively, this may be a result of velocity clusters being less dense than those for depths, and less likely to contain the correct value.

When comparing mean velocity estimates to mean ADCP measurements, it is visible the overestimated mean values and a wide spread of estimations when compared to observations (Figure 5.14). There is no correlation between the two, independent of the comparison (clusters or sub-clusters, removing outliers or not). All correlation scores were between 0.02 and 0.08. An average MAE of 0.26 m/s, was found between clusters and sub-cluster assessments, with a good reduction in error to 0.15 m/s when removing outliers (Table 5.7). Even so, most errors are still overestimations (Figure 5.15). The high variance in velocities and lack of correlation indicate that the estimates are not yet good enough as a substitute for traditional measurements.

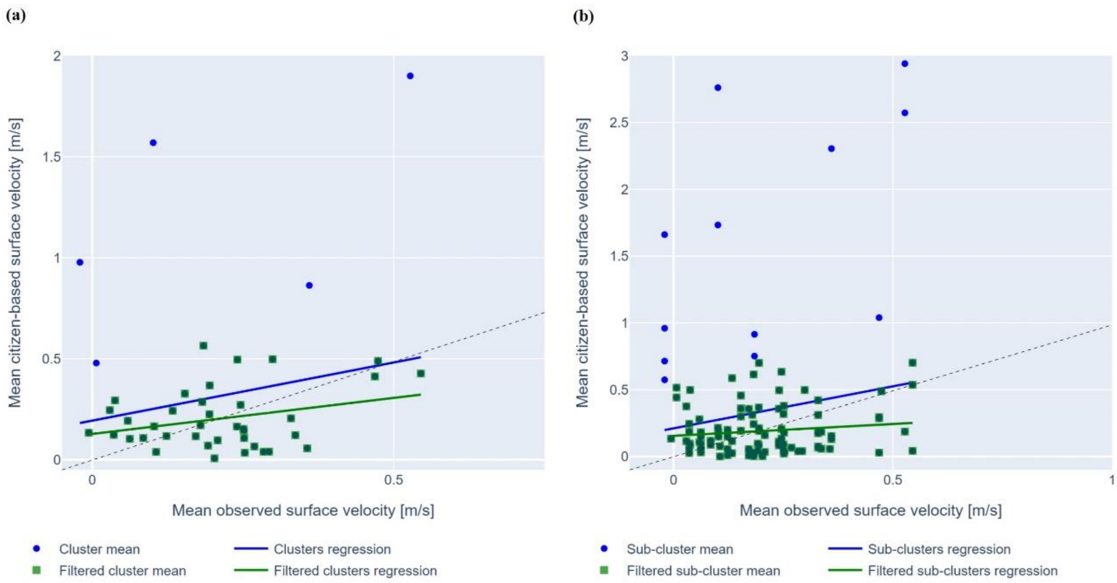

Figure 5.14. Correlation between the mean velocity estimate and the mean observed velocity, considering all estimates or estimates filtered for outliers (absolute errors above the 90% percentile). (a) Considering the mean of clusters; (b) considering the mean of sub-clusters

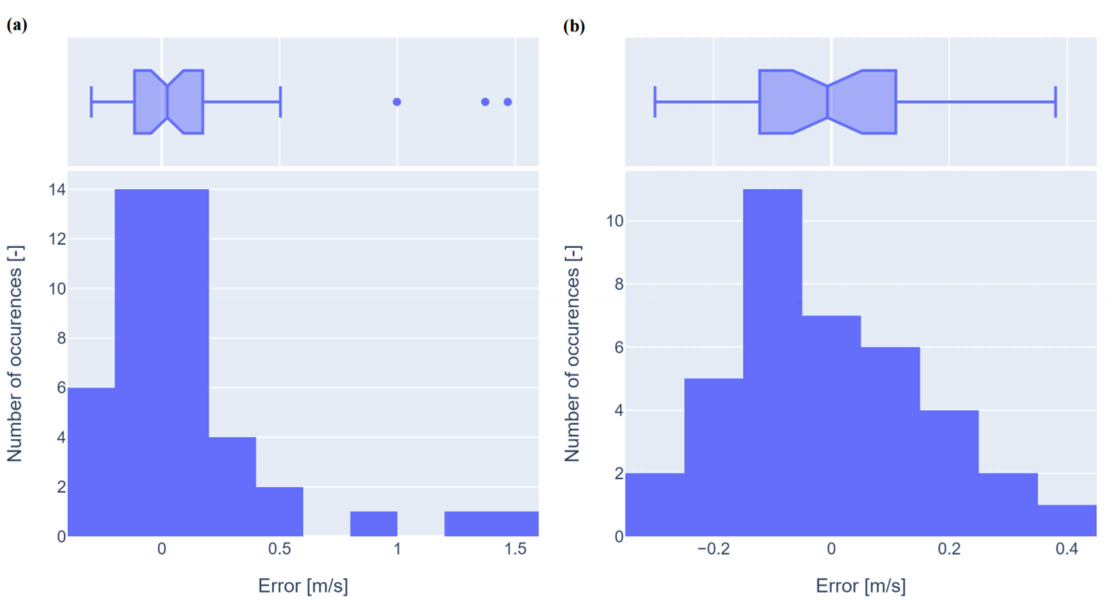

Figure 5.15. Distribution of velocity errors. (a) With all estimates, (b) removing outliers

Table 5.7. Comparison between estimated and observed velocities for three metrics (R^2, MAE and Hit Rate) in three scenarios (direct comparison, dense sub-clusters only, good quality estimates only), considering all estimates or estimates without outliers. Bold values are the best statistics for the metric; underlined values are the second best.

			Direct comparison	**High-density estimates only***	**Good quality estimates only****
R^2 [-]	Clusters	All	0.04	0.02	0.08
		Filtered	0.08	**0.2**	0.13
	Sub-clusters	All	0.03	0	0.11
		Filtered	0.02	<u>0.14</u>	0.02
MAE [m/s]	Clusters	All	0.23	0.12	0.23
		Filtered	0.13	**0.09**	0.14
	Sub-clusters	All	0.29	0.15	0.25
		Filtered	0.16	<u>0.10</u>	0.16
Hit rate [%]	Clusters	All	91	**100**	84
		Filtered	92	**100**	85
	Sub-clusters	All	71	94	76
		Filtered	78	<u>97</u>	81

* Only sub-clusters of 3 or more members

**Only videos with none to mild negative effects

Differently from its depth counterpart, citizen-based velocity estimates have significant sub-cluster intra-variability, due to the unknown accuracy of velocity value extraction from videos. To understand the influence of this effect on the results, less dense sub-clusters were removed, leading to a 71% loss in sub-clusters and a 49% loss in clusters. With only dense sub-clusters, more videos collected by citizens per measurement meant a 30% increase in the percentage of sub-clusters that got the velocity in the right range; bringing the hit rate to 100% (Table 5.7). There is also a 37 to 48% decrease in the mean absolute error – so the effect expected of increasing accuracy with more citizen-based data is observed. However, despite some increase in correlation after filtering outliers, only a very weak correlation with observations was found.

Once more differently unlike the depth case, there is a significant reduction in the velocities dataset velocities when filtering out videos identified with medium to severe negative effects. Half of the sub-clusters are removed and a bit less than a third of the clusters. Further, data density reduces, i.e. there are fewer data points per sub-cluster and cluster. The latter did not result in a smaller standard deviation in sub-clusters, but yes in clusters (from 0.3 m/s to 0.25 m/s). The reduction in spread occurs across the dataset because correlation statistics increase by 50% or double, thus going from no correlation to a very weak correlation (Table 5.7). This means that some sub-clusters that had bad values were removed. However, sub-clusters that had good values were also removed, seen by the almost 20% decrease in their hit rate, influencing also the hit rate for clusters. Keeping only good quality videos did not affect the MAE, which could be a balancing of the big errors and smaller errors, both removed. This shows that the velocity extraction algorithm, although lightly responsive to the quality factors described in sub-section 5.2.2, is not very sensitive to them. The algorithm may be robust enough to handle quality issues marked as negative in the visual inspection, thus creating estimates that were correct but were eliminated in this analysis. The inaccuracies in the algorithm are likely determined by factors not considered in the visual inspection, as also observed in Table 5.3.

In terms of impact on campaign design, the experiments showed a great need to pilot the velocity extraction algorithm more extensively. It will allow us to better understand the factors influencing data quality and tailor the data quality control methodology for that. This process could include more videos taken at the same spot instead of multiple points of interest, using high volumes until better results are acquired.

5.4 CONCLUSIONS

To make citizen science campaigns useful beyond academia, understanding the effort to obtain a usable dataset is essential. This study investigated data rejection rates when monitoring water depths and surface velocities via two multi-day citizen campaigns in Romania's Danube Delta. Citizens, after two to three hours of training, used a smartphone application to collect photos of gauges and videos of floaters from a boat. Covering over 60 points of interest, the campaigns yielded approximately 1400 images and 1200 videos.

By controlling the quality of the raw multimedia (e.g. filtering out images that were too dark or videos that were too short), a quarter to half of the multimedia pieces were discarded, mostly due to citizen mistakes, environmental conditions and technological restrictions. It is much more than the 7% rejection rate due to wrong GPS coordinates, timestamps or outliers. Overall, 30 to 50% of the collected multimedia was lost. In terms of accuracy, depth and velocity estimates (the product of merging retained data points) presented a 70 to 100% range overlap when compared to ADCP-measured ranges. For depths, we found a moderate to strong correlation between observed and estimated means (overall MAE of 0.5 meters), corroborating with other citizen science studies. The depth variability in ADCP measurement zones was of the same magnitude as the error. It suggests that discrepancies between citizen and measured estimates may not result solely from inaccuracies in citizen data, but may also reflect local conditions. Surface velocity estimates, despite an acceptable mean absolute error (average 0.17 m/s), did not show a correlation to observations in many cases. For both water depths and velocities, merging data points from all measurements executed within a point of interest worked better than subdividing them to potentially represent single measurements. For depths, taking more pictures per measurement did not improve accuracy, as their gauge readings were nearly identical. For velocities, filtering for high-density estimates (i.e. measurements with at least 3 videos) achieved a very weak correlation and the lowest error (0.09 m/s). The impact of remaining multimedia quality issues did not propagate into depth estimates, because there were almost no issues after quality control. However, videos still had issues with camera shaking or low floater visibility. Removing moderate to severe cases of videos with quality issues resulted in almost no improvement in statistics. It highlights the extraction algorithm’s insensitivity to these factors and the need for refinement to better estimate velocities. Aggregating water levels and velocity estimates into discharge values may lead to more comparable observations.

Overall, we learned that reporting on rejection rates can highlight significant inefficiencies in citizen science campaigns. This is particularly true when measuring complex environmental parameters, at a large scale, with a less controlled design or in a remote location. Systematically assessing the reasons behind these rejection rates helps distinguish issues intrinsic to citizen science monitoring (e.g. citizen mistakes, how to merge estimates); and to the methodologies applied (e.g. camera-based). It ultimately allows the citizen science community to build on it. Future research lies in reducing errors and improving data quality by investigating more effective training programs, as well as implementing environmental guidelines or automated tools that orient citizens during bad environmental conditions. More exploration is also needed on how to design campaigns that better balance data volume and quality, in which more strategic setups could also reduce rejection rates. Beyond data quality, operationalizing citizen science also involves balancing accuracy and efficiency with costs and monitoring goals (e.g. modelling, ecosystem monitoring, increased citizen literacy). Further research on these topics will make citizen science more transparent, useful and likely will support a wider range of applications.

6

MODELLING APPLICATIONS

This chapter aims to explore how the information derived from the data collected via citizen campaigns can be used in modelling applications that were identified as relevant by local authorities. In the Sontea-Fortuna case study, we observe whether the depth and velocity estimates obtained via citizen contributions can calibrate and validate a hydrodynamic model, and if they concur with traditional measurements. In the Kifissos catchment case study, hydrological modelling using different land cover maps is performed, with one of the land cover maps being generated based on the land cover data collected by citizens[13]. In both cases, citizen-based information was able to be informative to modelling applications – to a lesser extent in the case of velocity estimates in the Sontea-Fortuna case study, and to a higher extent in the case of land cover maps in the Kifissos case study. Modelling choices were also shown to impact the results, sometimes to a greater extent than the citizen data itself, showing that having hydrodynamic or hydrological data in high volumes does not automatically translate into modelling gains.

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[13] This chapter contains research from:

Pudasaini, P., Assumpção, T. H., Jonoski, A., & Popescu, I. (2024). Sensitivity Analysis and Parameterization of Gridded and Lumped Models Representation for Heterogeneous Land Use and Land Cover. Water, 16(18), 2608. https://doi.org/10.3390/w16182608

Venturini, A. B., Assumpção, T. H., Popescu, I., Jonoski, A., & Solomatine, D. P. (2019). Modelling support to citizen observatories for strategic Danube Delta planning: Sontea-Fortuna case study. Journal of Environmental Planning and Management, 62(11), 1972–1989. https://doi.org/10.1080/09640568.2018.1523787

6.1 INTRODUCTION

Hydrodynamic processes are shaped by the interplay of environmental conditions, including channel geometry, bed roughness, upstream/downstream forcing, and hydraulic connectivity. Artificial modifications to waterways, such as canal expansions and hydraulic infrastructures, can significantly alter flow and sediment regimes, having positive (economic) and negative (ecological and socio-cultural) in ecosystem services (Ekka et al., 2020). By the 2050s, climate change is projected to cause substantial shifts in river flow regimes, with ecological impacts that may surpass those historically caused by dam construction and water extraction (Döll and Zhang, 2010). In this context, hydrodynamic modelling becomes an essential tool, enabling local authorities to better understand regional flow behavior, simulate future scenarios for informed decision-making, and quantify the impacts of interventions (Guse et al., 2015).

Likewise, the hydrological cycle is influenced by many factors, such as the type of soil, land use and land cover, and climatic and weather conditions. Specifically, land cover and climate variability are important features affecting hydrological processes, causing significant changes to overland flow and evapotranspiration (Berihun et al., 2019; Zhang et al., 2013). Increased overland flow can be linked to an increase in floods, as the main reasons behind the increase in flood events (i.e., from around 100 in 1980 to 321 in 2010 in Europe, Jacobs, n.d.) are population growth, climate change, and human activities such as deforestation and changes in land use patterns. Urbanization, generally also linked to flash floods, is also increasing over the globe, from 30% of urbanized areas in 1950 to 55% in 2018 (Anon, 2018), while in 2010, 75% of Europe was considered urban (Jock et al., 2010). The use of yearly and spatially distributed land cover data that depicts these changes increases the accuracy of hydrological models (Wickramarachchi et al., 2023), which are generally used for water resources and flood risk management. Moreover, for rural and ungauged areas, where the influence of humans on the hydrological cycle is higher (de Sherbinin et al., 2021), such analysis is important. However, it is costly and time-consuming to get updated land cover data in highly changing systems. That is the case of Greece, where only 6% of people lived in urbanized areas until 1821 (Baxevanis, 1965), and by 2017, around 80% of the area was urbanized (Plecher, 2020).

The citizen science campaigns executed and assessed in Chapter 4 provide novel datasets that could significantly contribute to modelling applications of interest in their case study areas. For the Sontea-Fortuna area, the campaign data covers a large spatial extent and allows for a hydrodynamic model to be developed, calibrated and validated to account for the interconnected channels' dynamics. The model and these applications are discussed in sub-section 6.2. The campaigns also culminated in a novel land cover map for the Kifissos catchment, which can be used in hydrological models for the area. In sub-section 6.3, the model and the applicability of this new data source are assessed and compared with those of conventional land cover maps.

6.2 SONTEA-FORTUNA – HYDRODYNAMIC MODELLING

6.2.1 Model description

Hydrodynamic models were developed using HEC-RAS modeling software, created by the United States Army Corps of Engineers (USACE). The data used to build the models and their sources are shown in Table 6.1. The local authority, DDNI, supplied most of the data and the river network and cross-sections from a previous 1D SOBEK model. Since the earlier model data were not georeferenced, the river network was redrawn based on satellite images and the cross sections were repositioned accordingly. Elevation models and bathymetric data were combined to ensure full coverage of the study area.

Table 6.1. Data requirements and sources for the Danube Delta hydrodynamic models

Data required	Data source
River network	DDNI & Open Street Maps
Cross sections	DDNI
Lake's bathymetry	DDNI
Sontea-Fortuna bathymetry	EnviroGRIDS[14](5mx5m)
Digital Elevation Map (DEM)	DDNI (5mx5m) NASA (SRTM, 30mx30m) Copernicus (EU-DEM, 25mx25m)
Land cover map	Copernicus (CORINE)
Upstream boundary condition	DDNI (discharge)
Downstream boundary condition	DDNI (water level)
Calibration/Validation	DDNI (discharge)
Simulation data	DDNI (discharge time series)

[14] EnviroGRIDS – EU FP7 project about environmental data sharing in the Black Sea catchment.

Upstream boundary conditions and calibration and validation discharge data were obtained from ADCP surveys conducted in August 2015 and on August 31, 2012, respectively. The 2015 campaign covered multiple measurement sites, from which ten were selected, and measurements were adjusted to account for time discrepancies (Figure 6.1). The 2012 survey covered six locations (Figure 6.2). A constant water level at 0.6 m.a.s.l. was used as a downstream boundary condition, as mentioned in Section 3.2.

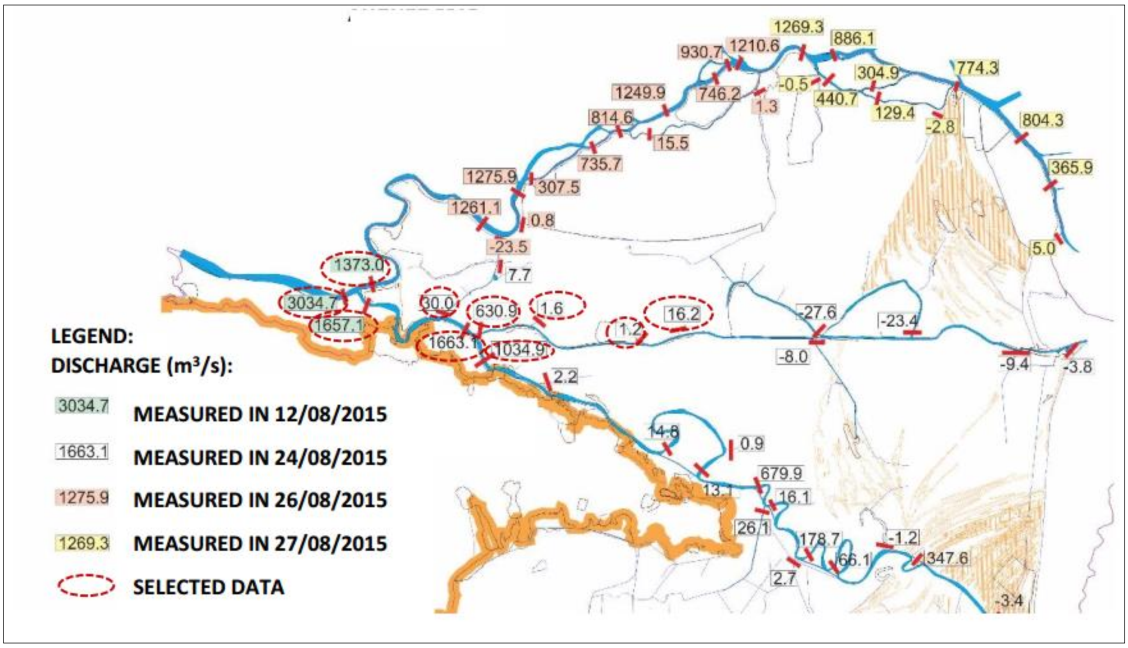

Figure 6.1. Danube Delta calibration data. Source: DDNI

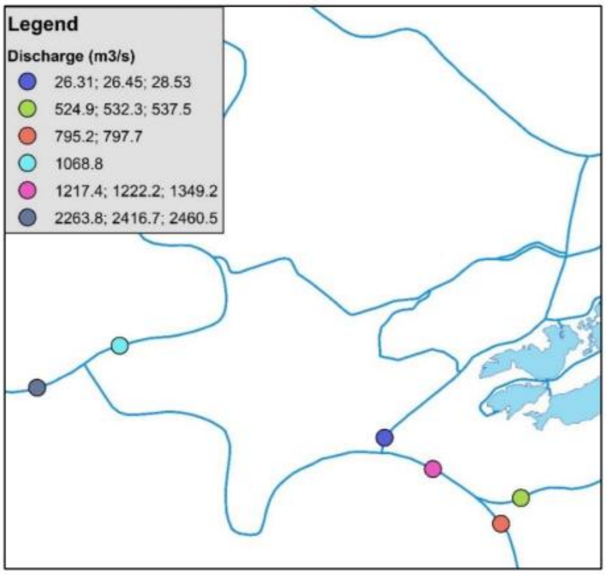

Figure 6.2. Data for validation. Data source: DDNI

First modelling efforts encompassed the entire Danube Delta, by attempting different model structures, assessing the influence of the elevation models and ultimately, aiming to define the best downstream boundary conditions for a localized model in the Sontea-Fortuna area. The best results were obtained by extending the river network of the Sontea-Fortuna area into the sea and applying the constant water level condition.

For the Sontea-Fortuna case study area, two model structures were explored: a 1D model added with conceptual storage areas, representing the most relevant lakes in the area (hereon 1D+SA); and a 1D/2D model in which the Danube Delta tributaries and the main canals were represented in 1D, while the internal canals, lakes and overflow areas were modelled with 2D areas (as terrain covered by a 2D computational grid, 50m cells).

The 1D+SA model was used to spot locations of water stagnation in the river network, which was one of the identified purposes for data collection via citizen campaigns (see sub-section 4.4.2). The 1D/2D model allows for a better representation of flooding dynamics in the Sontea-Fortuna area.

The implemented geometries in HEC-RAS are presented in Figure 6.4 and Figure 6.4.

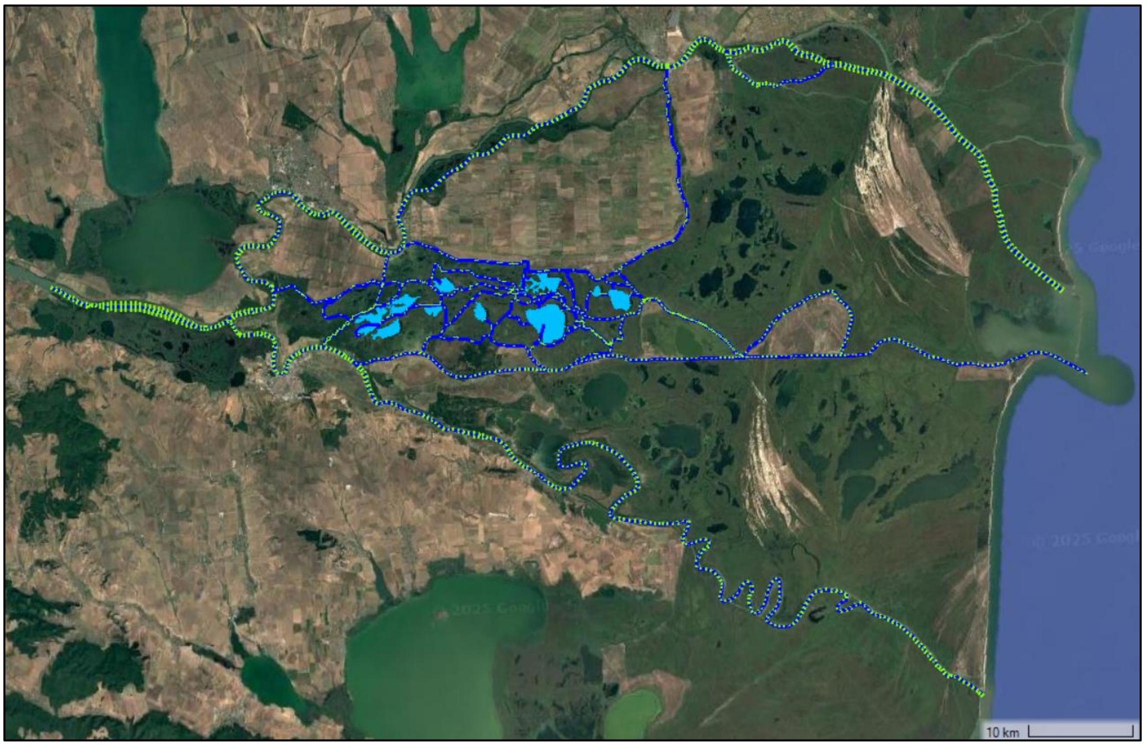

Figure 6.3. Sontea-Fortuna 1D+SA model geometry

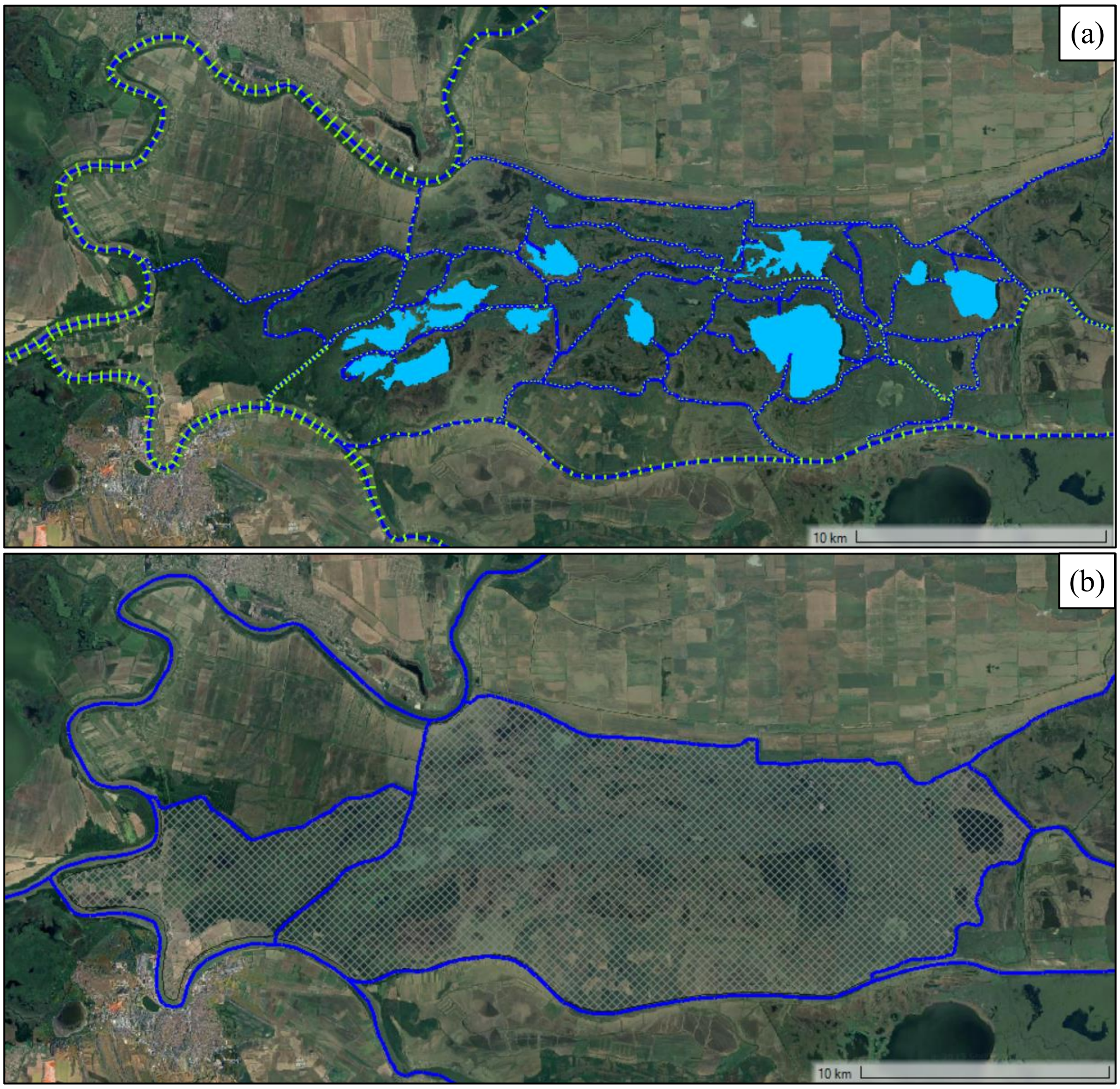

Figure 6.4. Sontea-Fortuna model geometries, focused on the case study area, for models: (a) 1D+SA; (b) 1D/2D

The calibration process focused mostly on adjusting Manning's roughness coefficient. In the 1D+SA model, the coefficient was calibrated for 11 reaches, while for the 1D/2D model, roughness values were calibrated for the 2D calculation grid and the weir coefficients. Constant upstream inflows of 3,035 m^3/s and 2,380 m^3/s were used for calibration and validation, respectively. Both are characteristic of low-flow conditions, so model results under high-flow scenarios should be interpreted with caution.

For the 1D+SA model, the highest roughness value (0.095) was found in the smaller canals of the Sontea–Fortuna area, matching where the dense vegetation and lack of maintenance significantly reduce flow velocities. In terms of Root Mean Square Error (RMSE), the model performance obtained for calibration and validation was 1.4 and 23 m^3/s, respectively. It is a great performance for the large distributaries, where discharges reach 2 to 3 orders of magnitude higher than the error, and it is still a reasonable performance for the smaller canals. Absolute error averaged 33% for the Mila 35 Canal (around 30 m^3/s discharge), and 90% for inner canals (around 1 m^3/s discharge). However, most calibrated and validated locations were in the main distributaries, limiting the calibration process from doing better within the wetland. For the 1D/2D model, a Manning coefficient of 0.08 was found optimal, under slightly higher errors for calibration and validation, which were 9 and 30 m^3/s, respectively.

To capture different flow dynamics in Sontea-Fortuna, constant flow scenarios were run with the calibrated models (Table 6.2). These were selected based on an available discharge time series from the Danube River (Figure 6.5). These are also the flow regimes mentioned in sub-section 4.3.4 used to study accessibility for the field campaigns. For stagnations, analyses on the number of consecutive days with no flow were done by running the model for a dry (2003) and a wet year (2006). More details are presented in Venturini (2017).

Table 6.2. Flow regimes and boundary conditions assessed in Sontea-Fortuna

Flow regime	**Upstream boundary condition**	**Downstream boundary condition**
Dry	2,300 m^3/s	
Average	7,000 m^3/s	0.6 m
Wet	15,800 m^3/s	

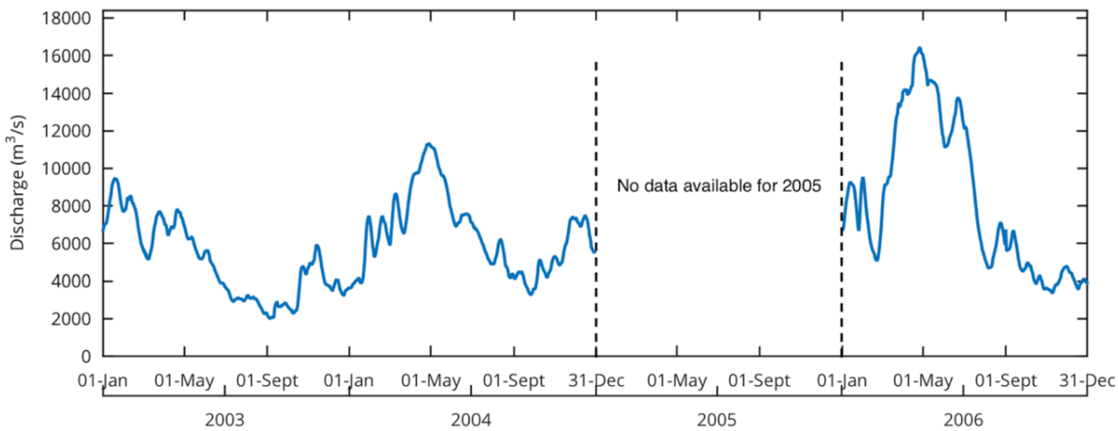

Figure 6.5. Measured discharge time series in the Danube River (before bifurcation), from 2003 to 2006. Data source: DDNI

6.2.2 Model calibration

The model described in Section 6.2.1 was the first step towards representing the flows in a complex delta and wetland system. However, the data available for calibration and validation were very limited, as they covered only dry conditions and mostly only the large river reaches, not the inner part of the Sontea-Fortuna area. Improving the model was established as one of the purposes for citizen campaigns (sub-section 4.3.4).

The model was recalibrated for the period of the second river citizen science campaign in the Danube Delta (May 2019). This campaign was selected because it covers wet conditions, the ones not captured in the model before, and it is the campaign in which citizen-based velocity estimates are available (more on sub-section 5.3.1). The Manning's roughness coefficient of the 2D area was recalibrated (between 0.02 and 0.16). Differential Evolution Algorithm was used for the optimization, supplemented by brute force simulations to cover empty parametric spaces, for analysis of the results. Upstream boundary conditions covered one week before and after the campaign (Figure 6.6). Flow conditions in the Delta were below average, despite expectations of wet conditions. Modelled velocities were converted to surface velocity, assuming that the average velocity is 85% of surface velocity (Le Coz et al., 2010).

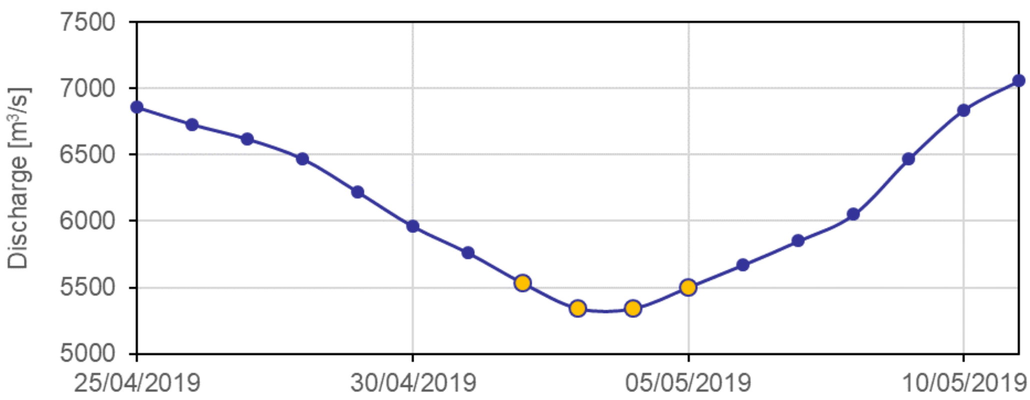

Figure 6.6. Measured discharge time series in the Danube River (before bifurcation), during the second river citizen campaigns. Orange records correspond to campaign days. Data source: DDNI

Calibration was run with ADCP estimates and citizen-based estimates obtained in Chapter 5. It was performed for both depth and velocity estimates. The data was filtered to encompass pairs of ADCP and citizen-based estimates that were at a maximum distance of 5 meters from each other, to avoid the possibility that other uncertainties played a role in the calibration and to ensure convergence. Calibration was run for both Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) as objective functions.

Modeling results indicate that even under below-average flow conditions, the Sontea-Fortuna area remains inundated (Figure 6.7a). Water depths inside the wetland system ranged mostly between 0.5 and 1.5 m (excluding lakes). Surface velocities of up to 1.3 m/s were simulated in the distributaries, up to 0.85 m/s in the Canal Mila 35 and less than 0.1 m/s across the wetland (Figure 6.7b). Despite patterns in the velocity field indicating increased flow in some channels, those occur at extremely low velocities (0.01 to 0.02 m/s), not enough to indicate clear circulation patterns in the area. The overall low velocity is a consequence of the flow dissipation over the entire area due to channel overflow.

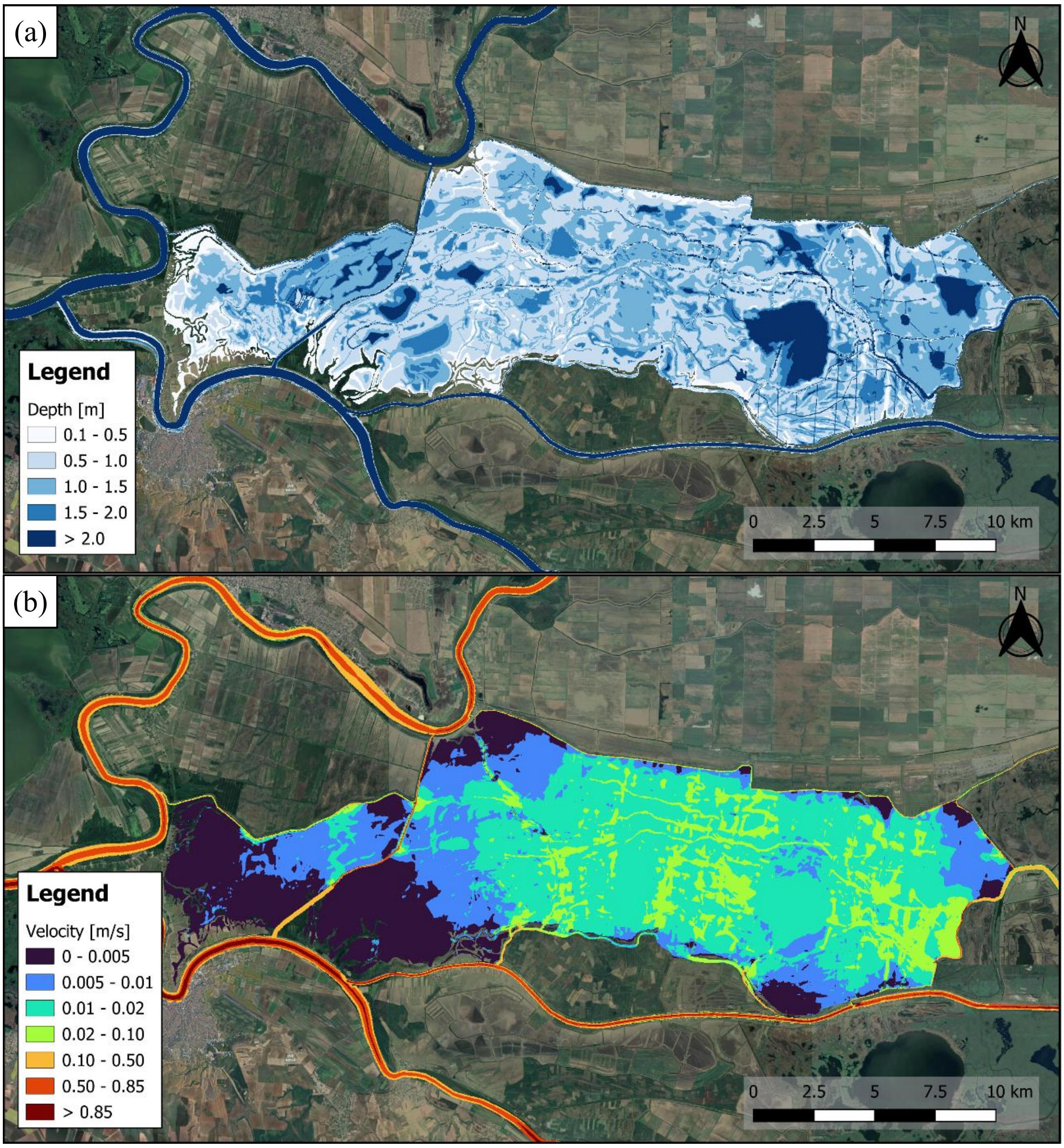

Figure 6.7. Model results on 4th May 2019 at 07:00: (a) Depth (b) Surface velocity

ADCP results indicate that there are large discrepancies between the model and observed depth conditions, with a minimum mean of absolute error of 1.28 m (Figure 6.8). This large error is also captured by citizen campaigns, which diagnosed errors to be 5 cm smaller than ADCP-based errors. The calibration converged to similar minima for both datasets (around 0.15 Manning n coefficient). In both cases, the error varied by less than 5 cm through the calibration process. This indicates that the model is insensitive to varying the Manning's roughness coefficient as a whole for the wetland area.

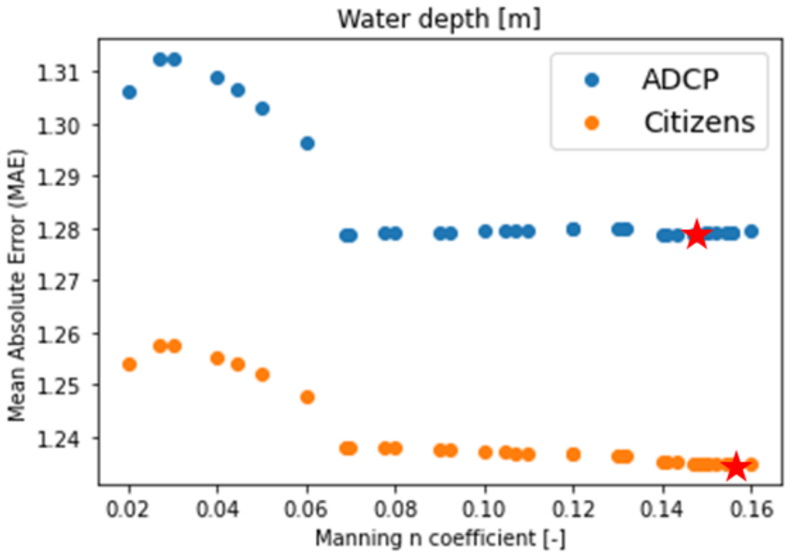

Figure 6.8. Modelled water depths by varying the 2D area Manning n coefficient. The red star represented the minima reached via calibration

Velocity results show significant errors, considering the magnitude of flows in the area, reaching 0.18 m/s (Figure 6.9). Different from water depth, the model error when calibrating using citizen-based velocity estimates is doubled the error from estimating errors with ADCP readings. They converge to different minima, but it also happens when using different performance metrics with only ADCP measurements (Figure 6.10). The model was also insensitive to calibration with velocities.

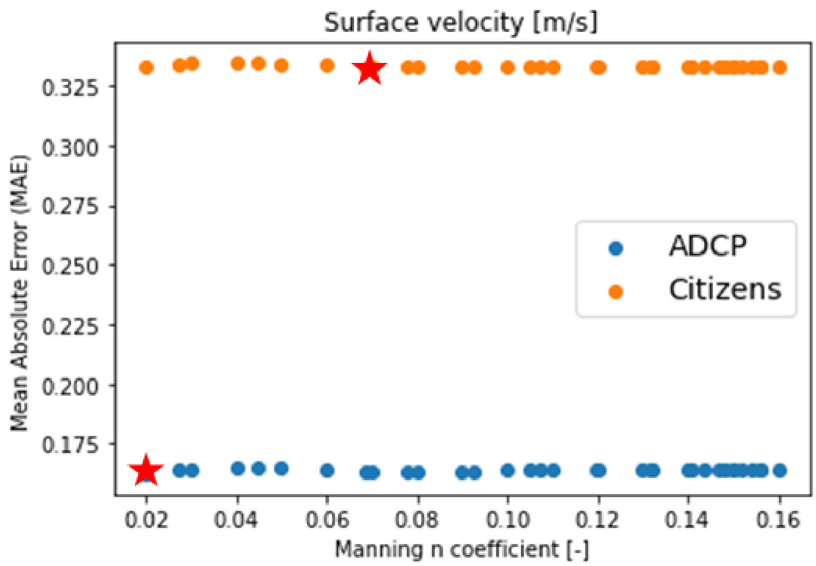

Figure 6.9. Modelled surface velocity values by varying the 2D area Manning n coefficient. The red star represented the minima reached via calibration

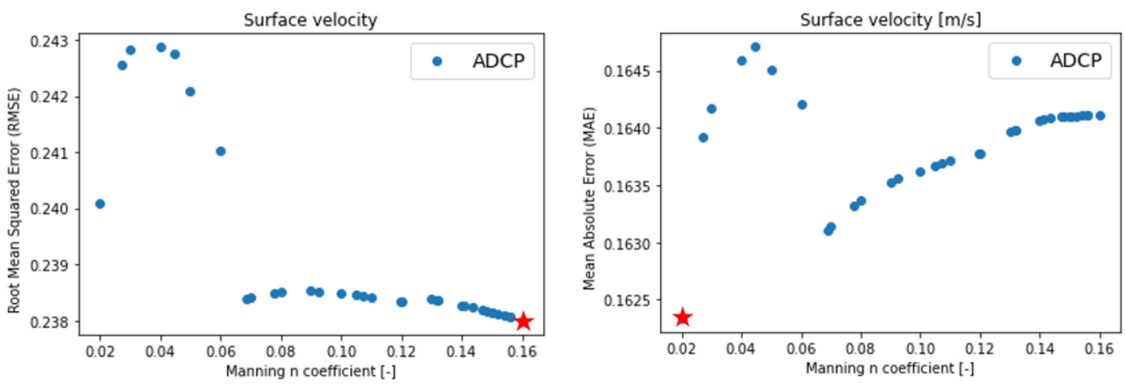

Figure 6.10. Modelled surface velocity values by varying the 2D area Manning n coefficient. The red star represented the minima reached via calibration. (left) Using Root Mean Squared Error as the objective function; (right) using Mean Absolute Error.

These findings suggest that citizen-based estimates of water depth were able to match the ability of traditional measurements to calibrate a model. Citizen-based estimates of velocity exposed the lack of model sensitivity, but with an overestimated error. Regardless, once velocity citizen-based estimates did not correlate with ADCP ones (sub-section 5.3.4), there is a risk of achieving acceptable performance for the wrong reasons. For instance, errors could be considered reasonable because they were averaged out, not because they captured well the conditions in channels. Further research includes broadening the calibration exercise so that it involves the 1D channels and varied Manning coefficients in the floodplain.

6.2.3 Model validation

To assess the full diagnostic capacity of citizen-based data, validation is performed as a separate application from calibration. The dataset used for the citizen estimates is that of the cluster estimates from Chapter 5, without any filtering.

For water depth, the valuation of model results against observations yields similar results for both observation datasets (ADCP- and citizen-based), in terms of qualitative spread in a correlation plot (Figure 6.11) and metrics computed from the comparisons (Table 6.3). ADCP-based statistics indicate that the model is more correlated but has more error than citizen-based ones, but ultimately, these differences are small. By using more comparison points in this validation exercise compared to the calibration, the diagnosed model errors were reduced (while still quite high).

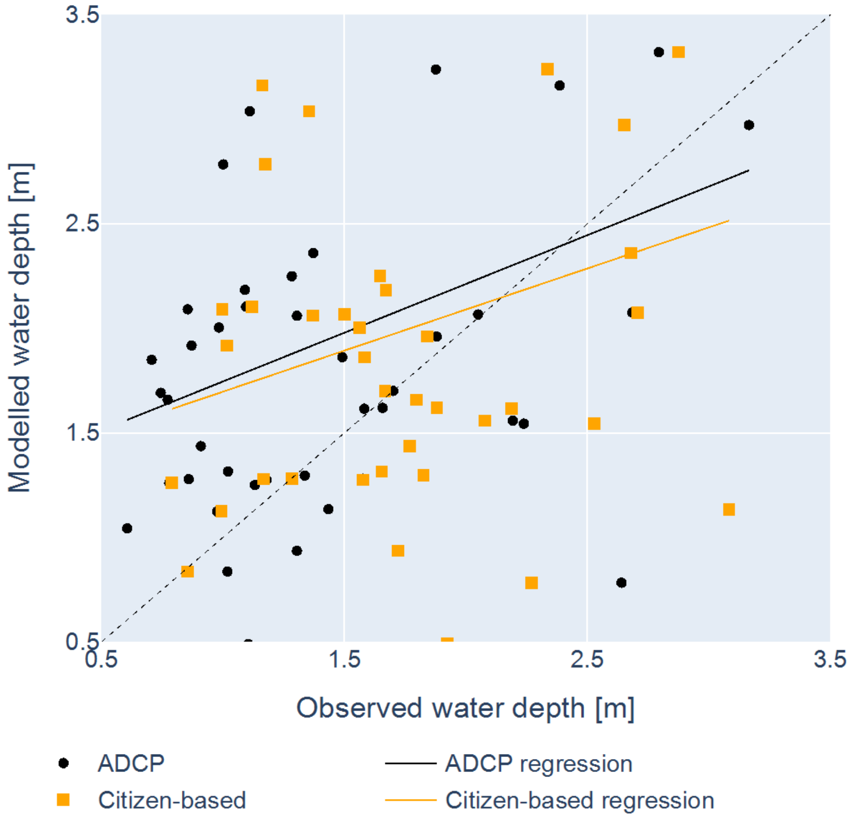

Figure 6.11. Modelled water depth values versus citizen-based and traditional water depth values, for Campaign 2 (May 2019)

Table 6.3. Comparison between using ADCP and citizen-based depth estimates for model validation, based on R^2 and MAE. Bold values are the best statistics for the metric; underlined values are the second best.

Variable	Metric	ADCP-based estimates	Citizen-based estimates
Water depth	**R^2 [-]**	0.12	0.07
	MAE [m]	0.76	0.73
Velocity	**R^2 [-]**	0.04	0.01
	MAE [m/s]	0.16	0.25

For surface velocities, despite the difference in the regression line inclination between both comparisons to the model, the cloud of points in both cases indicates a large mass of modelled data that is underestimated, forming a horizontal cloud at the base of the graph (Figure 6.12). This is reflected in the metrics, which indicate no correlation between the model and flow in the Sontea-Fortuna area. Different observation datasets did lead to different error estimates, and similarly to the calibration process, here citizen-based estimates almost double the error rates compared to ADCP ones (Table 6.3). Errors are nevertheless high for the area (same order of magnitude as the average). In this sense, and also as mentioned, there is a certain diagnostic power in this velocity data, in showing how much underestimation there is. This needs to be done with care, especially if no ADCP validation data exists or if the velocity extraction method is not fully validated. Indiscriminate use of citizen-based velocity estimates for model validation is not recommended.

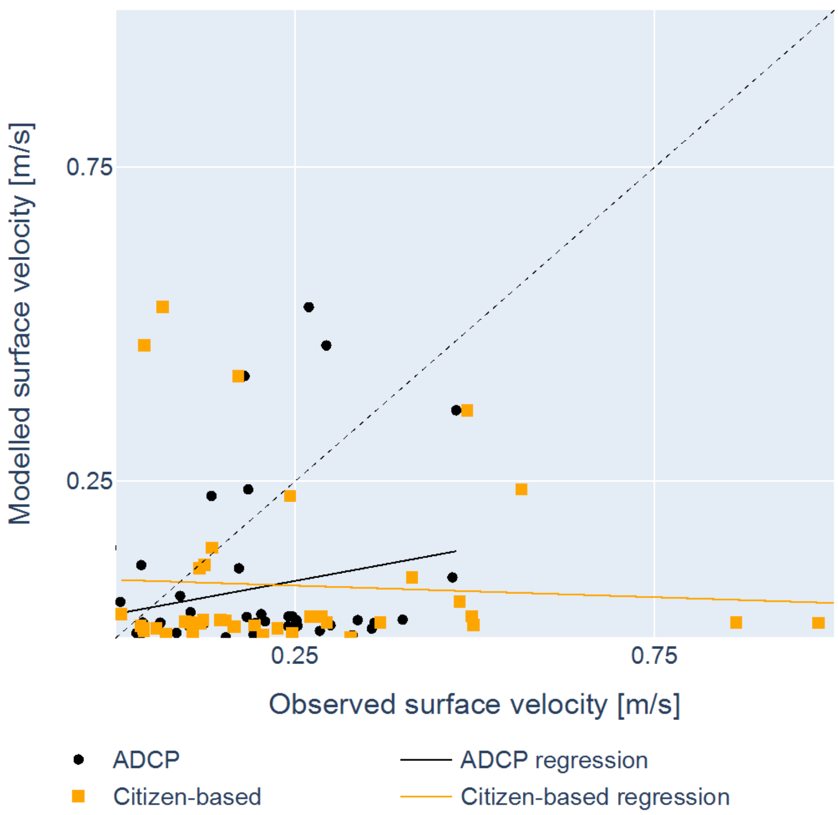

Figure 6.12. Modelled surface velocity values versus citizen-based and traditional surface velocity values, for Campaign 2 (May 2019)

6.3 Kifissos catchment – Hydrological modelling

6.3.1 Model description

For this modelling application, HEC-HMS was the hydrological modelling tool, also developed by USACE. The focus of this application is on variations in land use and land cover (LU/LC) input data and their impact on the model outputs. Continuous modelling was performed, and lumped and gridded model instances were created. A lumped model uses parameters that represent spatially averaged characteristics of a hydrological system. When more detailed spatial information can be included in a model, catchments can be divided into cells (grids), where each will act as a lumped hydrological model. The contribution of each grid cell is added together to obtain the response of the basin (Feldman, 2000). Lumped and gridded models were set up with 21 sub-basins to capture the spatial variability of catchment characteristics (Figure 6.14). For gridded models, a 500 by 500 m grid was employed to further subdivide the sub-basins.

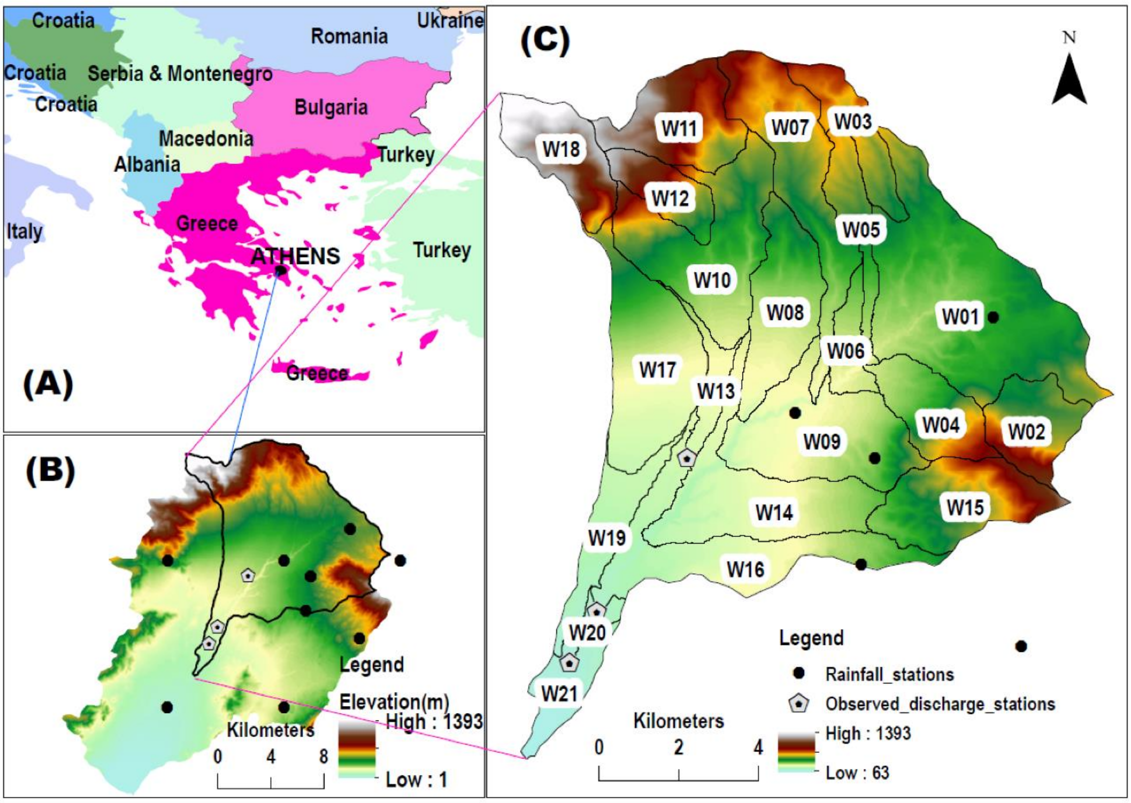

Figure 6.13. Location map of (A) Greece, (B) Kifissos catchment with delineated study area and (C) study area with 21 sub-basins and observation stations

In total, six hydrological models were developed, three lumped and three gridded, using three land cover datasets: CORINE[15], Urban Atlas [16](Gitas, n.d.) and Scent (Table 6.4). Each developed model has an identifier, consisting of a letter indicating the model structure and parametrization (L for lumped and G for gridded), followed by a letter denoting the land cover dataset used (C stands for CORINE, E stands for European Union Urban Atlas, and S stands for Scent). "CALC" stands for calculated imperviousness; a Copernicus imperviousness map was available, but a calculated version that reflects each land cover dataset is more suited for this research. Based on data availability, the simulation period was 1 July 2017 to 30 September 2019.

[15] https://land.copernicus.eu/pan-european/corine-land-cover, accessed on 1 November 2020

[16] https://land.copernicus.eu/local/urban-atlas, accessed on 1 November 2020

Table 6.4. HEC-HMS models set up.

Model Identifier	Lumped or Gridded	Land Cover dataset
M0LC:CALC	Lumped	CORINE
M0LE:CALC	Lumped	Urban Atlas
M0LS:CALC	Lumped	Scent project
M0GC:CALC	Gridded	CORINE
M0GE:CALC	Gridded	Urban Atlas
M0GS:CALC	Gridded	Scent project

The European Union's Earth Observation Programme (Copernicus) provides the CORINE land cover inventory every four to six years at the European level. In this chapter, the 2018 map was used, with 17 land classes at a 100 m resolution. This study also investigates a sub-product provided by the same institution, the Urban Atlas, which contains details of urban features in vector form with 22 land classes. Lastly, via the Scent project, citizens took pictures and annotated land cover features, which went through a Map Segmentation tool (see sub-section 4.3.3). The generated land cover map has a cell size of 40 by 40 cm with 4 land classes: bare soil, forest, agricultural land and concrete. Comparing these three land cover maps (Figure 6.14), it can be seen that the upstream portion of the basin is more covered with forest, vegetation and agriculture, whereas the downstream is mainly urban with built-up areas. The main differences among these datasets are the number of land classes and the resolution. The Urban Atlas has a more detailed characterization in classes and CORINE has the largest pixel size, whereas Scent has a smaller pixel size but very few land classes.

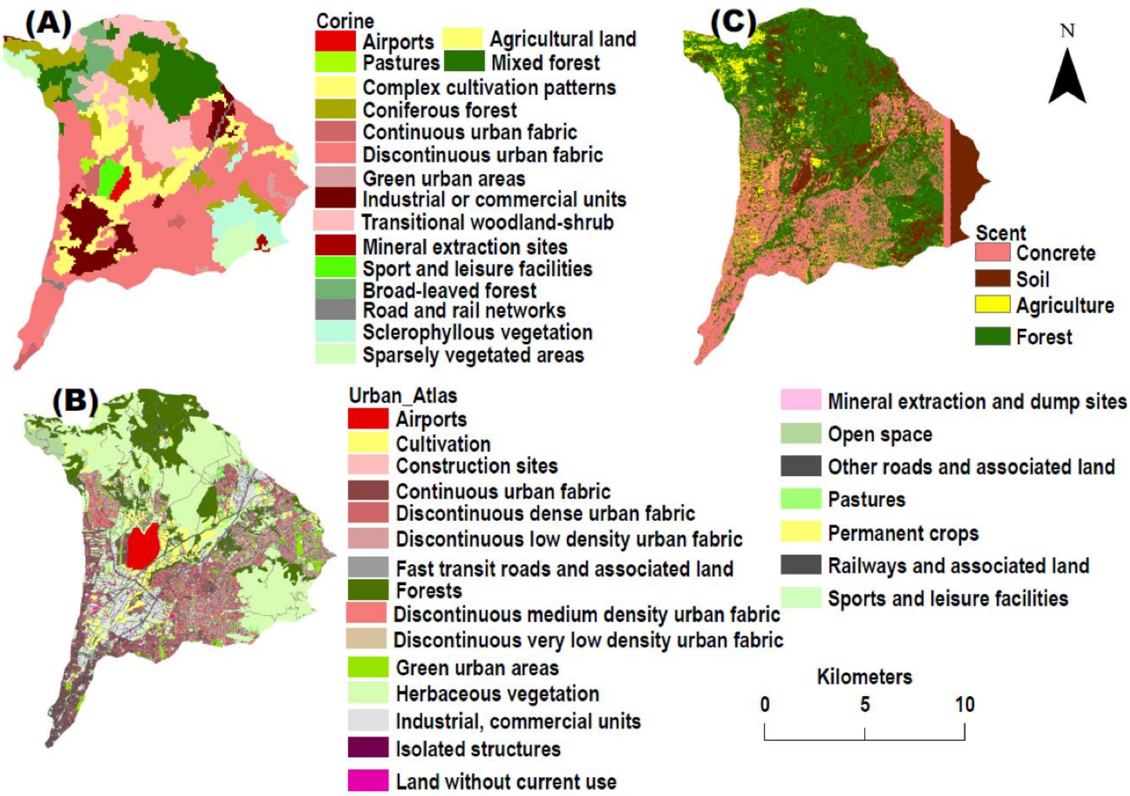

Figure 6.14. Land use land cover maps for (A) CORINE, (B) Urban Atlas and (C) Scent

LU/LC datasets affect lumped and gridded models differently. In the considered lumped models, the spatial resolution impacts the area proportions of each land cover class within sub-basins, which in turn may influence how certain sub-basin parameters are weighted by land cover class. The spatial resolution is irrelevant if both coarse and high-resolution LU/LC datasets result in similar land cover class proportions. In the gridded models, most sub-basins are covered by 2 to 3 grid cells. As a result, increasing the model resolution allows for greater refinement in hydrological process representation.

USGS imperviousness maps were calculated for each land cover dataset, using the coefficient of imperviousness adopted from Tilley and Slonecker (2006). A hydrologic soil properties map was taken from soil information provided by the European Soil Data Centre (ESDAC) (Panagos, 2006). The European Soil Database (ESDB) was developed in collaboration with the European Soil Bureau Network. Information on the soil texture was used for parameterizing the hydrological models. The digital elevation map used for the gridded hydrological model has a resolution of 5 by 5 m. It was provided by the Scent project, which was obtained upon request from Greek authorities.

The National Observatory of Athens makes available daily precipitation information in Greece, and nine stations were identified near the study area (Figure 6.13). The northwest side of the basin does not have a rainfall station, and only three stations are inside the basin, fairly well distributed. These are used for precipitation inputs for the determined period. Averaged monthly data for potential evapotranspiration (ET) were taken from the estimation made by Tegos et al. (1937), based on data from a meteorological station located in Athens, around 15 km from the study area. They employed various calculation methods, from which we adopted the Penman–Monteith values, as they were the most accurate estimates of potential ET mentioned in their study.

Water depth time series were obtained from stations installed for the Scent project (Figure 6.13). Based on the stations' locations, from downstream to upstream, the stations are hereon named J09, J12 and J08. Due to a sensor malfunction, data from station J12 was incorrect and therefore was not used in this study. The water depth values were then converted to discharges using Manning's equation and measured river cross-sectional data. The telemetric data were recorded in 15-minute intervals, and they were converted to average daily discharge.

The HEC-HMS software, in its lumped configuration, is structured around four main components: the basin model, meteorological model, control specifications, and time series data. The basin model encapsulates the physical characteristics of the watershed and includes subcomponents such as canopy, surface, loss, transform, and routing. These simulate processes like rainfall interception, surface depression storage, infiltration, runoff generation, and flow routing. The meteorological model supplies rainfall and evapotranspiration (ET) data, while control specifications define the simulation period. Time series data provide the temporal inputs, such as rainfall and discharge. For gridded models, additional spatial data such as terrain and grid discretization (e.g., 500 × 500 m resolution) are used. In this study, the first lumped model was built based on an existing event-based model (Ali, 2018), for which the basin component was modified to better fit continuous simulations and the current datasets.

The hydrological processes related to infiltration (loss) are modelled using the deficit and constant method, which applies to both lumped and gridded models. This method differentiates between pervious and impervious surfaces. When rainfall occurs, the canopy stores some of the precipitation, which either evaporates or infiltrates into the ground. For pervious areas, percolation is dependent upon the soil properties and only occurs if the soil is saturated, and similarly, evapotranspiration only occurs when there is no rainfall and there is moisture in the soil. The soil is represented by a single reservoir and base-flow is added separately. Excess precipitation is generated due to soil saturation. When soil gets saturated and there is still rainfall, then surface depressions retain some of the precipitation. The fluctuation in the linear reservoir is dependent upon the moisture content in the soil from the previous day (or initial condition) and addition due to infiltration or deduction due to evapotranspiration. Once evapotranspiration occurs, water is lost permanently. Over impervious areas, precipitation not intercepted by the canopy becomes excess precipitation. Impervious areas are defined by the percentage of imperviousness.

Many of these processes are parameterized based on land cover or other physical characteristics of the basins. For example, the canopy interception values were adopted from Verbeiren et al. (2016) and have the storage value per land cover type. Surface storage is linked to slope characteristics. Loss parameters like maximum and initial soil moisture deficits are derived from curve numbers, which vary by land cover dataset, influencing spatial patterns of hydrological behaviour across the basin. Imperviousness was also derived from land cover, as mentioned, and lastly, a constant percolation rate, indicating how fast water infiltrates, was derived from soil texture data. Overall, for lumped models, parameter values were averaged per sub-basin, while gridded models used raster maps upscaled to 500 by 500 m.

To simulate runoff transformation, the Clark unit hydrograph was used for lumped models and ModClark for gridded ones. The time of concentration was calculated from lag time values, and storage coefficients were estimated using observed flow data, capturing how water is temporarily stored and released in the basin.

As the objective of this study is to investigate the influence of land cover on hydrological processes, parameters defined based on land cover data and physical catchment characteristics were not calibrated. The lumped and gridded CORINE-based models (M0LC and M0GC) were calibrated and validated. Calibrated parameters were used in further model instances. Calibration of the base-flow method parameters was performed: initial discharge, recession constant and ratio to peak. Calibration was performed manually by comparing simulated and observed flow hydrographs derived for the two station locations.

The total simulation time was about 27 months (1 July 2017 to 28 September 2019). Since there was a lot of absence of data, the longest time of available data was about six months (28 September 2017 to 31 March 2018), and hence, it was chosen for calibration. Similarly, the period of 14 September 2018 to 12 January 2019 was chosen for validation.

For both lumped and gridded models, the obtained value for the ratio to peak for all sub-basins is 0.5 and the recession constant is 1. Initial discharge values varied, such that the initial discharges for gridded sub-basins were higher. The base flow for lumped and gridded models matched, whereas the peaks of observed flow are higher than modelled ones, mainly in the validation period (Figure 6.15). Similarly, the time of the peak for both models is the same and matches the timing for observations.

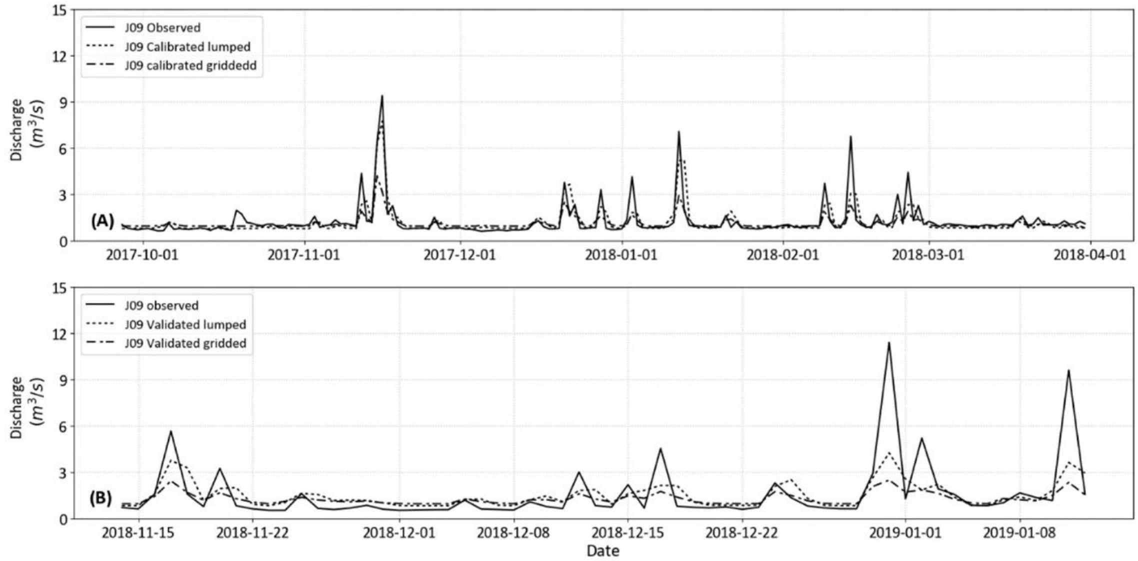

Figure 6.15. (A) Calibration of basic lumped and gridded models and (B) validation of lumped and gridded models

6.3.2 Model results comparison

Model results are analysed under three different perspectives: considering how land cover datasets influence hydrological processes, considering the differences between lumped and gridded models and lastly, comparing among all models regarding flow outputs. For the first two assessments, sub-basin W08 is taken as a case in point, a mixed sub-basin having urban, forest and agricultural areas. All analyses are done for a period representative of the dynamics over the entire simulated time. By varying the land cover dataset and model structure, the main parameters that changed were the maximum deficit (i.e. maximum amount of water the soil can hold) and the imperviousness percentage. These affect excess precipitation, potential evapotranspiration (ET) and changes in the linear reservoir (saturated fraction).

Assessing the sensitivity of the models to land cover, the ET value for Scent is higher than the ones for the other two datasets (Figure 6.16a). This is because it has the biggest forest area coverage (72%). However, Urban Atlas has almost as high ET because of having a significant amount of vegetation (54%) and small coverage of agriculture (11%) and forest (13%), all of which contribute to ET. In the case of CORINE, there is a less combined contribution for ET from its land classes. The Scent linear reservoir is filled up first and fluctuation occurs more rapidly and frequently than the others (Figure 6.16c). That is because it has the smallest reservoir (42.9 mm) and the highest ET among all the LU/LC datasets. In contrast, the CORINE land cover has the biggest linear reservoir (108.92 mm) and the lowest amount of ET, thus taking a longer time to fill up than the other LU/LC datasets. Whereas Urban Atlas has a reservoir size of 60.41 mm and ET similar to Scent, variations in the reservoir level are intermediate between these two cases.

The excess precipitation for CORINE and Urban Atlas is similar (Figure 6.16b), while for Scent it is lower. This pattern correlates with the imperviousness calculated for their associated models (i.e. for CORINE, Urban Atlas and Scent they are 28%, 24.5% and 16.8%, respectively). Despite that, the amount of excess precipitation is only up to a third of the total precipitation (Figure 6.16d), with most being lost to percolation.

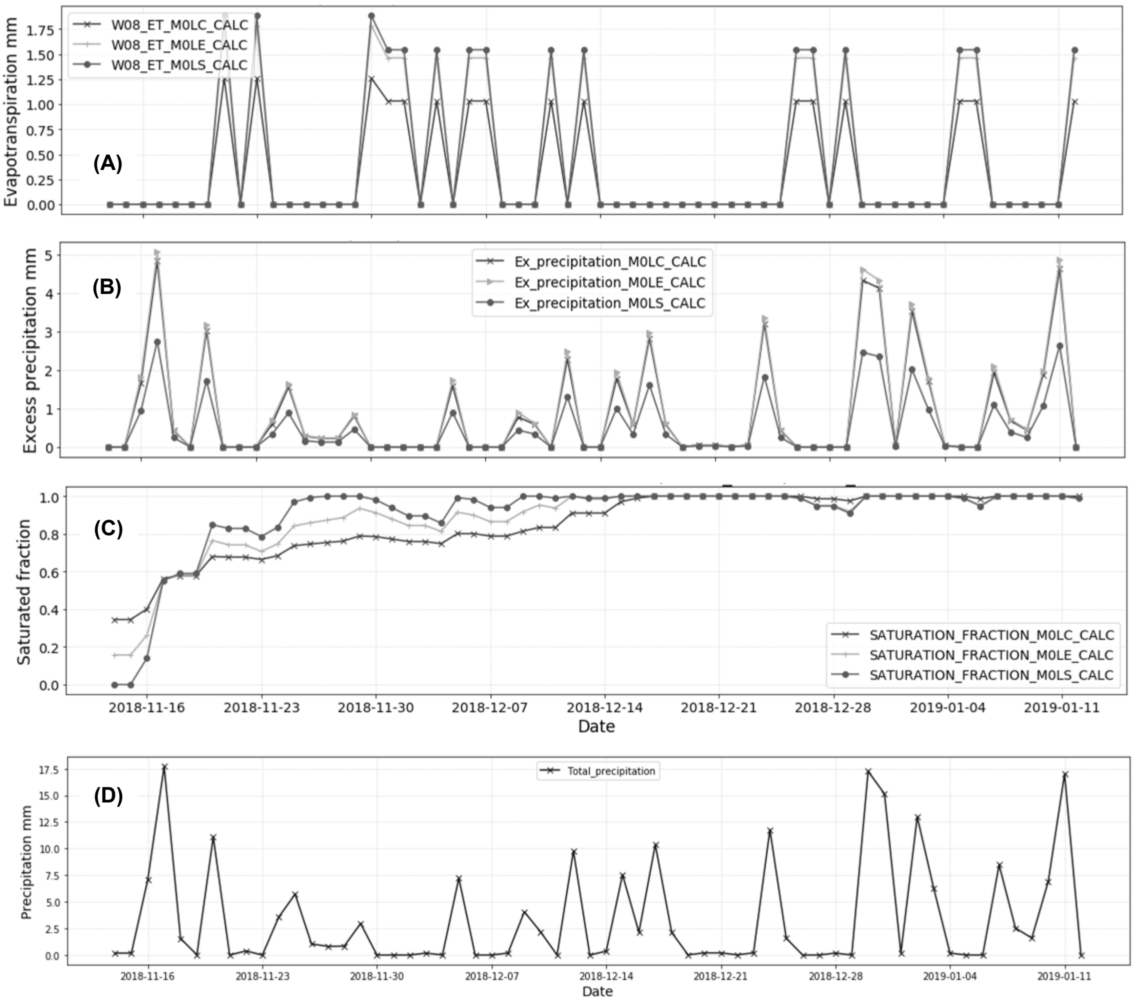

Figure 6.16. Variables for CORINE, Urban Atlas and Scent models for W08 M0LC:CALC, M0LE:CALC and M0LS:CALC: (A) evapotranspiration, (B) excess precipitation, (C) saturated fraction and (D) total precipitation

The ET of the lumped models for all LU/LC datasets is 1.8 times higher than the one from the gridded models (Figure 6.17a-c), most likely linked to the higher variability of the crop coefficient (canopy-related) in gridded models. The reservoir of the gridded models saturated faster than the lumped models, mainly when using Scent and Urban Atlas land cover (Figure 6.17d-f). This is because in gridded models, cells can fill up with infiltrated water independently of each other, whereas for the lumped models, the equivalent of the entire area should be filled up to be saturated.

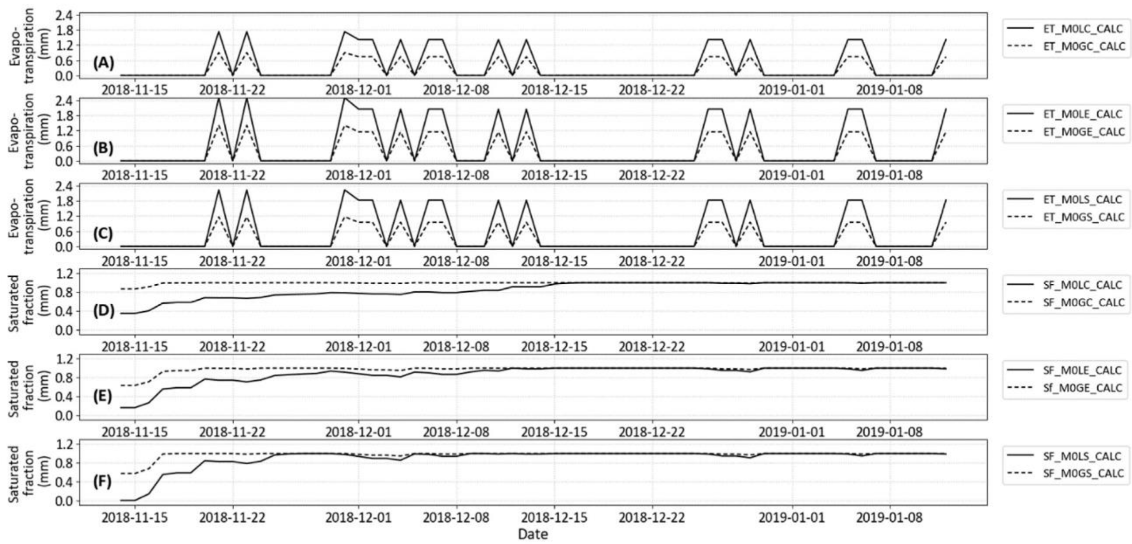

Figure 6.17. Lumped vs gridded evapotranspiration for sub-catchment W08 for (A) CORINE, (B) Urban Atlas and (C) Scent and saturated fraction for (D) CORINE, (E) Urban Atlas and (F) Scent

The amount of excess precipitation generated in the lumped and gridded models for CORINE and Scent is almost equal; however, for Urban Atlas, the lumped model produces about 60% of the amount of the gridded model (Figure 6.17a-c). The main reason behind this is due to the difference in the imperviousness percentage in W08 for lumped and gridded models. Figure 6.17e-g presents the spatial distribution in the gridded model, where the basin's imperviousness for CORINE, Urban Atlas and Scent are 28%, 24.5% and 16.8%, respectively. In the lumped model, they are 27.23%, 28.56% and 15.5%, respectively. Therefore, the gridded Urban Atlas model has around 4% higher imperviousness than the lumped one.

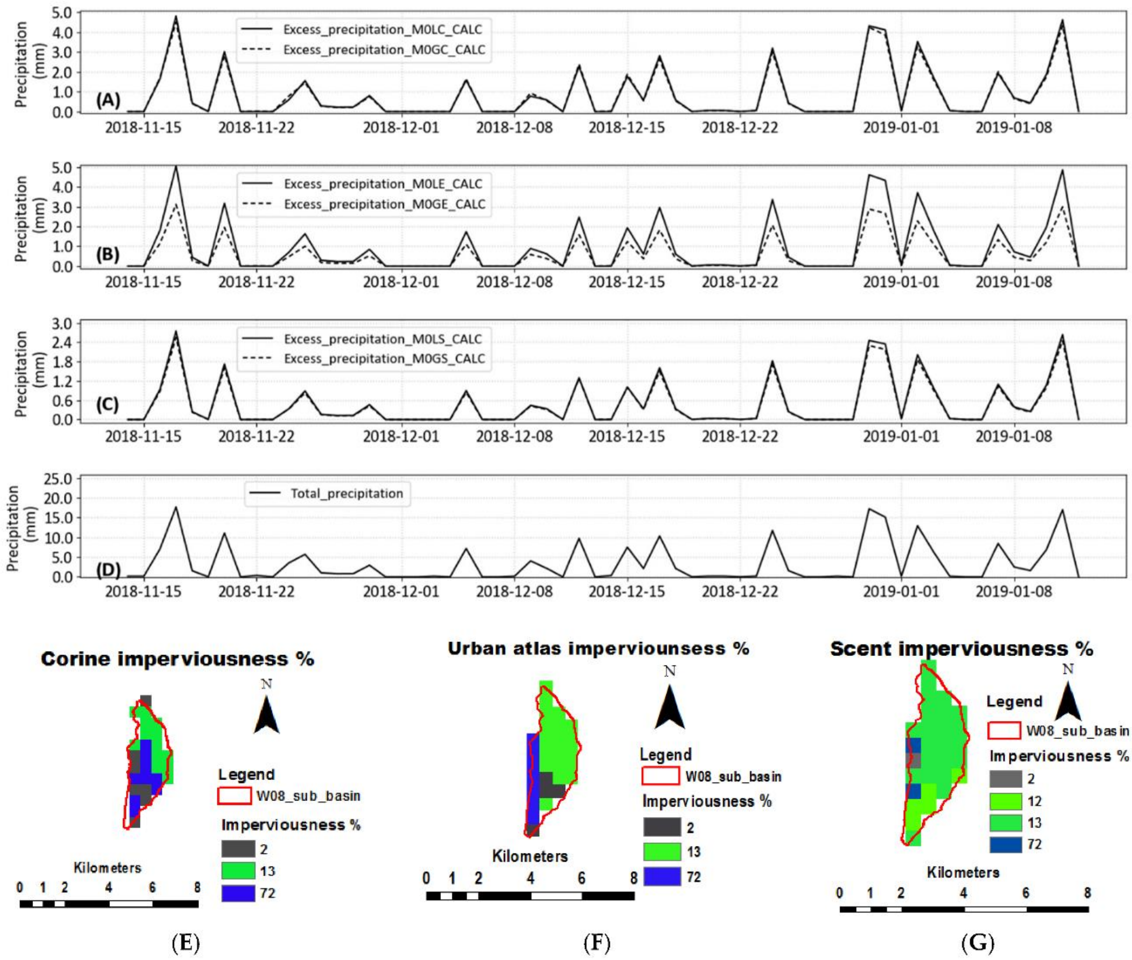

Figure 6.18. Excess precipitation for W08 for (A) CORINE, (B) Urban Atlas and (C) Scent and (D) total precipitation and imperviousness percentage for W08 for (E) CORINE, (F) Urban Atlas and (G) Scent

Before analyzing flow, it is important to highlight that flows at junctions are influenced by a lot of parameters of routing and transformation, which were calibrated for the CORINE LU/LC model only. Overall, for the most downstream station (J09), the timing of the peaks from the models matches observed ones, for lumped and gridded models (Figure 6.19a-b). For the J08 upstream station, there is one day shift in the observed flow (Figure 6.19c-d). For J09, a trend is visible in the data; simulated peaks from the lumped models just after 16 November 2018 are higher than the observed ones, while lumped simulated peaks at a later moment (i.e., after 28 December 2018) are of the same magnitude as the observed peaks. The same decreasing trend is visible in the gridded simulation results. For the case of J08, observed flows are significantly lower than all simulated flows, for both lumped and gridded models.

The CORINE and Urban Atlas models have similar flows in J09, while Scent has the lowest flow in comparison. This indicates that the higher number of classes used to distinguish the Urban Atlas from CORINE did not generate an effect on the final output. The lower value for Scent is likely due to overall lower imperviousness values across all basins, similar to what has been observed in W08. Looking at results upstream (J08), there is a more marked difference in peak flows for the different datasets. At J08, the discharge from only four sub-basins is concentrated, and their land class divisions are different for all datasets, which could explain the differences. Given how low discharge values are for this basin, and uncertainties in the modelling process, these could also be the cause for differences in datasets. Despite differences in magnitude, the pattern for all three datasets is similar.

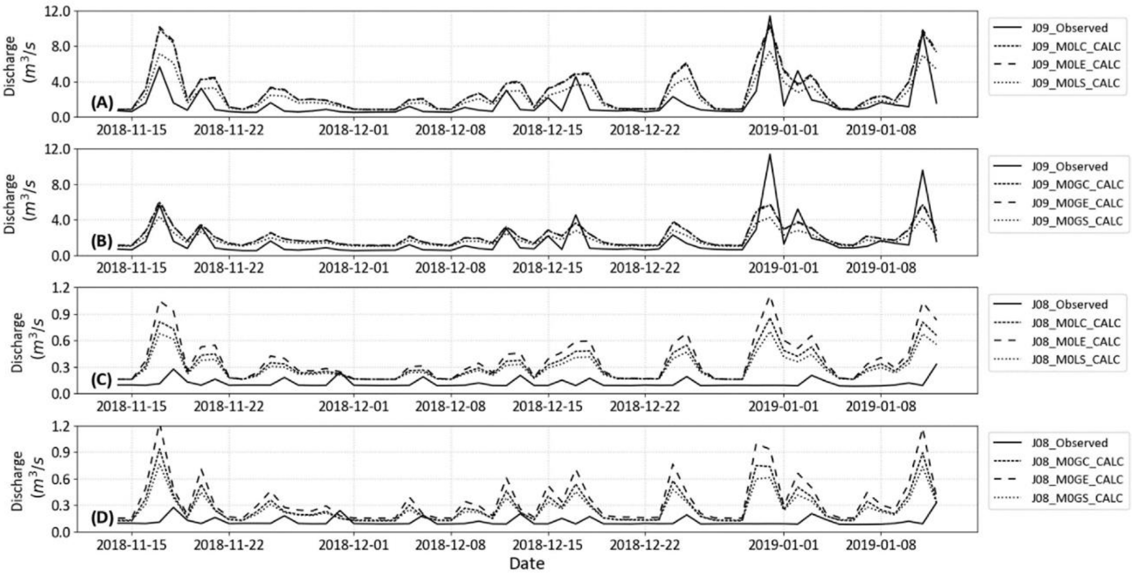

Figure 6.19. Lumped and gridded models flow for J09, (A) lumped vs observed and (B) gridded vs observed, and J08, (C) lumped vs observed and (D) gridded vs observed.

In conclusion, the results demonstrate that by varying the land cover datasets, there were perceived differences in hydrological processes. Influences in pervious areas were noted in the evapotranspiration and the saturated soil fraction, resulting from different reservoir sizes as derived from the land cover datasets. However, these differences did not result in an expressive contribution to excess precipitation from pervious areas, and the differences encountered in excess precipitation were due to imperviousness differences. The impact of imperviousness is also present when comparing the lumped and gridded model structures, once differences emerged only occurred when there were significant changes in imperviousness. Ultimately, for urban and peri-urban catchments, the Scent dataset exhibited an equal or slightly better capacity to represent physical processes than established land cover datasets. Future work lies in investigating further the increase in performance when using an updated land cover model to represent more recent hydrological events, when compared to using outdated ones.

7

CONCLUSIONS AND OUTLOOK

7.1 INTRODUCTION

This chapter summarizes and reflects on the research outcomes discussed in the previous chapters, in relation to the research objectives delineated in Chapter 1. Section 7.2 also addresses the strengths and limitations of the work. The reflections therein portray the personal opinion of the researcher in matters of citizen science, data collection and flood modelling. Section 7.3 reflects on outcomes generalization and provides indications for future work.

7.2 RESEARCH OUTCOMES & REFLECTIONS

Below we discuss how the research outcomes achieved the four research objectives described in the introduction chapter.

On assessing how the design of citizen campaigns influences the amount of multimedia pieces collected by citizens. To tend to this research objective, we conceptualized a framework to position the challenges of citizen science campaigns and proposed an adaptive framework to deal with recognized challenges. The identified obstacles primarily concerned how to navigate the information cycle in a way that ensures data needs from authorities are effectively communicated. Authorities in the Danube Delta faced issues in understanding the complex balance of flows in their wetland ecosystem, needing models and the data to feed models. Authorities in the Kifissos catchment faced issues with the fast urbanization of their city and with the consequent flooding impact. Both cases had distinct data needs, but both cases had similar technological needs: need to have a platform to setup the campaigns and the points of interest, apps for the data collection itself, and centralized access to the collected information and visualization. Further, it was observed the need to optimize the design of the routes for data collection, so they were targeted at fulfilling the data needs highlighted by authorities.

The needs for data, technology and strategic route placement were met by the design of citizen science campaigns as proposed and executed in this research. Campaigns were designed to collect water depths, velocities and land cover information, employing a series of tools to guarantee information and data flow and increase engagement of citizens. For the case of the Danube Delta, analyses of routes proved useful in exposing the accessibility of the wetland, maximizing data collection in potential paths, and showing that a single start/ending point would be sufficient for effective data collection.

The execution of the campaigns demonstrated that operating in an integrated and adaptive campaign design framework yielded high citizen participation (approximately 400 volunteers in the 2018 campaigns). It also resulted in a high ratio between planned and executed scopes (over 70% of points of interest set for the campaigns were visited) and a high ratio between planned and executed amounts of multimedia pieces collected. Over 75% of planned multimedia pieces were collected, except for the technical issues with videos, which were fixed for the campaigns of 2019. The outcomes of this application also showed challenges in execution (such as blocked waterways and working in a limited internet connectivity zone), in engagement (citizens identified the need of a bigger purpose and less buggy application) and in initial data results (automated tools did not perform well to extract data from multimedia). The research conducted achieved the objective of providing a method and assessing how the design of the campaign could influence the outcome in terms of numbers.

The tool and designs proposed and executed were successful and strong in the sense that they maximized the completion of campaigns with thousands of multimedia pieces collected. Still, the challenges identified need to be incorporated into and accounted for the design of citizen science campaigns. Further, although the campaigns were participatory in their beginning and end, authorities were not directly involved in the design of the tools themselves, or of the models in which the data was ingested and neither was the developer community. This resulted in limited uptake of the tools and models after the research was completed.

On developing methods for quality control and analysis of multimedia pieces, data and merging of estimates. To accomplish this objective and ultimately understand what is the efficiency of citizen campaigns, step-wise quality control and analysis methodologies were proposed and implemented. The first step on quality control and analysis of the multimedia collected (images and videos), resulted in information on the rejection rates for multimedia pieces, according to the effect that caused pieces to be of insufficient quality. A quarter to half of the multimedia pieces were rejected, mostly due to citizen mistakes, environmental conditions and technological restrictions, while problems in campaign design played a lesser role. The next step assured that quality issues regarding timestamps, geotags and outliers were diagnosed, which in this case study amounted to less than a less than 10% rejection for these three. Further quality analysis scored the quality of multimedia pieces according to the severity of the listed effects on their quality. Using such methodology indicates that water depth images were overall of excellent quality when not rejected, and that videos of floaters suffered from more severe issues – hinting at potentially higher errors. Approaches to merge extracted data points from multimedia were also tested, either by grouping them in big clusters for an entire point of interest or for sub-clusters per expected measurement. Ultimately, results showed that larger groupings work better. These results demonstrate that the objective was achieved of developing and testing methodologies to process data collected via multimedia by citizens in campaigns.

The methods proposed are comprehensive in their assessment of the different sources of error. It proved to have great value as a diagnostic tool, once the results pointed to the elements of campaign design that caused the most issues. It also served as evidence that, when collecting data via citizen science campaigns, using smartphones and multimedia, the trade-off of volume versus quality is significant. Thus, one must understand the rate at which data is discarded to understand if the desired level of accuracy is reached. This trade-off is particularly important in the applicability of citizen science, when citizen science leaves the academic environment and is applied as a tool by other private and public institutions. In the sense that, as any data collection strategy, citizen campaigns also cost time and money and, without proper quantification and understanding of what it takes to get what is needed, there is little chance of operationalizing citizen science campaigns as measurement methods. Despite the extensive categorization of data quality factors and their potential applicability to other types of multimedia data collection campaigns by citizens - the methods as discussed in this dissertation are still specific to the settings in which this research is conducted (e.g. in a delta, or the use of floaters). More importantly, these methods and research did not explore the level at which training could influence the results, and were implemented via computational tools that were fit for purpose but are not currently reproducible, limiting their generalization power.

On validating citizen-based estimates against traditional measurements. For this objective, validation was performed in comparing the citizen-based estimates with measurements obtained with an ADCP device. The research showed that even for measurements as simple as depth measurements, when the reading can be taken from a picture and one could assume it to be correct, when applied in large scale campaigns, the errors can stack and the correlation was not as high as expected. Within the uncertainty of the executed setup, depth measurements showed to be as accurate as traditional measurements and the natural variability of depths could account for discrepancies. For velocities, the use of floaters and videos did result in a large dataset from citizens, but with little correlation with traditional measurements. This persisted after removing data points of perceived bad quality, hinting at the complexity of extracting surface velocities from videos. With these results, the objective of validating citizen-based estimates is achieved.

Overall, the comparison carried out in this research contributes to a body of literature on citizen-based velocity estimates that is still rather limited. The comparisons were done for waterways with varied widths and depths, fully testing the approach in difficult and complex situations. However, realizing campaigns in a wetland environment also meant that velocities in general in the case study area were very low, and at times stagnant, limiting the application of the results and potentially exacerbating the errors.

On the usefulness of estimates in flood modelling applications. In this objective, modelling applications employed citizen-based data in varied modelling strategies and case studies. The usefulness of citizen-derived water depth estimates in the calibration and validation of hydrodynamic models for the Sontea-Fortuna area was clear; the same minimum was found as when using ADCP-based observations, and similar errors and correlations. In the same manner, land cover maps generated from using photos and annotations from citizens let to similar or even slightly improved results in terms of simulated discharges in the hydrological model of the Kifissos catchment, when compared to the performance of using land cover maps available publicly. It was also demonstrated that despite citizen-based velocity estimates having a potential diagnostic use in model calibration and validation (i.e. indicating the model gross underestimation of velocities), results were not good enough. Doubling of model errors identified with ADCP observations and lack of correlation with ADCP measurements indicate that a straightforward application risks erroneous interpretation of the results. The mentioned results successfully assessed the value of citizen data in the context of modelling.

The complexities of the Sontea-Fortuna wetland system meant that calibration of the area’s roughness with or without data contributed by citizens did not matter; the model was insensitive to the roughness and most likely needs to be investigated under more model parameterization and flow conditions, citizens or not. In the hydrological modelling for Kifissos, different results were obtained by using land cover maps generated by citizens in comparison with those obtained via traditional sources. These differences translated into differences in imperviousness. Both applications corroborated that estimates obtained via citizen science can inform models at similar or better levels than traditional measurements. The usefulness though can be constrained by the model's own predictive capacity and sensitivities, highlighting that new data sources are not necessarily the solution to better modelling.

7.3 OUTLOOK

The studies presented in this dissertation offered an overview of the complete application of citizen science campaigns as data collection tools in the context of water resources. The research outcomes have limitations, as discussed in the section above, but also pave the way for a deeper understanding, application and value of citizen science. Particular directions for research to be taken from this work are suggested in this section.

With regard to the design of citizen science campaigns. The use of multimedia did land large volumes of data, contrasting with the quite high rejection rates, parts of them due to citizen mistakes. Thus, structured research into how much training can reduce citizen mistakes is a great follow-up, also because it dives into the more social aspects of this method – the citizen part of citizen science - and will provide a more polished conclusion on how intrinsic rejection rates are for certain volumes of data generated. It is also corroborated by other research that piloting and small-scale trials can already hint at these error facets. So future frameworks for citizen science campaigns could investigate if an iterative approach with increased complexity at each step would result in more efficient and effective campaigns. Lastly, this dissertation did not compare the costs of engaging a large base of volunteers to the costs of acquiring the data via traditional measurements. This should also be considered when further refining the trade-offs of citizen science campaigns.

With regard to tools for citizen science campaigns. Multimedia and smartphones are more and more ubiquitous and can be tools for involving citizens in water resources management. Citizens engaged well despite the long-dedicated time and the highly technical scope, compared to other citizen science engagement strategies in which the citizens' inner motivations are sufficient to contribute (e.g. interest in flora and fauna). With less reliance on the citizen comes a higher burden on quality control and analysis, which in this research was done at a very expensive research capacity, given the manual application of methods in this research. Future work lies in applying more modern smartphone-sensed data and machine learning methods for data extraction, to reduce rejection rates due to technological restrictions and reduce the burden of environmental conditions. There is also work in assessing the trade-off between developing tools that have higher uptake, thus potentially more unique and fit for purpose, against making them more general and reproducible so they can be tested in more environments.

With regards to the citizen science data itself and its use in modelling. Citizen science data can be much more flexible in providing insights into the environment than traditional approaches. Without the deployment of expensive ADCP surveys, with the evidence of a few floaters in low-moving waters, insights on the low flow velocities, stagnations and flow direction can already be derived. The use of citizens to inform data within bands of proxy data has not been investigated in this dissertation, but it has true potential in reducing the burden of data collection to what matters to stakeholders at a lower cost. So, investigations on how other data formats can be obtained are encouraged. Likewise, how models ingest such data is still quite numeric and single variable-oriented. Research using new variables to measure model performance (e.g. flow direction) or objective functions that blend velocity and water depth error estimates, and more flexible land cover characterisations, can facilitate the absorption of a data source that could come at a lower cost and provide a more participatory approach to water resources.

In conclusion, citizen science for data collection in water resources persists as a challenging endeavour due to data spatio-temporal demands and technical complexity, requiring a lot of effort, as demonstrated in this research. Still, citizen science campaigns can be further explored to the benefit of local authorities, especially if combined with other purposes, for instance, with citizen science for more participation of citizens in governance. For the value to be seen in practical terms, more reflection and documentation on the costs of campaigns, in terms of setup and data losses, needs to be had. It is also important for the research to leave the academic setup and reach the offices where the data will be used, so the real costs are estimated already in an integrated and co-created environment. Further, a different outlook on data collection and modelling could shift problems with citizen data from liabilities to strengths. To make use of citizens' abilities to capture more than what traditional measurements can get, to incorporate non-standard data in modelling, and to lean into the human behaviour and technologies, may be the way to more efficient and even more effective data collections with citizens.

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APPENDIX A

The description of the criteria used to assess multimedia are presented in Table A.1 and Table A.2.

Table A.1. Description of criteria used to evaluate the quality of raw images collected by citizens.

Category	Criteria	Description
Citizen mistake	Gauge presence	The gauge is present in the image. Image is insufficient without a gauge.
	Water level presence	The interface between the water and the gauge is visible in the image. Image is insufficient without the water level.
	Gauge vertical tilt	How far from the vertical position the staff gauge is. If the gauge is tilted too much, the image is considered insufficient (e.g. gauge is about 45 degrees tilted or further). The less gauge tilt the higher the image quality.
	Lateral capturing angle	How far from a front view from the gauge the image was taken, from a lateral perspective. Images taken from the side of the gauge, where no markings are visible, are considered insufficient. The more frontal view from the gauge, the higher the image quality.
	Top-down capturing angle	How far from a front view from the gauge the image was taken, from a top-down perspective. Images taken from the top of the gauge, where no markings are visible, are considered insufficient. The more frontal view from the gauge, the higher the image quality.
	Image focus	How clear it is to read the water level from the gauge. Images that are too blurry to distinguish any markings are insufficient. The more distinguishable the markings, the higher the image quality. Categorized as a citizen mistake because instructions were given to use the right focus and to assess focus quality before taking the picture.
	Presence of riverbank as reference	Indicates if the riverbank can be seen in the image. No image is insufficient if there is no riverbank, but the presence of a riverbank indicates that the image could be better evaluated. Therefore, the more contextual references to evaluate the image, the higher the image quality.
Campaign design	Gauge print quality	The quality of the printed number and markings on the gauge. Images where the water level cannot be read or inferred from the

		gauge are considered insufficient. The more readable the markings on the gauge, the higher the quality.
	Distance to gauge	The distance between the gauge and the image-capturing position. Image is insufficient when the gauge is too distant to read or infer the water level. The closer the gauge, the higher the image quality.
	Image resolution	How clear it is to read the water level from the gauge. In comparison to focus, here images are unclear because it is visible that the number of pixels is not enough to capture the markings. This is connected to campaign design because a drop in quality due to resolution is highly related to the distance to the gauge. Images that are too coarse to distinguish or infer any markings are insufficient. The more distinguishable the markings, the higher the image quality.
Environmental conditions	Brightness	The level of brightness in an image. The image is insufficient if too dark or bright to read or infer markings from the gauge. The more balanced the brightness in the image, the higher the image quality.
Environmental conditions/ Campaign design	Flow velocity	Indicates if the movement of water around the gauge influences the image quality. No image is insufficient due to the influence of flow velocity. The clearer and more horizontal the water level line in the image the higher the image quality.
Not applicable	Other	Other criteria observed during image processing which can classify an image as insufficient or that can influence the image quality.

Table A.2. Description of criteria used to evaluate the quality of raw videos collected by citizens.

Category	**Criteria**	**Description**
Citizen mistake	Floating object presence	The floating object is present in the video. Video is insufficient without a floating object.
	Multiple floating objects presence	Presence of more than one floating object. Video is insufficient with more than one floating object.
	Floating object release present in video	The period when the floating object is being released/thrown in the water, in which its velocity does not correspond to the water velocity. Video is insufficient if it contains this period, even if partially.
	Floating object recovery present in video	The period when the floating object is being recovered/removed from the water, in which its velocity does not correspond to the water velocity. Video is insufficient if it contains this period, even if partially.

	Camera follows the floating object	The citizen moves the smartphone to follow the passage of the floating object, moving the field of view. If the field of view is changed too much, the video is considered insufficient (e.g. about 90 degrees or further). The more static the field of field of view the higher the video quality.
	Camera shaking	Citizen is not able to keep the smartphone static, moving the field of view erratically. If the field of view is changed too much, the video is considered insufficient (e.g. movements bigger than the floating object size). The more static the field of field of view the higher the video quality.
	Recording angle deviation	How far from the position parallel to the river bank the video was recorded in. If the deviation is too high the video is considered insufficient (e.g. about 45 degrees or higher). The more parallel to the riverbank the higher the video quality.
	Video duration	The video duration. Video is insufficient if the duration is smaller than 5s. The longer the duration the higher the video quality.
	Presence of riverbank as reference	Indicates if the riverbank can be seen in the video. No video is insufficient if there is no riverbank, but the presence of a riverbank indicates that the video could be better evaluated. Therefore, the more contextual reference to evaluate the video, the higher the video quality.
Campaign design	Floating object contact with the riverbank	Floating object comes in contact with the riverbank. Video is considered insufficient in this case.
	Interference in floating object movement	Floating object movement is altered by pulling a cord attached to the floating object so that it does not move at water velocity anymore. Video is insufficient if this interference is detected.
	Distance to floating object	The distance between the floating object and the video recording position. Video is insufficient when the floating object is too distant to be well identified (e.g. only a color point is visible, not the object). The closer the floating object, the higher the video quality.
Environmental conditions	Floating object visibility/contrast	How easy it is to recognize the object. If the object color is too similar to the surroundings and could be barely found or it disappears mid-recording, the video is insufficient. The higher the contrast between the floating object and its surroundings, the higher the video quality.
	Floating object trajectory - cross-sectional deviations	The floating object moves across flow lines and along the cross-section, instead of parallel with flow lines. If the trajectory changes too much the video is insufficient (e.g. floating object travels across the cross-section). The more horizontal the trajectory, the higher the video quality.

	Floating object trajectory – wave presence	The floating object's trajectory follows the movement of water waves. If the trajectory changes too much the video is insufficient (e.g. floating object travels across the cross-section). The more horizontal the trajectory, the higher the video quality.
	Disturbance to float movement	The floating object's trajectory or speed can be altered by natural elements, such as underwater vegetation. The lower the disturbance to the float movement, the higher the video quality.
Technology restriction	Video freezing	Some frames of the video remain the same due to the video freezing. If the freezing is persistent the video is insufficient (e.g. most of the video). The least amount of freezing, the higher the video quality.
Not applicable	Other	Other criteria observed during video processing which can classify a video as insufficient or that can influence the video quality.

LIST OF ACRONYMS

1D	One Dimensional
2D	Two Dimensional
ADCP	Acoustic Doppler Current Profiler
CAPTCHA	Completely Automated Public Turing test to tell Computers and Humans Apart
DDNI	Danube Delta National Institute
DEM	Digital Elevation Model
ESDAC	European Soil Data Centre
ESDB	European Soil Database
ET	Evapotranspiration
GPS	Global Positioning System
H2020	Horizon 2020
HEC	Hydrologic Engineering Center
HRTA	Hellenic Rescue Team of Attica
HOG	Histogram of Oriented Gradients
IoT	Internet of Things
LU/LC	Land Use / Land Cover
LiDAR	Light Detection and Ranging
LSPIV	Large Scale Particle Image Velocimetry
MAE	Mean Absolute Error

NGOs	Non-Governmental Organizations
OCR	Optical Character Recognition
OGC	Open Geospatial Consortium
OSM	Open Street Maps
PDOP	Position (3D) Dilution of Precision
PoI	Point of Interest
RMSE	Root Mean Square Error
RoA	Region of Attica
Scent	Smart Toolbox for Engaging Citizens into a People-Centric Observation Web
SIE	Scent Intelligence Engine
SOR	Romanian Ornithological Society
SOS	Sensor Observation Service
SRTM	Shuttle Radar Topography Mission
VGI	Volunteered Geographic Information
UAVs	Unmanned Aerial Vehicles
USACE	United States Army Corps of Engineers, Davis
USGS	United States Geological Survey
WFS	Web Feature Service
WLET	Water Level Extraction Tool
WMS	Web Map Service
WVET	Water Velocity Extraction Tool

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Thaine H. Assumpção graduated with a Bachelor's degree in Environmental Engineering from the Federal University of Paraná (UFPR) in 2012, in Brazil. She then pursued a Master of Science in Water Science and Engineering, specialising in Hydroinformatics, at UNESCO-IHE in Delft, the Netherlands, graduating with distinction in 2015. Her MSc thesis focused on statistical methods for stopping uncertainty analysis of hydrological models using the Monte Carlo method.

Thaine began her professional career as an intern and later as junior researcher at Simepar, the Paraná State Meteorological Agency in Brazil, where she contributed to several activities, including data quality control and analysis of hydro-meteorological data, development and improvement of flood forecasting systems; and hydrological modelling for river basins across the Paraná State.

In 2016, she commenced her PhD research at IHE Delft, in the department of Hydroinformatics and Socio-Technical Innovation. Her PhD was funded by the Horizon 2020 project Scent (Smart Toolbox for Engaging Citizens into a People-Centric Observation Web). She contributed to varied work scopes within the project, including the organization of several field campaigns. She also mentored several master students.

Since 2021, Thaine has worked as a River Survey Engineer at The Ocean Cleanup. In this role, she has led data collection, monitoring, and modelling of plastic pollution and riverine conditions across multiple countries, including Nigeria, Albania, Italy, the USA, and Jamaica.

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Netherlands Research School for the
Socio-Economic and Natural Sciences of the Environment

D I P L O M A

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The Netherlands research school for the
Socio-Economic and Natural Sciences of the Environment
(SENSE) declares that

Thaine Herman Assumpção

born on 10 August 1990 in Curitiba, Brazil

has successfully fulfilled all requirements of the
educational PhD programme of SENSE.

Delft, 28 January 2026

SENSE coordinator PhD education

Dr Ir Peter Vermeulen

The SENSE Director

Dr Jampel Dell'Angelo

The SENSE Research School declares that **Thaine Herman Assumpção** has successfully fulfilled all requirements of the educational PhD programme of SENSE with a work load of 44.9 EC, including the following activities:

SENSE PhD Courses

- Environmental research in context (2017)
- Research in context activity: 'Organising several outreach activities to authorities, developers and the general public to transfer knowledge on crowdsourced data' (2024)

Other PhD and Advanced MSc Courses

- PhD start-up, TU Delft (2017)
- The informed researcher: Information and data skills, TU Delft (2017)
- Data Visualisation - A practical approach, TU Delft (2017)
- Time management – first things first, TU Delft (2018)
- Career development – Exploring a research career outside academia, TU Delft (2020)
- Writing a scientific article in English, TU Delft (2019)
- Deep Learning, TU Delft (2020)
- Machine Learning with Python - From Linear Models to Deep Learning, MIT, Online (2020)
- Artificial Intelligence for Earth System Science, National Center for Atmospheric Research, Online (2020)

Management and Didactic Skills Training

- PhD Association Board – Vice-chair (2019-2020)
- Co-convener of EGU General Assembly session - Innovative sensing techniques for water monitoring, modelling, and management: Satellites, gauges and citizens (2018-2020)
- Supervising seven MSc students with thesis (2016-2021)
- Teaching assistant in the MSc course and short course 'Hydrodynamic modelling with HEC-RAS' (2017-2020)

Selection of Oral Presentations

- Challenges of citizen science contributions to modelling hydrodynamics of floods. EGU General Assembly, 23–28 April, 2017, Vienna, Austria
- *Shape-based Performance Metrics For Hydrodynamic Models*. AGU Fall Meeting, 10-14 December 2018, Washington, United States of America
- Flood modelling and citizen observatories: analysing pathways for data collection in the Sontea-Fortuna case study. 13th International Conference on Hydroinformatics, 1-5 July 2018, Palermo, Italy
- Exploring contributions of citizens' data to improvements in modelling of an urbanized catchment: a case study in Kifissos catchment. River Flow, 6-10 July 2020, Online

IHE DELFT
Institute for Water Education under the auspices of UNESCO

TU Delft Delft University of Technology

Hydrometeorological extremes such as floods and droughts have severe impacts on both human and natural systems, and understanding these events requires reliable data. The demand for such data has grown significantly, especially in regions where conventional monitoring networks are sparse. Citizen science is seen as an important provider of tools and procedures that are complementing traditional hydrological monitoring. Enabled by advances in low-cost sensors, mobile technologies, and open data platforms, citizen science allows non-experts to contribute to data collection, interpretation, and co-design of monitoring systems. However, scientists and authorities require more detailed accounts for the utility of various types of citizen science data needed to meet their specific data needs. This dissertation presents a critical assessment of the design, efficiency and accuracy of citizen campaigns in obtaining data to inform flood modelling applications. A theoretical framework was developed to identify weaknesses in the data cycle and propose new tools to handle them. Citizen science campaigns were then organized to meet local authorities' data needs, to collect water depth, surface velocity, and land cover information. Quality control and analysis methodologies were developed and employed to identify factors that typically cause the rejection of information. Citizen science data was also used for modelling studies, and its ability to fulfil the same role as traditional approaches was assessed. The results of this research contribute to the application of citizen science as an important supplier of data for water-related studies and management, within and outside an academic context.

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