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**Combining process-based and data-based approaches
to predict high water levels: Application to the city of
Pontianak in the Kapuas River delta**

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grade de docteur en sciences agronomiques et ingénierie
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Louvain-la-Neuve, August 2022

Preface

My story in the city of Louvain-la-Neuve, in particular, and Belgium, in general, began in February 2018. It was the first time I had to live abroad for an extended period, especially for study purposes. I understood that my research skills, language skills (mainly French), and computational skills at that moment were limited. Also, I had to change my research topic halfway because the initial subject was unfruitful. Therefore, conducting and finalizing the current research and thesis would not have been possible without many people's support, collaboration, and help.

First and foremost, I thank God for all the mercy and blessings so I can finally finish this thesis. Next, I would like to thank my supervisor, Prof. Emmanuel Hanert, who has kindly dedicated his time to the supervision and given me his endless support and advice to achieve my goals. My sincere gratitude also goes to my co-supervisor (of the initial subject), Prof. Patrick Bogaert, for his advice and support during my first year, particularly in statistic and machine learning techniques. I am also grateful to the jury members, Prof. Jacques Mahillon (Président), Prof. Charles Bièdiers, Prof. Sandra Soares Frazao, Dr. Olivier Gourgue, and Dr. Agus Saleh Atmadipoera; and greatly indebted to the member of the doctoral committee for my initial subject, Prof. Pierre Defourny, and Dr. Julien Radoux.

All thanks also to my colleagues in the (past and present) SLIM Teams (Valentin, François, David, Antoine, Thomas, Lauranne, Riana, and Apolline) and the (past and present) ELI-ENGE teams. Thanks also to my colleague, Afshin Farhadi, who helped me understand more about the Fast Fourier Transform subject. Thanks also to Earth and Life Institute (ELI), which provides support to improve my skills in research and communications. I would also like to thank my colleague, Randy Ardianto, for helping me to access the water level observational data from the local water manager in Pontianak.

Also, I would like to express my gratitude to my mom, my wife (Irfana Diah Faryuni), my childrens (Shofiyah Elkhonsa, Qonita Elhafidzhoh, Aisyah Elkarima, and Shofa Elmarwa), and all my family in Indonesia for all the supports and encouragement for me to carry on, wherever this path has led me to. I also express my gratitude to my friends in CCIOLN and the family of Ayang Utriza Yakin, who supported and comforted me during my study in Louvain-la-Neuve. My appreciation also goes to all staff in the Embassy of Indonesia in Brussels, all members of KPMI (especially Pak Wawan, Pak Mufti, Pak Arif, Pak Chandra, Habib Fahmi, and Pak Ucok), and the Indonesian community in the Netherlands (particularly FORKOM-NL and SGB Utrecht), who have given me and my family supports and moments to cherish during our stay in Belgium. Special thanks also to Jean-Luc van Kempen, who welcomed me the first time I arrived in Ottignies-LLN and rented me a room in his house during my settling-in moment in this city.

Lastly, I would like to acknowledge that this work was carried out with scholarship support from the Indonesia Endowment Fund for Education (LPDP) under Grant No. 201712220212183. Then, the computational resources (HPC) to support my work were provided by the supercomputing facilities of the Université Catholique de Louvain (CISM/UCL) and the Consortium des Équipements de Calcul Intensif en Fédération Wallonie Bruxelles (CÉCI), funded by the Fond de la Recherche Scientifique de Belgique (F.R.S.-FNRS) under convention 2.5020.11 and by the Walloon Region.

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CHAPTER 1

Introduction

The earth has undergone dramatic changes over its geologic history. Ice sheets have advanced and receded as the earth has cooled and warmed. Ice melts during the warming period expand the water volume, causing sea-level rise (SLR). Many studies have shown how this phenomenon affects vulnerable areas worldwide (Hao and Singh, 2020; Jacob et al., 2018; Hirabayashi et al., 2013).

Coastal areas are among those most vulnerable to climate change. As the coastal population is expected to grow further in the following decades, from 625 million in 2000 to about 949 million in 2030, and then 1.4 billion in 2060, climate change threatens the areas even more (Neumann et al., 2015). Extreme weather-related events, such as hurricanes, storms, and high-amplitude waves, are predicted to become more frequent (Mousavi et al., 2010). Hurricanes and storms can bring heavy rains, high winds, and storm surges that cause tides to swell and push water further onshore. High-amplitude waves can also erode natural barriers, such as coral reefs, leaving coastal communities more vulnerable.

Located at the interface between the land and the sea, the climate change impact on coastal regions can have ripple effects (Sekovski et al., 2012), affecting not only safety but also economic activities and socioeconomic well-being. The abundance, distribution, and health of natural ecosystems can be altered. Interacting with land-use mismanagement, such ocean hazards can pose severe risks to the coastal population.

Flooding is one of the most common natural disasters, with occurrences in coastal areas often exacerbated by climate change (Bevacqua et al., 2020). More than 268 million people will be at risk from coastal flooding in 2030, increasing to about 411 million in 2060 (Neumann et al., 2015). Flooding in coastal areas also has a severe economic impact because it destroys infrastructure and buildings. Recovering from flooding takes a long time because drying out and rebuilding the impacted areas needs an overhaul and lengthy undertaking. Additionally, flooding can have a traumatic effect on mental health.

Flooding events in coastal areas worsen by climate change because of the rising greenhouse gas concentrations. This phenomenon has made the air warmer and

changed the distribution of precipitation and evaporation significantly (Seager et al., 2012). Warmer air can hold more water vapor. When the rain falls, the volume of water is high, so the draining requires more time and effort. Aside from this increasingly intense rainfall, global heating is also raising the level of the oceans because melting ice caps and seawater thermal expansion. Therefore, when cyclones and hurricanes blow in, the higher water's starting point due to SLR can make flooding more severe and reach inland further.

Three types of flooding occur in coastal areas in general (Monirul Qader Mirza, 2002). The first is river flooding, which occurs when heavy rain falls into a river, and the river cannot carry it away quickly enough to the ocean. Therefore, the river level rises and bursts at its banks. The water goes into the towns or cities along the river bank. The second is flash flooding, which occurs when heavy rain falls in a particular area, and the land cannot take it away. It often happens in cities, where sewers and drains can quickly get overfilled. The third type of flooding is coastal flooding, when cyclones/hurricanes bring fierce winds that push water onto the land and breach the sea defenses.

Currently, the climate crisis makes flooding in coastal regions less natural and more disastrous (Koks et al., 2014). In those coastal areas where flooding occurs, it will happen more frequently and severely. Meanwhile, coastal regions in developing countries lack studies about the local flood hazards and strategies to mitigate the risks. In other words, the preparation to face flood events is generally inadequate (Few, 2016). In addition, rapid urbanization occurs in developing countries' coastal areas (Celliers and Ntombela, 2015), which creates impermeable surfaces on roads and roofs, making the runoff much faster. This factor also intensifies the flood risk in coastal areas. If urbanization is not managed concertedly, people and assets in the areas will be jeopardized.

1.1 Kapuas River Delta

The Kapuas River is the most extended island river in Indonesia. Its length is about 1,143 kilometers (Goltenboth et al., 2006), stretching from the center of Borneo island toward Karimata Strait on the western coast. Its topography comprises hills over its upstream and plains over its downstream. The river's role is vital for the local communities as a source of fresh water and transportation.

In the downstream area, the Kapuas River flow debouches into the ocean through five major branches (MacKinnon et al., 1996). The biggest branch is Kapuas Besar, followed by Kapuas Kecil, Kubu, South Kubu, and Mendawat (Fig. 1.1). The highest population density is over the second-largest branch, i.e., Kapuas Kecil, which starts from the Rasau Jaya district and ends at the estuary

area in the Jungkat district. Midway at about 20 km before the river mouth, the Landak tributary joins the Kapuas Kecil.

Like other rivers, the Kapuas River has created a delta, i.e., the Kapuas River delta (KRD), in its river mouth areas—an area where freshwater falls into the sea's salty water (Kereszturi et al., 2015). The term delta derives from the triangle-shaped area where the river meets the sea. The triangle shape emerges from the sediments brought by the river flows when encountering the ocean. While the river flows from the higher places through the valleys, it leaches out the soil from the eroded rocks. As the accumulates, the piles up create an obstacle to the river mouth. Therefore, river flows circumvent this obstacle, creating a Delta triangle at the seafront. The longer the river flows, the more sediments accumulate; hence, the delta becomes larger and larger.

The KRD's area extends north to south over a distance of more than 140 km and from the river mouth to upstream about 60 km (MacKinnon et al., 1996; Kästner, 2019). The KRD has formed geologically since the end of the last glaciation 15 thousand years ago (Kästner, 2019). As the bathymetry of the Karimata Strait is shallow, the coastline retreats during glacial periods by more than 880 km (Voris, 2000).

Major processes that operate on deltas, like in the KRD, include fluvial, waves, and tides (Galloway, 1975). The fluvial or river processes bring the sediment to the delta, while waves and tides redistribute the sediment once the rivers deliver the material to the river mouth. The form of deltas depends mainly on the relative strength of these processes and is influenced by the size of the transported sediment (Orton and Reading, 1993). Due to these processes, different environments emerge on a delta. The first environment is distributary channels, i.e., the river itself. The second is the distributary mouth bars (DMBs), where the river enters the ocean and consists mainly of sand. The third is levees at the edges of the distributary channels produced by flooding—little mounds that make the river channel bigger. The following environment is front sheet sands, which distribute the sand delivered to the DMBs. The next is the interdistributary bay between the distributary channels, which includes swamps and large lakes. The last is the pro-delta, a place for most fine material deposition and is generally located in front of the delta.

The KRD is a low-lying marshy delta, where silt deposits cover the delta from the coastline up to about 60 km inland (MacKinnon et al., 1996), creating floodplains for the Kapuas river downstream. The delta remains primarily natural, with no dams, dikes, or groins built on its river stream. As a low-lying area, the delta is prone to flood. The flood, and the hazardous effects, could be exacerbated by a combination of storm surges, intense rainfalls, and high

discharges. These hazards are further intensified by SLR caused by climate change (Moftakhari et al., 2017).

The most populated urban area within the KRD is the city of Pontianak. As the capital of West Kalimantan province, Pontianak is home to about 600,000 people, and this number keeps increasing. Located on low-lying land within the KRD, the city has 61 canals spread across the city area, working as the city drainage system that empties excess water into the Kapuas Kecil and the joining Landak River streams (Kondisi Geografis Kota Pontianak, 2021).

Due to the geographical and hydrodynamic conditions, the city of Pontianak often experiences floods. Wells et al., (2016) reports that floods affected 868 settlements 966 times (including 89 in urban areas) over three years (2009-2012) and inundated at least 197 000 houses on Borneo island in general. While in Pontianak, floods occurred eight times over four years, from 2015 to 2019 (Pemerintah Kota Pontianak, 2019). This flooding risk may further increase in the future due to urbanization, SLR, or other extreme weather events caused by climate change.

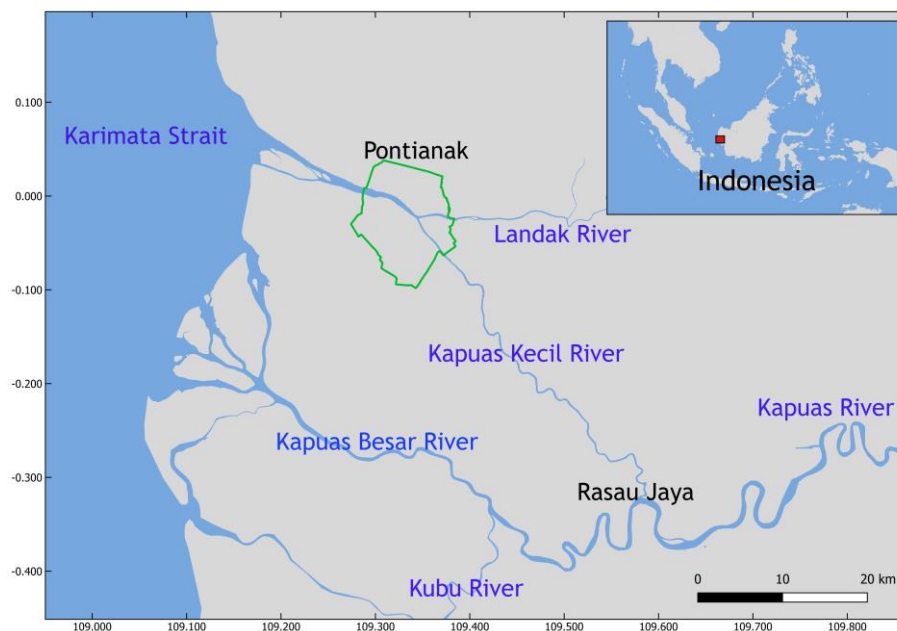


Figure 1.1 The region of interest, where the green enclosed perimeter represents the city of Pontianak. The red box (in the inset) shows where the region of interest is set in this study. The flow from the Kapuas River's upstream bifurcates in Rasau Jaya, the furthest inland boundary of the KRD area. The main branch (the Kapuas Besar) bifurcates again (the Kubu branch), and the second-largest branch (the Kapuas Kecil) joins the end stream of the Landak River in Pontianak before it debouching into the sea.

In the last decades, palm oil cultivation and forest fires have encroached on the Kapuas water catchment (Semedi, 2014; Jadmiko et al., 2017), resulting in changes in the Kapuas hydrological regime that can trigger more intense riverine flooding in the KRD. As population density rises in these areas, future flooding risks attributed to riverine and coastal surges must be properly assessed. This is imperative for urban planning and coastal protection development.

However, as in most developing countries, local water managers in the KRD lack data and tools to conduct flooding assessments. As a consequence, creating robust forecasting to predict future flooding is challenging. Therefore, local water management is often late in issuing a warning system when flooding occurs, making its impact higher. Moreover, limited computational resources and observational data hinder the assessment process further. Without these, the mechanisms that drive the flooding events in the KRD remain poorly known.

1.2 Hydrology of the Kapuas River and its catchment

The Kapuas River's basin is located on the equator in the western part of Borneo Island, Indonesia (Fig. 1.2). The air temperature and humidity are high throughout the year. The water catchment area of the Kapuas River spreads over about 93,000 km², with about 66.7% consisting of forests (Wahyu et al., 2010). Its topography comprises hills over its upstream, covered mainly by *Orthic Acrisols* soils (Fig. 1.2). Meanwhile, its downstream comprises plains with more heterogeneous soil types, such as *Dystic Histosols* (typical of peat bogs, moors, and swamps with high organic content) and *Dystic Fluvisols* (young soil in alluvial deposits).

The Kapuas River discharge varies from 2,000 m³/s in the dry season to 10,000 m³/s in the wet season, with an annual average of 6,000 m³/s (Goltenboth et al., 2006; MacKinnon et al., 1996). During the wet seasons, the water level in the upstream and middle stream areas can rise by 10 m overnight (MacKinnon et al., 1996). The areas near the river banks are therefore prone to flooding.

Downstream, a fraction of the Kapuas River's discharge (about 17%) is diverted at Rasau Jaya into Kapuas Kecil towards Pontianak (Kästner and Hoitink, 2019). Meanwhile, 83% of the discharge continues to flow through Kapuas Besar. Then, a portion of Kapuas Besar's flow is diverted again towards the Kubu branch (see Fig 1.1 for the location of the branches).

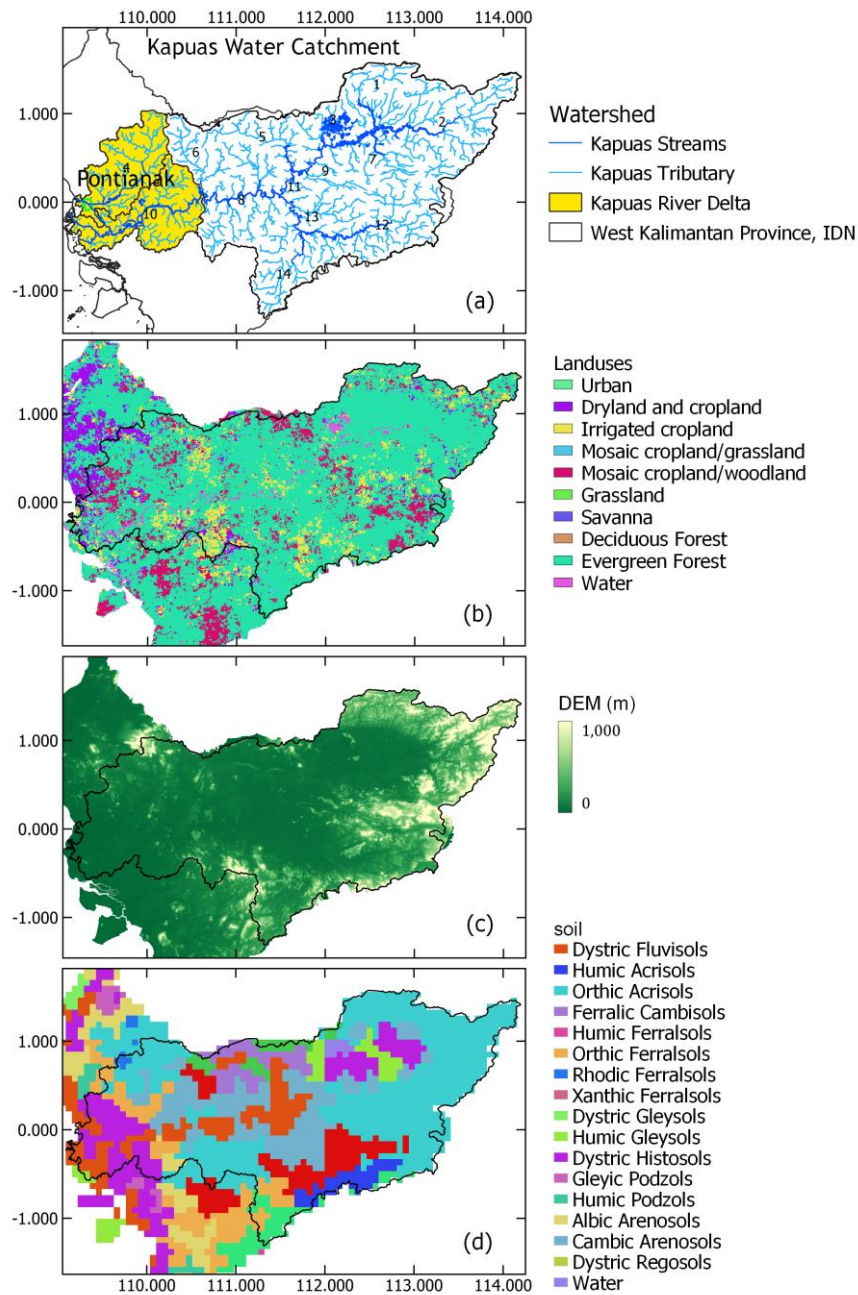


Figure 1.2 Kapuas watershed area (a), land cover maps (b) retrieved from CGLOPS1 (Buchhorn et al., 2020), digital elevation map (DEM) (c) retrieved from SRTM (Farr et al., 2007), and soil type maps (d) retrieved from FAO (Sanchez et al., 2009) for the Kapuas River catchment area.

Unfortunately, the Kapuas River hydrological data (such as the discharge and the river water level) are scarce and not easily accessible. The discharge data's access is open but only available in the middle stream at Sanggau (about 284 km from the river mouth) from November 2013 to May 2015 (Kästner et al., 2018). The water level data collected by the Pontianak Maritime Meteorological Station (PMMS) covers Pontianak only (20 km from the Kapuas Kecil river mouth) and can only be accessed by request. The data were measured hourly from 2010-2012 for only half-days (from 7 a.m. to 7 p.m.). Then, from 2012-2015 they observed the data for 15 hours (from 7 a.m. to 10 p.m.), and from 2016 until now, they observed the hourly data in full days (24 times per day).

1.3 Climatic conditions

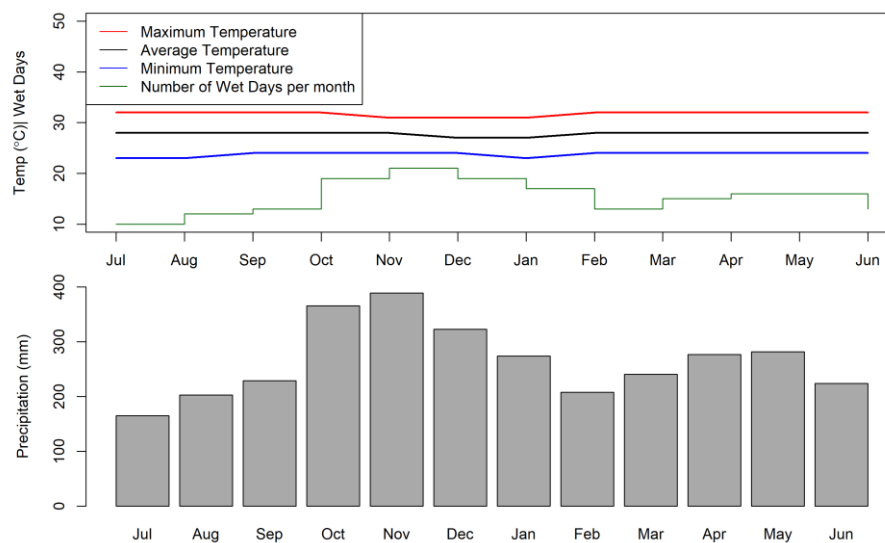


Figure 1.3 Monthly average temperature (upper) and precipitation (lower) in the KRD. Data were retrieved and reproduced from 2009 to 2017 (www.pontianak.climatemps.com)

Since the Kapuas River delta is located on the equator, the climate is generally humid and warm. Meteorologically, the KRD has bimodal monthly rainfall distribution with two maximum peaks in the equinox, namely March and October (Aldrian and Susanto, 2003). The daily temperature is stable throughout the year, with variations between 24 °C to 32 °C and an annual average of 27.8 °C (Fig 1.3, upper panel). The monthly average precipitation varies between 165 mm and 389 mm (Fig 1.3, lower panel), with whole rainy days per month ranging from 10 to 21 days (Fig 1.3, upper panel). The driest weather generally occurs in July and the wettest in November.

The KRD area has two seasons, i.e., dry and rainy. The dry season is characterized by low rainfall and relative humidity. These conditions often trigger forest fires in peatland areas, occurring naturally or caused by human activities. The rainy season is characterized by high daily rainfall and relative humidity. Generally, flooding events occur in lowland areas along the riverbanks during the rainy season.

1.4 Hydrodynamic conditions

The hydrodynamics of the waterways within the KRD is strongly influenced by tides, affecting up to 285 km upstream (Kästner and Hoitink, 2019). However, as the tides travel farther upstream, their influence is attenuated by the river discharge (Buschman et al., 2010). Together with the bed frictions, the river discharge attenuates the tidal energy along the river (Pauta, 2018). Moreover, the attenuation is impacted by isolated topographic features, such as potholes (Zhong and Li, 2006).

As a typical delta, several processes also alter the propagation of tides within the KRD, such as attenuation, reflection, deformation, and amplification (Van Rijn, 2011). Attenuation occurs when the tidal propagation interacts with the river bed, resulting in friction, leading to energy loss and exponential wave height reduction. Reflection occurs when tidal propagation towards upstream channels encounters obstacles. The obstacles reflect the propagating tides, creating a new counter-propagating wave. Deformation occurs when tidal propagation encounters shallow depth that alters the wave's shape because the upper part of the wave (crest) travels faster than the lower part (trough). Lastly, amplification occurs when tidal propagation changes its geometry vertically and horizontally. As tides propagate upstream, the depth and width of the river channels gradually decrease. Those progressive changes tend to increase the amplitude of the tidal wave (Pugh and Woodworth, 2014).

According to Webb's (2021) tidal classification, the tides in the KRD can be classified as diurnal. The propagation upstream is modified by riverbanks width convergence and depth difference (Guo et al., 2014). There is also an influence of backwater at the observation point within the delta (Kästner et al., 2019). The interaction between tidal and river flows alters the ocean tides (Parker, 1991).

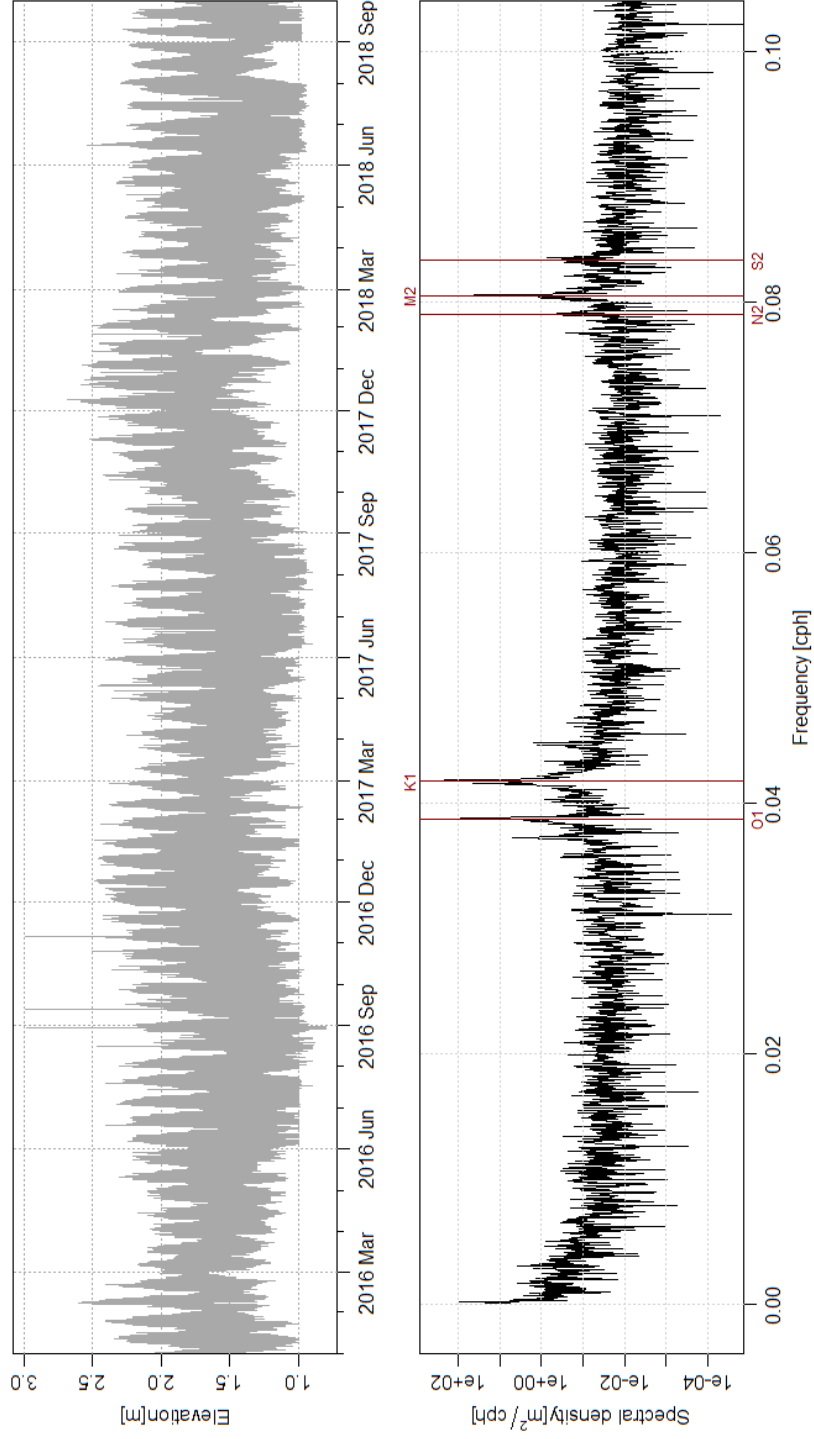


Figure 1.4 Tidal analysis of Kapuas water level dynamics in 2016-2018. Since the data is hourly, the frequency unit is defined in cycles per hour (cph).

More detail about tidal constituents in the KRD is provided in Fig 1.4 and Appendix Table A.1, showing the three-year (2016-2018) observed water-level dynamics in Pontianak (-0.020431°S, 109.33852°E) analyzed by using the R *OCE* library (Kelley and Richards, 2022). The main tidal constituents that control the hydrodynamic processes in the KRD are lunar diurnal constituents (K1 and O1), annual solar constituent (SA), and lunar semidiurnal constituent (M2). The diurnal components explain most of the total variances of the tidal dynamics. Then, the solar annual, the semidiurnal, and the shallow water terdiurnal components explain the rest.

1.5 Compound flooding hazards

In 2012, the Intergovernmental Panel on Climate Change (IPCC, 2012) defined compound events as two or more extreme events occurring simultaneously or successively. Compound events can also be defined as a combination of extreme events whose underlying conditions amplify the impact of the events. It is also defined as a combination of events that are not themselves extremes but lead to an extreme event when combined. The contributing events can be of similar or different types.

Based on the definitions of compound events by IPCC, we can infer that compound flooding is a phenomenon where two or more flooding sources happen simultaneously or in close succession. In a delta, a compound flooding event is caused by the interaction of oceanic masses (tide and storm surges), atmospheric conditions (strong wind and rainfall), and river discharges. The most common type of compound flooding in coastal areas is a combination of storm surges and river flooding, which can produce floodwaters that are longer in duration and more spatially extensive. The complex interaction among the processes involved, such as tides, storm surges, SLR, winds, and river discharges, poses a challenge to existing coastal models.

As a delta located along a tidal river stream, the KRD is prone to experiencing compound flooding. Compound flooding within the delta can occur due to storm surges from the ocean, high discharges from the upstream watershed, excessive rainfall over the area, or a combination of these phenomena. The compound flood hazard depends on how high the joint probability's amplitude within the tidal cycle, the river discharges, the rainfall, and the skew surges. The skew surges refer to the sea level rising from its expected tide level due to the atmospheric pressure gradient and wind stress (Fig 1.5). Since the coastal area is shallow, the stronger the wind, the higher the skew surges prompted by tide and surge components' interaction (Santamaria-Aguilar and Vafeidis, 2018). In the

future, the compound flood hazards in the KRD may worsen due to SLR or other climate-related extreme weather events.

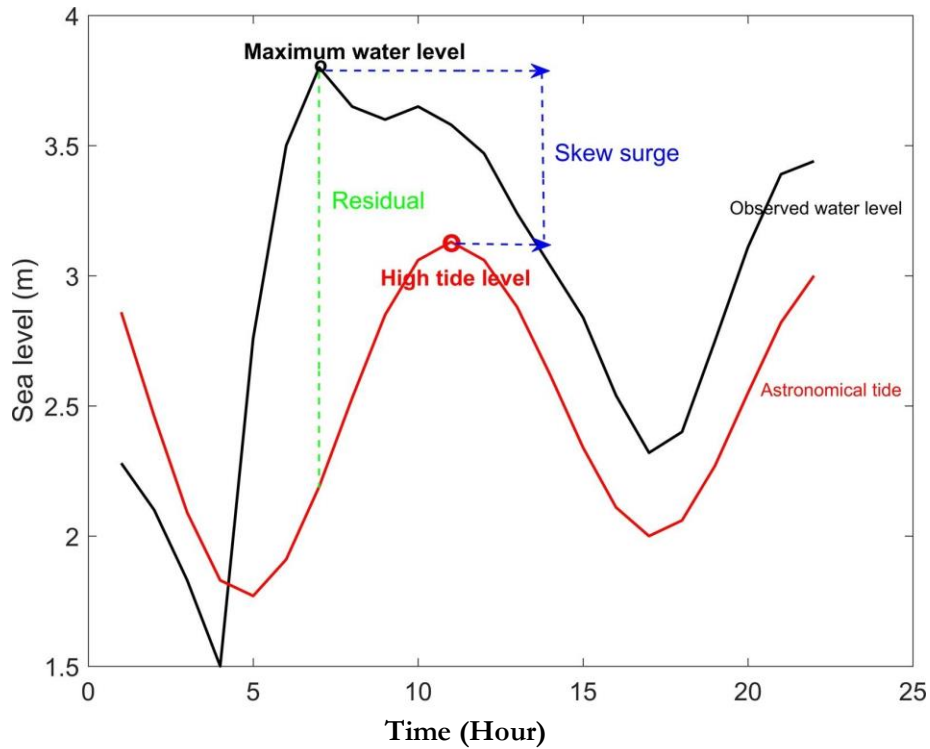


Figure 1.5 Schematic of a skew surge (Feng et al., 2021). It defines the difference between the maximum observed water level and the highest predicted astronomical tide during the tidal cycle, regardless of timing.

Storm surges in the KRD can occur due to low atmospheric pressure in the South China Sea. This phenomenon will cause a bulge in the offshore. As the wind blows across the sea, it will blow a water mass against the coastline. Those storms slowly push water against the edges of the South China Sea, and then it moves toward the Karimata Straits. The water propagation will trigger high water excursions over several hours in coastline areas, such as up to 142 cm in the southern region of Thailand (Anuar et al., 2018) and 30 cm in Singapore (Tklich et al., 2013).

1.6 Water level modeling for flood forecasting

Water level modeling for flood forecasting is increasingly crucial in deltas with high compound flooding hazards (Ward et al., 2018). Firstly, climate change has impacted storm surges and rainfall frequency and intensity. Secondly, with the

increasing urbanization, more buildings are developed over delta areas, which increases the overall exposure. Therefore, early preparedness and warning systems need to be developed in the disaster risk management and mitigation (Perera et al., 2019).

Water level modeling for flood forecasting is commonly built using a process-based approach. This approach can provide information about complex physical processes and has proven to aid disaster mitigation and evacuation planning (Olbert et al., 2017; Serafin et al., 2019; Davidson et al., 2020). However, due to the intricacy of the modeling, some physical procedures essential in delineating an inundation's spatial extent are often simplified (Maskell et al., 2014; Orton et al., 2020). For instance, many compound flooding models for coastal areas have focused on quantifying discharge and storm surge interaction while neglecting the surface runoff and the direct effect of the precipitation over those areas (Santiago-Collazo et al., 2019). Therefore, these approaches may misrepresent the actual physical processes because the superposition of runoff and surge can overestimate total water levels (Bilskie and Hagen, 2018).

Moreover, no process-based models have been designed to account for the entire processes involved in a compound flooding event (Ye et al., 2020). In other words, the current existed models have simulated some of the processes involved in compound flooding but not all of them. As a common practice, modelers typically couple two or more models to cover the hydrologic and the hydrodynamic systems in the tidal river, bay, estuarine, and coastal systems.

The ideal scenario would be to use a dynamic coupling, where we could run different models simultaneously with feedback among them (Santiago-Collazo et al., 2019). For instance, we can look at the large domain generally required for storm surge modeling using a coastal storm surge model. Meanwhile, a hydrologic model could provide high-quality flow data, such as surface runoff, that can be used as input for the hydrodynamic model. Then, we couple these models to predict water levels and forecast compound flooding in coastal areas.

Another approach is using a data-based model, i.e., machine learning (ML)—a technique used to help computers solve problems that otherwise require human brainpower (Choi et al., 2020; Wang and Wang, 2020; Mosavi et al., 2018). ML aims to teach a computer how to perform a task without explicitly programming it to perform the task, instead feeding data into an algorithm to improve outcomes with experience gradually. ML models generally perform two fundamental jobs: classification and prediction. The first job aims to classify data input, while the second aims to make predictions about future outcomes.

There are several steps to build a robust ML model (Bishop, 2006). The first step is to acquire and clean up data. The better the data represents the problem, the

better the results. The data needs some signal/pattern to be valuable to the algorithm for making predictions. The next step is to separate the data into training and testing datasets. The training data is fed into an algorithm to build a model. Then, the testing data is used to validate the accuracy or error of the model. The further step is to choose an algorithm. The algorithm can be a simple statistical model such as linear- or logistic- regression or a decision tree that assigns different weights to features in the data, and each algorithm has pros and cons (Table 1.1). Every algorithm learns to improve its performance by comparing its predictions to an error function. For a classification problem, the error function used generally is the accuracy. While for a regression problem, the error function can be the mean absolute error.

Table 1.1 The pros and cons of the ML algorithms implemented in this study (Mirjalili et al., 2020; Chahar and Kaur, 2020).

ML algorithm	Pros	Cons
Multiple linear regression (MLR)	• A simple algorithm • Good to determine the relative influence of predictor variables • Good to identify outliers or anomalies	• Incapable of handling incomplete data (containing missing values) • Poor in handling a huge amount of data.
Random Forest (RF)	• Good performance on imbalanced datasets • Capable of handling a huge amount of data • Good handling of missing data • Outliers will not have a huge impact • Can avoid overfitting	• Predictions of the trees need to be uncorrelated. • Appears as a "black-box" algorithm
Support Vector Machine (SVM)	• Performs well in higher dimensions. • Outliers have less impact • Suited for extreme case binary classification	• Requires a significant amount of time to process. • Poor performance with overlapped classes • Selecting the appropriate kernel function can be tricky

Similar to water level modeling, compound flood hazards are generally assessed using a process-based model. However, the model may require many adjusted parameters for every given catchment area. The implementation of the model also requires a high computational cost. Therefore, local water managers with low computational resources will be hindered in implementing this, hence unable to build reliable flood warning systems. In this situation, ML models can be an alternative solution. Using ML, local water managers can build and calibrate the model using available data for any catchment areas, thus requiring lower

computational resources in implementation. Therefore, ML technique is promising to improve early flood warning systems for local water management in developing countries.

1.7 Metrics for model performance evaluation

To evaluate the model performance or select the best predictors implemented in this study, we use the goodness of fit indicators, i.e., Nash–Sutcliffe efficiency (NSE), root mean square errors (RMSE), and mutual information (*MI*). The NSE assesses the performance of the models in producing the predicted water level. A perfect model corresponds to $NSE = 1$, while a model with the same predictive skill as the mean of the observed data is represented by $NSE = 0$. Meanwhile, $NSE < 0$ implies that the mean value of observed data predicts better than the model. The closer the NSE value is to 1, the better the predictive skill of the model. The NSE coefficient is calculated as follows:

$$NSE = 1 - \frac{\sum_{t=1}^T \{H_m^t - H_0^t\}^2}{\sum_{t=1}^T (H_0^t - \bar{H}_0)^2} \quad (1.1)$$

where H_m^t represents the water level model at time t , H_0^t represents the observed water level at the same time, and $\bar{H}_0$ is the mean of the observed water level.

Root mean square errors (RMSEs) of peaks between predicted water level and observation during the flood events are also used as an additional performance indicator. The RMSE is used to represent the model's ability to predict flood events. The RMSE between the model outputs and the observations is calculated by

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (x_i - y_i)^2}{N}} \quad (1.2)$$

where x_i is the water level as the model's output at the i -th peak, and y_i is the observed water level at the same time. The number of total peak data is N .

Next, we used *MI* as a goodness of fit indicator to evaluate a parameter that will be used as a model's predictor, particularly in machine learning. *MI* is a statistical tool that measures the degree of relatedness between variables in a dataset, implemented to evaluate the relationship between each predictor and the dependent variable. The *MI*'s value will be greater than zero if there is a correlation between the evaluated variables. The stronger the correlation, the greater the *MI*'s coefficient value is (Kinney and Atwal, 2014). The greater the *MI* value between two variables, the stronger the relatedness, regardless of how nonlinear its dependency. The value is determined by the following equation (Choi et al., 2020):

$$MI = \sum_{x \in X} \sum_{y \in Y} p(x, y) \log \left(\frac{p(x, y)}{p(x) \cdot p(y)} \right) \quad (1.3)$$

where X represents the independent variable, Y represents the dependent variable, $p(x)$ is the probability of the independent variable (X), $p(y)$ is the probability of the dependent variable (Y), and $p(x, y)$ is the joint probability distribution of both variables.

1.8 Scope of the thesis

The present thesis aims to create an integrated modeling framework for local water management covering the flood hazard information and risks, mainly compound flooding risk in a data-scarce delta, i.e., the KRD. Here, we assessed flood risk for the study area by considering the spatial distribution of flood hazards and their exposure. Water levels are used as a proxy to define flood hazards, where hazardous areas are represented by the regions submerged under certain water levels. Meantime, exposure means infrastructures in hazard zones that are subject to potential submerged in the event of a flood.

The three main components of this thesis are the hazardous zone delineation, the integrated flood modeling framework, and the future risk assessment analysis. The hazardous zone delineation will inform the local water management in planning better mitigation strategies for the impacted areas. The integrated flood modeling framework will generate a model capable of predicting compound flooding events without needing much observational data in building phase and need only low computational resources in the implementation. The future risk assessment will provide information about flood hazards, risks, and projected exposed areas needed to anticipate the worst-case scenarios driven by climate change.

More specifically, this study aims to answer the following three main questions:

1. How do we delineate flood hazard zones along the Kapuas River banks by considering the interactions between tides, storm surges, and river discharges?
2. How do we build a model for water level dynamics prediction in a data-scarce delta with limited computational resources, such as the KRD?
3. How do we assess future flood risk due to climate change in the KRD using limited observation data?

To answer the questions, we have three main objectives to be achieved. The first objective is to investigate the interaction between tides, storm surges, and river discharges in the Kapuas River delta and its surrounding area. We used a hydrodynamic model, commonly used to simulate compound flood events (Liu et al., 2022; Paprotny et al., 2020; Kumbier et al., 2018), to simulate the interactions between these driving forces and their effects on compound floods in the KRD, particularly in Pontianak. Then, we delineated flood hazard zones

along the Kapuas River banks. We present the outcomes in chapter 2 of this thesis.

The second objective is to tackle the limited computational resources and the scarcity of observational data in the KRD by combining the process-based and data-based modeling approaches. Firstly, we build a hydrodynamic model to run some flood scenarios in the KRD. Then, we create machine learning models, trained by using the outputs of the hydrodynamic model, to predict the water level and forecast future floods. To obtain a robust machine learning model, we evaluate the algorithms and select the most accurate one for our application. For a case study, the integrated scheme is implemented in the city of Pontianak to assist the local water management in assessing their compound flood hazards. We detail this objective in chapter 3 of this thesis.

The last objective is to assess future compound flooding risks in the KRD using limited observation data under climate change in the three emission scenarios: low (RCP2.6), medium (RCP4.5), and high (RCP8.5). We implemented an integrated multiple linear regression (MLR) algorithm and GIS-based bathtub models to assess future flood risks in the city of Pontianak. Firstly, we modeled the river water level dynamics in the KRD. Then, we trained the MLR algorithm using three-month data (October-December 2020) when 26 flood events occurred. We then simulated the future extreme water levels within the KRD under the influence of rainfall changes, wind surface changes, and sea-level rises. Next, we created flood maps with inundated areas under a 100-year flood (1% annual exceedance probability) scenario using a GIS-based bathtub model. Finally, we assess the impact of these future flood extents on infrastructures in the city. The assessment output is essential for Pontianak's local water resource managers to mitigate and create adaptation strategies. We elaborate on this objective in chapter 4 of this thesis. More detail about the conceptualization of how these objectives are connected is presented in Fig. 1.6.

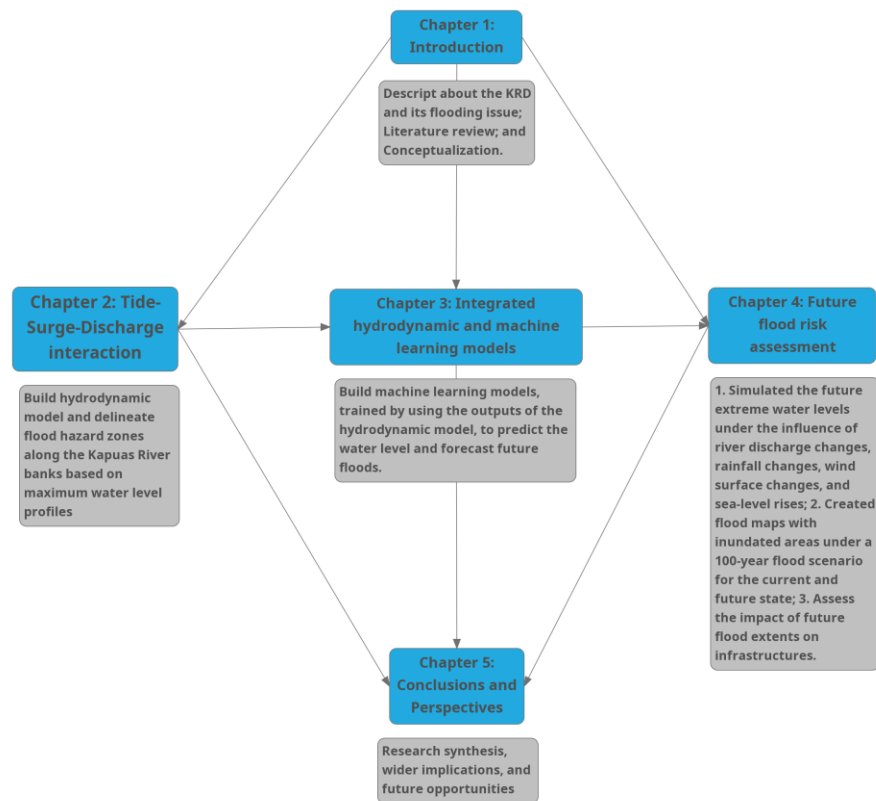


Figure 1.6 This diagram provides an overview of the thesis structure.

Tide-Surge-Discharge interaction

This chapter reproduces the following article¹:

Sampurno, J., Vallaey, V., Ardianto, R., and Hanert, E.: Modeling interactions between tides, storm surges, and river discharges in the Kapuas River delta, *Biogeosciences*, 19, 2741–2757, <https://doi.org/10.5194/bg-19-2741-2022>, 2022.

Abstract. The Kapuas River delta is a unique estuary system on the western coast of the island of Borneo, Indonesia. Its hydrodynamics are driven by an interplay between storm surges, tides, and river discharges. These interactions are likely to be exacerbated by global warming, leading to more frequent compound flooding in the area. The mechanisms driving compound flooding events in the Kapuas River delta remain, however, poorly known. Here we attempt to fill this gap by assessing the interactions between river discharges, tides, and storm surges and how they can drive a compound inundation over the riverbanks, particularly within Pontianak, the main city along the Kapuas River. We simulated these interactions using the multi-scale hydrodynamic model SLIM (Second-generation Louvain-la-Neuve, Ice-ocean Model). Our model correctly reproduces the Kapuas River's hydrodynamics and its interactions with tides and storm surge from the Karimata Strait. We considered several extreme-scenario test cases to evaluate the impact of tide-storm-discharge interactions on the maximum water level profile from the river mouth to the upstream part of the river. Based on the maximum water level profiles, we divide the Kapuas River's stream into three zones, i.e., the tidally dominated region (from the river mouth to about 30 km upstream), the transition region (from about 30 km to about 150 km upstream), and the river-dominated region (beyond 150 km upstream). Thus, the local water management can define proper mitigation for handling compound flooding hazards along the riverbanks by using this zoning category. The model also successfully reproduced a compound flooding event in Pontianak, which occurred on 29 December 2018. For this event, the wind-generated surge appeared to be the dominant trigger.

¹Only minor modification were made.

2.1. Introduction

Global warming leads to more frequent tropical storms, rising sea levels, and more intense rainfalls, which all concur in increasing the occurrence of compound flooding events in a coastal area and its surrounding environment (Bevacqua et al., 2020). Such disasters impact the lives of more and more people worldwide (Moftakhari et al., 2015). Compound flooding occurs when dry low-lying land (over a coastal area) is flooded by water from the ocean and the river. Compound flooding is driven by the interaction between a coastal inundation and a riverine inundation. The former happens from the seaward direction due to high (spring) tides and storm surges, while the latter occurs from the landward due to high discharges from upstream rivers. Coastal communities, which have been growing in population over the past decades, have become increasingly vulnerable to those events. Cities located along an estuary are at the crossroad between the ocean and the river catchment, hence particularly vulnerable (Herdman et al., 2018; Vitousek et al., 2017; Zhang and Liu, 2017).

One of the most significant drivers that can trigger compound flooding over a coastal area is storm surges (Herdman et al., 2018; Zijl et al., 2013). A storm surge is defined as the difference between the observed water level and the expected water level that results from tidal dynamics in a coastal area. A storm surge effect on usual tidal dynamics is the altered timing of high and low water through non-linear processes (Zijl et al., 2013). A storm surge is composed of low- and high-frequency components (Spicer et al., 2019). The former modifies the non-tidal water level, and the latter represents a tide-surge interaction during the event. A storm surge is generally quantified by the skew surge (Giloy et al., 2019), which is a tidal cycle average measurement—the difference between the observed height and the expected height. It reflects the level of surge generated over a tidal cycle. To mitigate compound flooding hazards in a coastal area, a storm surge is a critical component that should always be taken into account.

Several factors must be considered regarding the assessment of compound flooding risks in a river delta. The first factor is the coincidence of the sources (Herdman et al., 2018), which means there is a possibility for the delta to receive an extreme flow from the upstream, while, at the same time, there could be an intense surge occurring in the tide or excessive rainfall over the coastal area. The second factor is the dependency and interdependency of the sources, indicating whether the interaction between these sources (extreme flows, tides, and excessive rainfall) could significantly impact the inundation processes (Bilskie and Hagen, 2018; Herdman et al., 2018; Santiago-Collazo et al., 2019). Other important factors include the vegetation properties along the riverbanks that resist the flow of water, the vegetative properties over the estuary that reduce the

momentum transfer of wind, the landscape characteristics of the coastal area, and how they interacted with each other (Twilley et al., 2016).

Flooding events in a delta area can be simulated and assessed using hydrodynamic models (Deb and Ferreira, 2017; Olbert et al., 2017; Patel et al., 2017). The most useful models are those that can seamlessly simulate the processes occurring along the land-sea continuum, which corresponds to the area encompassing the coast, the estuary, and the river channels. Such models allow for a study of past flooding events and an assessment of flood mitigation strategies (Vu and Ranzi, 2017). However, realistic input variables and forcing are needed to create an accurate physics-based hydrodynamic model. Since the processes that drive compound flooding are three-dimensional, a 3D model is the most appropriate tool to evaluate the event. However, the area of interest represents a well-mixed and relatively shallow waterbody. Therefore, we applied a 2D barotropic solution to reduce computational costs (Huybrechts et al., 2010; Néelz, 2009).

As an archipelago country with about 100,000 km of coastlines, Indonesia is faced with significant coastal flooding risks (World Meteorological Organization, 2021). Indonesian coastal flood hazards are classified as high (Think Hazard - Indonesia, 2022). It means that the potentially damaging waves are expected to flood the coasts at least once every 10 years. Based on this risk and concerns about the impact of climate change in the future, a hazard assessment study in Indonesian low-lying coastal areas (such as deltas) has become critical for Indonesian water management authorities. One area in Indonesia that is vulnerable to coastal or even compound flooding is the Kapuas River delta. In this delta, flooding events happen more than once a year (Wells et al., 2016). Unfortunately, there is no previous study addressing the process that underlies the flood events in there. The previous study (Hidayat et al., 2014) successfully evaluated the inundation frequency, but it only did so for the upstream area and did not evaluate the underlying process. Therefore, this study attempts to fill in the gap and provide the first compound flood assessment in the area.

This chapter investigates the interaction between tides, storm surges, and river discharges in the Kapuas River downstream and its surrounding area. We use a 2D hydrodynamic model to simulate the interaction between these driving forces and their effects on the compound flooding in the Kapuas River delta, particularly in Pontianak. Then, we create a detailed flood assessment, determine the area's extent, and calculate the inundation depth. As a case study, we implemented the model explicitly to a compound flooding event on 29 December 2018.

2.2. Materials and methods

2.2.1 Hydrodynamic model

The interplay between the river discharges, the tides, and wind surges from the sea and their effect on the inundation processes in Pontianak is investigated by using the Second-generation Louvain-la-Neuve Ice-ocean Model (SLIM, <https://www.slim-ocean.be/>). The model equations are discretized with the discontinuous Galerkin finite element method. The model uses an unstructured mesh, whose resolution can vary in space. The model has successfully been applied to several areas, such as the Great Barrier Reef (Lambrechts et al., 2010), the Mahakam delta (Pham Van et al., 2016), the Scheldt estuary (Gourgue et al., 2013), and the Columbia River (Vallaey et al., 2018).

Here, we use the wetting-drying barotropic version of SLIM that solves the conservative form of the shallow-water-equations (SWEs):

$$\frac{\partial H}{\partial t} + \nabla \cdot \mathbf{U} = 0 \quad (1)$$

$$\begin{aligned} \frac{\partial \mathbf{U}}{\partial t} + \nabla \cdot \left(\frac{\mathbf{U}\mathbf{U}}{H} \right) + f \mathbf{e}_z \times \mathbf{U} - \nabla \cdot (\nu \nabla \mathbf{U}) = \alpha g H \nabla (H - h) - \frac{Cd}{H^2} |\mathbf{U}| \mathbf{U} + \\ \frac{1}{\rho} \tau_{wind} - \frac{H}{\rho} \nabla p_{atm} \end{aligned} \quad (2)$$

where $\mathbf{U} = H\bar{\mathbf{u}}$ is the horizontal transport, H is the water column height, h is the bathymetry, t is the time, and $\bar{\mathbf{u}} = (u, v)$ is the depth-averaged horizontal velocity and where α is a constant that is set to zero over dry elements and one over wet elements (Le et al., 2020), ∇ is the horizontal gradient operator, $g = 9.81 \text{ m/s}^2$ is the gravitational acceleration, Cd is the bulk drag coefficient, f is the Coriolis parameter, $\mathbf{e}_z$ is the vertical unit vector pointing upward, ν is the horizontal eddy viscosity, ρ is the water density, τ_{wind} is the wind stress, and ∇p_{atm} is the atmospheric pressure gradient. Here, the wind stress (τ_{wind}) was computed with the Smith and Banke (1975) formula for the wind speed of less than 20 m/s and was computed with the Moon et al. (2007) formula for wind speed higher than 20 m/s.

The model equations are solved using a wetting-drying algorithm with an implicit time-stepping scheme. With this algorithm, a mesh element can be defined as wet or dry. It requires a procedure that guarantees that the water column height

(H) is always positive at the end of the time step to solve the equations. To achieve that, we set first a threshold b^* that indicates the water height below which an element is assumed to be dry (here $b^* = 0.1$ m). Then, we define a parameter representing the total water column height on an element as a combination of maximum water level and minimum bathymetry: $s = \max(\eta) + \min(b)$. When s is smaller than b^* , gravity will be canceled on the element so that the artificial gradient of surface elevation would not remove water from an already-dry element ($\alpha = 0$). On the contrary, if s is greater than b^* , then the gravitational force will be preserved as usual ($\alpha = 1$). The transition between $\alpha = 0$ and $\alpha = 1$ occurs smoothly. More details about this procedure can be found in Le et al. (2020).

2.2.2 Model setup

Before creating the model, we first define a domain covering both the ocean and the Kapuas River delta. Since we focused on evaluating the impact of tide-surge-discharge interaction on extreme water levels along the Kapuas Kecil branch (particularly in Pontianak), we leave out several distributaries that may not significantly influence that dynamics, such as the southern Kubu branch. Next, we mesh the domain, set the bathymetry and the bulk drag coefficient, define the boundary conditions (surface elevation and velocity), and finally impose some forcings. After the model is created and run successfully, we validate the results using observational data.

Here, we generate a multi-scale mesh of the entire domain by using the mesh-generation algorithm of Remacle and Lambrechts (2018). The mesh consists of 206,359 triangular elements. Fine mesh elements are used to accurately represent inundation events over the land area of Pontianak and along the Kapuas riverbanks, while the coarser mesh elements are used far away from the delta. The mesh resolution reaches 50 m along the Kapuas riverbanks and over the city of Pontianak. It decreases to 10 km in the middle of the Karimata Strait (Fig. 2.1).

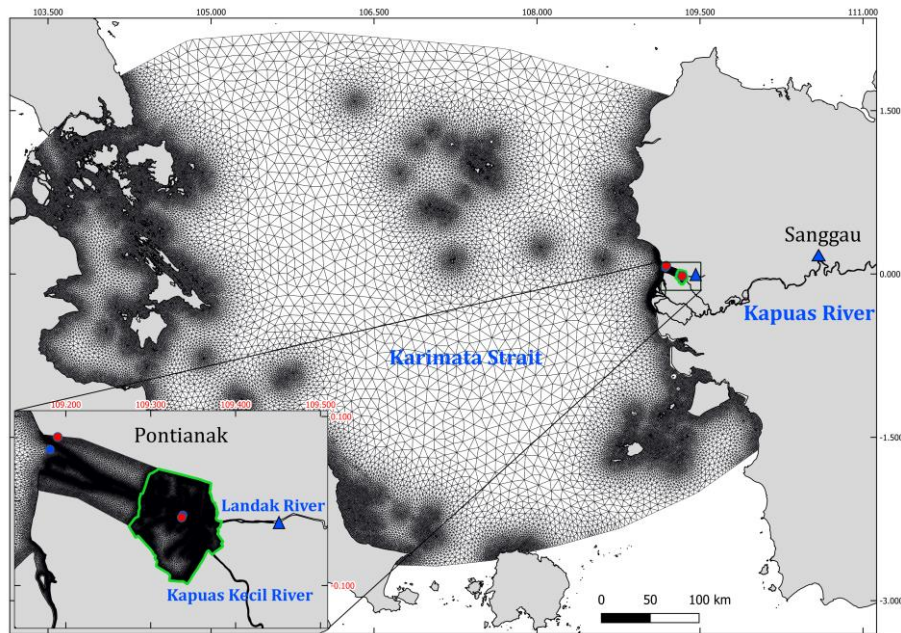


Figure 2.1 The region of interest includes the Karimata Strait, the Kapuas River and its estuary, and the city of Pontianak, whose limits are shown in green. The unstructured mesh is made of triangles whose resolution ranges from 50 m over the river and estuary to 1 km near the coastlines, and 10 km in the middle of the Karimata Strait. The mesh is composed of 206,359 triangular elements. Red dots represent the weather station's locations, and blue dots represent the tidal validation points (on the left is the river mouth; on the right is the Pontianak Maritime Meteorological Station (PMMS) observation point, where the weather and the tidal validations points are superimposed). Blue triangles depict the river boundary where discharges are imposed in the model. The background map was retrieved from OpenStreetMap (planet dump retrieved from <https://planet.osm.org>, 2020). © OpenStreetMap contributors 2017. Distributed under the Open Data Commons Open Database License (ODbL) v1.0.

The bathymetry is created from a combination of three different data sources. The first is the river and estuary bathymetry obtained from the Indonesian Navy (Kästner et al., 2019) with a 100×100 m grid resolution. The second is the Karimata Strait bathymetry, obtained from BATNAS (BATNAS, 2021) with a 180×180 m grid resolution. The last is the digital elevation model from DEMNAS (Seamless Digital Elevation Model dan Batimetri Nasional; DEMNAS, 2022) with 0.27-arcsecond resolution. The Karimata Strait bathymetry shows that the strait is shallow (less than 100 m) and relatively flat (Fig. 2.2). On the other hand, the bathymetry of the river is more heterogeneous. The river is shallow in the estuary but deeper in the middle stream. The depth

ranges from 1 m (in the estuary area) to 40 m in the middle stream area (Kästner et al., 2017). The Kapuas Kecil River, which flows through Pontianak, has a depth that decreases from 15 m in the middle stream to 1 m in the river mouth.

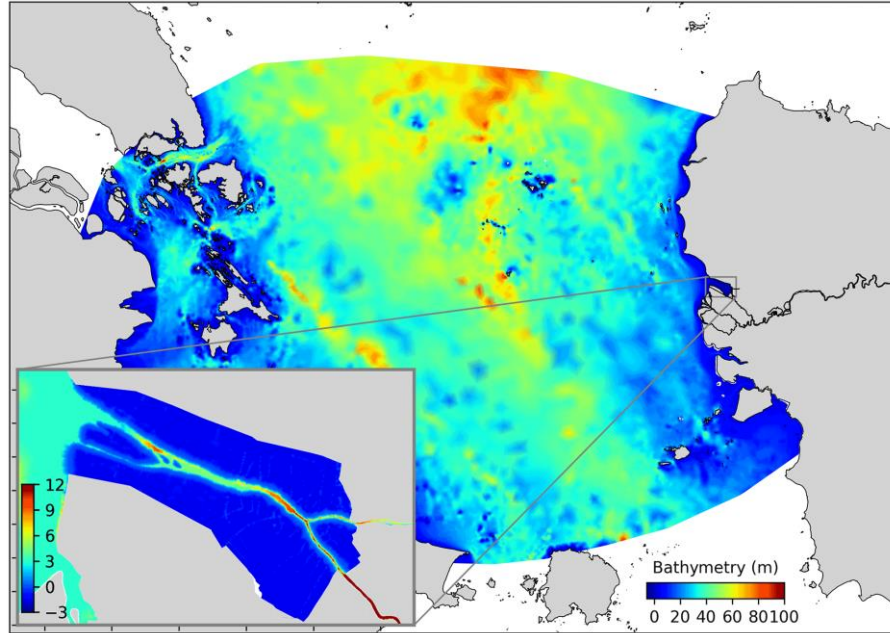


Figure 2.2 Bathymetry map, with positive values meaning under the mean sea level.

The wind velocity and the atmospheric pressure data are the ERA5 reanalysis dataset obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF). The data have a spatial resolution of 31 km (Hersbach et al., 2020), while the temporal resolution is hourly and available at 137 vertical levels (0 to 80 km from the surface). The model wind stress parametrization uses the wind speed at 10 m height. Unfortunately, compared with observational data from the Stasiun Klimatologi Mempawah (<http://iklim.kalbar.bmkg.go.id>), measured at 10 m above the surface, there are clear differences in amplitude. The observed wind velocity is more significant than the wind velocity from ERA5 during a wind surge (Fig. 2.3). Therefore, in the case study, we adjust the magnitude of the wind input data (ERA5) during the wind surge event. We multiplied the wind magnitude with a ratio between both peaks (the observed and ERA5 data).

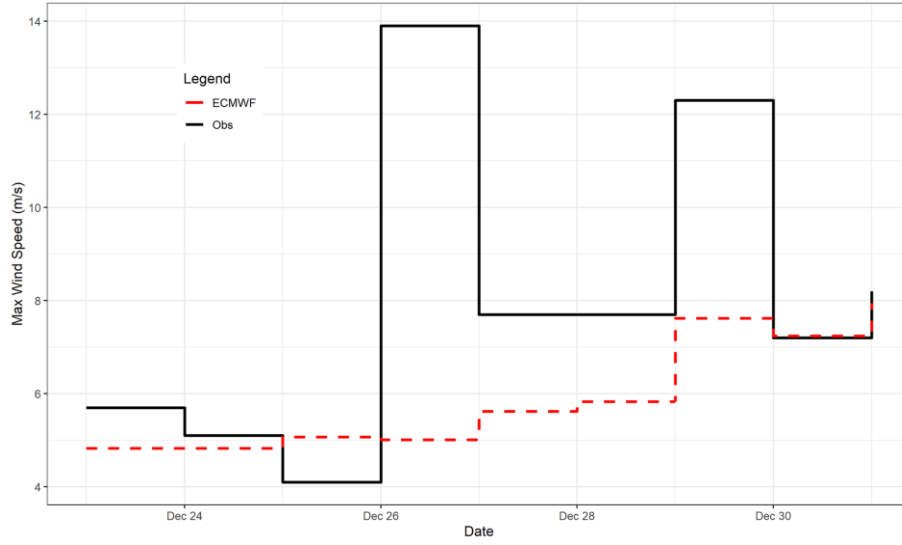


Figure 2.3 Maximum daily wind speed from ECMWF ERA5 compared to observations at the Kapuas Kecil River mouth. During strong wind events, the ERA5 data tend to underestimate the actual wind speed.

Next, we set the bulk drag coefficient to 2.5×10^{-3} over the ocean and 1.9×10^{-2} (average bulk drag during December 2018, since it is slightly increasing with the river discharge) over the river part (Kästner et al., 2018). Both coefficients correspond to a sandy bed. Over the dry area, the drag coefficient is determined by two types of land cover (urban and non-urban area), as defined in the Copernicus Global Land Service land cover map (Buchhorn et al., 2020). For the urban area, the bottom drag coefficient is 2.05 (Hashimoto and Park, 2008). Over the non-urban area, it is set to 2.0, which corresponds to dense vegetation (Li and Busari, 2019).

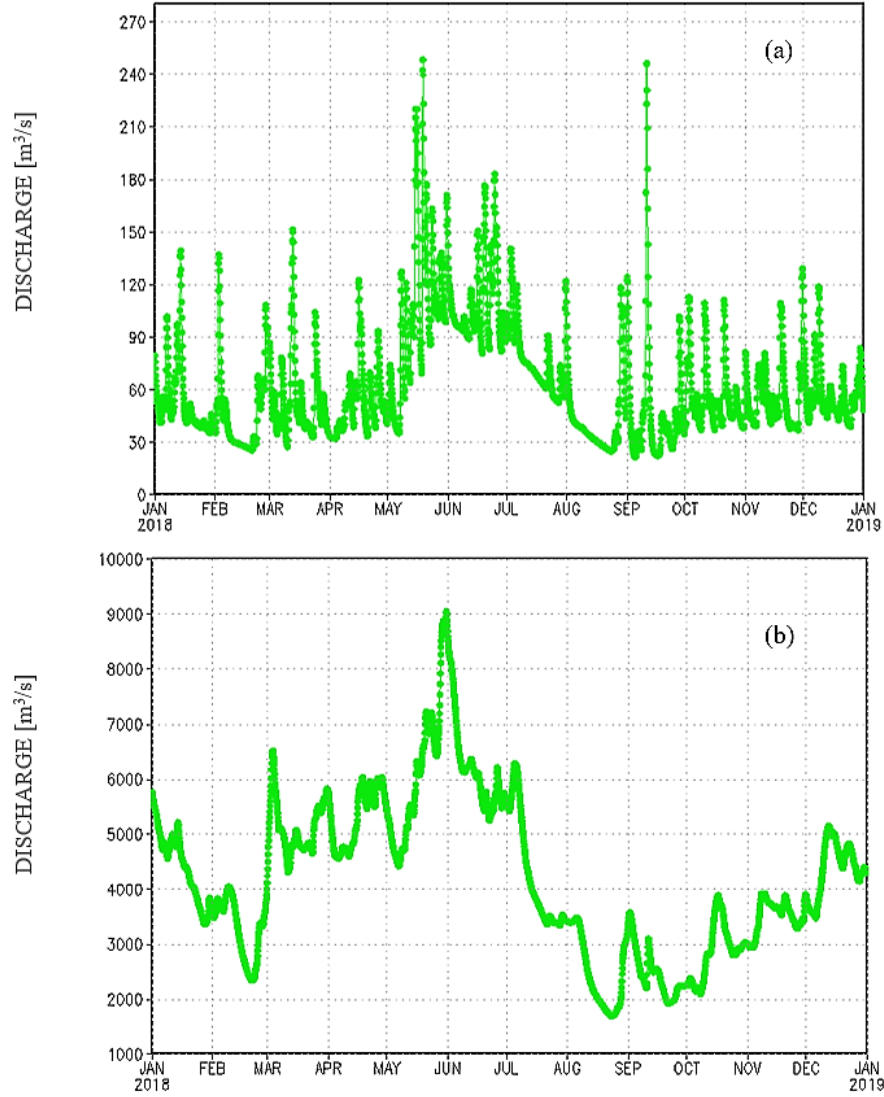


Figure 2.4 River discharge of (a) the Landak (prescribed at 0.0282° S, 109.445° E) and (b) the Kapuas (prescribed at 0.3623° S, 109.6394° E) retrieved from Wu et al. (2014).

Then, we imposed discharge at the rivers and tides at the open ocean for the open boundaries. Upstream of the rivers, we imposed the discharge of the Kapuas River and the Landak River. Since there are no observational data for both rivers, we set constant discharges for the simulations in some scenarios. However, to reconstruct the observed inundation (discussed in the case study), we imposed the discharges obtained from the Global Flood Monitoring System (GFMS). The GFMS estimated the global discharge based on Tropical Rainfall

Measuring Mission (TRMM) Multi-satellite Precipitation Analysis and Global Precipitation Measurement data (Wu et al., 2014). The Kapuas River discharge is bigger than the Landak River discharge (Fig. 2.4). At the open boundaries in the ocean, we prescribed the tidal elevation and current of 15 harmonics from the global tide model dataset, the OSU (Oregon State University) TPXO (TOPEX/Poseidon) Tide Models TPXO9-atlas (Egbert and Erofeeva, 2002). We also prescribed global ocean circulation from HYCOM (HYbrid Coordinate Ocean Model; Chassignet et al., 2007) at these boundaries.

To evaluate the model performance, we performed the tidal analysis on the simulated surface elevation and compared it to the observed water level at the tide gauges. The analysis was conducted using the Unified Tidal Analysis and Prediction (UTide) Python package (Codiga, 2011). The tidal analysis assumes that a tidal signal is a linear combination of multiple sinusoidal signals associated with its astronomical forcing. Each of these signal components has a different phase, amplitude, and temporal frequency. The analysis aims to obtain tidal harmonic constituents. Since we only ran the model for a limited time duration (in order to minimize the computational cost), it is impossible to extract all tidal constituents from the model's signal output. As a rule of thumb to select the appropriate tidal constituent, we used the Rayleigh criterion (Godin, 1970). Based on this criterion, we obtained nine tidal constituents, i.e., K1, O1, Q1, P1, and J1 (as the representation of the diurnal components); M2 and S2 (as the representation of the semidiurnal components); and MK3 and MO3 (as the representation of the third-diurnal constituents).

To perform tidal analysis, water level signals were extracted and analyzed at two points. The first point is located at the river mouth (0.0617° N, 109.1751° E), and the second point (-0.020431° S, 109.33852° E) is located along the Kapuas Kecil River within the city of Pontianak (Fig. 1). The second point is located about 20 km from the river mouth. At the first point, the model's output signal is compared with the tidal signal from the Indonesian Consortium of Oceanic and Atmospheric Prediction (ina-COAP) (Prediksi Pasang Surut Online, 2021). Meanwhile, for the second point, the model's signal output is compared to the observational data collected by the PMMS.

To quantify the agreement between the simulated water level and observation, we calculated the Nash-Sutcliffe efficiency (NSE) and root mean square error (RMSE) between both time series. The former coefficient measures how well the model's performance represents the observed data. $NSE = 1$ represents a perfect model; $NSE = 0$ depicts a model with a predictive skill the same as the mean of the observed data; and $NSE < 0$ informs that the mean of the observed data is a better predictor than the model output. The latter coefficient indicates the average of the difference in the peaks between both time series. Both of these

coefficients were calculated using the library hydroGof (goodness of fit) in R (Zambrano-Bigiarini, 2020).

In order to better investigate the inundation extent and depth over the city of Pontianak, we used the HEC-RAS model (Hydrologic Engineering Center River Analysis System; HEC-RAS, 2022). We firstly created a secosnd mesh to cover the computational domain over the city and used water levels from the SLIM output model as the boundary conditions (Fig. 2.5). The second mesh has a 10 m resolution; hence it can better represent canals that spread in the city. Like the SLIM model, the HEC-RAS model also solves the shallow-water equations (SWEs).

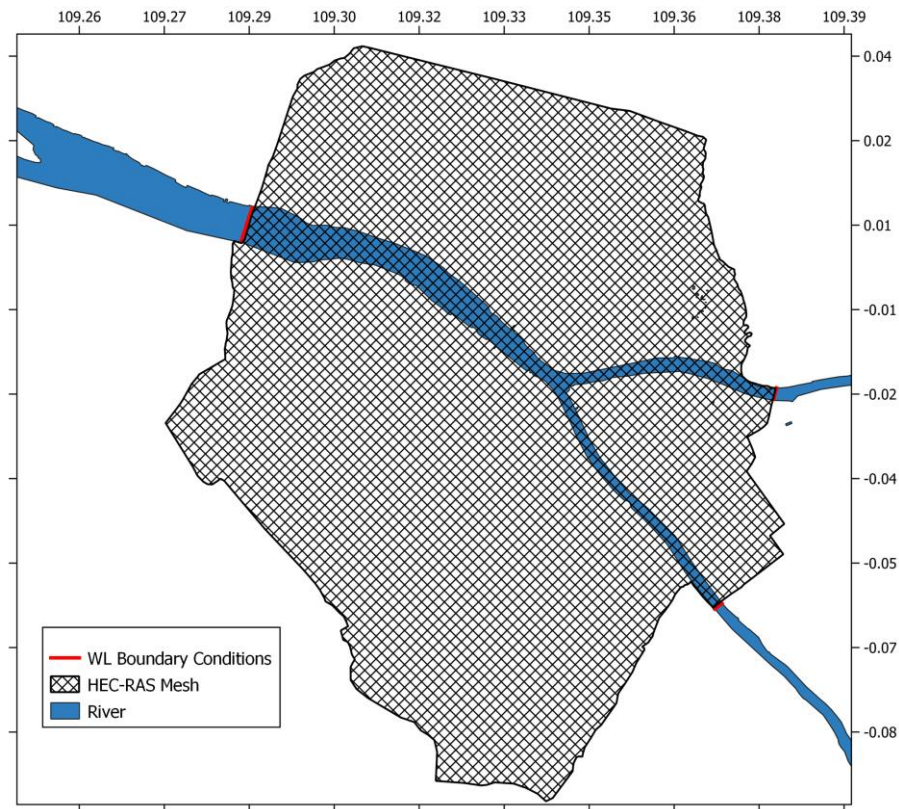


Figure 2.5 HEC-RAS 2D mesh with a resolution of 10 m for flood extent analysis in the city of Pontianak. WL: water level.

2.3 Results

2.3.1 Model validation

The validation results show a good agreement between the model output and the ina-COAP's tidal signal at the Kapuas Kecil River mouth (0.0617° N, 109.1751° E), with a coefficient of determination of $R^2 = 0.95$ and $RMSE = 0.09$ m. At this point, the model produces a tidal signal that has constituent attributes (phase and amplitude) similar to the ina-COAP's tidal signal. The diurnal components explain about 90.69% of the total variances of the estuary's tidal dynamics, while the semidiurnal components only account for about 9.31% (see Fig. 2.6 and Appendix Table A2 for more detail). Next, the tidal analysis result at the observation point in Pontianak (-0.020431° S, 109.33852° E) also shows a good agreement between the model output and observation with a coefficient of determination of $R^2 = 0.83$ and $RMSE = 0.14$ m. The model output signal also has similar constituents attributed to the PMMS observational water level signal (Fig. 2.7 and Appendix Table A3). At this point, the diurnal components explain about 89.6% of the total variances of the estuary's tidal dynamics, which is lower from the river mouth. Then, the semidiurnal components account for about 9.9%, and the shallow-water terdiurnal components explain the rest. The analysis at this second point also confirms that the model successfully reproduces the observed hydrodynamics.

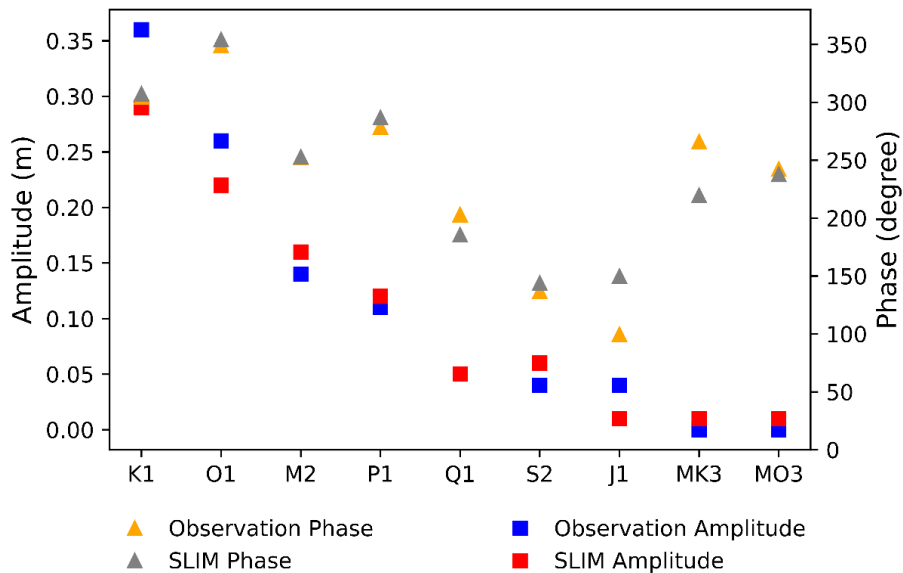


Figure 2.6 Observed and simulated tidal constituents (amplitude and phase) at the Kapuas Kecil River mouth (0.0617° N, 109.1751° E) during December 2018.

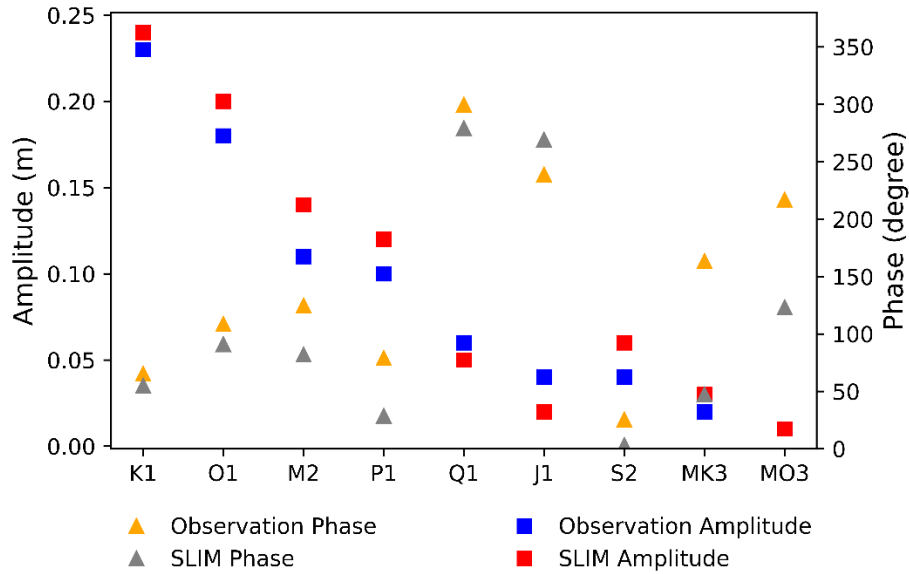


Figure 2.7 Observed and simulated tidal constituents (amplitude and phase) in the middle of Pontianak (-0.020431° S, 109.33852° E) during December 2018.

2.3.2 The impact of river discharges on the river's maximum water level.

The impact of the Kapuas River upstream discharge on its downstream hydrodynamics is assessed by imposing different discharge values, ranging from $3,000 \text{ m}^3/\text{s}$ to $9,000 \text{ m}^3/\text{s}$ (the highest discharge based on the simulated data in 2018, see Fig. 2.4 and Table A4). Only 17% of these values will divert to the Kapuas Kecil branch, while 83% of it continues to flow through the Kapuas Besar (Kästner and Hoitink, 2019). Meanwhile, the Landak River upstream discharge is set to $300 \text{ m}^3/\text{s}$ in all scenarios. The tides used in the ocean part were retrieved from TPXO for December 2018, with a tidal range of 1.8 m at the river mouth. The maximum water level (MXWL) at different points along the Kapuas River stream is then calculated based on these different discharge scenarios (Fig. 2.8). The MXWL profiles show that the river discharge dominates the maximum water level from the river upstream to about 150 km before the river mouth. The MXWL profile increases along with the discharge's increases, so the water level fluctuation in this stream part can be said to be river-dominated. Within about 150 km from the river mouth, the MXWL profiles between the "with-tides" and "without-tides" scenarios show a different pattern. The MXWL profiles no longer increase along with the upstream discharge's increases. In fact, the closer to the river mouth, the lower the gap between the MXWL profiles. Then, all

MXWL profiles converge at about 30 km before the river mouth. We define the part of the river as a transition region. Meanwhile, at about 30 km from the river mouth, the discharge variations have almost no influence on the MXWL. In this area, the tides control the MXWL, so we define this river part as a tidally dominated region.

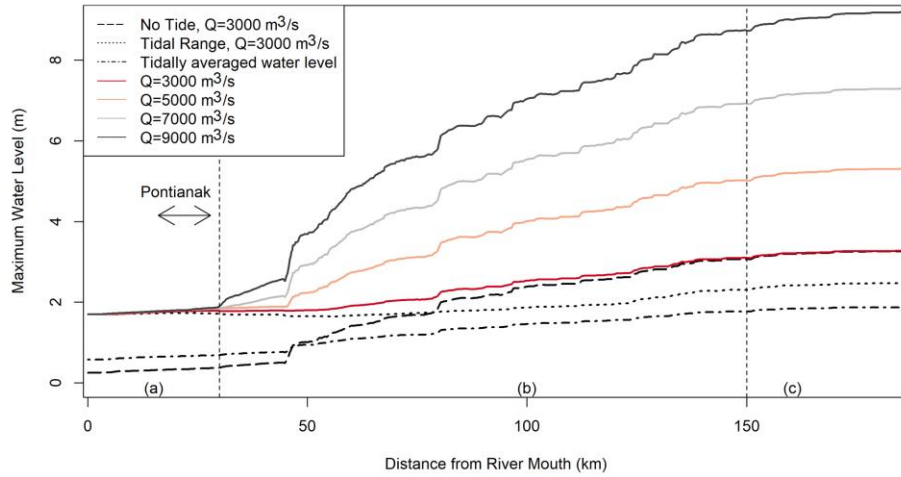


Figure 2.8 River discharge affecting the maximum water level, with measurements for the (a) tidally dominated region, (b) transition region, and (c) river-dominated region. The dashed vertical lines indicate the limits between the different regions. The arrow shows the river stream that flows inside Pontianak, where the population is the densest in the domain.

2.3.3 The impact of wind surges on the river's maximum water level

To evaluate the storm surge effect, we consider wind velocity scenarios (Fig. 2.9). For each scenario, we multiplied the wind speed over the domain during the inundation event by a constant value ranging from 1 to 5 (Table A4). Then, we evaluated their impact on the MXWL profiles along the Kapuas Kecil River stream. Based on the profiles (Fig. 2.10), we thus know that the increasing wind speed beyond 16 m s^{-1} (the highest wind speed in scenario Wind 2x) changes the MXWL distribution profile. The stronger the wind speed, the higher the MXWL. On the contrary, if the wind speed is less than 16 m s^{-1} , the MXWL profiles remain the same.

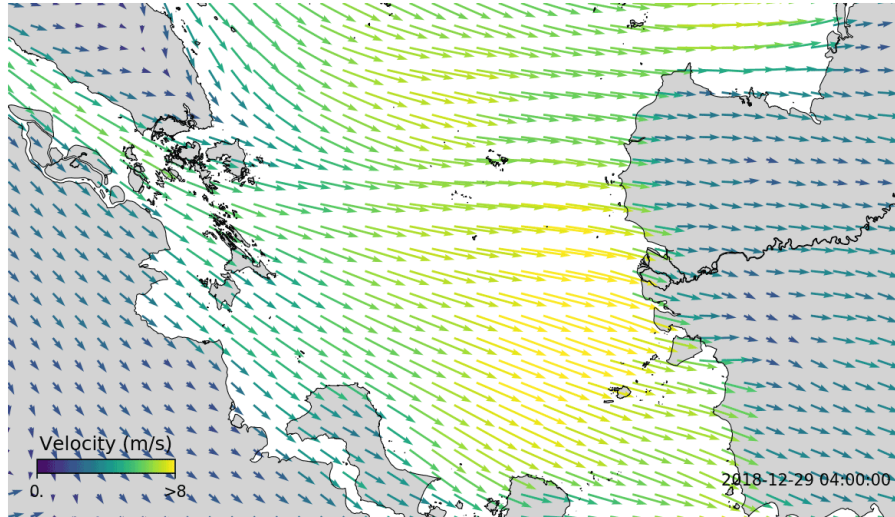


Figure 2.9 Wind direction and magnitude over the domain on 29-12-2018 at 04.00 UTC.

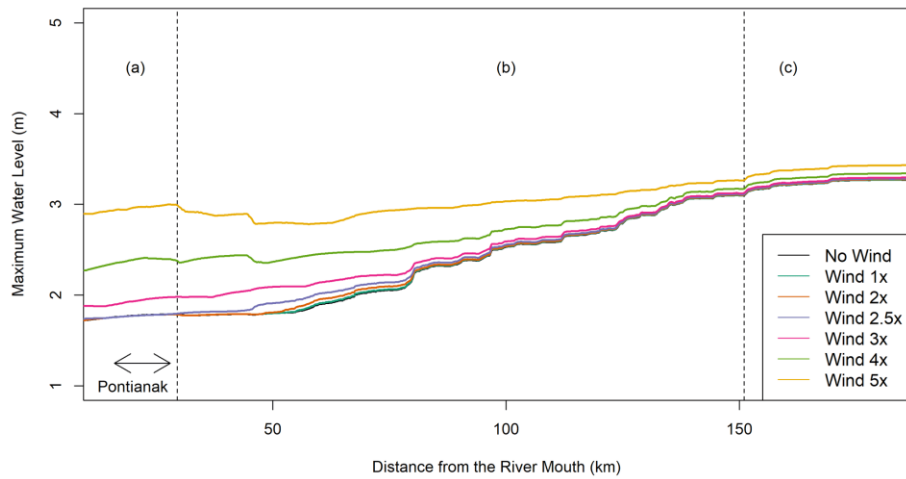


Figure 2.10 Wind surge affects the maximum water level, with measurements for the (a) tidally dominated region, (b) transition region, and (c) river-dominated region. The arrow shows the river stream that flows inside Pontianak. River discharges are constant during the simulation, i.e., 3000 m³/s for the Kapuas River and 300 m³/s for the Landak River.

Furthermore, the storm surge strongly dominates the MXWL from the river mouth to about 30 km up the river. If the wind speed exceeds 20 m s⁻¹ (the highest wind speed in scenario Wind_2.5x), the MXWL profile will increase linearly due to the wind speed. However, at about 30 km from the river mouth, the MXWL profile drops for the Wind_4x and the Wind_5x scenarios. The

decline in the MXWL profile could be due to the fact that the water levels within the river are higher than its riverbanks and then outflows to the floodplain. The outflow to floodplains reduced the water level in the main river. Then, the MXWL profiles of all scenarios with wind speed of less than 24 m s^{-1} (the highest wind speed in the Wind_3x scenario) converged at about 150 km upstream. This convergence matches with the previous study of Kästner et al. (2019), which found that at this point, the admittance of the tidal propagation upstream has a knickpoint, where dumping strongly increases. This point also confirmed that it is the upstream boundary of the transition zone. However, if the wind speed is greater than 24 m s^{-1} (the Wind_4x and the Wind_5x scenario), the MXWL profiles remain slightly higher (do not converge). It means the surge impact is still traveling further upstream.

Besides the wind speed, the flood duration and flood extent along the river are also influenced by the storm duration (Höffken et al., 2020). Figure 2.11 shows that the impact of the wind surge duration on the maximum water level is not significant. Still, it makes the flooding event longer—backwater that comes from the river mouth upstream stays longer inland before flowing back to the ocean.

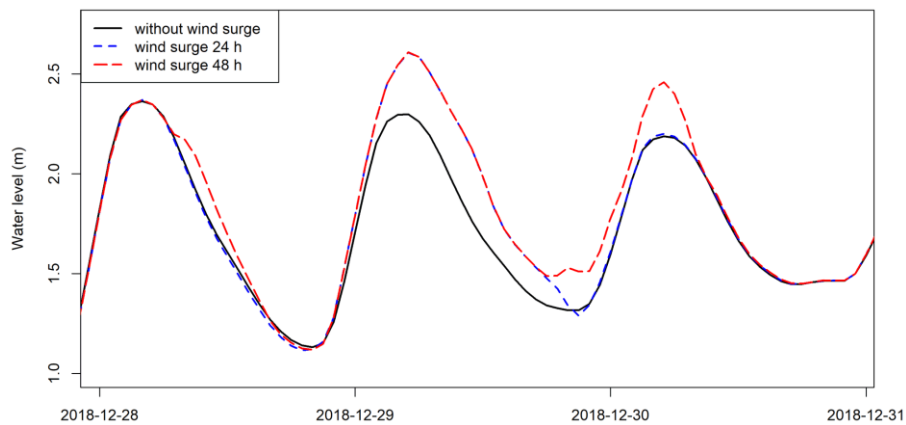


Figure 2.11 Wind surge duration affecting the increasing water level in Pontianak. Please note that the date format used in this figure and below is year-month-day.

2.3.4 A case study: analysis of the flood event on 29 December 2018

Based on the water level observed by the Pontianak Maritime Meteorological Station (see Fig. 1 for the location), on 29 December 2018, there was a significant increase in water levels from 05.20 to 07.50UTC. The maximum water level reached 2.8 meters and produced a significant inundation in the city of Pontianak. The 2.8 m water level reference is the lowest astronomical tide (LAT). It

corresponds roughly to 1.8 m above mean sea level and 0.7 m above the highest astronomical tide (HAT). During the event, the Kapuas and Landak rivers had discharges of 4400 m³/s and 502 m³/s, respectively. At the river mouth, the tidal range reached 1.8 m.

In order to investigate the main drivers of the event, we simulated the hydrodynamical process along the land-sea continuum for the full month of December 2018. We simulated the hydrodynamical process without and with storm surge scenarios when the expected tidal range during the event is 1.8 m. Since there was no observed discharge upstream during the date, we imposed the river discharge retrieved from the GFMS for the Kapuas and Landak rivers (Table A4).

The validation result shows that the NSE is 0.82, indicating that the model has a good performance. The RMSE of its peaks is 0.04 m. These results suggest that the model correctly reproduces the actual hydrodynamic processes. The inundation event on 29 December 2018 is well depicted by the model (light-grey box in Fig. 2.12). The observational data profile (black) shows that the water level dynamic is at the peak moment during the event, where its peak seems lower than the previous peak period. The water level dynamic is about to go down when suddenly a strong force pushes it to go up again for a short moment. The storm alone is responsible for a 30 cm increase in the water level during this short moment (light-grey box in Fig. 2.12). After this additional forcing effect disappeared, the water level then decreased steeply and started following the tidal signal again.

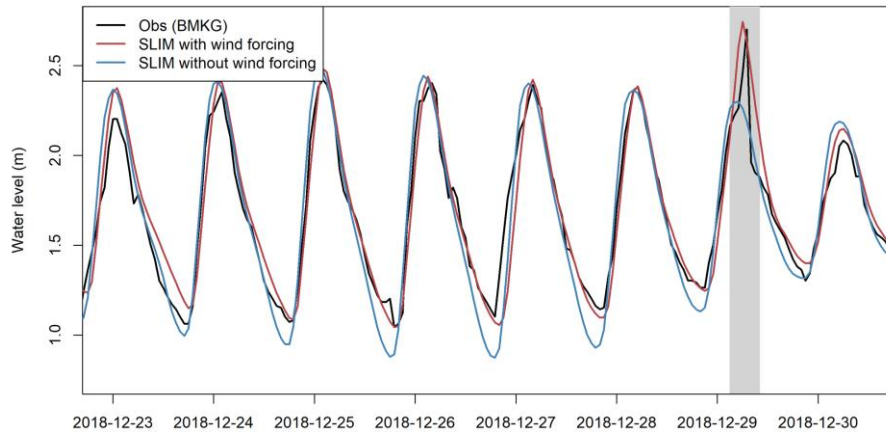


Figure 2.12 Validation of water level at Pontianak, where the light-grey box depicts the peak of the inundation. BMKG: Badan Meteorologi, Klamatologi, dan Geofisika (Meteorology, Climatology, and Geophysical Agency of Indonesia).

A more qualitative validation of the model has also been performed by comparing the extent of the simulated inundation area with observations reported by the local media (Madrosid, 2018). The report mentioned some areas that were confirmed as inundated when the flooding occurred (represented by the red dots in Fig. 2.13). As a result, our model output validated that these areas were flooded during the flooding event.

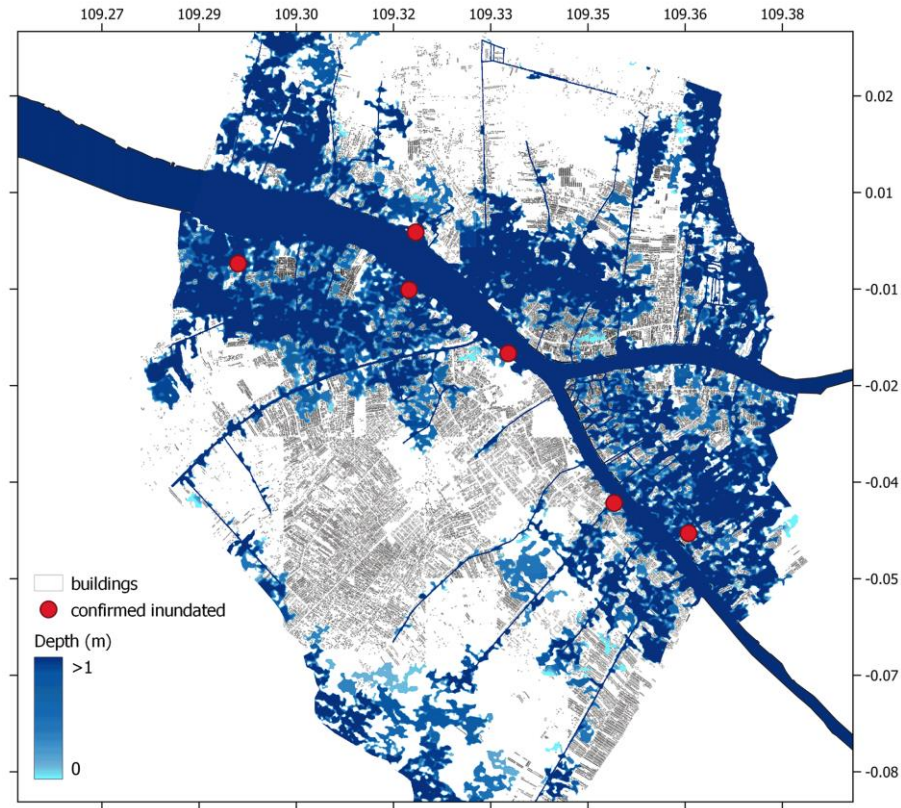


Figure 2.13 Inundation extent map and its depth during the flood event on the 29 December 2018 at 06.00 UTC. The red dots represent places that were reported as inundated during the event. City's building map retrieved from (Planet dump retrieved from <https://planet.osm.org>, 2020). © OpenStreetMap contributors 2017. Distributed under the Open Data Commons Open Database License (ODbL) v1.0.

We further investigated the inundation extent and depth over the city of Pontianak using the output of the HEC-RAS model. From the model outputs, we thus know that the extent of this inundation reached lowland within the city located far from the riverbanks (Fig. 2.13). The overtopped water flooded densely populated areas near riverbanks and propagated much further into the city through the drainage channels. In the western part of the city, floods

impacted major areas near riverbanks, while in the eastern part, the major flooded areas fell in lowland areas, located between the Kapuas Kecil and the Landak rivers (district of Pontianak Timur), and portioned the lowland area in the northeast. Next, the flooding event occurred during a short period. It started at 01.00 UTC, peaked at 06.00 UTC, and finished at 15.00 UTC. At the peak moment, the area inundated was about 12 km² (Fig. 2.14), in varying depths.

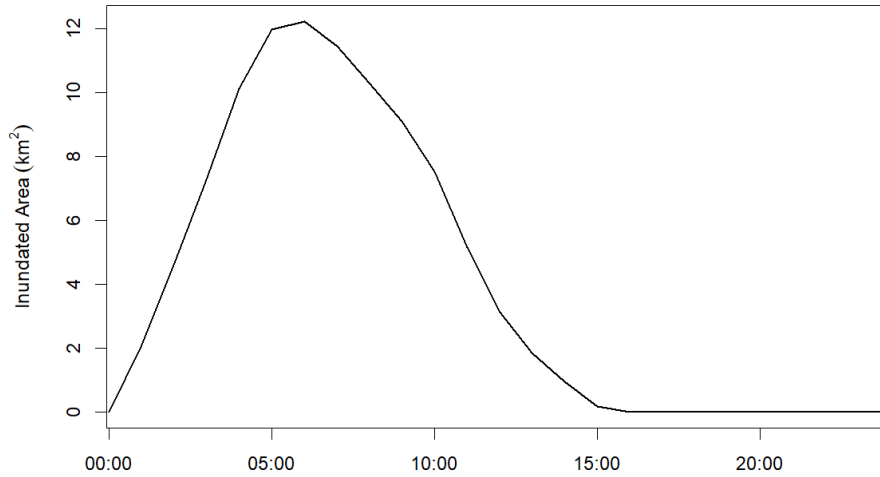


Figure 2.14 The total inundated area within the city of Pontianak during the flood event on 29 December 2018

2.4. Discussion and conclusion

Based on the discharge scenarios, we found that the city of Pontianak is located in a tidally dominated region. Therefore, the MXWL of the river in the city is not controlled by discharges upstream anymore. Next, we also found that an extreme eastward wind speed with a magnitude greater than 16 m s⁻¹ (the highest wind speed in the Wind_2x scenario) can drive the seawater into the river channels based on the wind surge scenarios. As the storm surge continues to push the water upstream, the pileup water in the estuary will enter the river stream and propagate over several kilometers. If the water propagation is in co-occurrence with high river discharge, the water level can hence overtop riverbanks and lead to a compound inundation over the floodplain. However, if the wind speed is less than 16 m s⁻¹, it does not impact the MXWL profiles. Therefore, the wind speed of m s⁻¹ becomes the minimum wind speed that can drive surges inside the river stream.

On 29 December 2018, rainfall over the city of Pontianak was less than 7 mm so that the effect of excessive rainfall could be ruled out in this event. Meanwhile, an intense wind speed was observed over the coastal area for a few hours. The

radar data show cumulonimbus convective clouds formed and moving eastward from the Karimata Strait towards the land (see Appendix Fig. B). Cumulonimbus is a cloud type that could produce wind surges, tornadoes, and excessive rainfall (Cotton et al., 1992). These clouds reached and covered the Kapuas River's mouth on that date, from 04.30 to 05.25UTC. Therefore, these clouds most likely triggered a storm over the coastal area with wind speed ranging from 13 to 21 m s⁻¹.

The wind direction was oriented from the west to the east during the event. Hence, the total wind effect became the combination of the direct wind stress effect and the indirect wave run-up effect. Consequently, it drove the water column from the ocean to the western coast of the island of Borneo, where the Kapuas estuary is located. Then, the wind piled up the tidal waters inside the Kapuas River mouth. The piled-up water then propagated upstream from the river mouth and was coincidentally met with an intermediate river discharge. This phenomenon created an increasing water level and caused a short-duration overflow over the floodplain. Therefore, using this scenario, we suggest that the main trigger for the compound flooding, which occurred on 29 December 2018, was an interaction between a storm surge at the estuary area and a medium discharge from the Kapuas River.

As with all modeling studies, there are some limitations related to the model that should be mentioned. Firstly, many different compound flooding schemes possibly occur in this area that have not yet been simulated. Therefore, the delineation of the compound flooding risk zones based on the MXWL proposed for the Kapuas River needs further investigation in the future. Secondly, we have not yet imposed excessive rainfall scenarios in the model so that the model only depicts inundation processes as the effect of the river discharges, tides, and wind surge. In the actual case, a single instance of excessive rainfall is enough to trigger urban flooding over the floodplain area. Next, the computational domain does not cover all of the dry land over the delta. It is only limited to Pontianak and the Kapuas Kecil riverbanks from the city to the river mouth. Consequently, the simulation might not wholly describe the inundation processes and the real extent of the inundated area. These limitations will be improved in future work.

Regarding the event's impact on 29 December 2018, the flooding occurred on a day of low precipitation. Therefore, the residents were not aware and not prepared for such a significant flood event. Even though it happened only for a short period, the economic loss was severe (Madrosid, 2018). Such loss can hopefully be avoided after the local water management agency installs a flood warning system built based on our proposed models.

Integrated hydrodynamic and machine learning models

This chapter reproduces the following article²:

Sampurno, J., Vallaes, V., Ardianto, R., and Hanert, E.: Integrated hydrodynamic and machine learning models for compound flooding prediction in a data-scarce estuarine delta, *Nonlin. Processes Geophys.*, 29, 301–315, <https://doi.org/10.5194/npg-29-301-2022>, 2022.

Abstract. Flood forecasting based on hydrodynamic modeling is an essential non-structural measure against compound flooding across the globe. With the risk increasing under climate change, all coastal areas are now in need of flood risk management strategies. Unfortunately, for local water management agencies in developing countries, building such a model is challenging due to the limited computational resources and the scarcity of observational data. We attempt to solve this issue by proposing an integrated hydrodynamic and machine learning (ML) approach to predict water level dynamics as a proxy for the risk of compound flooding in a data-scarce delta. As a case study, this integrated approach is implemented in Pontianak, the densest coastal urban area over the Kapuas River delta, Indonesia. Firstly, we build a hydrodynamic model to simulate several compound flooding scenarios. The outputs are then used to train the ML model. To obtain a robust ML model, we consider three ML algorithms, i.e., random forest (RF), multi linear regression (MLR), and support vector machine (SVM). Our results show that the integrated scheme works well. The RF is the most accurate algorithm to model water level dynamics in the study area. Meanwhile, the ML model using the RF algorithm can predict 11 out of 17 compound flooding events during the implementation phase. It could be concluded that RF is the most appropriate algorithm to build a reliable ML model capable of estimating the river's water level dynamics within Pontianak, whose output can be used as a proxy for predicting compound flooding events in the city.

²Only minor modification were made.

3.1 Introduction

Compound flooding in low-lying coastal areas is a recognized hazard that can be exacerbated by global warming (Hao and Singh, 2020; Santiago-Collazo et al., 2021; Gori et al., 2022; Hsiao et al., 2021; Ghanbari et al., 2021). A compound flooding hazard is derived from the interaction of storm surge penetration, riverine flooding, and intense rainfall over the areas (as the impact of extreme meteorological events) that coincide or nearly coincide (Bilskie and Hagen, 2018; Ikeuchi et al., 2017; Wahl et al., 2015). This natural hazard can endanger the population and the coastal area's infrastructures, which have been growing fast in the last decade (Bhaskaran et al., 2014). Without appropriate mitigation, the consequences of the hazard can be severe for the coastal environment (Costabile et al., 2013) and the coastal communities both economically (Karamouz et al., 2014) and socially (Comer et al., 2017).

There are various mechanisms driving compound flooding in low-lying urban coastal areas (Santiago-Collazo et al., 2019). Firstly, the water level increases with the tide, and the sea level rises due to climate change. In addition to this, a storm surge may occur. The water can enter the dry land by wave overtopping. Secondly, extreme precipitation and a high-upstream flow discharge can also elevate water in a low-lying delta. In this case, water can overflow and cause flooding as well. These flood pathways are often naturally correlated, so those mechanisms occur coincidentally (or in close succession), creating a compound event and worsening the hazard.

Flood forecasting based on water level prediction in a tidal river area is an essential non-structural measure against compound flooding (Chan, 2015; Tucci and Villanueva, 1999; Mosavi et al., 2018). Non-structural measures refer to any actions that manage the risk of compound flooding without involving a physical construction (UNDRR, 2022), including land-use regulations, flood forecasting, warning systems, flood-proofing and disaster prevention, and preparedness and response mechanisms. The water level could be predicted using a process- or data-based approach. The process-based approach is more commonly used to tackle the water level prediction issue (Costabile and Macchione, 2015; Ye et al., 2021), but it requires many assumptions to reduce the complexity—making it computationally tractable. The data-based approach, e.g., machine learning (ML) and statistical models, can also predict water level changes and compound flooding without the underlying physical attributes and high computational resources (Choi et al., 2020; Wang and Wang, 2020; Assem et al., 2017; Couasnon et al., 2020; Bevacqua et al., 2019). Part of the ML process involves developing a model that can improve task performance over time by learning from examples, with minimal human efforts instructing them how to do so. The ML allows users to test hypotheses and generate confidence bonds for mitigation strategies. The

ML models can capture and represent a complex input and output relationship using only historical data (Chen and Asch, 2017). For instance, by assuming that flood events are stochastic, ML can predict major flood events based on certain probability distributions from the historical discharge data (Mosavi et al., 2018). In some cases, their performance is even more accurate than traditional statistical models (Xu and Li, 2002). In other words, we can prepare strategies to mitigate the flood risks using an ML model.

However, building a flood forecasting model in developing countries can be challenging. Implementing a process-based approach requires expensive computational resources (Nayak et al., 2005). Meanwhile, resources owned by local agencies are often limited, so local operational management may not have access to it. Additionally, building a robust ML model requires a sufficient amount of data for the training (Naqa et al., 2018), but the availability of observational data in these areas is also limited. Some studies proposed a remote sensing technique (optical and SAR images) as a solution (Mokkenstorm et al., 2021; Kabenge et al., 2017; Haq et al., 2012). Nevertheless, due to the limitation of its time resolution, the technique cannot always detect compound flooding. Therefore, a remote-sensing technique is more suitable for detection, monitoring, validation, and mitigation purposes rather than prediction.

A new paradigm that combines deterministic and ML components has been proposed to tackle data and computational limitations in environmental modeling, such as hybrid climate models (Krasnopolsky and Fox-Rabinovitz, 2006) and an ML model for 2D surface water catchment problems (Maxwell et al., 2021). However, to the best of our knowledge, no previous modeling frameworks have developed a deterministic model to train an ML model for compound flooding studies. As a common practice, compound flood modeling typically uses the coupling of two or more hydrodynamic, hydraulic, or hydrological models (Hsiao et al., 2021; Santiago-Collazo et al., 2021; Ikeuchi et al., 2017). The coupling could be one-way, two-way, or dynamic coupling. Another approach is deep learning and data fusion (Muñoz et al., 2021), and data assimilation (Muñoz et al., 2022).

In this chapter, we attempt to fill the gap by combining the process-based and data-based approaches as a state-of-the-art framework to predict water level dynamics, a proxy for compound flooding in a data-scarce delta. Firstly, we build a hydrodynamic model to run some flood scenarios in a data-scarce estuary. Then, we create ML models trained using the hydrodynamic model's outputs to predict the water level and forecast future floods. To obtain a robust ML model, we evaluate three ML algorithms and select the most accurate one for our application. As a case study, the integrated framework is implemented in the city of Pontianak, with a population density at its highest within the Kapuas River

delta. This city experienced a compound flooding event on 29 December 2018 (Sampurno et al., 2022), and the impact was severe (Madrosid, 2018). At that moment, the water level dynamic was about to go down after passing its peak elevation, when suddenly a strong force pushed it to go up again for a short moment. The interaction between tides, storm surges, and discharges along the tidal river in the Kapuas River delta is responsible for a 30 cm increase in the water level during the event. The finding is expected to assist the local water management agency in assessing their compound flood hazards and mitigating their risk despite the limited data and computational resources.

3.2 Materials and methods

3.2.1 Hydrodynamic model description

To simulate hydrodynamics within the Kapuas River delta, we again use the multi-scale hydrodynamic model SLIM 2D (Lambrechts et al., 2008; Gourgue et al., 2009; Remacle and Lambrechts, 2016) with an additional source, i.e., rainfall (R). Therefore, the 2D shallow water equations (SWEs) which used are:

$$\frac{\partial H}{\partial t} + \nabla \cdot \mathbf{U} = R \quad (3.1)$$

$$\frac{\partial \mathbf{U}}{\partial t} + \nabla \cdot \left(\frac{\mathbf{U}\mathbf{U}}{H} \right) + f \mathbf{e}_z \times \mathbf{U} = \nabla \cdot (\nu \nabla \mathbf{U}) + \alpha g H \nabla (H - h) - \frac{cd}{H^2} |\mathbf{U}| \mathbf{U} + \frac{1}{\rho} \tau_{wind} - \frac{H}{\rho} \nabla P_{atm} \quad (3.2)$$

where H is the water column height, ∇ is the horizontal gradient operator, $\mathbf{U} = H\bar{\mathbf{u}}$ is the horizontal transport, R is the rainfall, t is the time, $\bar{\mathbf{u}} = (u, v)$ is the depth-averaged horizontal velocity, f is the Coriolis parameter, $\mathbf{e}_z$ is the vertical unit vector pointing upward, ν is the horizontal eddy viscosity, α is a constant to define dry elements ($\alpha = 0$) and wet elements ($\alpha = 1$) (Le et al., 2020), h is the bathymetry, $g = 9.81 \text{ m/s}^2$ is the gravitational acceleration, cd is the bulk drag coefficient, τ_{wind} is the wind stress, and ∇P_{atm} is the atmospheric pressure gradient.

3.2.2 Hydrodynamic model setup and calibration

In order to run the hydrodynamic model, we defined a computational domain that covers both the river and ocean parts. Next, we generated an unstructured mesh to cover the domain, with a resolution of 50 m over the riverbanks, 400 m over the coast near the river mouth, 1 km over the rest of the coastline, and 5 km offshore (Fig. 3.1). The multi-scale mesh was generated using an algorithm developed by Remacle and Lambrechts (2018). We then set the bathymetry

constructed from two datasets: (i) the river and estuary bathymetry maps, obtained from the Indonesian Navy (Kästner, 2019), and (ii) the Karimata Strait bathymetry, obtained from BATimetri NASional (BATNAS, 2021). Furthermore, we set the bulk bottom drag coefficients, which are 2.5×10^{-3} over the ocean (corresponding to a sandy seabed) and 1.9×10^{-2} over the riverbed (Kästner et al., 2018). Lastly, we imposed the rainfall, as observed by the Pontianak Maritime Meteorological Station (PMMS).

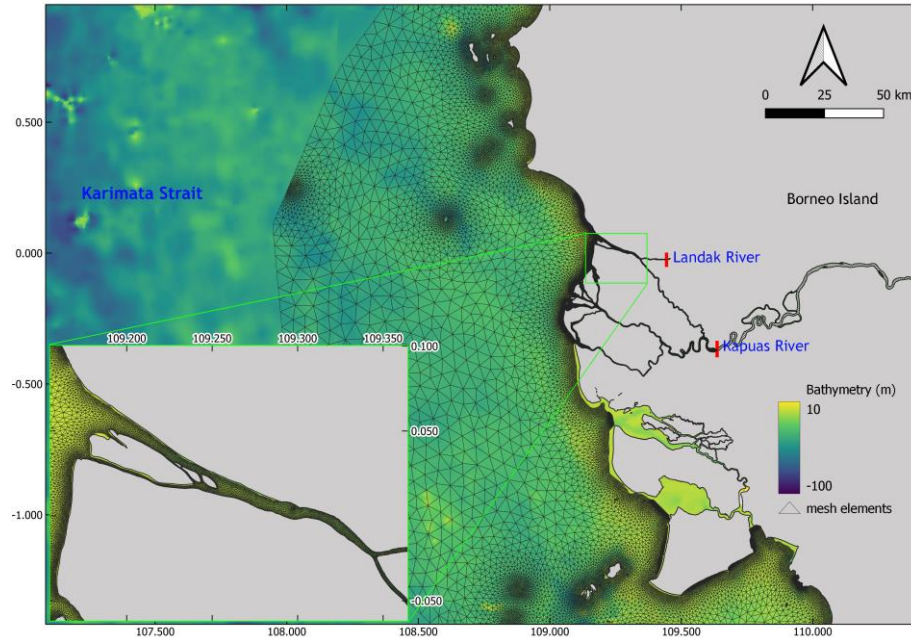


Figure 3.1 The hydrodynamic model domain is discretized with an unstructured mesh with its resolution set to 50 m along the riverbanks, 400 m along the coast near the estuary, 1 km over the rest of the coastline, and 5 km offshore. The bathymetry of the model domain ranges from ~ 100 m depth offshore to 1 m in the river mouth.

The hydrodynamic model simulation is forced by wind and atmospheric pressure from ECMWF (Hersbach et al., 2020), and tides from TPXO (Egbert and Erofeeva, 2002). As upstream boundary conditions, we imposed discharge from the Kapuas and Landak rivers and the discharge data were retrieved from the Global Flood Monitoring System (GFMS) (Wu et al., 2014) at about 70 km and 40 km from the river mouth, respectively (Fig. 3.2). Since the GFMS calculates the flow using Integrated Multi-Satellite Retrievals for GPM (IMERG) precipitation information as input, the coastal processes do not affect the model output (predicted river flow).

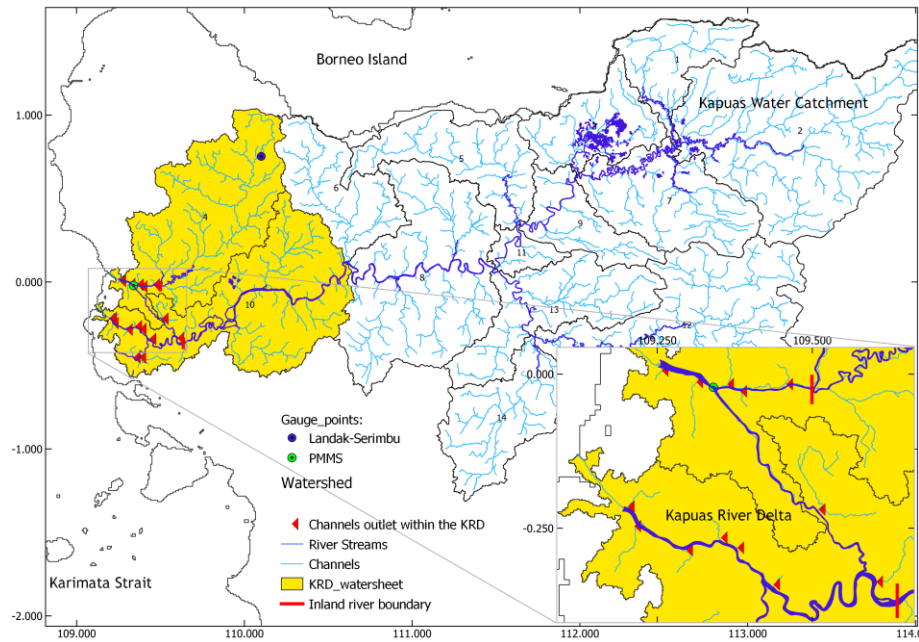


Figure 3.2 The Kapuas River watershed and its sub-basins. Since the discharges of the Kapuas River are retrieved at the middle stream, only two sub-basins are considered for the SWAT+ model (yellow area). The runoffs (channel outlets of the SWAT+ model that enter the river stream within the KRD) are set as inlets for the hydrodynamic model domain.

We also imposed runoff, obtained by converting rainfall over the Kapuas Kecil River catchment area as an inlet water flux at 15 channels entering the domain (Fig. 3.2). The runoff of every channel was calculated from rainfall data using SWAT+ (Bieger et al., 2017), which considered the pressure, humidity, and other weather parameter input. Here, we use one-way coupling, where the SWAT+ model runs first and independently. The SWAT+ model only produces the flow of channels that enter the river stream within the Kapuas River delta. Then, we used these channel outlets as boundary conditions for the SLIM model. Unfortunately, during the tuning of the SWAT+ model, the correlation between the model's output (runoff) and the observation data is still low (Pearson correlation coefficient = 0.32). However, we decided to use the output as the channels' inlet boundary condition in the hydrodynamic model because the channel runoff volume is much less than the river discharge. Therefore, we assumed that it does not significantly affect the hydrodynamics of the river.

To evaluate the SLIM model's performance, we ran a simulation for January 2019 and compared the simulated water elevation with the observations in Pontianak. The model errors correspond to an NSE of 0.87 and an RMSE of 0.12 m (Fig.

3.3). This RMSE is deemed sufficiently small to consider model outputs as a good proxy for the real system (Moriassi et al., 2015).

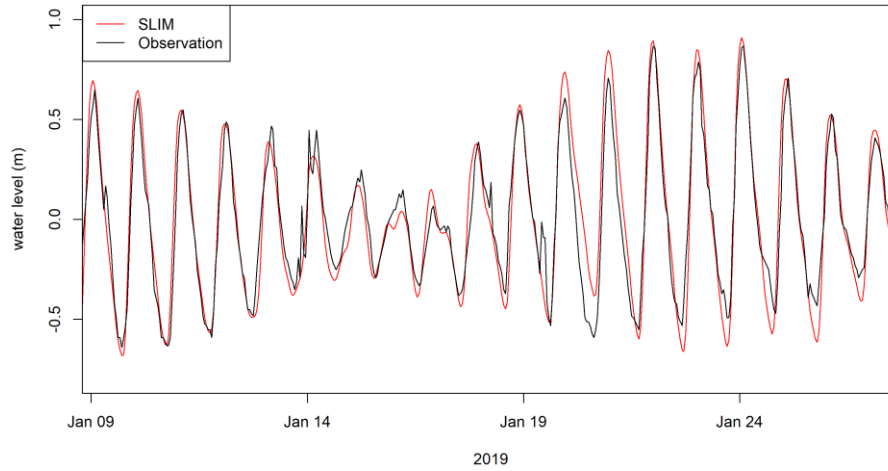


Figure 3.3 SLIM model’s output validation with respect to observational data at Pontianak in January 2019, with $NSE = 0.87$ and $RMSE = 0.12$ m, indicating that the model has satisfactory performance.

We simulated the hydrodynamics with different oceanic, atmospheric, and river forcings to forecast flood events based on the water levels in Pontianak. Based on the PMMS report, the city is flooded when the water level exceeds 2.5 m. We, therefore, set this value as the threshold of a flood event. We ran the hydrodynamic model for ten months and extracted the output hourly to produce the scenarios (see Table 3.1). Then, we selected 6,000 sample points of the predicted water levels at Pontianak with their associated input dataset using a random sampling technique. We merged the data as a single dataset to train the ML model, encompassing all possible flood events resulting from the combination of the external forcings. The dataset shows that several flooding occurred within the simulations, indicated by sample points with water elevations greater than 2.5 m (Fig. 3.4).

Table 3.1 Scenarios used to force the process-based hydrodynamic model

n-dataset	Wind speed (ms ⁻¹)	Wind direction (°)	Pressure (kPa)	Kapuas discharge (m ³ s ⁻¹)	Landak discharge (m ³ s ⁻¹)	Rainfall (mm)
1-600	2 - 8	0 – 360	100.5 - 101.5	6×10^3	600	0
601-1200	4-16	0 – 360	100.5 - 101.5	6×10^3	600	0
1201-1800	8-32	0 – 360	100.5 - 101.5	6×10^3	600	0
1801-2400	2 – 8	0 – 360	100.5 - 101.5	$10^4 - 1.5 \times 10^4$	600	0
2401-3000	2 – 8	0 – 360	100.5 - 101.5	6×10^3	800-2100	0
3001-3600	2 – 8	0 – 360	100.5 - 101.5	$10^4 - 1.5 \times 10^4$	800-2100	0
3601-4200	5 – 20	0 – 360	100.5 - 101.5	$10^4 - 1.5 \times 10^4$	800-2100	0
4201-4800	2 – 8	0 – 360	100.5 - 101.5	$3.3 \times 10^3 - 5 \times 10^3$	250-700	0
4801-5400	2 – 8	0 – 360	100.5 - 101.5	$3.3 \times 10^3 - 5 \times 10^3$	250-700	0 – 150
5401-6000	8-32	0 – 360	100.5 - 101.5	6×10^3	600	0 – 150

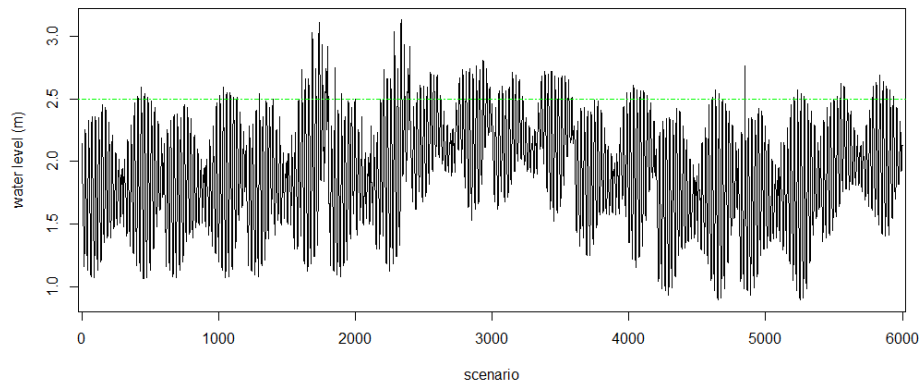


Figure 3.4 The Kapuas Kecil River's water level in Pontianak, obtained from the hydrodynamic model. The green dashed line is the threshold above which the water starts to overflow the riverbanks in Pontianak.

3.2.3 Machine learning (ML) model

3.2.2.1 Dependent and predictor variables

To develop the ML models, we used the river water level at Pontianak as the dependent variable. Then, we considered atmospheric, oceanic, and riverine variables as predictors of the water level in the city. Atmospheric variables include average and maximum wind speed, wind direction, precipitation, and average atmospheric pressure. Oceanic variables cover tides at the river mouth, and the riverine variables consist of the Kapuas River, and the Landak River discharges. To evaluate the impact of each predictor before the flood event, we imposed the prior state (one and two hours before) of these parameters (see Table 3.2). The datasets were recorded hourly and combined with the SLIM output (used in the training and testing phases) and the observational data (used in the implementation phase).

Table 3.2 The variables which used as the predictors in this study.

Code	Variable Description
X1	Tidal elevation at Kapuas Kecil river mouth (m)
X2	Tidal elevation at Kapuas Kecil river mouth 1 hour before (m)
X3	Tidal elevation at Kapuas Kecil river mouth 2 hours before (m)
X4	Hourly discharge of the Kapuas river at Rasau Jaya in time (m^3s^{-1})
X5	Hourly discharge of the Kapuas river at Rasau Jaya 1 hour before (m^3s^{-1})
X6	Hourly discharge of the Kapuas river at Rasau Jaya 2 hours before (m^3s^{-1})
X7	Hourly discharge of the Landak river at Kuala Mandor in time (m^3s^{-1})
X8	Hourly discharge of the Landak river at Kuala Mandor 1 hour before (m^3s^{-1})
X9	Hourly discharge of the Landak river at Kuala Mandor 2 hours before (m^3s^{-1})
X10	Hourly precipitation at the time (mm)
X11	Hourly precipitation one hour before (mm)
X12	Hourly precipitation two hours before (mm)
X13	Hourly average wind speed at the time (ms^{-1})
X14	Hourly average wind speed one hour before (ms^{-1})
X15	Hourly average wind speed two hours before (ms^{-1})
X16	Hourly maximum instantaneous wind speed at the time (ms^{-1})
X17	Hourly maximum instantaneous wind speed one hour before (ms^{-1})
X18	Hourly maximum instantaneous wind speed two hours before (ms^{-1})
X19	Hourly average wind direction at the time (degree, in the range: 0 - 360)
X20	Hourly average wind direction one hours before (degree, in the range: 0 - 360)
X21	Hourly average wind direction two hours before (degree, in the range: 0 - 360)
X22	Hourly atmospheric pressure at the time (millibars)
X23	Hourly atmospheric pressure one hour before (millibars)
X24	Hourly atmospheric pressure two hours before (millibars)

Mutual information (MI) was implemented to evaluate the relation between each proposed predictor and observed water level. As a result, all predictors considered in the ML model have an MI coefficient greater than zero, which means all predictor variables impact the river water level in Pontianak (Fig. 3.5). The relationship between these predictors and the water level could be linear or nonlinear (as shown by MI capturing both relation types). Here, we found that the tidal elevations in the river mouth (X1, X2, and X3) have the most decisive impact on the river water level in the city ($MI > 0.5$), while tidal elevation observed 1 h before (X2) is the strongest one. Next, the wind speed (maximum and average), the discharges (from both the Kapuas and Landak rivers), and the pressure have a moderate relatedness. In contrast, the wind direction and the rainfall only have weak relatedness ($MI < 0.1$). This means that both parameters have no significant impact.

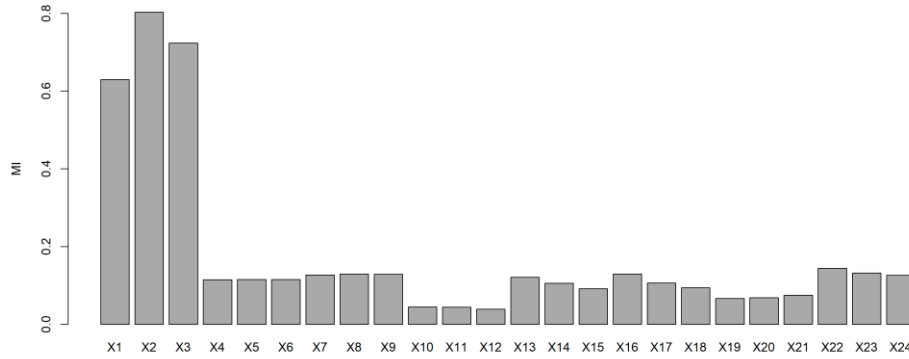


Figure 3.5 Mutual information (MI) of all predictor variables to hourly water level dynamics in 3 months of observational data.

3.2.2.2 Machine learning (ML) algorithm

Here, we consider three different machine learning algorithms, i.e., random forest (RF), multiple linear regression (MLR), and support vector machine (SVM). The RF is a supervised learning algorithm that operates by constructing many decision trees during the training (Breiman, 2001). The algorithm can be implemented for classification or regression. The model aggregates its multiple decision tree outcomes to generate the ultimate output, which is called the sub-sample outcomes (Han et al., 2012). The technique was enhanced by combining bootstrap with its aggregating processes (Breiman, 2001). Using this strategy, the algorithm became an effective tool for classification and regression. In this study, the RF algorithm was obtained from the R randomForest library (Liaw and Wiener, 2002). To obtain the optimal parameter for RF, we first tune the

algorithm by searching for the optimal value of the number of variables randomly sampled as candidates at each split (m_{try}). As a result, the optimal number is 16 (see Fig. 3.6).

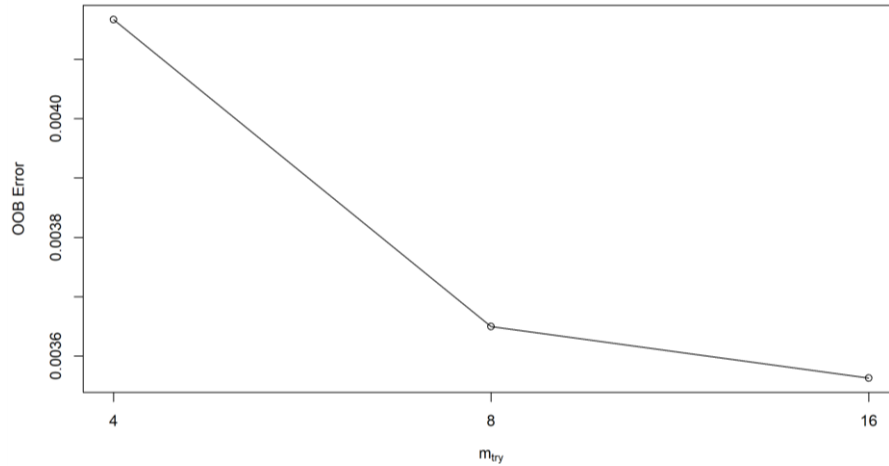


Figure 3.6 Tuned randomForest algorithm for the optimal number of variables randomly sampled as candidates at each split (m_{try}) parameter.

The MLR is a statistical technique that uses several explanatory variables to predict the outcome of a response variable (James et al., 2013). This method fits the linear relationship between input features and the target (observed data) using the least-squared approach. In the least-squared approach, the best relationship model will be obtained by minimizing the sum of the squared distance between the calculated values (as model outputs) and the target values (James et al., 2013). This algorithm is the most straightforward approach in ML models and is generally used as the baseline method. The MLR algorithm implemented in this study was obtained from the R RWeka library (Hornik et al., 2008).

To obtain the best performance of the MLR algorithm, we did a statistical analysis to evaluate the multicollinearity among the predictor variables using the Variance inflation factor (VIF). Since multicollinearity negatively affects the performance of the MLR model, VIF can help reduce the number of predictors (Alipour et al., 2020). Here, we found that some variables have a VIF more significant than 5, which indicates a potentially severe correlation between these variables in the model (Fig. 3.7). Therefore, combined with the output of the *MI* analysis, we removed some variables which have low *MI* and a high VIF.

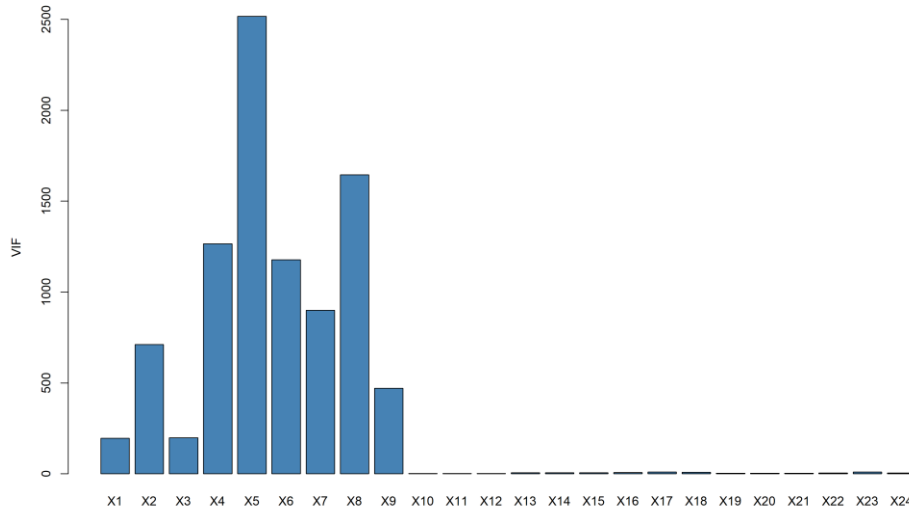


Figure 3.7 Variance inflation factor (VIF) values of all predictor's variables in 3 months of observational data.

The SVM is a supervised ML algorithm based on statistical learning frameworks (Gholami and Fakhari, 2017). This method is robust for modeling a complex nonlinear relationship. The kernel function transforms the input features into a high-dimensional space to tackle the complexity. This transforms the non-linear relationship of input features into linear ones. Finally, linear regression is carried out to obtain the ultimate output. Compared to the other algorithms, SVM needs less computational resources because it can be trained by only a few features (Gholami and Fakhari, 2017). Previously, SVM was only implemented for classification purposes, but it has also been implemented for regression purposes after some enhancement. The SVM algorithm implemented in this study was obtained from the R MARSSVRhybrid library (MARSSVRhybrid: MARS SVR Hybrid, 2021).

Since the kernel function is critical in SVM, we tuned the SVM algorithm to obtain good results by selecting the most appropriate kernel parameter. We tested four kernels, i.e., linear, polynomial, radial basis, and sigmoid, as the candidates. We found that the radial basis kernel performed the best for the SVM algorithm.

3.2.4 Model limitations

During the development process, we encountered potential errors that could be highlighted as model limitations. Firstly, we assumed that the channel runoff volume would not affect the hydrodynamics of the river due to its small volume

compared to the riverine volume. The average daily discharge of the Kapuas and Landak rivers during the simulation is about 4,137 m³/s and 406 m³/s, respectively. At the same time, the total daily runoff of all channels that enter the hydrodynamic model domain in the KRD is about 32 m³/s. The runoff contributes only about 0.7% of the total inlets in the hydrodynamic simulations; therefore, we assumed it is insignificant.

Secondly, we assumed that all the possible compound flood scenarios would occur within ten months. Since we had already set some extreme values in the predictor parameters during the time, we assumed that all possible causes that drive compound flooding in the domain are represented. However, this assumption may not be accurate.

Next, we only imposed the runoffs as inlets on the riverbanks in the hydrodynamic model domain. Hence, the model did not capture the hydrodynamic processes in the channels within the city. This means that the inundation processes in Pontianak were still not well represented. The model still lacks drainage systems for the urban region.

Moreover, the accuracy of the ML model depends on the hydrodynamic model's accuracy. The more accurate the hydrodynamic model in predicting observational floods, the better the ML model will perform. Therefore, we need to tune the hydrodynamic model as accurately as possible.

Furthermore, since the rainfall impact on river water level is minor compared to other parameters, the model could not optimally capture urban flooding due to excessive rainfall. Based on the field observation, the city is shortly inundated if rain falls excessively for a few hours. This inundation could be due to the poor quality of the urban drainage system. Unfortunately, this phenomenon is not directly captured by the water level observation located within the river. The increase in the river water level due to the heavy rain is minor.

Lastly, the model relies on the predicted input parameters such as weather parameters and river discharges to predict the future water level. Consequently, the more biased the predictors, the higher the uncertainty in the water level prediction. Therefore, observational data as input parameters are needed to reduce the uncertainty and create a more robust model.

3.3 Results

All NSE coefficients were greater than 0.8 in both the training and testing phases, which means that all algorithms perform very well. The most accurate algorithm is RF, followed by SVM and MLR (Fig. 3.8). As such, we know that all the tested

ML algorithms are promising and need to be evaluated in the implementation phase using observational data.

Therefore, we implemented the ML models on the selected observational data, which were obtained during the high discharge season for 3 months in 3 years when inundations occurred (Dec 2018, Jan 2020, Jan 2021). Fig. 3.9 shows each proposed algorithm's predicted water levels compared to the observational data. Subsequently, the accuracy of models to predict flooding events, marked by points in Fig. 3.9, is evaluated.

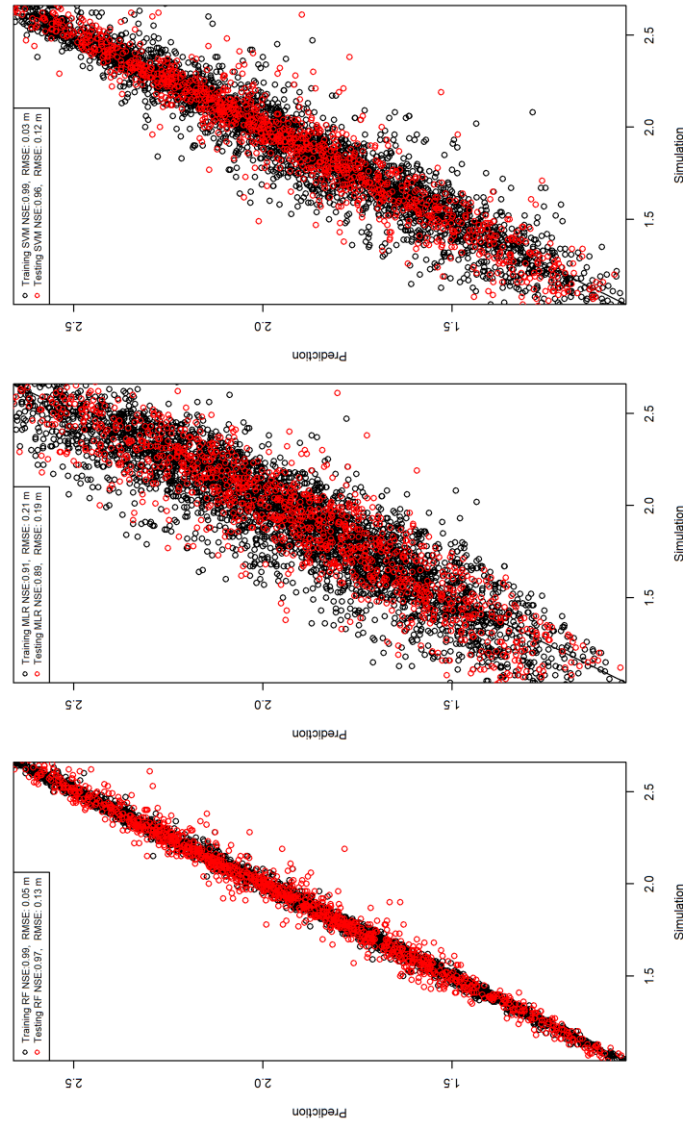


Figure 3.8 Figure 3.8 Comparison of predicted and simulated hourly water levels to evaluate the algorithm performances. The bias for testing data of each algorithm is -9.06e-05, -0.00383, and 0.000681 for RF, MLR, and SVM, respectively.

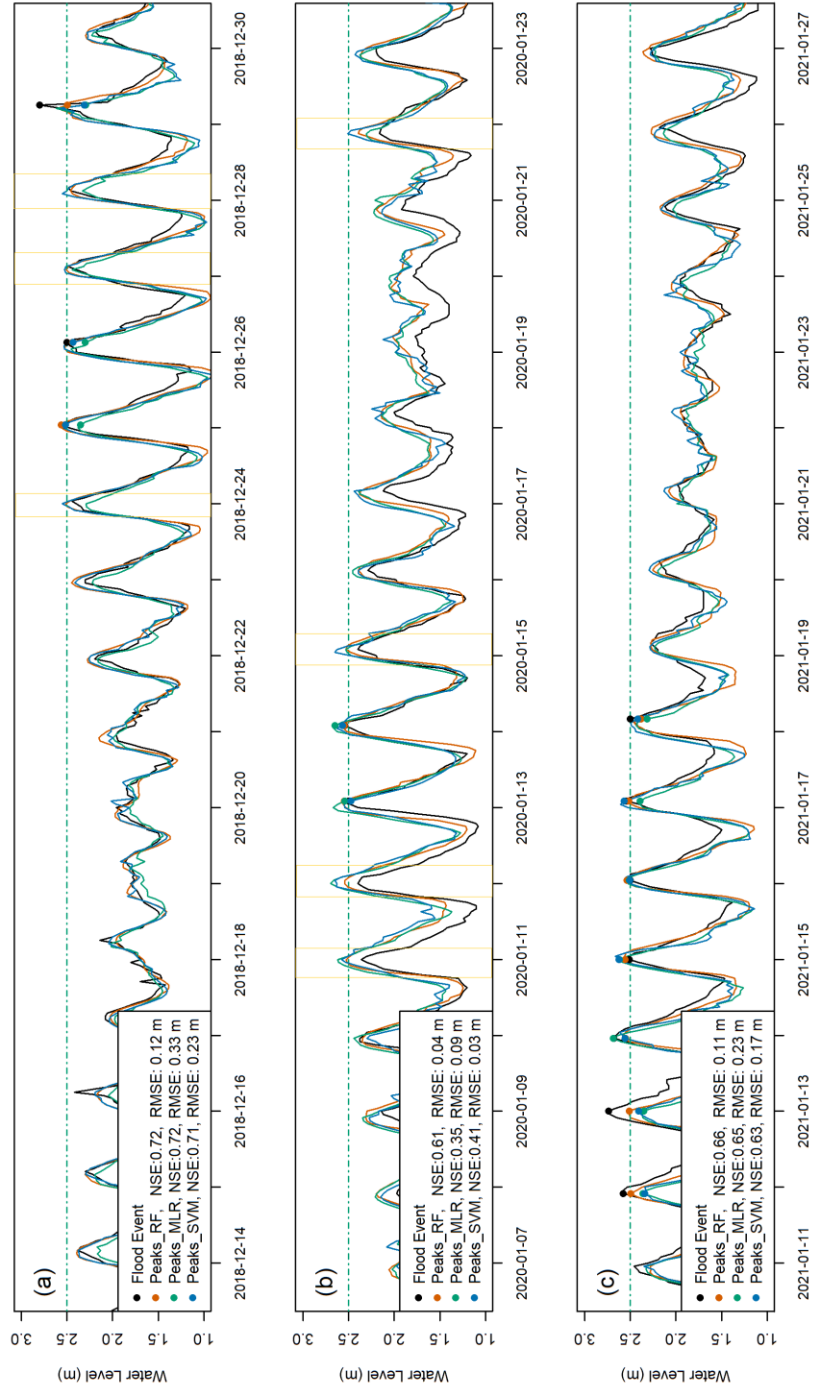


Figure 3.9 Comparison of predicted hourly water levels models and measured hourly water levels for the implementation phase on: (a) December 2018, (b) January 2020, and (c) January 2021. The yellow boxes highlight the false positive events.

Even though all algorithms performed very well during the training and testing phases, the performances differed during the implementation phase (Table 3.3). However, RF showed high accuracy in the three different implementation phases. From the three different observational datasets, RF's NSE values range from 0.61 to 0.72, which is a good performance.

Table 3.3 Performance of the three ML algorithms in implementation phase

Goodness of Fit	RF	MLR	SVM
NSE Training	0.99	0.91	0.99
NSE Testing	0.97	0.96	0.89
NSE Implementation1 (Dec 2018)	0.72	0.72	0.71
NSE Implementation2 (Jan 2020)	0.61	0.35	0.41
NSE Implementation3 (Jan 2021)	0.66	0.65	0.63
Total of flood predicted (out of 17 events)	11	6	10
Percent of flood predicted	65%	35%	59%
False Positive (event)	4	3	3

While the MLR algorithm succeeded in the training and testing phases, it only succeeded in the first and third implementation phases, with NSE of 0.72 and 0.65, respectively. The model was less successful in the second implementation phase, with NSE hitting only 0.35 for this implementation dataset.

Next, the SVM algorithm's performance is similar to that of the MLR algorithm. It succeeded in the training and testing phases but only succeeded in the first and third implementation phases, with NSE reaching 0.71 and 0.63, respectively. However, it failed in the second implementation dataset, with an NSE of only 0.41, which is slightly better than MLR.

Regarding the prediction of flood events, the RF algorithm also performed better than the other algorithms. It could predict 11 out of 17 events (65% accuracy). On the other hand, MLR and SVM could only predict 6 and 10 events (35% and 59% accuracy), respectively. Therefore, we know that RF is the most accurate ML algorithm to predict floods for our test case.

Unfortunately, these three algorithms also predicted false-positive events, i.e., flood events that never occurred during implementation (Table 3.3). While RF predicted four false events, MLR and SVM predicted three false events. This false event prediction is the shortcoming of the algorithm, which should be addressed in future studies.

3.4 Discussion and conclusion

The two main issues that have been tackled in this study are data scarcity and low computational resources for building flood forecasting models based on the water level dynamics in developing countries (Brocca et al., 2020; Singh et al., 2021). Here, we showed that using an approach that combines hydrodynamic and ML models is promising for obtaining a reliable and robust water level model. We succeeded in building and evaluating ML models trained by the hydrodynamic model output; hence, they did not require extensive observational data in their training phase and did not need high computational costs in their implementation. Therefore, the proposed model is reliable for areas where observational data are scarce and computational resources are limited.

Since the proposed model can accurately forecast water levels, local water management agencies can rely on the model outputs for flood forecasting. Since ML does not require high computational resources, limited computational resources will not hinder the assessment and mitigation of compound flooding hazards. Using the model, agencies can re-assess their compound flood hazards and predict future events. Moreover, once they have more observation data, they can use it to re-adjust the proposed model or build a more robust one (Muñoz et al., 2021).

Next, we found that the RF algorithm is the best ML algorithm to predict water level as a proxy for compound flooding in the area of interest. In general, the performances of all tested ML algorithms for water level prediction are reasonable and acceptable. However, considering the NSE values in all implementation phases, the bias, the number of flood events that are accurately predicted, and how close the predicted water level is during the events, it could be concluded that RF performs better than other algorithms. The superiority of the RF algorithm in predicting water levels has also been shown in previous studies in the Upo Wetland (Choi et al., 2020) and the Poyang Lake (Li et al., 2016). Therefore, we proposed a ML model with RF algorithm as the most appropriate model for the study area.

In addition, we found that the tidal elevation measured one-hour prior at the river mouth is the main parameter controlling the river water level in Pontianak. Even though the city is located 20 km from the river mouth, the tidal dynamics still strongly affect the river water level in the city. This result confirms previous studies, revealing that the tide propagation on the Kapuas River dominantly controls the river water level up to 30 km upstream (Sampurno et al., 2022), and still impacts up to 285 km from the river mouth (Kästner et al., 2019).

Overall, our integrated approach can provide a model to predict compound flooding driven by the interaction of tide, wind surge from the ocean, and high

discharge from the river upstream. Regarding the limitation of the chosen indicator's capability to capture flood events, we will look for more data and indicators to enhance the model capability in future studies. Moreover, we will reduce the number of predictors to minimize the model output's uncertainty. We will also evaluate mean sea-level rise due to climate change to broaden the model implementation and create better flood mitigation.

CHAPTER 4

Future flood risk assessment

This chapter reproduces the following article³:

Sampurno, J., Ardianto, R., and Hanert, E.: Integrated machine learning and GIS-based bathtub models to assess the future flood risk in the Kapuas River delta, Indonesia [Under review in the Journal of Hydroinformatics], 2022.

Abstract. Global warming increases flood hazards in low-lying coastal areas, endangering coastal populations worldwide. As more and more people live near the sea, future flood risk must be properly assessed for sustainable urban planning and coastal protection. However, this is rarely the case in developing countries where there is both lack of in-situ data collection and forecasting tools. Here, we consider the case of the Kapuas River delta (KRD), a data-scarce delta on the west coast of Borneo Island, Indonesia. We assessed future flood risk under three climate change scenarios: low (RCP2.6), medium (RCP4.5), and high (RCP8.5) emissions. We combined multiple linear regression (MLR) technique and a GIS-based bathtub inundation model, to assess the future flood risk. We implemented an MLR algorithm to model the river's water-level dynamics in the KRD, particularly in the city of Pontianak. The MLR algorithm was trained using a three-month surface elevation dataset (October-December 2020) when 26 flood events occurred. We then simulated the future extreme water levels within the KRD under the influence of rainfall changes, surface wind changes, and sea-level rise. We created flood maps with inundated areas under a 100-year flood scenario (1% annual exceedance probability) using a GIS-based bathtub inundation model, representing Pontianak's current and future flood extent. We found that the 100-year flood level in the KRD will increase from 2.64 m (current state) to 2.92 m (RCP2.6), 3.03 m (RCP4.5), and 3.34 m (RCP8.5) by 2100. Hence, the flooded area within the city of Pontianak under these flood levels will increase from 78.16 km² (current state) to 85.65 km² (RCP2.6), 87.85 km² (RCP4.5), and 93.54 km² (RCP8.5). Consequently, we predict that about 6.4% - 11.9% more buildings and about 6.8% - 12.7% more roads will be impacted by a 100-year flood in 2100. Our assessment should inform the local water manager in preparing adequate flood mitigation strategies.

³Only minor modification were made.

4.1 Introduction

Climate change has been accelerating at an alarming rate in the last century and is likely to continue in the future (IPCC, 2012). Certain regions will experience more intense and frequent rainfalls (Marengo et al., 2020), which will increase the flooding risk. In contrast, other regions will experience decreasing rainfall and increasing evaporation, which will accelerate soil's progressive drying, leading to drought (Mukherjee et al., 2018). In coastal areas, climate change impacts the frequency and intensity of coastal flooding. The coastal flooding hazard arises through changes in mean sea level and the storminess of the atmosphere that creates storm surges in the first place (Lilai et al., 2016; Vousdoukas et al., 2016). Extreme events, such as the 100-year flood under the current climate, with future sea-level projections, will occur much more frequently.

Urban areas in deltas are particularly vulnerable to climate change (Ridha et al., 2022). These urban areas will face multiple ocean and land threats simultaneously. With the areas' rapid population growth (Bhatta, 2010), disaster could impact more people and cause more damage. This risk highlights the importance of preparedness in disaster mitigation (Chan et al., 2021; Dinh et al., 2012). Communities in disaster-prone cities should properly assess the hazards and adapt to the changing climate, by for instance mapping their flood hazards and building flood defense systems. Adaptation strategies should be informed by proper risk projections so they can effectively mitigate the impacts (Hallegatte, 2009).

The Kapuas River delta (KRD) is a low-lying marshy delta. Its water levels are influenced by tide and wind surges from Karimata Strait, as well as the river discharges from the Kapuas and Landak rivers (Sampurno et al., 2022). Consequently, as with other low-lying deltas, the flood risk here is likely to increase in future climate (Kundzewicz et al., 2014). The rising sea levels and excessive rainfall in the coming years will cause a severe impact because the KRD is densely populated. Flood will be more intensive and frequent in a delta such as this (Lange, 2020). A forecasting system is needed to assist local water management in assessing potential flood hazards, mitigating the risks, and planning adequate measures (Ngo et al., 2018).

Flood forecasting can leverage water-level modeling based on a machine learning (ML) technique (Ruslan, Samad, et al., 2014; Gallien, 2016; Habert, Ricci, et al., 2016; Noymanee and Theeramunkong, 2019; Nguyen and Chen, 2020). ML is based on evidence of relationships manifested in records of input and output data without analyzing the internal structure of the physical process. Using only historical data, an ML model can represent a complex input and output relationship, such as, the relationship between water level and its predictor

variables (Bishop, 2006). The knowledge can subsequently be used to predict future water levels.

This chapter aims to assess the flood risk of an urban area within the KRD in future climates. We used an ML algorithm to predict the water level in the city of Pontianak, the most populated urban area in the KRD. Based on the previous chapter's recommendation, Random Forest (RF) is the best algorithm for water level prediction in the KRD. However, here we prefer to use the multiple linear regression (MLR) algorithms for its simplicity. Hence, we can easily evaluate the model's structure and the significance of each predictor. Since observational data was scarce, we selected three months of data containing many extreme events (26 flood events) in 2020 as a reference case. The predictors we set comprised sea surface elevation in the river mouth, river discharge, wind velocity, and rainfall. The predicted water levels were used as a proxy to estimate the flood hazards in the city. Next, using a GIS-based bathtub model, we created flooding hazard maps under a 100-year flood scenario for the city with three climate change plots. Lastly, we conducted a risk analysis of these hazards to the nearby infrastructures (buildings and roads). The assessment output is essential for the local water resource managers in Pontianak to mitigate the impacts and create future adaptation strategies.

4.2 Methods

4.2.1 Data Used

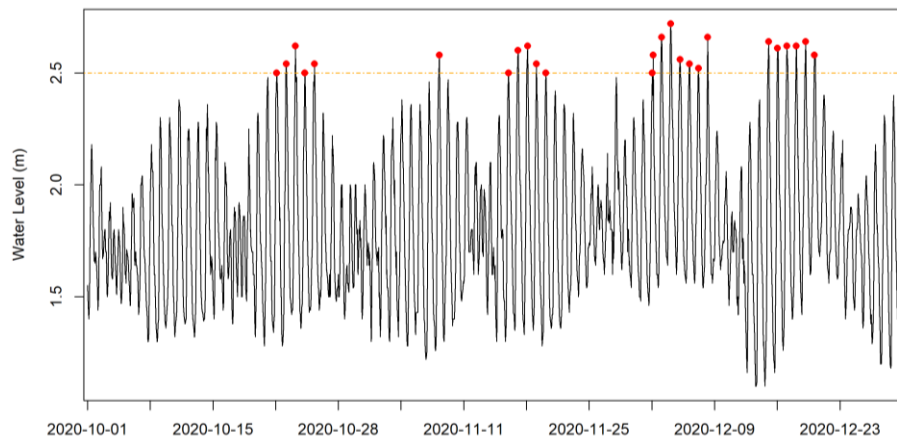


Figure 4.1 Hourly riverine water levels in Pontianak, with the orange dash line representing the threshold of flooding, and the red dots representing the peaks of flood events

To forecast the flood, we used the observed water levels in Pontianak (Fig. 4.1) as a proxy. The Pontianak Maritime Meteorological Station (PMMS) measures

the river's water levels to support the Dwikora Port's operations and monitor the city's flood hazards. The data selected in this study were measured hourly for three months, from 1 October 2020 to 31 December 2020, at the PMMS' observation point (-0.020431° S, 109.33852° E). The data captured some flood events when high tides coincided with high river discharges or excessive rainfalls (Ganguli et al., 2020). Based on the field observation, PMMS considers that 2.5 m water level is the benchmark where the river begins to overflow the riverbanks.

Since the study area is located in a tidal river, where water levels are influenced by ocean tides, rivers discharges, and weather conditions, we used seven predictors: the sea surface elevation (SSE); the weather variables measured in Pontianak, i.e., precipitation, average wind speed, maximum instantaneous wind speed, and average wind direction; discharges from Kapuas River retrieved at about 50 km upstream from the observation point; and discharges from Landak River retrieved at about 18 km upstream from the observation point (Table 4.1). Before training the model, we split the dataset between 80% for training and 20% for testing purposes.

Table 4.1 Predictor variables used as water level predictors

Code	Variable	Description	Source
x_1	SSE	Sea surface elevation retrieved at the river mouth (m)	PUSRIKEL KKP (https://pusriskel.litbang.kp.go.id/)
x_2	Qkapuas	Hourly discharge of the Kapuas River (m ³ /s)	Global Flood Monitoring System (Wu et al., 2014)
x_3	Qlandak	Hourly discharge of the Landak River (m ³ /s)	Global Flood Monitoring System
x_4	RR	Hourly precipitation in Pontianak (mm)	PMMS
x_5	WSavg	Hourly average wind speed in Pontianak (m/s)	PMMS
x_6	WSmax	Hourly maximum instantaneous wind speed in Pontianak (m/s)	PMMS
x_7	WD	Hourly average wind direction in Pontianak (degree, in the range: 0 - 360)	PMMS

4.2.2 Multiple linear regression and GIS-based bathtub model

Since we assume the relationship between the dependent and independent variables used as water level predictors is linear, here we use a well-known ML technique, multiple linear regression (MLR), to model water levels and predict future inundations. MLR aims to model a linear relationship between a set of independent variables and a dependent variable. This method is built upon a least-square algorithm to find the best-fitting model that connects a set of observed data and its predictors. MLR has been successfully applied in hydrology to predict a runoff signature (Zhang et al., 2018) and forecast streamflow (Block

et al., 2009). In the current study, we used the MLR algorithm provided in the RWeka R library (Hornik et al., 2008). The MLR model is defined as:

$$H_i = \beta_0 + \beta_1 x_{1,i} + \beta_2 x_{2,i} + \beta_3 x_{3,i} + \beta_4 x_{4,i} + \beta_5 x_{5,i} + \beta_6 x_{6,i} + \beta_7 x_{7,i} + \epsilon \quad (4.1)$$

where i is the observation index, H_i is the water level at i -th time, $x_{j(j=1,...,7)}$ are the predictor variables (see Table 1), β_0 is the water level intercept, $\beta_{j(j=1,...,7)}$ are the slope coefficients, and ϵ is the residual.

Furthermore, we used a GIS-based bathtub model to create a flood extent map associated with the predicted water levels in the study area. Using the bathtub model, we assume that all areas within a model domain will be inundated if their elevation is less than the river's projected water level (Yunus et al., 2016). However, since we only focus on floods connected to the river, we consider the hydrology connectivity between the river streams and the land area (Van de Sande et al., 2012). Any area within the city will be inundated if a channel connects it to the Kapuas River stream, i.e., city canals. Therefore, using an algorithm created by Wang and Liu (2007), we identify and fill surface depressions in our DEM map that are not connected to the river.

4.2.3 Predictor selection

We applied the Mutual Information (MI) analysis to evaluate the dependency level of the dependent variables on each predictor because it can assess the correlation between the dependent and the independent variables (Ross, 2014). Next, since we employed the MLR algorithm, we also checked the linear regression assumptions between the dependent variables and the predictors to diagnose the model adequacy. Then, we selected the variables that significantly impacted the model and omitted the non-essential ones. To do so, we produced a scatter plot between variables, created histograms of each variable, and calculated the Pearson's correlation coefficients for all pairs of predictor and dependent variable. We also checked the correlation among predictors to detect and avoid multicollinearity. We used the psych library in R to check the linear assumption (Psych: Procedures for Psychological, Psychometric, and Personality Research, 2021). To enhance the prediction skill of the model, we also run a sensitivity analysis before predicting the future flood scenarios impacted by climate change. By doing so, we could evaluate the effect of each parameter on the model's output (Chu, 1999). Therefore, we could tune in the model parameters involved in the model-building to improve the prediction results by adjusting only the sensitive parameters (Cacuci, 2003). To conduct the sensitivity analysis, we used the konfound R library (Xu et al., 2019).

4.2.4 Future scenarios

To evaluate the impacts of climate change, we used the projection of sea-level rises, precipitation changes, and surface wind changes in three climate scenarios for Southeast Asia's regional level (see Fig. D, Fig. E, and Fig. F in the appendix). The scenarios are the low (RCP2.6), the medium (RCP4.5), and the high emission scenarios (RCP8.5). Based on these projections, we created projection datasets (SSE, Precipitation, Wind average, and Wind maximum) for each year into the future (from 2021 to 2100). We then re-ran the ML model to predict future water levels and extract each year's annual maximum water level. Then, we computed the flood frequency (see Appendix A) for every ten years of data using the Gumbel (1958) distribution curve. Here, we took only the flood frequencies between 2020 and 2030 (as the current state) and between 2090 and 2100 (as the future state). Based on the flood frequency curves, we estimated the 100-year flood level as the annual maximum flood hazard levels in 2020 (current) and 2100 (future hazard state).

4.2.5 Flood risk analysis

We used a simple bathtub inundation model to assess the risk of inundated areas under the 100-year flood level condition (Murdukhayeva et al., 2013). We firstly retrieved the DEM of the city of Pontianak from DEMNAS (<https://tanahair.indonesia.go.id/demnas/>) and corrected it using elevation benchmark points from SRGI (<https://srgi.big.go.id/>). Next, based on the elevations in the corrected DEM, we defined wet areas as any points on the map with an elevation lower than the 100-year flood level. Wet areas mean either inundated areas (with an elevation greater than zero) or standing water areas (with an elevation less than zero). We repeated this procedure for all future scenarios.

Next, we conducted a flood risk assessment for further analysis. Here, we identified the infrastructures (buildings and roads) over the study area, retrieved from OpenStreetMap (OpenStreetMap contributors, 2017), that may be affected by inundation hazards under the 100-year flood condition in 2100. We analyzed the flood impact on infrastructures using a QGIS plugin: InaSAFE (InaSAFE, 2022).

4.3 Results

4.3.1 Features selection and model performance

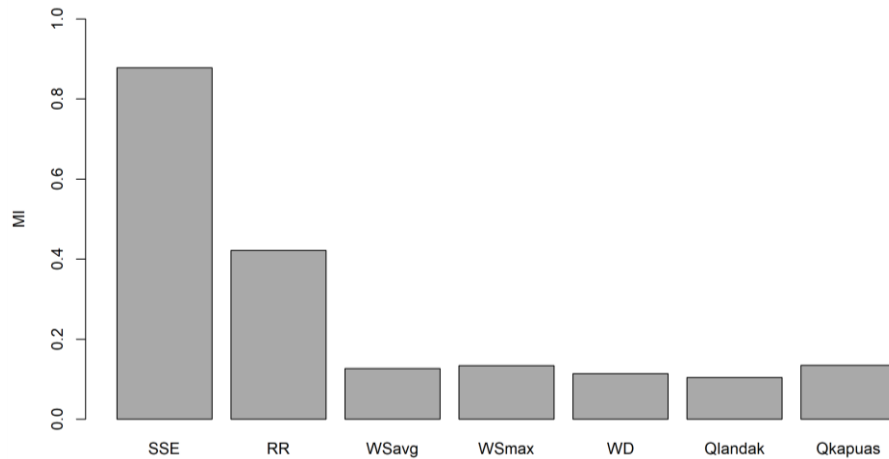


Figure 4.2 Mutual information of proposed predictors (see Table 4.2) to the observed water level

Fig. 4.2 shows the MI coefficient of each independent variable relative to the observed water levels. Overall, all independent variables show a positive MI coefficient, which means they influence the water levels. In particular, two independent variables show a strong relationship, i.e., tidal elevation and precipitation. The rest of the variables show only a moderate relationship.

However, based on the correlation among predictors, two variables (WSmax and WSavg) have significant multicollinearity (Fig. 4.3). The correlation between these two predictors is 0.91. Therefore, we had to omit one of them; otherwise, it would decrease the model's performance. We implemented a sensitivity analysis to determine which variable could be omitted (Table 4.2). The sensitivity analysis shows that the maximum wind speed (WSmax) contribution to the model was insignificant, so we canceled it and retained the other variables.

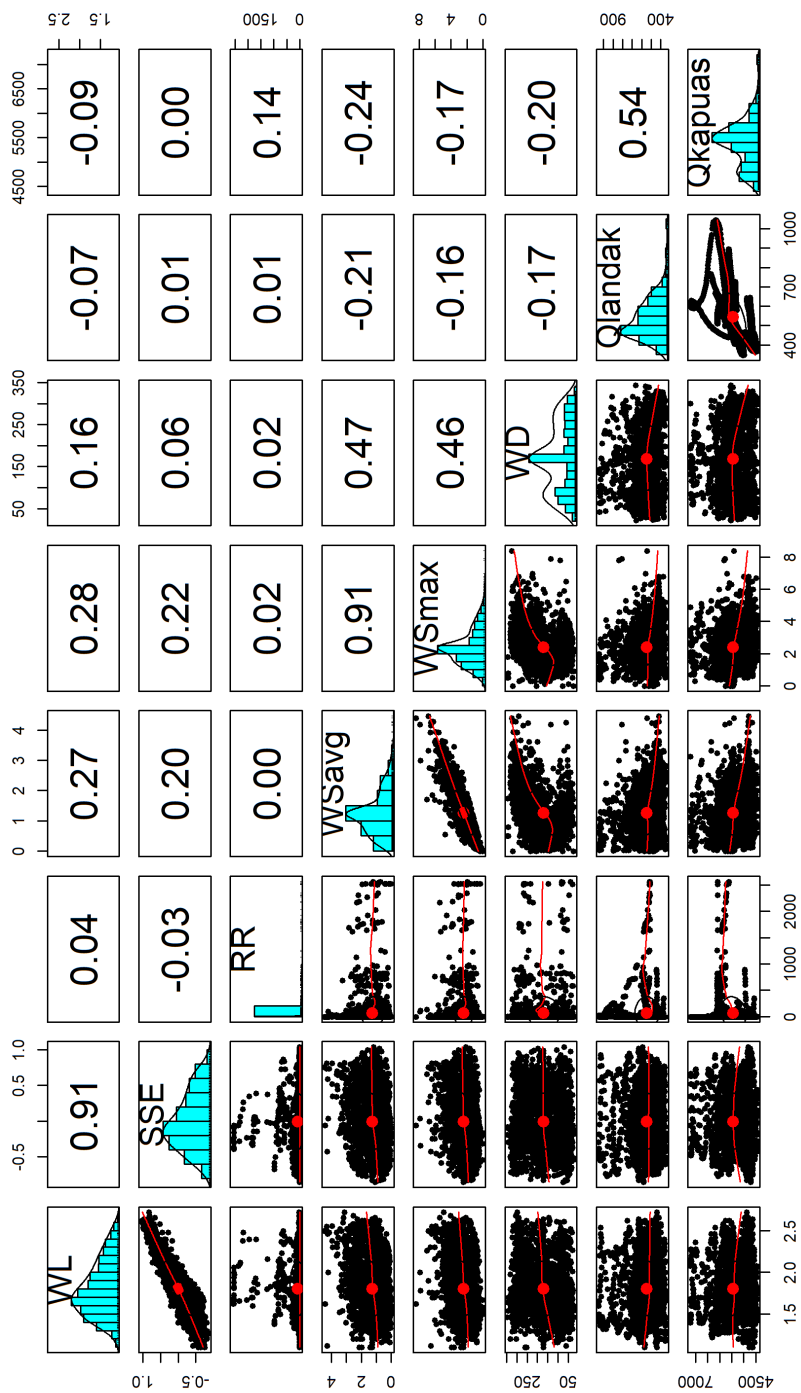


Figure 4.3 Linearity assumption evaluation consisting of scatter plots, histograms, and the Pearson correlation coefficient between all proposed variables

Table 4.2 Sensitivity analysis outputs for the predictors

Coefficients	Estimate slope	Std. Error	t-value	p_test	Significance
SSE	7.50E-01	7.73E-03	97.084	2.0E-16	Significant
RR	8.24E-05	9.42E-06	8.752	2.0E-16	Significant
WSavg	2.66E-02	9.49E-03	2.806	5.0E-03	Significant
WSmax	-9.71E-03	6.08E-03	-1.597	1.1E-01	Not significant
WD	3.30E-04	4.30E-05	7.670	2.8E-14	significant
Qlandak	-6.78E-05	2.76E-05	-2.455	1.4E-02	significant
Qkapuas	-4.09E-05	6.82E-06	-6.000	2.4E-09	significant

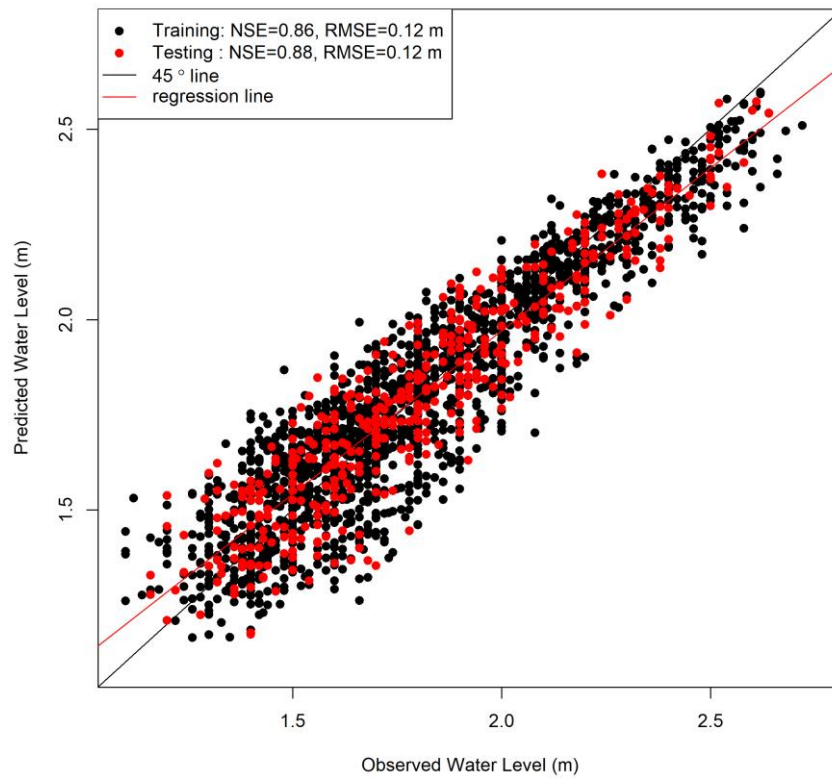


Figure 4.4 Model performance during training and testing phases, with a comparison of the regression line orientation and the 45°-line representing the relative quality of the model's prediction. The percent bias between prediction and observation for the testing phase is 0.2%.

We then trained the MLR algorithm using the training dataset to build the model. Next, we assessed its performance on the testing dataset. The model performed

well and was stable in the training and testing phases, indicated by the NSE= 0.86 and NSE= 0.88 for the training and testing phases, respectively (Fig. 4.4). In addition, both the training and testing phases show a consistent accuracy (RMSE= 0.12 m). These performance indicators suggest that the model is reliable in predicting water levels (prediction and observation pair points tend to cluster along the 45° line). However, extreme water levels are slightly under-estimated as the regression line has a slope < 45°.

4.3.2 Future flood risk analysis

After successfully building the model, we simulated future water levels in the study area under the three climate change scenarios. We then calculated the flood frequency curve of these predicted water levels at the PMMS's observation point within the city (-0.020431° S, 109.33852° E). Fig. 4.5 shows how climate change impacts the 100-year flood level in the study area. Based on the current flood frequency curve, the 100-year flood level is 2.64 m. Under a low emission scenario (RCP2.6), the 100-year flood level will increase by about 0.28 m to reach a 2.92 m water level in 2100. Next, under a medium emission scenario (RCP4.5), the 100-year flood level in 2100 will increase by about 0.39 m and reach 3.03 m. Lastly, under a high emission scenario (RCP8.5), in 2100, it will increase by 0.7 m to 3.34 m.

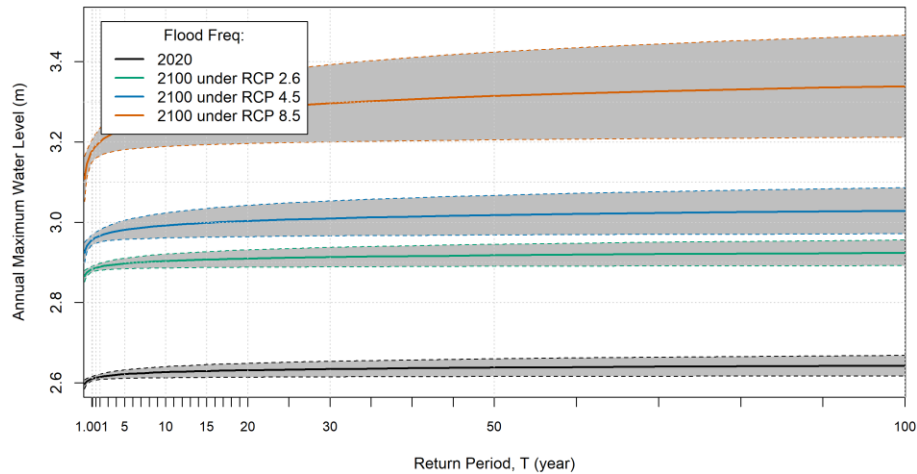


Figure 4.5 Flood frequency analysis in Pontianak for 2090-2100 under the three future climate scenarios. Gray shading areas show a 95% confidence interval for each future scenario.

Using the GIS-based bathtub inundation model, we estimated that the extent of the hazardous area under the 100-year flood level condition is 78.16 km² (Fig. 4.6a). If the 100-year flood level increases to 2.92 m in 2100 (under RCP2.6), the flooded area will increase to 85.65 km² (Fig 4.6b). The flooded area becomes

wider in 2100 to 87.85 km² (estimated under RCP4.5, Fig. 4.6c) or 93.54 km² (estimated under RCP8.5, Fig. 4.6d).

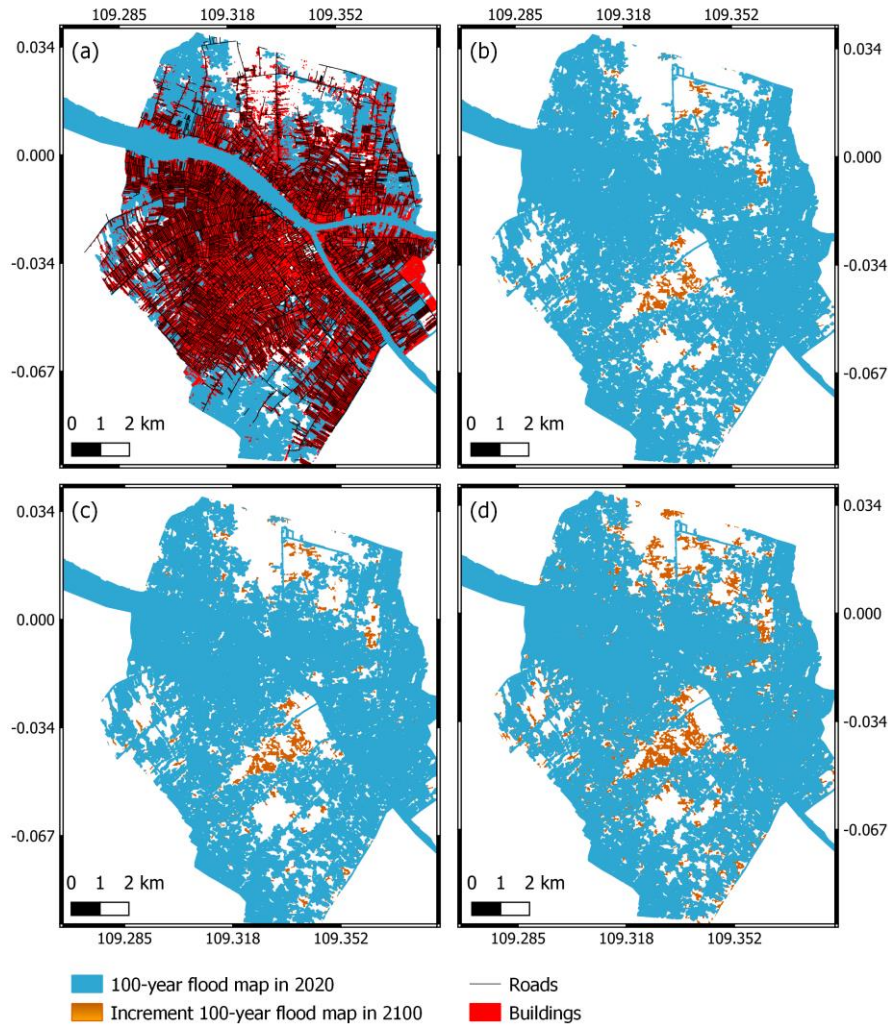


Figure 4.6 Flood risk maps in Pontianak under the 100-year flood level condition, comparing the current state (a), under RCP2.6 (b), RCP4.5 (c), and RCP8.5 (d). Note that roads and buildings are only shown in (a), where the blue area (inundated areas) below the red (buildings) is covered (cannot be seen).

Next, we investigated how the increase of flooded areas impacted by climate change increases the infrastructure's exposure (Table 4.3). We estimated the number of infrastructures affected by each increase in the flood-hazard level. However, the estimation was only made for the infrastructures located within the city of Pontianak. Our results show that the number of affected buildings in 2100 will increase by about 6%, 8%, and 12% under the RCP2.6, RCP4.5, and RCP8.5

scenarios. Similarly, the fraction of impacted road length will rise from about 72% (in the current state) to about 78%, 80%, and 84% in 2100 under the RCP2.6, RCP4.5, and RCP8.5 scenarios, respectively.

Table 4.3 Flood risk analysis in the city of Pontianak and the impacted infrastructures

Scenario	Flood 100yr (m)	Flood Extent Area (km ²)	Impacted Buildings			Impacted Roads		
			NWet	NDry	%	Length_wet (km)	Length_dry (km)	%
2020_Current	2.64	78.16	1.16×10 ⁵	3.52×10 ⁴	76.7	1,323	526	71.6
2100_RCP26	2.92	85.65	1.26×10 ⁵	2.56×10 ⁴	83.1	1,448	400	78.4
2100_RCP45	3.03	87.85	1.28×10 ⁵	2.30×10 ⁴	84.8	1,480	369	80.0
2100_RCP85	3.34	93.54	1.34×10 ⁵	1.72×10 ⁴	88.6	1,558	290	84.3

4.4 Discussion and conclusion

Since the area of interest is low-lying land with a generally low slope ($\leq 8\%$) (Arianti et al., 2020) and in almost a natural state (with no dams, dikes, or levees), a 2.64 m flood level (1% annual exceedance probability) already causes an inundation in a significantly large part of the study area (Table 4.3). The overflow water runs freely into the city through the drainage canals. Therefore, an increase of 100-year flood level of 28 cm, in a low emission scenario (RCP2.6), already affects infrastructures severely (6.4% increase in impacted buildings and 6.8% increase in impacted road lengths). In the medium emission scenario (RCP4.5), while the 100-year flood level will increase by about 39 cm in 2100, the inundation will cause 8.1% more impacted buildings and 8.4% more affected road lengths. Lastly, in the highest emission scenario (RCP8.5), when the 100-year flood level increases by 70 cm from the current state, there will be 11.9% more impacted buildings and 12.7% more affected roads.

Here, we qualitatively categorized the flood risk for each sub-area (district) as high and low regarding the spatial distribution of flood hazards and exposed infrastructures, i.e., buildings and roads (Environment Agency UK, 2013). Fig. 4.6 shows that the high-risk area is located in the eastern and western parts of the city. Most of these areas will be inundated under the 100-year flood level condition. Therefore, the flood hazard in these areas is high. The exposure is also high because there are many infrastructures in these areas, which means they are highly populated or function as, for example, a business center. The high hazards and dense infrastructures made this area a high-risk flood zone.

Meanwhile, the northern part of the city has a lower infrastructure density. The flood hazard in this area is also low due to its higher altitude. A significant portion of this area will not be inundated under all 100-year flood scenarios. Therefore, the flood risk of this zone is categorized as low (Environment Agency UK, 2013). Another non-inundated area is the southern part of the joining point of the Landak River and the Kapuas Kecil River, as well as some parts of the city's southwestern area. Even though these areas have dense infrastructures, we still classified the flood risk of these zones as low.

Nevertheless, this study has some limitations. Firstly, these estimates are rather conservative or we do not account for potential collapse of the Antarctic ice sheet (van de Wal et al., 2019). Secondly, the flood analysis is limited to the extent of the city of Pontianak. Hazards and exposure areas outside the city are not included in the assessment. Next, the hazards are classified only in two states: inundated and not inundated, without considering the depth of the flood (Islam and Sado, 2000). In addition, the impact assessment on the infrastructure (buildings and roads) only depends on the DEM map (FEMA, 2003). The analysis result may differ due to local conditions, such as higher local terrain maps and infrastructure types. Furthermore, it is also essential to notice that the MLR model is trained by only three months of data in 2020. The water levels could be higher if we considered other flood events in other years. Lastly, even though the percent bias between prediction and observation for the testing phase is only 0.2%, the predicted extreme water levels are still slightly under-estimated (the regression line has a slope of less than 45°). The actual flood levels are likely higher than expected. Hence, a more robust model is still needed to overcome this limitation.

Despite the limitations, the local water management or government can use this study's results to mitigate future flood events in the study area. The model's evaluation of climate change impacts can guide the adaptation strategies, such as whether or not it is urgent to adjust the height of flood defense structures along the riverbanks within the city. Next, they can track the hazardous area throughout the city and watch what happens as the water comes from all possible causes. Moreover, other deltas with similar characteristics and limitations can adopt the approach to assess their future flood risk.

Conclusions and Perspectives

5.1 Conclusions

5.1.1 Extreme water level for flood hazard zone delineation

This study has proposed a method to delineate compound-flooding hazard zones based on a maximum water-level profile due to a tide-surge-discharge interaction along a river's downstream area. The method was implemented in the Kapuas River delta (KRD), where Pontianak urban area is located. The local water managers in Pontianak need the delineation because houses in the area are mostly flooded at the floor level when high tides coincide with intense local precipitation (Deynoot, 2011). Environmental protection is essential to tackle flood issues in the KRD (Wells et al., 2016), so this thesis provides scientific background to the developments of mitigation strategies against compound flooding.

Here, we built a model depicting the Kapuas River's hydrodynamic processes and their interaction with the Karimata Strait tides and wind surges. We simulated the processes during extreme events using the model and assessed their impact on the maximum water level along the river. We found that wind surges with speeds between 16 m/s to 24 m/s over the Kapuas estuary can raise the water level to 150 km upstream. If the wind speed exceeds 24 m/s, the surge impact can travel beyond this point. The stronger the wind speed, the further the surge impact will travel upstream. If the surge propagation upstream occurs during intermediate or high river discharges, it can significantly increase the river water level and trigger an inundation over the floodplain, including the city of Pontianak.

Based on the maximum water-level profile, we successfully delineated flood hazard zones along the Kapuas River. The region from the river mouth to about 30 km upstream is tidally-dominated, where river discharge levels do not impact the maximum water level. The region from about 30 km to 150 km upstream is transitional, where the maximum water level is influenced by the interaction between the tides, the surges, and the river discharges. Then, the region is river-dominated from about 150 km upstream, where surges (with wind speed less

than 24 m/s) no longer impact the maximum water level. It remains the same with and without tides scenarios. The local water management agency in the KRD can use these zoning categories in assessing and mitigating the compound flooding hazard along the riverbanks.

The delineation of flood hazard zones is important to assess flood risks within coastal landscapes. The local water management agency can create different mitigation strategies for each area along the river. However, currently, there is no consensus regarding compound flooding hazard zones in coastal areas. The existing, established methods are mainly due to the surge-rainfall interaction (Gori et al., 2020; Shen et al., 2019; Bilskie and Hagen, 2018), which categorized the hazards into three regions: rainfall-dominated, transitional, and surge-dominated. Unfortunately, the definitions of the transition zone remain inconclusive. Therefore, our proposed method gave a new alternative approach to address the issue.

5.1.2 Integrated framework for high water-level predictions

We show how integrating the hydrodynamic and the machine learning (ML) models successfully overcomes river water level modeling issues and predict compound flooding hazards in a data-scarce environment with limited computational resources. Therefore, the approach suits local water management agencies in developing countries, including the KRD. However, the ML model's accuracy depends on the hydrodynamic model's accuracy. If the hydrodynamic model is inaccurate in predicting real-life floods, the ML model's accuracy will also be lower. Besides, the integrated model has not yet optimally captured urban flooding caused by excessive rainfalls. Including more indicators for flooding is essential to enhance the model in the future. Regarding the implementation in Pontianak, our framework worked well. We found that the ML model with RF algorithm has the most accurate output compared to the other algorithms. In addition, the tidal elevation, measured one hour prior, is the main predictor for water level modeling in the study area.

The integrated approach is essential for local water management in developing countries because they deal with a data-scarce environment. Artificial flood scenarios seem to be a reasonable choice to assess the flood risk. Besides, they deal with limited computational resources, which necessitates seeking an alternative approach. The idea we put forward here is to create flood scenarios based on a hydrodynamic model using high-performance computing (HPC) facilities only once, at the initial stage. Then, a robust ML model is built and trained based on the output of the hydrodynamics model. The local water management can implement the ultimate model in the field with minimum computational cost using a desktop computer. This solution is feasible to create

a robust flood forecast model in the KRD. Hence, both issues (data scarcity and limited computational resources) are resolved. Other deltas facing similar problems can follow suit. However, they still need to partner with HPC facilities at the beginning of the model development and redo the modeling and ML training process.

5.1.3 Future flood-risk assessment in the KRD

More and more people are now affected by extreme weather events, such as cyclones and tropical storms, which have been spreading worldwide. Coastal areas must assess their exposure and risks to extreme weather events and develop mitigation strategies, including deltas in developing countries with limited resources. Therefore, assessing and simulating flood risks should be made affordable yet robust.

Here, we proposed a simple way to assess future flood risks in delta areas. Using integrated ML and GIS-based bathtub inundation models, we successfully assess the future flood risks in the KRD, particularly in Pontianak. We simulated the water level dynamics and quantified the flood frequency curve in the current and future states as modulated by climate change. We created the flood maps of the potentially inundated areas in 100-year flood (1% annual exceedance probability) scenarios. We found that the 100-year flood level in the study area will increase from the current 2.64 m to 2.92 m, 3.03 m, and 3.34 m in 2100 under the low (RCP2.6), medium (RCP4.5), and high-emission (RCP8.5) climate scenarios, respectively. These increases correlate to the increment of flood hazard areas over the region of interest. We found that, in 2100, more buildings will be exposed (increased by about 6.4% - 11.9%), and more roads will be impacted (increased by approximately 6.8% - 12.7%) depending on the climate scenario. This assessment can inform the local water managers in preparing adequate mitigation strategies and disaster management plans.

Using this flood risk assessment, we can track the hazardous area and assess how the water comes from the possible sources and its impacts. Mapping the distribution of risk areas is necessary to establish effective mitigation strategies. Using the flood risk maps, we can delineate no-build zones and identify evacuation routes when a flood occurs. Therefore, this work can provide a foundation for the local water management in the KRD to mitigate the climate change impacts, particularly the future compound flooding hazards. The more they know about the distribution of risk areas, the better they can prepare a mitigation strategy.

5.2 Perspectives

5.2.1 Enhancing high water-level prediction in the KRD

Some components urgently needed to build a better model to predict water levels, as a proxy for compound flooding hazards, in the KRD: data monitoring and analysis, integrated water levels modeling framework, and planning and outreach. Each can be built independently, case by case, or interconnected.

Data monitoring and analysis need to consider spatial (distribution of gauge locations) and temporal (gauging periodicity) factors to see what is missing in order to build a comprehensive model. To complete the missing data, the local water management must install discharge gauges for the Kapuas and Landak rivers that flow into the KRD. They also have to install a tide gauge in the river mouth. The gauges are critical for collecting data to create better forecasting in the future. Moreover, new approaches such as remote sensing (Domeneghetti et al., 2019) and the Internet of Things (Ghapar et al., 2018) must be explored. The former can be implemented for flood mapping and dynamics monitoring, and the latter for real-time water-level data observation along the Kapuas River. This endeavor could close the gap in the data.

The modeling framework also needs to consider all existing water level prediction models. The different techniques for coupling models (Kumbier et al., 2018; Ye et al., 2020) need to be explored. The coupling techniques may be one-way or two-way between hydrologic, hydraulic, and hydrodynamic models. The coupling model may run independently or simultaneously. Moreover, the joint probability for risk analysis also needs to be evaluated (Ming et al., 2022). These modeling frameworks can be implemented differently in flood hazard zones, i.e., the tidally-dominated, the transitional, and the river-dominated regions (as discussed in the second chapter).

Regarding planning and outreach, it is essential to identify the end-users of the model outputs, i.e., local citizens and authorities. Strategic output dissemination to end-users will optimize the model benefits. An example would be the development of WebFRIS, a web-based flood risk information system in India (Mohanty and Karmakar, 2021). The local water management designed the system's layout and architecture using various open-source web tools, such as Google Map, PHP, MySQL, and JSON. Then, they ask for feedback from the end-users with different backgrounds to improve the system.

5.2.2 Managing the impact of high-water levels: Integrated flood risk management

In dealing with the high water levels, local water management in the KRD and other similar deltas in developing countries must implement integrated flood risk management (Juarez Lucas and Kibler, 2015). Firstly, a single mean sea-level

projection in the RCP 8.5 scenario will make about 10 km of the West Kalimantan shoreline retreat in 2100 (Church et al., 2013). A combination of wind surges and extreme weather will cause more areas over the KRD to be submerged during the flood events. This condition may worsen because the peatland that covers most delta areas is likely to subside ten times more rapidly than the sea-level rise (Hooijer et al., 2012). Good practices to mitigate the flood hazards from the sea, e.g., wind surges and sea-level rise, may include natural protection defense such as mangrove forests (Blankespoor et al., 2017). Next, the government should regulate the massive sand mining along the Kapuas River (Soeryamassoeka et al., 2018) as it can damage the river systems and trigger more severe flooding downstream (Padmalal and Maya, 2014). Then, the riverbank within the delta must be kept in its natural state, without dikes or groins, to allow deposition by the overbank flows (Kästner, 2019).

Pontianak urban area is only 20 km from the river mouth, so climate change is an imminent threat. Since it has no sea defenses, sea-level rise will threaten the city directly. Compound flooding events could be more frequent and severe. Therefore, the government should immediately formulate mitigation strategies. For instance, as a short-term solution, the local water managers can encourage citizens to construct higher ground floors for their houses (Kästner, 2019). Mangrove planting (Blankespoor et al., 2017; Marois and Mitsch, 2015) on the river banks within the KRD could be intensified—from the river mouth to about 60 km upstream. The planting program should be prioritized in areas with high flood risk, such as the high-density urban area. The public should be involved in the implementation so that they will be aware of the importance of the mangrove habitat.

However, it should be noted that however much people invest in reducing the flooding risk, there will always be a residual risk from flooding (The Associated Programme on Flood Management, 2013), which leads to the idea of emergency preparedness. Flooding will likely occur when a potential storm surge is predicted over the Karimata Strait, and rainfall over the area is expected to exceed a certain threshold. People need to invest in an early warning system built based on a hydrological concept connected to the Kapuas River basin.

Next, local water management often believes in concrete in the ground, such as higher sea walls and dikes, to reduce the flood risk. The strategy certainly has a place in integrated flood risk management, but engineered structures often transfer the risk somewhere else. Therefore, integrated flood management systems should strive for a balance between structural and non-structural measures (Saito, 2014). Structural measures keep water away from people, and non-structural measures keep people away from water. An integrated strategy is a middle ground.

Furthermore, local water managers should prepare complete scenarios for compound flood hazards and their impacts. A flood hazard map is an essential tool (Hagemeyer-Klose and Wagner, 2009). Over the past few years, the explosion in geospatial data has allowed local water management to produce high-quality visualization maps quickly, showing them the possible impact of floods and the trade-offs between various policy measures. For example, if a dyke of a certain height is built or the river bed is dredged, the impact on the area under risk can be known. Therefore, making information public is necessary.

Regarding climate change, the local water management in the KRD and the other deltas must address the issue adequately. It is scientifically accepted that climate change will increase the probability of more extreme weather events in the future (Stott, 2016). However, it is impossible to attribute individual extreme weather events to climate change. Poor development planning also has a severe impact. Rapid and unplanned urbanization increases flood risk more rapidly than climate change (Pervin et al., 2020). For example, the coastal city of Jakarta, Indonesia, is sinking ten times faster than the sea-level rise (Takagi et al., 2016). This situation is caused by poor groundwater management. So, if the city were to improve its groundwater management, it would do much more to reduce its flood risk, which would be a significant step. Local water managers in deltas, including in the KRD, can learn from the case of Jakarta.

Discussion about climate change unavoidably discusses the uncertainty (Blázquez and Nuñez, 2013). When we project out into 100 years, we do not know what the precipitation will be or what the intensity/frequency of the storm will be. Therefore, local water managers need to make decision-making more robust—an optimal decision under a comprehensive scenario of climate change projections. Consequently, they need to formulate flood defense strategies with higher benefits than costs and be resilient in the face of uncertainty posed by climate change.

Finally, regarding balancing structural and non-structural measures against flooding, local water management in the KRD and similar deltas in developing countries may adopt some simple strategies (Chan, 2015). The first is creating more space for rivers by letting rivers follow their natural course. This underlines an assumption that flooding is a normal, natural phenomenon. We cannot remove the hazard, but we can mitigate its impact. The second is that if flooding does happen, what can be done is retain it in remote areas where the damages will be more minor. Lastly, urban development in floodplains should be controlled using the most stringent regulations. In other words, planning new urban areas in floodplains should be prohibited by law, and the enforcement must be stricter, especially in developing countries.

Appendix

A. Details on the tidal constituents

The amplitude, phase and energy of each tidal constituent at the river mouth and in Pontianak are summarized in Table A1, A2 and A3.

Table A1 Tidal Constituents in the KRD from 3 years data

Constituent	Description	Frequency (cph)	Amplitude (m)	Phase (°)
K1	Lunar diurnal constituent	4.18E-02	3.29E-01	35.31
O1	Lunar diurnal constituent	3.87E-02	2.70E-01	332.23
SA	Solar annual constituent	1.14E-04	1.25E-01	359.75
M2	Principal lunar semidiurnal constituent	8.05E-02	1.17E-01	312.5
P1	Solar diurnal constituent	4.16E-02	9.79E-02	40.27
S2	Principal solar semidiurnal constituent	8.33E-02	4.97E-02	337.48
Q1	Larger lunar elliptic diurnal constituent	3.72E-02	4.33E-02	304.29
SSA	Solar semiannual constituent	2.28E-04	4.09E-02	153.5
S1	Solar diurnal constituent	4.17E-02	2.85E-02	158.63
MF	Lunisolar fortnightly constituent	3.05E-03	2.79E-02	267.29
MSF	Lunisolar synodic fortnightly constituent	2.82E-03	2.07E-02	59.65
MK3	Shallow water terdiurnal constituent	1.22E-01	1.91E-02	290.23
SO1	Shallow water diurnal constituent	4.46E-02	1.81E-02	283.96
MO3	Shallow water terdiurnal constituent	1.19E-01	1.61E-02	230.51
J1	Smaller lunar elliptic diurnal constituent	4.33E-02	1.33E-02	102.72
K2	semidiurnal tide constituent	8.36E-02	1.27E-02	295.49
MM	monthly tide constituent	1.51E-03	1.22E-02	34.84
M4	Shallow water over tides of principal lunar constituent	1.61E-01	1.08E-02	88.44
MS4	Shallow water quarter diurnal constituent	1.64E-01	1.01E-02	132.09

Table A2 Tide Constituents at the Kapuas Kecil River mouth (0.06170 N, 109.17510 E) in December 2018.

Tidal constituent	inaCOAP			SLIM			Error		Rayleigh Criterion
	Amplitude (m)	Phase (°)	Percent Energy (%)	Amplitude (m)	Phase (°)	Percent Energy (%)	Δ Amplitude (m)	Δ Phase (°)	
K1	0.36	304.59	54.39	0.29	307.29	48.03	0.06	2.71	0.16
O1	0.26	349.21	29.56	0.22	353.95	27.30	0.04	4.75	1.09
M2	0.14	252.24	8.62	0.16	252.74	13.46	0.02	0.50	26.80
P1	0.11	278.45	4.95	0.12	286.67	7.88	0.01	8.22	2.03
Q1	0.05	202.88	1.03	0.05	185.47	1.31	0.00	17.40	24.77
J1	0.04	99.54	0.69	0.01	149.53	0.11	0.03	50.00	1.09
S2	0.04	136.68	0.76	0.06	143.77	1.75	0.01	7.10	2.03

Table A3 Tide Constituents at the middle of Pontianak (-0.0204310 S, 109.338520 E) in December 2018.

Tidal constituent	Observation			SLIM			Error		Rayleigh Criterion
	Amplitude (m)	Phase (°)	Percent Energy (%)	Amplitude (m)	Phase (°)	Percent Energy (%)	Δ Amplitude (m)	Δ Phase (°)	
K1	0.23	65.24	42.42	0.24	54.85	42.11	0.01	10.39	0.16
O1	0.18	108.39	25.33	0.20	90.81	28.71	0.02	17.58	1.09
M2	0.11	124.73	13.34	0.14	81.92	14.53	0.04	42.81	26.80
P1	0.1	78.8	10.54	0.12	28.50	9.73	0.02	50.30	2.03
Q1	0.06	299.63	4.11	0.05	279.19	1.71	0.01	20.44	24.77
J1	0.04	238.67	1.78	0.02	269.16	0.37	0.02	30.49	1.09
S2	0.04	25.4	1.54	0.06	3.22	2.21	0.02	22.18	2.03
MK3	0.02	163.32	0.52	0.03	47.35	0.46	0.01	115.97	2.20
MO3	0.01	216.89	0.42	0.01	122.99	0.17	0.00	93.90	25.85

Table A4 Scenarios used to force the model. The simulation duration is one whole month, with wind direction varying from 00 to 3600, pressure varying from 100.5 kPa to 101.5 kPa, and tidal range 1.8 m.

Scenario	Wind Speed (ms ⁻¹)	Discharge Kapuas (m ³ s ⁻¹)	Discharge Landak (m ³ s ⁻¹)
Discharge1	2 - 8	3×10^3	300
Discharge2	2 - 8	5×10^3	300
Discharge3	2 - 8	7×10^3	300
Discharge4	2 - 8	9×10^3	300
Wind_1x	2 - 8	3×10^3	300
Wind_1.5x	3 - 12	3×10^3	300
Wind_2x	4 - 16	3×10^3	300
Wind_2.5x	5 - 20	3×10^3	300
Wind_3x	6 - 24	3×10^3	300
Wind_4x	8 - 32	3×10^3	300
Wind_5x	10 - 40	3×10^3	300
Case Study	2 - 21	$3.3 \times 10^3 - 5 \times 10^3$	250-700

B. Local weather condition on 29 December 2018

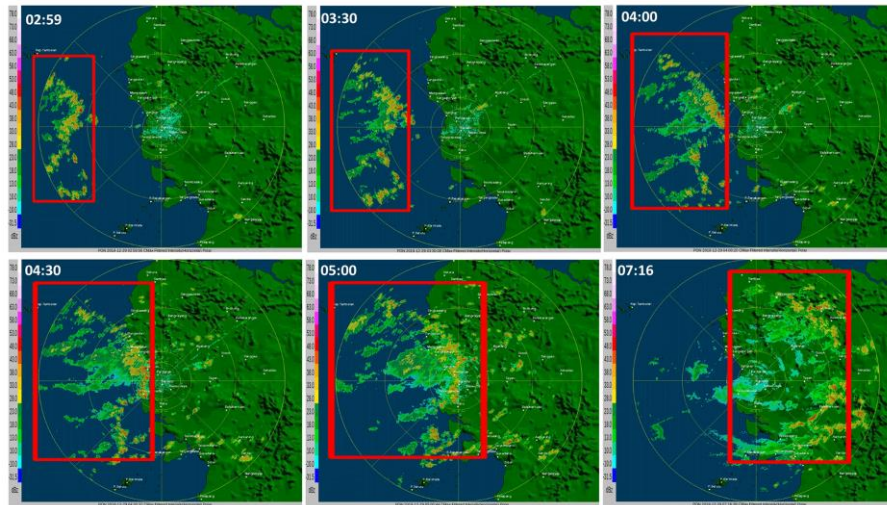


Figure B Radar data, observed by the Supadio Meteorological Station (<http://kalbar.bmkg.go.id/profil/>), depicts the clouds' growth and movement (in the red box) on 29 December 2018. The clouds started to grow over the ocean and are pushed by the wind to move eastward at 02.59 UTC. The clouds reach their maximum intensity at 05.00 UTC while located above the Kapuas Estuary. Furthermore, the clouds spread over a wider area with a weakening intensity at 07.00 UTC.

C. Flood Frequency Analysis

Flood frequency analysis aims to determine the probability of a flood with a specific height happening in a year. The flood frequency is calculated based on a historical flood record. The data is the annual peak water level, which records the highest instantaneous water level measured in a year. It is the single measurement in a whole year, where the water level is the highest at the gauges.

To conduct the flood frequency analysis, firstly, we take the annual peak of the water level. Then, we rank the data from the lowest to the highest. Next, we assign the probability of exceeding for each event using the Gumbel distribution (Gumbel, 1958):

$$p_i = \exp \left[-\exp \left(-\frac{x_i - u}{\alpha} \right) \right]$$

where:

p_i = probability of exceeding for each data point, i-th

x_i = annual maxima water level for each data point, i-th

u and α are parameters that shape the Gumbel distribution, that can be calculated from the mean ($\bar{x}$) and the variance (S_x^2) of n data points:

$$\bar{x} = \sum_{i=1}^n \frac{x_i}{n}$$

$$S_x^2 = \frac{1}{(n-1)} \sum_{i=1}^n (x_i - \bar{x})^2$$

So,

$$\alpha = \frac{\sqrt{6S_x^2}}{\pi} \text{ and } u = \bar{x} - 0.5772\alpha$$

Finally, the return period of each data point is calculated using

$$T_{p(i)} = \frac{1}{(1 - p(i))}$$

Furthermore, we plot these annual maxima water levels versus their return period using a scatterplot to obtain the flood frequency. Then, we examine the relationship between both parameters using the curve fitting method. The commonly used curve fitting method for flood frequency analysis is the Log-

Pearson Type 3 (Griffis and Stedinger, 2007). Once we get the best fitting line, we can estimate the flood height for any return period, such as 10-year, 100-year, and 500-year. Since we used the curve fitting method to extrapolate the recurrence flood, we can put uncertainty bounds in our frequency curve. The more data we have, the less uncertainty we find. On the contrary, the less data we provide, the more uncertainty we obtain. However, we did not address this uncertainty yet in this study.

D. Sea-level rise

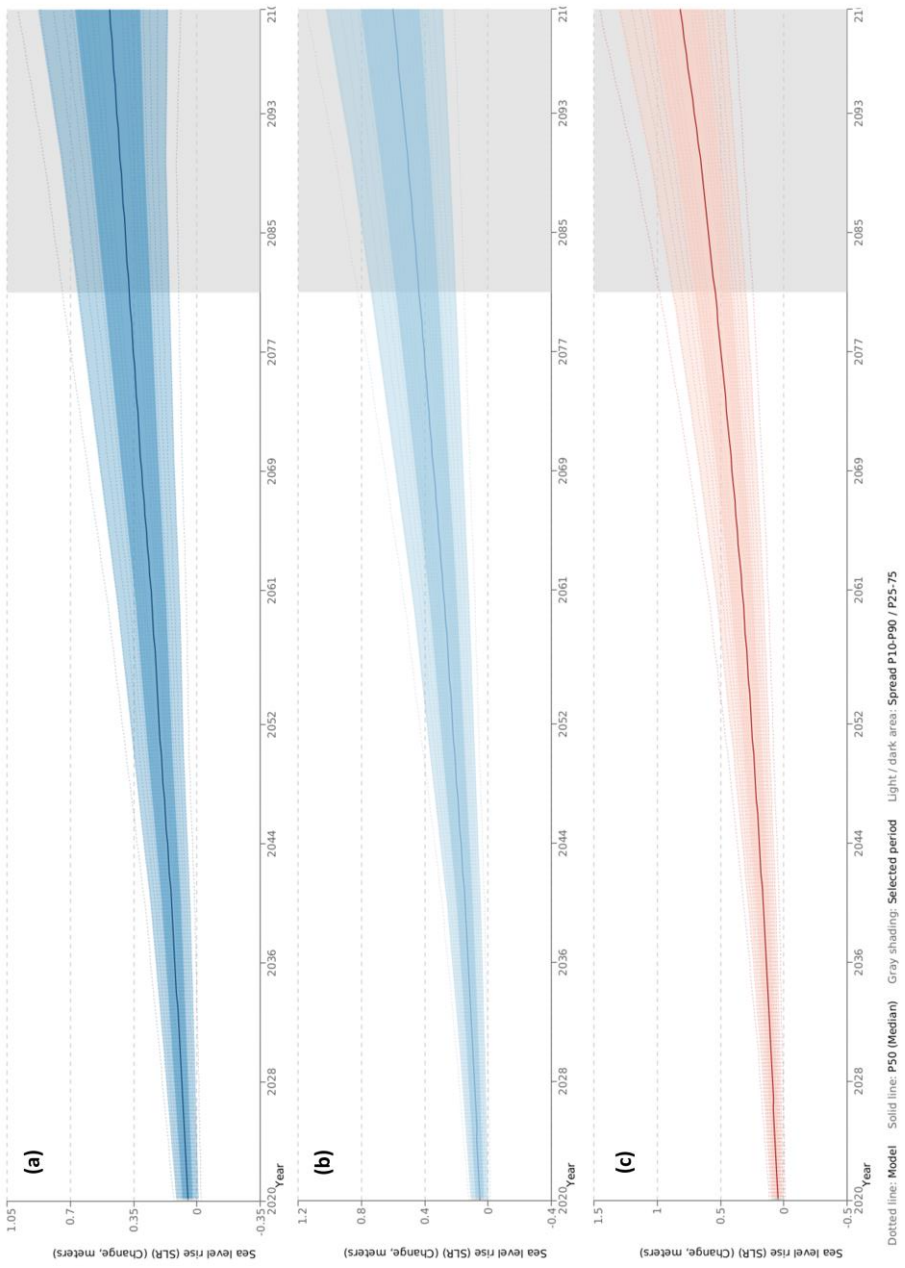


Figure D Mean sea-level rise for three different scenarios at the region of South East Asia (Special Report on the Ocean and Cryosphere in a Changing Climate, 2022): (a) RCP 2.6, (b) RCP 4.5, and (c) RCP 8.5 (Iturbide et al., 2021)

E. Total precipitation changes

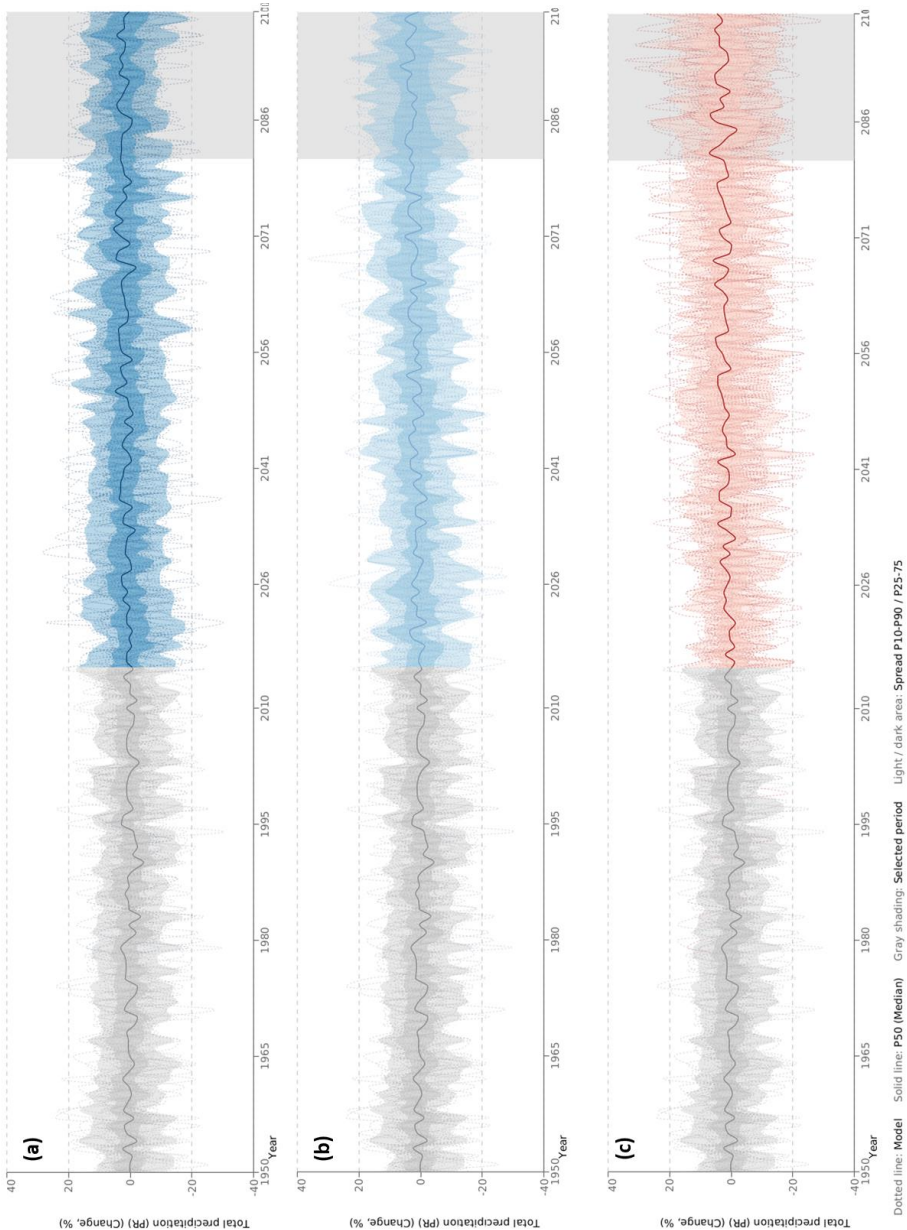


Figure E Total precipitation change for three different scenarios at the region of South East Asia (Special Report on the Ocean and Cryosphere in a Changing Climate, 2022): (a) RCP 2.6, (b) RCP 4.5, and (c) RCP 8.5 (Iturbide et al., 2021)

F. Surface wind changes

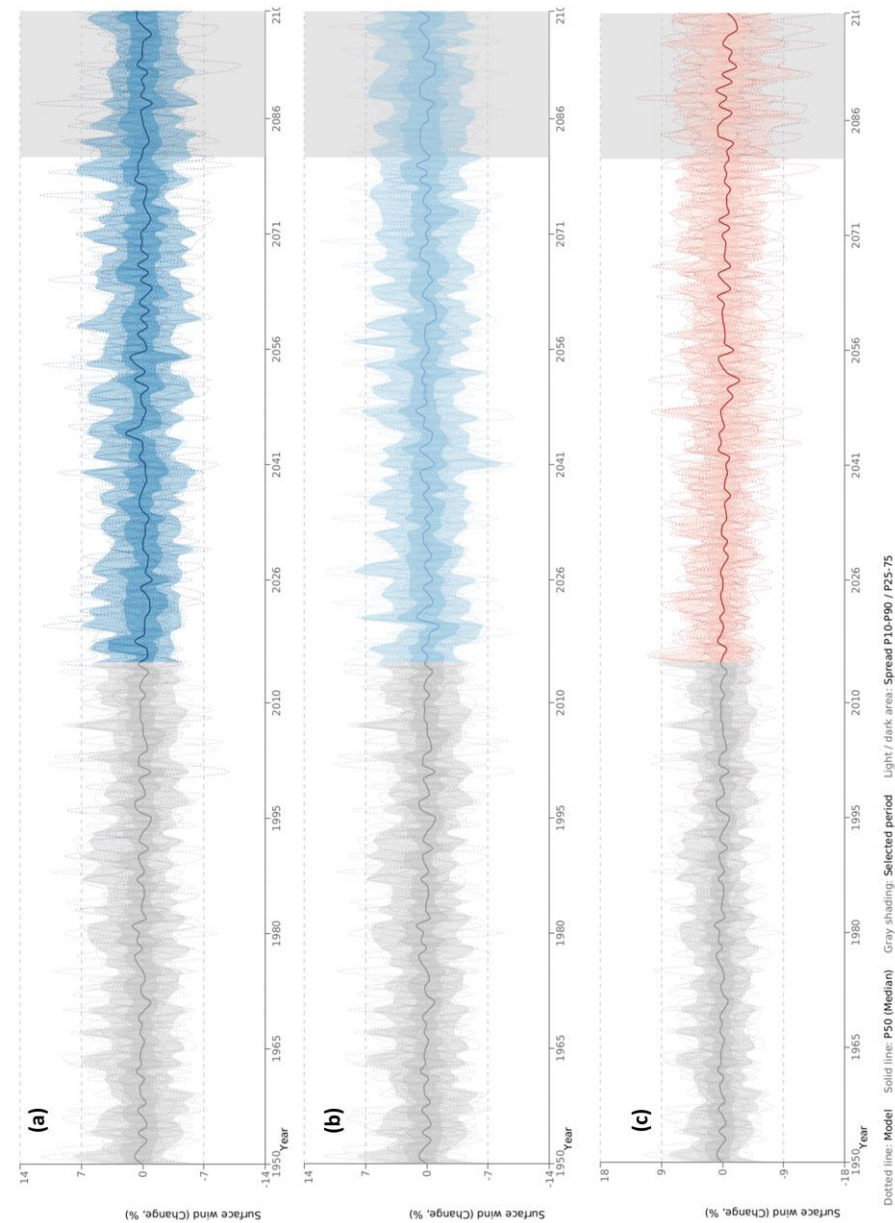


Figure F Surface wind change for three different scenarios at the region of South East Asia (Special Report on the Ocean and Cryosphere in a Changing Climate, 2022): (a) RCP 2.6, (b) RCP 4.5, and (c) RCP 8.5 (Iturbide et al., 2021)

G. Supporting Publications

List of publications:

Sampurno, J., Vallaey, V., Ardianto, R., and Hanert, E.: *Modeling interactions between tides, storm surges, and river discharges in the Kapuas River delta*, Biogeosciences, 19, 2741–2757, <https://doi.org/10.5194/bg-19-2741-2022>, 2022.

Sampurno, J., Vallaey, V., Ardianto, R., and Hanert, E.: *Integrated hydrodynamic and machine learning models for compound flooding prediction in a data-scarce estuarine delta*, Nonlin. Processes Geophys., 29, 301–315, <https://doi.org/10.5194/npg-29-301-2022>, 2022.

Sampurno, J., Ardianto, R., and Hanert, E.: *Integrated machine learning and GIS-based bathtub models to assess the future flood risk in the Kapuas River delta* [Under review in the Journal of Hydroinformatics], 2022

Other publication:

Sampurno, J., Apriansyah, A. and Adriat, R.: *Heat distribution modeling of the subsurface of Wapsalit geothermal area based on land surface temperature from Landsat-8 thermal infrared sensor imagery*. Malaysian Journal of Fundamental and Applied Sciences, 15(2), pp.182-184, 2019

Sampurno, Joko: *Modeling the evolution of the Covid-19 pandemic in the city of Pontianak*. Jurnal Fisika, Vol. 10, no. 1, p. 22-29, 2020

Ardianto, R., Ismanto, A., **Sampurno, J.,** Widada S.: *Integrated tidal flood model simulation using land subsidence parameters in Pontianak, Indonesia*. [Submitted to Geographia Technica], 2022.

Reference

- Aldrian, E. and Susanto, R. D.: Identification of three dominant rainfall regions within Indonesia and their relationship to sea surface temperature, *Int. J. Climatol.*, 23, 1435–1452, <https://doi.org/10.1002/joc.950>, 2003.
- Alipour, A., Ahmadalipour, A., Abbaszadeh, P., and Moradkhani, H.: Leveraging machine learning for predicting flash flood damage in the Southeast US, *Environ. Res. Lett.*, 15, 024011, <https://doi.org/10.1088/1748-9326/AB6EDD>, 2020.
- Anuar, Norzana Mohd, Ahmad Mustafa Hashim, Nor Aslinda Awang, and Mohd Radzi Abd Hamid.: Historical Storm Surges: Consequences on Coastal Resources and Shoreline Protection in East Coast of Peninsular Malaysia, In 7th IAHR International Symposium on Hydraulic Structures, pp. 434–443. ISHS, 2018.
- Arianti, I., Soemarno, Hasyim, W., and Sulistyono, R.: Determining Variable Weight of Flood Vulnerability Spatial Model in Pontianak City Based on Analytic Hierarchy Process (AHP), *Int. J. Humanit. Relig. Soc. Sci.*, 4, 2548–5725, 2020.
- Assem, H., Ghariba, S., Makrai, G., Johnston, P., Gill, L., and Pilla, F.: Urban Water Flow and Water Level Prediction Based on Deep Learning, *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, 10536 LNAI, 317–329, https://doi.org/10.1007/978-3-319-71273-4_26, 2017.
- BATNAS: <https://tanahair.indonesia.go.id/demnas/#/batnas>, last access: 14 July 2021.
- Bevacqua, E., Maraun, D., Vousdoukas, M. I., Voukouvalas, E., Vrac, M., Mentaschi, L., and Widmann, M.: Higher probability of compound flooding from precipitation and storm surge in Europe under anthropogenic climate change, *Sci. Adv.*, 5, 2019.
- Bevacqua, E., Vousdoukas, M. I., Zappa, G., Hodges, K., Shepherd, T. G., Maraun, D., Mentaschi, L., and Feyen, L.: More meteorological events that drive compound coastal flooding are projected under climate change, *Commun. Earth Environ.* 2020 11, 1, 1–11, <https://doi.org/10.1038/s43247-020-00044-z>, 2020.
- Bhaskaran, P. K., Gayathri, R., Murty, P. L. N., Bonthu, S. R., and Sen, D.: A numerical study of coastal inundation and its validation for Thane cyclone in the Bay of Bengal, *Coast. Eng.*, 83, 108–118, <https://doi.org/10.1016/J.COASTALENG.2013.10.005>, 2014.
- Bhatta, B.: Causes and Consequences of Urban Growth and Sprawl, *Adv. Geogr. Inf. Sci.*, 17–36, https://doi.org/10.1007/978-3-642-05299-6_2, 2010.

- Bieger, K., Arnold, J. G., Rathjens, H., White, M. J., Bosch, D. D., Allen, P. M., Volk, M., and Srinivasan, R.: Introduction to SWAT+, a Completely Restructured Version of the Soil and Water Assessment Tool, *J. Am. Water Resour. Assoc.*, 53, 115–130, <https://doi.org/10.1111/1752-1688.12482>, 2017.
- Bilskie, M. V. and Hagen, S. C.: Defining Flood Zone Transitions in Low-Gradient Coastal Regions, *Geophys. Res. Lett.*, 45, 2761–2770, <https://doi.org/10.1002/2018GL077524>, 2018.
- Bishop, C. M.: Pattern recognition and machine learning, Springer, Singapore, 738 pp., 2006.
- Blankespoor, B., Dasgupta, S., and Lange, G. M.: Mangroves as a protection from storm surges in a changing climate, *Ambio*, 46, 478–491, <https://doi.org/10.1007/S13280-016-0838-X>, 2017.
- Blázquez, J. and Nuñez, M. N.: Analysis of uncertainties in future climate projections for South America: Comparison of WCRP-CMIP3 and WCRP-CMIP5 models, *Clim. Dyn.*, 41, 1039–1056, <https://doi.org/10.1007/S00382-012-1489-7>, 2013.
- Block, P. J., Filho, F. A. S., Sun, L., and Kwon, H.-H.: A Streamflow Forecasting Framework using Multiple Climate and Hydrological Models¹, *JAWRA J. Am. Water Resour. Assoc.*, 45, 828–843, <https://doi.org/10.1111/J.1752-1688.2009.00327.X>, 2009.
- BNPB, Australian Government, and the World Bank (GFDRR): InaSAFE: <http://inasafe.org/>, last access: 26 January 2022.
- Breiman, L.: Random forests, *Mach. Learn.*, 45, 5–32, <https://doi.org/10.1023/A:1010933404324>, 2001.
- Brocca, L., Massari, C., Pellarin, T., Filippucci, P., Ciabatta, L., Camici, S., Kerr, Y. H., and Fernández-Prieto, D.: River flow prediction in data scarce regions: soil moisture integrated satellite rainfall products outperform rain gauge observations in West Africa, *Sci. Reports* 2020 101, 10, 1–14, <https://doi.org/10.1038/s41598-020-69343-x>, 2020.
- Buchhorn, M., Lesiv, M., Tsendbazar, N.-E., Herold, M., Bertels, L., and Smets, B.: Copernicus Global Land Cover Layers—Collection 2, *Remote Sens.* 2020, Vol. 12, Page 1044, 12, 1044, <https://doi.org/10.3390/RS12061044>, 2020.
- Buschman, F. A., Hoitink, A. J. F., Van Der Vegt, M., and Hoekstra, P.: Subtidal flow division at a shallow tidal junction, *Water Resour. Res.*, 46, 12515, <https://doi.org/10.1029/2010WR009266>, 2010.
- Cacuci, D. G.: Sensitivity and uncertainty analysis, Chapman & Hall/CRC Press, Boca Raton, 2003.
- Celliers, L. and Ntombela, C.: Urbanisation, coastal development and vulnerability, and catchments, in: UNEP-Nairobi Convention and WIOMSA. 2015. The Regional State of the Coast Report: Western Indian Ocean, Nairobi,

2015.

Chahar, R. and Kaur, D.: A systematic review of the machine learning algorithms for the computational analysis in different domains, *International Journal of Advanced Technology and Engineering Exploration*, 7, 147–164, <https://doi.org/10.19101/IJATEE.2020.762057>, 2020.

Chan, F. K. S., Yang, L. E., Scheffran, J., Mitchell, G., Adekola, O., Griffiths, J., Chen, Y., Li, G., Lu, X., Qi, Y., Li, L., Zheng, H., and McDonald, A.: Urban flood risks and emerging challenges in a Chinese delta: The case of the Pearl River Delta, *Environ. Sci. Policy*, 122, 101–115, <https://doi.org/10.1016/j.envsci.2021.04.009>, 2021.

Chan, N. W.: Impacts of Disasters and Disaster Risk Management in Malaysia: The Case of Floods, *Resil. Recover. Asian Disasters*, 239–265, https://doi.org/10.1007/978-4-431-55022-8_12, 2015.

Chassignet, E. P., Hurlburt, H. E., Smedstad, O. M., Halliwell, G. R., Hogan, P. J., Wallcraft, A. J., Baraille, R., and Bleck, R.: The HYCOM (HYbrid Coordinate Ocean Model) data assimilative system, *J. Mar. Syst.*, 65, 60–83, <https://doi.org/10.1016/J.JMARSYS.2005.09.016>, 2007.

Chen, J. H. and Asch, S. M.: Machine Learning and Prediction in Medicine — Beyond the Peak of Inflated Expectations, *N. Engl. J. Med.*, 376, 2507, <https://doi.org/10.1056/NEJMP1702071>, 2017.

Choi, C., Kim, J., Han, H., Han, D., and Kim, H. S.: Development of Water Level Prediction Models Using Machine Learning in Wetlands: A Case Study of Upo Wetland in South Korea, 12, 93, <https://doi.org/10.3390/w12010093>, 2020.

Chu, P. C.: Two Kinds of Predictability in the Lorenz System, *J. Atmos. Sci.*, 56, 1999.

Church, J. A., Clark, P. U., Cazenave, A., Gregory, J. M., Jevrejeva, S., Levermann, A., Merrifield, M. A., Milne, G. A., Nerem, R. S., Nunn, P. D., and Payne, A. J.: Sea level change. *Climate change 2013: the physical science basis. Contribution of working group I to the fifth assessment report of the intergovernmental panel on climate change.*, Cambridge, United Kingdom, 2013.

Codiga, D. L.: Unified Tidal Analysis and Prediction, Graduate School of Oceanography, University of Rhode Island, Narragansett, RI., 59 pp., 2011.

Comer, J., Indiana Olbert, A., Nash, S., and Hartnett, M.: Development of high-resolution multi-scale modelling system for simulation of coastal-fluvial urban flooding, *Nat. Hazards Earth Syst. Sci.*, 17, 205–224, <https://doi.org/10.5194/NHESS-17-205-2017>, 2017.

Costabile, P. and Macchione, F.: Enhancing river model set-up for 2-D dynamic flood modelling, *Environ. Model. Softw.*, 67, 89–107,

<https://doi.org/10.1016/J.ENVSOFT.2015.01.009>, 2015.

Costabile, P., Costanzo, C., and Macchione, F.: A storm event watershed model for surface runoff based on 2D fully dynamic wave equations, *Hydrol. Process.*, 27, 554–569, <https://doi.org/10.1002/HYP.9237>, 2013.

Cotton, W. R., Bryan, G., and Heever, S. C. van den: Cumulonimbus Clouds and Severe Convective Storms, in: *International Geophysics*, vol. 44, Academic Press, 455–592, [https://doi.org/10.1016/S0074-6142\(08\)60548-3](https://doi.org/10.1016/S0074-6142(08)60548-3), 1992.

Couasnon, A., Eilander, D., Muis, S., Veldkamp, T. I. E., Haigh, I. D., Wahl, T., Winsemius, H. C., and Ward, P. J.: Measuring compound flood potential from river discharge and storm surge extremes at the global scale, *Nat. Hazards Earth Syst. Sci.*, 20, 489–504, <https://doi.org/10.5194/NHESS-20-489-2020>, 2020.

Das, P., Achal Lama, and Girish Jha: MARS SVR Hybrid: <https://cran.r-project.org/web/packages/MARSSVRhybrid/index.html>, last access: 23 September 2021.

Davidson, R. A., Nozick, L. K., Wachtendorf, T., Blanton, B., Colle, B., Kolar, R. L., DeYoung, S., Dresback, K. M., Yi, W., Yang, K., and Leonardo, N.: An Integrated Scenario Ensemble-Based Framework for Hurricane Evacuation Modeling: Part 1—Decision Support System, *Risk Anal.*, 40, 97–116, <https://doi.org/10.1111/RISA.12990>, 2020.

Deb, M. and Ferreira, C. M.: Potential impacts of the Sunderban mangrove degradation on future coastal flooding in Bangladesh, *J. Hydro-Environment Res.*, 17, 30–46, <https://doi.org/10.1016/j.jher.2016.11.005>, 2017.

DEMNAS: <https://tanahair.indonesia.go.id/demnas/#/>, last access: 1 January 2022.

Deynoot, F. J. C.: Analytical modeling of Salt Intrusion in the Kapuas Estuary, Delft University of Technology, 2011.

Dinh, Q., Balica, S., Popescu, I., and Jonoski, A.: Climate change impact on flood hazard, vulnerability and risk of the Long Xuyen Quadrangle in the Mekong Delta, *Int. J. River Basin Manag.*, 10, 103–120, <https://doi.org/10.1080/15715124.2012.663383>, 2012.

Domeneghetti, A., Schumann, G. J.-P., and Tarpanelli, A.: Preface: Remote Sensing for Flood Mapping and Monitoring of Flood Dynamics, *Remote Sens.*, 11, 943, <https://doi.org/10.3390/RS11080943>, 2019.

Egbert, G. D. and Erofeeva, S. Y.: Efficient inverse modeling of barotropic ocean tides, *J. Atmos. Ocean. Technol.*, 19, 183–204, 2002.

Environment Agency UK: Northumbria River Basin District: flood risk maps for rivers and the sea, Flood Risk Map, Bristol, LIT 8966 pp., 2013.

Farr, T. G., Rosen, P. A., Caro, E., Crippen, R., Duren, R., Hensley, S.,

Kobrick, M., Paller, M., Rodriguez, E., Roth, L., Seal, D., Shaffer, S., Shimada, J., Umland, J., Werner, M., Oskin, M., Burbank, D., and Alsdorf, D. E.: The Shuttle Radar Topography Mission, *Rev. Geophys.*, 45, 2004, <https://doi.org/10.1029/2005RG000183>, 2007.

FEMA: Multi-hazard loss estimation methodology: HAZUS-MH, Technical manual, Washington DC, 2003.

Feng, J., Li, D., Li, D., Zhang, J., and Zhao, L.: Comparison between the skew surge and residual water level along the coastline of China, *J. Hydrol.*, 598, 126299, <https://doi.org/10.1016/J.JHYDROL.2021.126299>, 2021.

Few, R.: Flooding, vulnerability and coping strategies: local responses to a global threat, 3, 43–58, <https://doi.org/10.1191/1464993403PS049RA>, 2016.

Gallien, T. W.: Validated coastal flood modeling at Imperial Beach, California: Comparing total water level, empirical and numerical overtopping methodologies, *Coast. Eng.*, 111, 95–104, <https://doi.org/10.1016/j.coastaleng.2016.01.014>, 2016.

Galloway, W.: Process framework for describing the morphologic and stratigraphic evolution of deltaic depositional systems, 1975.

Ganguli, P., Paprotny, D., Hasan, M., Güntner, A., and Merz, B.: Projected Changes in Compound Flood Hazard From Riverine and Coastal Floods in Northwestern Europe, *Earth's Futur.*, 8, e2020EF001752, <https://doi.org/10.1029/2020EF001752>, 2020.

Think Hazard - Indonesia: <https://thinkhazard.org/en/report/116-indonesia>, last access: 8 January 2022.

Ghanbari, M., Arabi, M., Kao, S. C., Obeysekera, J., and Sweet, W.: Climate Change and Changes in Compound Coastal-Riverine Flooding Hazard Along the U.S. Coasts, *Earth's Futur.*, 9, e2021EF002055, <https://doi.org/10.1029/2021EF002055>, 2021.

Ghapar, A. A., Yussof, S., and Abu Bakar, A.: Internet of Things (IoT) Architecture for Flood Data Management, *Int. J. Futur. Gener. Commun. Netw.*, 11, 55–62, <https://doi.org/10.14257/ijfgcn.2018.11.1.06>, 2018.

Gholami, R. and Fakhari, N.: Support Vector Machine: Principles, Parameters, and Applications, in: *Handbook of Neural Computation*, Elsevier Inc., 515–535, <https://doi.org/10.1016/B978-0-12-811318-9.00027-2>, 2017.

Giloy, N., Hamdi, Y., Bardet, L., Garnier, E., and Duluc, C. M.: Quantifying historic skew surges: an example for the Dunkirk Area, France, *Nat. Hazards*, 98, 869–893, <https://doi.org/10.1007/s11069-018-3527-1>, 2019.

Godin, G.: The resolution of tidal constituents, *Int. Hydrogr. Rev.*, XLVII, 1970.

Goltenboth, F., Timotius, K. H., Milan, P. P., and Margraf, J.: Ecology of

- insular Southeast Asia: the Indonesian archipelago, Elsevier B.V., 2006.
- Gori, A., Lin, N., and Xi, D.: Tropical Cyclone Compound Flood Hazard Assessment: From Investigating Drivers to Quantifying Extreme Water Levels, *Earth's Futur.*, 8, <https://doi.org/10.1029/2020EF001660>, 2020.
- Gori, A., Lin, N., Xi, D., and Emanuel, K.: Tropical cyclone climatology change greatly exacerbates US extreme rainfall–surge hazard, *Nat. Clim. Chang.* 2022 122, 12, 171–178, <https://doi.org/10.1038/s41558-021-01272-7>, 2022.
- Gourgue, O., Comblen, R., Lambrechts, J., Kärnä, T., Legat, V., and Deleersnijder, E.: A flux-limiting wetting–drying method for finite-element shallow-water models, with application to the Scheldt Estuary, *Adv. Water Resour.*, 32, 1726–1739, <https://doi.org/10.1016/J.ADVWATRES.2009.09.005>, 2009.
- Gourgue, O., Baeyens, W., Chen, M. S., de Brauwere, A., de Brye, B., Deleersnijder, E., Elskens, M., and Legat, V.: A depth-averaged two-dimensional sediment transport model for environmental studies in the Scheldt Estuary and tidal river network, *J. Mar. Syst.*, 128, 27–39, <https://doi.org/10.1016/j.jmarsys.2013.03.014>, 2013.
- Griffis, V. W. and Stedinger, J. R.: Log-Pearson Type 3 Distribution and Its Application in Flood Frequency Analysis. II: Parameter Estimation Methods, *J. Hydrol. Eng.*, 12, 492–500, [https://doi.org/10.1061/\(ASCE\)1084-0699\(2007\)12:5\(492\)](https://doi.org/10.1061/(ASCE)1084-0699(2007)12:5(492)), 2007.
- Gumbel, E. J.: *Statistics of extremes.*, Columbia University Press, New York, 375 pp., 1958.
- Guo, L., Van Der Wegen, M., Roelvin, J. A., and He, Q.: The role of river flow and tidal asymmetry on 1-D estuarine morphodynamics, *J. Geophys. Res. Earth Surf.*, 119, 2315–2334, <https://doi.org/10.1002/2014JF003110>, 2014.
- Habert, J., Ricci, S., Le Pape, E., Thual, O., Piacentini, A., Goutal, N., Jonville, G., and Rochoux, M.: Reduction of the uncertainties in the water level–discharge relation of a 1D hydraulic model in the context of operational flood forecasting, *J. Hydrol.*, 532, 52–64, <https://doi.org/10.1016/j.jhydrol.2015.11.023>, 2016.
- Hagemeyer-Klose, M. and Wagner, K.: Evaluation of flood hazard maps in print and web mapping services as information tools in flood risk communication, *Nat. Hazards Earth Syst. Sci.*, 9, 563–574, <https://doi.org/10.5194/NHESS-9-563-2009>, 2009.
- Hallegatte, S.: Strategies to adapt to an uncertain climate change, *Glob. Environ. Chang.*, 19, 240–247, <https://doi.org/10.1016/j.gloenvcha.2008.12.003>, 2009.
- Han, J., Kamber, M., and Pei, J.: *Data Mining: Concepts and Techniques*, Elsevier Inc., <https://doi.org/10.1016/C2009-0-61819-5>, 2012.

- Hao, Z. and Singh, V. P.: Compound Events under Global Warming: A Dependence Perspective, *J. Hydrol. Eng.*, 25, 03120001, [https://doi.org/10.1061/\(ASCE\)HE.1943-5584.0001991](https://doi.org/10.1061/(ASCE)HE.1943-5584.0001991), 2020.
- Haq, M., Akhtar, M., Muhammad, S., Paras, S., and Rahmatullah, J.: Techniques of Remote Sensing and GIS for flood monitoring and damage assessment: A case study of Sindh province, Pakistan, Egypt. *J. Remote Sens. Sp. Sci.*, 15, 135–141, <https://doi.org/10.1016/J.EJRS.2012.07.002>, 2012.
- Hashimoto, H. and Park, K.: Two-dimensional urban flood simulation: Fukuoka flood disaster in 1999, *WIT Trans. Ecol. Environ.*, 118, 59–67, <https://doi.org/10.2495/FRIAR080061>, 2008.
- Herdman, L., Erikson, L., and Barnard, P.: Storm surge propagation and flooding in small tidal rivers during events of mixed coastal and fluvial influence, *J. Mar. Sci. Eng.*, 6, 158, <https://doi.org/10.3390/JMSE6040158>, 2018.
- Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., Simmons, A., Soci, C., Abdalla, S., Abellan, X., Balsamo, G., Bechtold, P., Biavati, G., Bidlot, J., Bonavita, M., Chiara, G., Dahlgren, P., Dee, D., Diamantakis, M., Dragani, R., Flemming, J., Forbes, R., Fuentes, M., Geer, A., Haimberger, L., Healy, S., Hogan, R. J., Hólm, E., Janisková, M., Keeley, S., Laloyaux, P., Lopez, P., Lupu, C., Radnoti, G., Rosnay, P., Rozum, I., Vamborg, F., Villaume, S., and Thépaut, J.: The ERA5 global reanalysis, *Q. J. R. Meteorol. Soc.*, 146, 1999–2049, <https://doi.org/10.1002/qj.3803>, 2020.
- Hidayat, H., Hoekman, D., Vissers, M., Hossain, M. M., Teuling, A., and Haryani, G.: Inundation Frequency Mapping of The Upper Kapuas Wetlands Using Radar Imagery, in: *International Conference On Ecohydrology (ICE)*, 250–257, 2014.
- Hirabayashi, Y., Mahendran, R., Koirala, S., Konoshima, L., Yamazaki, D., Watanabe, S., Kim, H., and Kanae, S.: Global flood risk under climate change, *Nat. Clim. Chang.* 2013 39, 3, 816–821, <https://doi.org/10.1038/nclimate1911>, 2013.
- Höffken, J., Vafeidis, A. T., MacPherson, L. R., and Dangendorf, S.: Effects of the Temporal Variability of Storm Surges on Coastal Flooding, *Front. Mar. Sci.*, 7, 98, <https://doi.org/10.3389/FMARS.2020.00098/BIBTEX>, 2020.
- Hooijer, A., Page, S., Jauhainen, J., Lee, W. A., Lu, X. X., Idris, A., and Anshari, G.: Subsidence and carbon loss in drained tropical peatlands, 9, 1053–1071, <https://doi.org/10.5194/bg-9-1053-2012>, 2012.
- Hornik, K., Buchta, C., and Zeileis, A.: Open-source machine learning: R meets Weka, *Comput. Stat.*, 24, 225–232, <https://doi.org/10.1007/S00180-008-0119-7>, 2008.
- Hsiao, S. C., Chiang, W. S., Jang, J. H., Wu, H. L., Lu, W. S., Chen, W. B., and

Wu, Y. T.: Flood risk influenced by the compound effect of storm surge and rainfall under climate change for low-lying coastal areas, *Sci. Total Environ.*, 764, 144439, <https://doi.org/10.1016/J.SCITOTENV.2020.144439>, 2021.

Huybrechts, N. ;, Villaret, C. ;, and Hervouet, J.-M.: Comparison between 2D and 3D modelling of sediment transport: application to the dune evolution, in: *River Flow 2010*, 887–894, 2010.

Ikeuchi, H., Hirabayashi, Y., Yamazaki, D., Muis, S., Ward, P. J., Winsemius, H. C., Verlaan, M., and Kanae, S.: Compound simulation of fluvial floods and storm surges in a global coupled river-coast flood model: Model development and its application to 2007 Cyclone Sidr in Bangladesh, *J. Adv. Model. Earth Syst.*, 9, 1847–1862, <https://doi.org/10.1002/2017MS000943>, 2017.

IPCC: Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change, edited by: Field, C. B., Barros, V., Stocker, T. F., Qin, D., Dokken, D. J., Ebi, K. L., Mastrandrea, M. D., Mach, K. J., Plattner, G.-K., Allen, S. K., Tignor, M., and Midgley, P. M., Cambridge University Press, Cambridge, UK, 2012.

Special Report on the Ocean and Cryosphere in a Changing Climate: <https://www.ipcc.ch/srocc/download/>, last access: 10 January 2022.

Islam, M. M. and Sado, K.: Flood hazard assessment in Bangladesh using NOAA AVHRR data with geographical information system, *Hydrol. Process.*, 14, 605–620, [https://doi.org/10.1002/\(SICI\)1099-1085\(20000228\)14:3<605::AID-HYP957>3.0.CO;2-L](https://doi.org/10.1002/(SICI)1099-1085(20000228)14:3<605::AID-HYP957>3.0.CO;2-L), 2000.

Iturbide, M., Fernández, J., Gutiérrez, J. M., Bedia, J., Cimadevilla, E., Díez-Sierra, J., Manzanar, R., Casanueva, A., Baño-Medina, J., Milovac, J., Herrera, S., Cofiño, A. S., San Martín, D., García-Díez, M., Hauser, M., Huard, D., and Yelekci, Ö.: Repository supporting the implementation of FAIR principles in the IPCC-WG1 Atlas. Zenodo, DOI: 10.5281/zenodo.3691645., <https://doi.org/10.5281/zenodo.5171760>, 2021.

Jackson, E. K., Roberts, W., Nelsen, B., Williams, G. P., Nelson, E. J., and Ames, D. P.: Introductory overview: Error metrics for hydrologic modelling – A review of common practices and an open source library to facilitate use and adoption, *Environ. Model. Softw.*, 119, 32–48, <https://doi.org/10.1016/j.envsoft.2019.05.001>, 2019.

Jacob, D., Kotova, L., Teichmann, C., Sobolowski, S. P., Vautard, R., Donnelly, C., Koutroulis, A. G., Grillakis, M. G., Tsanis, I. K., Damm, A., Sakalli, A., and van Vliet, M. T. H.: Climate Impacts in Europe Under +1.5°C Global Warming, *Earth's Futur.*, 6, 264–285, <https://doi.org/10.1002/2017EF000710>, 2018.

Jadmiko, S. D., Murdiyarso, D., and Faqih, A.: Climate Changes Projection for Land and Forest Fire Risk Assessment in West Kalimantan, *IOP Conf. Ser.*

Earth Environ. Sci., 58, 012030, <https://doi.org/10.1088/1755-1315/58/1/012030>, 2017.

James, G., Witten, D., Hastie, T., and Tibshirani, R.: An Introduction to Statistical Learning with Applications in R, 8th ed., Springer, New York, 2013.

Juarez Lucas, A. M. and Kibler, K. M.: Integrated Flood Management in developing countries: balancing flood risk, sustainable livelihoods, and ecosystem services, 14, 19–31, <https://doi.org/10.1080/15715124.2015.1068180>, 2015.

Kabenge, M., Elaru, J., Wang, H., and Li, F.: Characterizing flood hazard risk in data-scarce areas, using a remote sensing and GIS-based flood hazard index, Nat. Hazards, 89, 1369–1387, <https://doi.org/10.1007/S11069-017-3024-Y>, 2017.

Karamouz, M., Zahmatkesh, Z., Goharian, E., and Nazif, S.: Combined Impact of Inland and Coastal Floods: Mapping Knowledge Base for Development of Planning Strategies, J. Water Resour. Plan. Manag., 141, 04014098, [https://doi.org/10.1061/\(ASCE\)WR.1943-5452.0000497](https://doi.org/10.1061/(ASCE)WR.1943-5452.0000497), 2014.

Kästner, K.: Multi-scale monitoring and modelling of the Kapuas River Delta, Wageningen University, <https://doi.org/10.18174/468716>, 2019.

Kästner, K. and Hoitink, A. J. F.: Flow and Suspended Sediment Division at Two Highly Asymmetric Bifurcations in a River Delta: Implications for Channel Stability, J. Geophys. Res. Earth Surf., 124, 2358–2380, <https://doi.org/10.1029/2018JF004994>, 2019.

Kästner, K., Hoitink, A. J. F., Vermeulen, B., Geertsema, T. J., and Ningsih, N. S.: Distributary channels in the fluvial to tidal transition zone, J. Geophys. Res. Earth Surf., 122, 696–710, <https://doi.org/10.1002/2016JF004075>, 2017.

Kästner, K., Hoitink, A. J. F., Torfs, P. J. J. F., Vermeulen, B., Ningsih, N. S., and Pramulya, M.: Prerequisites for Accurate Monitoring of River Discharge Based on Fixed-Location Velocity Measurements, Water Resour. Res., 54, 1058–1076, <https://doi.org/10.1002/2017WR020990>, 2018.

Kästner, K., Hoitink, A. J. F., Torfs, P. J. J. F., Deleersnijder, E., and Ningsih, N. S.: Propagation of tides along a river with a sloping bed, J. Fluid Mech., 872, 39–73, <https://doi.org/10.1017/JFM.2019.331>, 2019.

Kelley, D. and Richards, C.: oce: Analysis of Oceanographic Data, <https://dankelley.github.io/oce/>, 2022.

Kereszturi, Á., Hargitai, H., and Postma, G.: Delta, Encyclopedia of Planetary Landforms, 551–560, https://doi.org/10.1007/978-1-4614-3134-3_109, 2015.

Kinney, J. B. and Atwal, G. S.: Equitability, mutual information, and the maximal information coefficient, Proc. Natl. Acad. Sci., 111, 3354–3359, <https://doi.org/10.1073/pnas.1309933111>, 2014.

- Koks, E. E., de Moel, H., Aerts, J. C. J. H., and Bouwer, L. M.: Effect of spatial adaptation measures on flood risk: Study of coastal floods in Belgium, *Reg. Environ. Chang.*, 14, 413–425, <https://doi.org/10.1007/S10113-013-0514-7/TABLES/3>, 2014.
- Krasnopolsky, V. M. and Fox-Rabinovitz, M. S.: A new synergetic paradigm in environmental numerical modeling: Hybrid models combining deterministic and machine learning components, *Ecol. Modell.*, 191, 5–18, <https://doi.org/10.1016/J.ECOLMODEL.2005.08.009>, 2006.
- Kumbier, K., Carvalho, R. C., Vafeidis, A. T., and Woodroffe, C. D.: Investigating compound flooding in an estuary using hydrodynamic modelling: A case study from the Shoalhaven River, Australia, *Nat. Hazards Earth Syst. Sci.*, 18, 463–477, <https://doi.org/10.5194/NHESS-18-463-2018>, 2018.
- Kundzewicz, Z. W., Kanae, S., Seneviratne, S. I., Handmer, J., Nicholls, N., Peduzzi, P., Mechler, R., Bouwer, L. M., Arnell, N., Mach, K., Muir-Wood, R., Brakenridge, G. R., Kron, W., Benito, G., Honda, Y., Takahashi, K., and Sherstyukov, B.: Flood risk and climate change: global and regional perspectives, *Hydrol. Sci. J.*, 59, 1–28, <https://doi.org/10.1080/02626667.2013.857411>, 2014.
- Lambrechts, J., Hanert, E., Deleersnijder, E., Bernard, P. E., Legat, V., Remacle, J. F., and Wolanski, E.: A multi-scale model of the hydrodynamics of the whole Great Barrier Reef, *Estuar. Coast. Shelf Sci.*, 79, 143–151, <https://doi.org/10.1016/J.ECSS.2008.03.016>, 2008.
- Lambrechts, J., Humphrey, C., McKinna, L., Gource, O., Fabricius, K. E., Mehta, A. J., Lewis, S., and Wolanski, E.: Importance of wave-induced bed liquefaction in the fine sediment budget of Cleveland Bay, Great Barrier Reef, *Estuar. Coast. Shelf Sci.*, 89, 154–162, <https://doi.org/10.1016/j.ecss.2010.06.009>, 2010.
- Lange, J.: IU study shows coastal flooding will disproportionately impact river deltas populations, Environmental Resilience Institute Toolkit (ERIT), 2020.
- Le, H.-A., Lambrechts, J., Ortleb, S., Gratiot, N., Deleersnijder, E., and Soares-Frazão, S.: An implicit wetting-drying algorithm for the discontinuous Galerkin method: application to the Tonle Sap, Mekong River Basin, *Environ. Fluid Mech.*, 20, 923–951, <https://doi.org/10.1007/s10652-019-09732-7>, 2020.
- Li, B., Yang, G., Wan, R., Dai, X., and Zhang, Y.: Comparison of random forests and other statistical methods for the prediction of lake water level: a case study of the Poyang Lake in China, *Hydrol. Res.*, 47, 69–83, <https://doi.org/10.2166/NH.2016.264>, 2016.
- Li, C. and Busari, A. O.: Hybrid modeling of flows over submerged prismatic vegetation with different areal densities, *Eng. Appl. Comput. Fluid Mech.*, 13, 493–505, <https://doi.org/10.1080/19942060.2019.1610501>, 2019.
- Liaw, A. and Wiener, M.: Classification and regression by randomForest, R

News, 2, 18–22, 2002.

Lilai, X., Yuanrong, H., Wei, H., and Shenghui, C.: A multi-dimensional integrated approach to assess flood risks on a coastal city, induced by sea-level rise and storm tides, *Environ. Res. Lett.*, 11, 014001, <https://doi.org/10.1088/1748-9326/11/1/014001>, 2016.

Liu, Q., Xu, H., and Wang, J.: Assessing tropical cyclone compound flood risk using hydrodynamic modelling: a case study in Haikou City, China, *Nat. Hazards Earth Syst. Sci.*, 22, 665–675, <https://doi.org/10.5194/NHESS-22-665-2022>, 2022.

MacKinnon, K., Hatta, G., Mangalik, A., and Halim, H.: *The ecology of Kalimantan*. Vol. 3, Oxford University Press., 1996.

Madrosid: *Cerita Warga, Detik-detik Banjir Rob Melanda Kota Pontianak*, Trib. Pontianak, 2018.

Marengo, J. A., Alves, L. M., Ambrizzi, T., Young, A., Barreto, N. J. C., and Ramos, A. M.: Trends in extreme rainfall and hydrogeometeorological disasters in the Metropolitan Area of São Paulo: a review, *Ann. N. Y. Acad. Sci.*, 1472, 5–20, <https://doi.org/10.1111/NYAS.14307>, 2020.

Marois, D. E. and Mitsch, W. J.: Coastal protection from tsunamis and cyclones provided by mangrove wetlands – a review, 11, 71–83, <https://doi.org/10.1080/21513732.2014.997292>, 2015.

Maskell, J., Horsburgh, K., Lewis, M., and Bates, P.: Investigating River–Surge Interaction in Idealised Estuaries, *J. Coast. Res.*, 30, 248–259, <https://doi.org/10.2112/JCOASTRES-D-12-00221.1>, 2014.

Maxwell, R. M., Condon, L. E., and Melchior, P.: A Physics-Informed, Machine Learning Emulator of a 2D Surface Water Model: What Temporal Networks and Simulation-Based Inference Can Help Us Learn about Hydrologic Processes, *Water* 2021, Vol. 13, Page 3633, 13, 3633, <https://doi.org/10.3390/W13243633>, 2021.

Ming, X., Liang, Q., Dawson, R., Xia, X., and Hou, J.: A quantitative multi-hazard risk assessment framework for compound flooding considering hazard inter-dependencies and interactions, *J. Hydrol.*, 607, 127477, <https://doi.org/10.1016/J.JHYDROL.2022.127477>, 2022.

Mirjalili, S., Faris, H., and Aljarah, I.: *Evolutionary Machine Learning Techniques*, edited by: Mirjalili, S., Faris, H., and Aljarah, I., Springer Singapore, Singapore, <https://doi.org/10.1007/978-981-32-9990-0>, 2020.

Moftakhari, H. R., AghaKouchak, A., Sanders, B. F., Feldman, D. L., Sweet, W., Matthew, R. A., and Luke, A.: Increased nuisance flooding along the coasts of the United States due to sea level rise: Past and future, *Geophys. Res. Lett.*, 42, 9846–9852, <https://doi.org/10.1002/2015GL066072>, 2015.

Moftakhari, H. R., Salvadori, G., AghaKouchak, A., Sanders, B. F., and

- Matthew, R. A.: Compounding effects of sea level rise and fluvial flooding, *Proc. Natl. Acad. Sci. U. S. A.*, 114, 9785–9790, <https://doi.org/10.1073/pnas.1620325114>, 2017.
- Mohanty, M. P. and Karmakar, S.: WebFRIS: An efficient web-based decision support tool to disseminate end-to-end risk information for flood management, *J. Environ. Manage.*, 288, 112456, <https://doi.org/10.1016/J.JENVMAN.2021.112456>, 2021.
- Mokkenstorm, L. C., van den Homberg, M. J. C., Winsemius, H., and Persson, A.: River Flood Detection Using Passive Microwave Remote Sensing in a Data-Scarce Environment: A Case Study for Two River Basins in Malawi, *Front. Earth Sci.*, 9, 552, <https://doi.org/10.3389/FEART.2021.670997/BIBTEX>, 2021.
- Monirul Qader Mirza, M.: Global warming and changes in the probability of occurrence of floods in Bangladesh and implications, *Glob. Environ. Chang.*, 12, 127–138, [https://doi.org/10.1016/S0959-3780\(02\)00002-X](https://doi.org/10.1016/S0959-3780(02)00002-X), 2002.
- Moon, I. J., Ginis, I., Hara, T., and Thomas, B.: A Physics-Based Parameterization of Air–Sea Momentum Flux at High Wind Speeds and Its Impact on Hurricane Intensity Predictions, *Mon. Weather Rev.*, 135, 2869–2878, <https://doi.org/10.1175/MWR3432.1>, 2007.
- Moriasi, D. N., Gitau, M. W., Pai, N., and Daggupati, P.: Hydrologic and Water Quality Models: Performance Measures and Evaluation Criteria, *Trans. ASABE*, 58, 1763–1785, <https://doi.org/10.13031/TRANS.58.10715>, 2015.
- Mosavi, A., Ozturk, P., and Chau, K.: Flood Prediction Using Machine Learning Models: Literature Review, *Water* 2018, Vol. 10, Page 1536, 10, 1536, <https://doi.org/10.3390/W10111536>, 2018.
- Mousavi, M. E., Irish, J. L., Frey, A. E., Olivera, F., and Edge, B. L.: Global warming and hurricanes: the potential impact of hurricane intensification and sea level rise on coastal flooding, *Clim. Chang.* 2009 1043, 104, 575–597, <https://doi.org/10.1007/S10584-009-9790-0>, 2010.
- Mukherjee, S., Mishra, A., and Trenberth, K. E.: Climate Change and Drought: a Perspective on Drought Indices, *Curr. Clim. Chang. Reports*, 4, 145–163, <https://doi.org/10.1007/s40641-018-0098-x>, 2018.
- Muñoz, D. F., Muñoz, P., Mofstakhari, H., and Moradkhani, H.: From local to regional compound flood mapping with deep learning and data fusion techniques, *Sci. Total Environ.*, 782, 146927, <https://doi.org/10.1016/J.SCITOTENV.2021.146927>, 2021.
- Muñoz, D. F., Abbaszadeh, P., Mofstakhari, H., and Moradkhani, H.: Accounting for uncertainties in compound flood hazard assessment: The value of data assimilation, *Coast. Eng.*, 171, 104057, <https://doi.org/10.1016/J.COASTALENG.2021.104057>, 2022.

- Murdukhayeva, A., August, P., Bradley, M., Labash, C., and Shaw, N.: Assessment of Inundation Risk from Sea Level Rise and Storm Surge in Northeastern Coastal National Parks, *J. Coast. Res.*, 29, 1–16, <https://doi.org/10.2112/JCOASTRES-D-12-00196.1>, 2013.
- Naqa, I. El, Ruan, D., Valdes, G., Dekker, A., McNutt, T., Ge, Y., Wu, Q. J., Oh, J. H., Thor, M., Smith, W., Rao, A., Fuller, C., Xiao, Y., Manion, F., Schipper, M., Mayo, C., Moran, J. M., and Haken, R. Ten: Machine learning and modeling: Data, validation, communication challenges, *Med. Phys.*, 45, e834–e840, <https://doi.org/10.1002/MP.12811>, 2018.
- Nayak, P. C., Sudheer, K. P., Rangan, D. M., and Ramasastri, K. S.: Short-term flood forecasting with a neurofuzzy model, *Water Resour. Res.*, 41, 1–16, <https://doi.org/10.1029/2004WR003562>, 2005.
- Néelz, S.: Desktop review of 2D hydraulic modelling packages, Bristol: Environment Agency, 2009.
- Neumann, B., Vafeidis, A. T., Zimmermann, J., and Nicholls, R. J.: Future Coastal Population Growth and Exposure to Sea-Level Rise and Coastal Flooding - A Global Assessment, *PLoS One*, 10, e0118571, <https://doi.org/10.1371/JOURNAL.PONE.0118571>, 2015.
- Ngo, H., Pathirana, A., Zevenbergen, C., and Ranasinghe, R.: An Effective Modelling Approach to Support Probabilistic Flood Forecasting in Coastal Cities—Case Study: Can Tho, Mekong Delta, Vietnam, *J. Mar. Sci. Eng.* 2018, Vol. 6, Page 55, 6, 55, <https://doi.org/10.3390/jmse6020055>, 2018.
- Nguyen, D. T. and Chen, S. T.: Real-Time Probabilistic Flood Forecasting Using Multiple Machine Learning Methods, *Water* 2020, Vol. 12, Page 787, 12, 787, <https://doi.org/10.3390/w12030787>, 2020.
- Noymanee, J. and Theeramunkong, T.: Flood Forecasting with Machine Learning Technique on Hydrological Modeling, *Procedia Comput. Sci.*, 156, 377–386, <https://doi.org/10.1016/j.procs.2019.08.214>, 2019.
- Olbert, A. I., Comer, J., Nash, S., and Hartnett, M.: High-resolution multi-scale modelling of coastal flooding due to tides, storm surges and rivers inflows. A Cork City example, *Coast. Eng.*, 121, 278–296, <https://doi.org/10.1016/j.coastaleng.2016.12.006>, 2017.
- Planet dump retrieved from <https://planet.osm.org>: <https://www.openstreetmap.org>, last access: 20 October 2020.
- Orton, P. M., Conticello, F. R., Cioffi, F., Hall, T. M., Georgas, N., Lall, U., Blumberg, A. F., and MacManus, K.: Flood hazard assessment from storm tides, rain and sea level rise for a tidal river estuary, *Nat. Hazards*, 102, 729–757, <https://doi.org/10.1007/S11069-018-3251-X/FIGURES/13>, 2020.
- Orton, G.J. and Reading, H.G.: Variability of deltaic processes in terms of sediment supply, with particular emphasis on grain size. *Sedimentology*, 40(3),

pp.475-512, 1993.

Padmalal, D. and Maya, K.: Impacts of River Sand Mining, *Environ. Sci. Eng. (Subseries Environ. Sci.)*, 31–56, https://doi.org/10.1007/978-94-017-9144-1_4, 2014.

Paprotny, D., Voudoukas, M. I., Morales-Nápoles, O., Jonkman, S. N., and Feyen, L.: Pan-European hydrodynamic models and their ability to identify compound floods, *Nat. Hazards*, 101, 933–957, <https://doi.org/10.1007/S11069-020-03902-3/FIGURES/8>, 2020.

Parker, B. B.: *Tidal hydrodynamics*, J. Wiley, New York, 883 pp., 1991.

Patel, D. P., Ramirez, J. A., Srivastava, P. K., Bray, M., and Han, D.: Assessment of flood inundation mapping of Surat city by coupled 1D/2D hydrodynamic modeling: a case application of the new HEC-RAS 5, *Nat. Hazards*, 89, 93–130, <https://doi.org/10.1007/s11069-017-2956-6>, 2017.

Pauta, D. F. M.: *Tidal influence on the discharge distribution at two junctions of the Kapuas River (West Kalimantan, Indonesia)*, 2018.

Kondisi Geografis Kota Pontianak:

<https://www.pontianakkota.go.id/tentang/geografis>, last access: 5 April 2021.

Pemerintah Kota Pontianak: *Data Jumlah Penanganan Bencana yang Telah Dilakukan Tahun 2019*, Pontianak, 2019.

Perera, D., Seidou, O., Agnihotri, J., Wahid, A., and Rasmy, M.: Flood Early Warning Systems: A Review Of Benefits, Challenges And Prospects
Hydrodynamic Modelling of Large Floodplain: A case study of the Inner Niger Delta, Mali, West Africa View project Water Resources Management in Central Asia View project, <https://doi.org/10.13140/RG.2.2.28339.78880>, 2019.

Pervin, I. A., Rahman, S. M. M., Nepal, M., Haque, A. K. E., Karim, H., and Dhakal, G.: Adapting to urban flooding: a case of two cities in South Asia, 22, 162–188, <https://doi.org/10.2166/WP.2019.174>, 2020.

Pham Van, C., de Brye, B., Deleersnijder, E., F Hoitink, A. J., Sassi, M., Spinewine, B., Hidayat, H., and Soares-Frazão, S.: Simulations of the flow in the Mahakam river-lake-delta system, Indonesia, *Environ. Fluid Mech.*, 16, 603–633, <https://doi.org/10.1007/s10652-016-9445-4>, 2016.

Pugh, D. and Woodworth, P.: *Sea-level science: Understanding tides, surges, tsunamis and mean sea-level changes*, Cambridge University Press, <https://doi.org/10.1017/CBO9781139235778>, 2014.

Online Tide Prediction / Prediksi Pasang Surut (Pasut) Online:

<http://tides.big.go.id/pasut/index.html>, last access: 5 April 2021.

Remacle, J. F. and Lambrechts, J.: Fast and Robust Mesh Generation on the Sphere-Application to Coastal Domains, in: *Procedia Engineering*, 20–32, <https://doi.org/10.1016/j.proeng.2016.11.011>, 2016.

Remacle, J. F. and Lambrechts, J.: Fast and robust mesh generation on the sphere—Application to coastal domains, *CAD Comput. Aided Des.*, 103, 14–23, <https://doi.org/10.1016/j.cad.2018.03.002>, 2018.

Psych: Procedures for Psychological, Psychometric, and Personality Research: <https://cran.r-project.org/package=psych>, last access: 16 December 2021.

Ridha, T., Ross, A. D., and Mostafavi, A.: Climate change impacts on infrastructure: Flood risk perceptions and evaluations of water systems in coastal urban areas, *Int. J. Disaster Risk Reduct.*, 73, 102883, <https://doi.org/10.1016/j.ijdrr.2022.102883>, 2022.

Van Rijn, L. C.: Analytical and numerical analysis of tides and salinities in estuaries; Part I: Tidal wave propagation in convergent estuaries, *Ocean Dyn.*, 61, 1719–1741, <https://doi.org/10.1007/S10236-011-0453-0>, 2011.

Ross, B. C.: Mutual Information between Discrete and Continuous Data Sets, *PLoS One*, 9, e87357, <https://doi.org/10.1371/journal.pone.0087357>, 2014.

Ruslan, F. A., Samad, A. M., Zain, Z. M., and Adnan, R.: Flood water level modeling and prediction using NARX neural network: Case study at Kelang river, *Proc. - 2014 IEEE 10th Int. Colloq. Signal Process. Its Appl. CSPA 2014*, 204–207, <https://doi.org/10.1109/CSPA.2014.6805748>, 2014.

Saito, N.: Challenges for adapting Bangkok’s flood management systems to climate change, *Urban Clim.*, 9, 89–100, <https://doi.org/10.1016/J.UCLIM.2014.07.006>, 2014.

Sampurno, J., Vallaeys, V., Ardianto, R., and Hanert, E.: Modeling interactions between tides, storm surges, and river discharges in the Kapuas River delta, 19, 2741–2757, <https://doi.org/10.5194/bg-19-2741-2022>, 2022.

Sanchez, P. A., Ahamed, S., Carré, F., Hartemink, A. E., Hempel, J., Huising, J., Lagacherie, P., McBratney, A. B., McKenzie, N. J., De Lourdes Mendonça-Santos, M., Minasny, B., Montanarella, L., Okoth, P., Palm, C. A., Sachs, J. D., Shepherd, K. D., Vågen, T. G., Vanlauwe, B., Walsh, M. G., Winowiecki, L. A., and Zhang, G. L.: Digital soil map of the world, *Science (80-.)*, 325, 680–681, 2009.

Van de Sande, B., Lansen, J., and Hoyng, C.: Sensitivity of Coastal Flood Risk Assessments to Digital Elevation Models, *Water* 2012, Vol. 4, Pages 568–579, 4, 568–579, <https://doi.org/10.3390/w4030568>, 2012.

Santamaria-Aguilar, S. and Vafeidis, A. T.: Are Extreme Skew Surges Independent of High Water Levels in a Mixed Semidiurnal Tidal Regime?, *J. Geophys. Res. Ocean.*, 123, 8877–8886, <https://doi.org/10.1029/2018JC014282>, 2018.

Santiago-Collazo, F. L., Bilskie, M. V., and Hagen, S. C.: A comprehensive review of compound inundation models in low-gradient coastal watersheds, *Environ. Model. Softw.*, 119, 166–181,

<https://doi.org/10.1016/J.ENVSOFT.2019.06.002>, 2019.

Santiago-Collazo, F. L., Bilskie, M. V., Bacopoulos, P., and Hagen, S. C.: An Examination of Compound Flood Hazard Zones for Past, Present, and Future Low-Gradient Coastal Land-Margins, *Front. Clim.*, 3, 76, <https://doi.org/10.3389/FCLIM.2021.684035/BIBTEX>, 2021.

Seager, R., Naik, N., and Vogel, L.: Does Global Warming Cause Intensified Interannual Hydroclimate Variability?, *J. Clim.*, 25, 3355–3372, <https://doi.org/10.1175/JCLI-D-11-00363.1>, 2012.

Sekovski, I., Newton, A., and Dennison, W. C.: Megacities in the coastal zone: Using a driver-pressure-state-impact-response framework to address complex environmental problems, *Estuar. Coast. Shelf Sci.*, 96, 48–59, <https://doi.org/10.1016/J.ECSS.2011.07.011>, 2012.

Semedi, P.: Palm Oil Wealth and Rumour Panics in West Kalimantan, *Forum Dev. Stud.*, 41, 233–252, <https://doi.org/10.1080/08039410.2014.901240>, 2014.

Serafin, K. A., Ruggiero, P., Parker, K., and Hill, D. F.: What's streamflow got to do with it? A probabilistic simulation of the competing oceanographic and fluvial processes driving extreme along-river water levels, *Nat. Hazards Earth Syst. Sci.*, 19, 1415–1431, <https://doi.org/10.5194/NHESS-19-1415-2019>, 2019.

Shen, Y., Morsy, M. M., Huxley, C., Tahvildari, N., and Goodall, J. L.: Flood risk assessment and increased resilience for coastal urban watersheds under the combined impact of storm tide and heavy rainfall, *J. Hydrol.*, 579, 124159, <https://doi.org/10.1016/J.JHYDROL.2019.124159>, 2019.

Singh, R. K., Soni, A., Kumar, S., Pasupuleti, S., and Govind, V.: Zonation of flood prone areas by an integrated framework of a hydrodynamic model and ANN, 21, 80–97, <https://doi.org/10.2166/WS.2020.252>, 2021.

Smith, S. D. and Banke, E. G.: Variation of the sea surface drag coefficient with wind speed, *Q. J. R. Meteorol. Soc.*, 101, 665–673, <https://doi.org/10.1002/QJ.49710142920>, 1975.

Soeryamassoeka, S. B., Triweko, R. W., Yudianto, D., and Kartini: Challenges of integrated water resources management in kapuas river basin, in: *Proceedings of the 21st IAHR-APD Congress 2018*, 2018.

Spicer, P., Huguenard, K., Ross, L., and Rickard, L. N.: High-Frequency Tide-Surge-River Interaction in Estuaries: Causes and Implications for Coastal Flooding, *J. Geophys. Res. Ocean.*, 124, 9517–9530, <https://doi.org/10.1029/2019JC015466>, 2019.

Stott, P.: How climate change affects extreme weather events: Research can increasingly determine the contribution of climate change to extreme events such as droughts, *Science* (80-.), 352, 1517–1518, 2016.

Takagi, H., Esteban, M., Mikami, T., and Fujii, D.: Projection of coastal floods in 2050 Jakarta, *Urban Clim.*, 17, 135–145, <https://doi.org/10.1016/J.UCLIM.2016.05.003>, 2016.

The Associated Programme on Flood Management: Risk Sharing in Flood Management, Geneva-Switzerland, 2013.

Tkalich, P., Vethamony, P., Babu, M.T. and Malanotte-Rizzoli, P.: Storm surges in the Singapore Strait due to winds in the South China Sea. *Natural hazards*, 66(3), pp.1345-1362, 2013.

Tucci, C. E. M. and Villanueva, A. O. N.: Flood control measures in União da Vitoria and Porto União: structural vs. non-structural measures, 1, 177–182, [https://doi.org/10.1016/S1462-0758\(00\)00012-1](https://doi.org/10.1016/S1462-0758(00)00012-1), 1999.

Twilley, R. R., Bentley, S. J., Chen, Q., Edmonds, D. A., Hagen, S. C., Lam, N. S. N., Willson, C. S., Xu, K., Braud, D. W., Hampton Peele, R., and McCall, A.: Co-evolution of wetland landscapes, flooding, and human settlement in the Mississippi River Delta Plain, *Sustain. Sci.*, 11, 711–731, <https://doi.org/10.1007/s11625-016-0374-4>, 2016.

HEC-RAS: <https://www.hec.usace.army.mil/software/hec-ras/>, last access: 8 January 2022.

UNDRR.ORG: Structural and non-structural measures, Sendai Framework-Sustainable Development Goals, 2022.

Vallaes, V., Kärnä, T., Delandmeter, P., Lambrechts, J., Baptista, A. M., Deleersnijder, E., and Hanert, E.: Discontinuous Galerkin modeling of the Columbia River's coupled estuary-plume dynamics, *Ocean Model.*, 124, 111–124, <https://doi.org/10.1016/j.ocemod.2018.02.004>, 2018.

Vitousek, S., Barnard, P. L., Fletcher, C. H., Frazer, N., Erikson, L., and Storlazzi, C. D.: Doubling of coastal flooding frequency within decades due to sea-level rise, *Sci. Rep.*, 7, 1–9, <https://doi.org/10.1038/s41598-017-01362-7>, 2017.

Vousdoukas, M. I., Voukouvalas, E., Mentaschi, L., Dottori, F., Giardino, A., Bouziotas, D., Bianchi, A., Salamon, P., and Feyen, L.: Developments in large-scale coastal flood hazard mapping, *Nat. Hazards Earth Syst. Sci.*, 16, 1841–1853, <https://doi.org/10.5194/NHESS-16-1841-2016>, 2016.

Vu, T. T. and Ranzi, R.: Flood risk assessment and coping capacity of floods in central Vietnam, *J. Hydro-Environment Res.*, 14, 44–60, <https://doi.org/10.1016/j.jher.2016.06.001>, 2017.

Wahl, T., Jain, S., Bender, J., Meyers, S. D., and Luther, M. E.: Increasing risk of compound flooding from storm surge and rainfall for major US cities, *Nat. Clim. Chang.* 2015 512, 5, 1093–1097, <https://doi.org/10.1038/nclimate2736>, 2015.

Wahyu, A., Kuntoro, A., and Yamashita, T.: Annual and Seasonal Discharge

Responses to Forest/Land Cover Changes and Climate Variations in Kapuas River Basin, Indonesia, *J. Int. Dev. Coop.*, 16, 81–100, <https://doi.org/10.15027/29807>, 2010.

van de Wal, R. S. W., Zhang, X., Minobe, S., Jevrejeva, S., Riva, R. E. M., Little, C., Richter, K., and Palmer, M. D.: Uncertainties in Long-Term Twenty-First Century Process-Based Coastal Sea-Level Projections, *Surv. Geophys.* 2019 406, 40, 1655–1671, <https://doi.org/10.1007/S10712-019-09575-3>, 2019.

Wang, L. and Liu, H.: An efficient method for identifying and filling surface depressions in digital elevation models for hydrologic analysis and modelling, 20, 193–213, <https://doi.org/10.1080/13658810500433453>, 2007.

Wang, Q. and Wang, S.: Machine Learning-Based Water Level Prediction in Lake Erie, *Water* 2020, Vol. 12, Page 2654, 12, 2654, <https://doi.org/10.3390/W12102654>, 2020.

Ward, P. J., Couasnon, A., Eilander, D., Haigh, I. D., Hendry, A., Muis, S., Veldkamp, T. I. E., Winsemius, H. C., and Wahl, T.: Dependence between high sea-level and high river discharge increases flood hazard in global deltas and estuaries, *Environ. Res. Lett.*, 13, 084012, <https://doi.org/10.1088/1748-9326/AAD400>, 2018.

Webb, P.: *Introduction to Oceanography*, Simple Book Publishing, 2021.

Wells, J. A., Wilson, K. A., Abram, N. K., Nunn, M., Gaveau, D. L. A., Runting, R. K., Tarniati, N., Mengersen, K. L., and Meijaard, E.: Rising floodwaters: Mapping impacts and perceptions of flooding in Indonesian Borneo, <https://doi.org/10.1088/1748-9326/11/6/064016>, 20 June 2016.

Coastal Flooding Forecast Strengthened in Indonesia | World Meteorological Organization: <https://public.wmo.int/en/media/news/coastal-flooding-forecast-strengthened-indonesia>, last access: 3 April 2021.

Wu, H., Adler, R. F., Tian, Y., Huffman, G. J., Li, H., and Wang, J.: Real-time global flood estimation using satellite-based precipitation and a coupled land surface and routing model, *Water Resour. Res.*, 50, 2693–2717, <https://doi.org/10.1002/2013WR014710>, 2014.

Xu, R., Frank, K. A., Maroulis, S. J., and Rosenberg, J. M.: konfound: Command to quantify robustness of causal inferences., *Stata J.*, 19, 523–550, <https://doi.org/10.1177/1536867X19874223>, 2019.

Xu, Z. X. and Li, J. Y.: Short-term inflow forecasting using an artificial neural network model, *Hydrol. Process.*, 16, 2423–2439, <https://doi.org/10.1002/HYP.1013>, 2002.

Ye, F., Zhang, Y. J., Yu, H., Sun, W., Moghimi, S., Myers, E., Nunez, K., Zhang, R., Wang, H. V., Roland, A., Martins, K., Bertin, X., Du, J., and Liu, Z.: Simulating storm surge and compound flooding events with a creek-to-ocean model: Importance of baroclinic effects, *Ocean Model.*, 145, 101526,

<https://doi.org/10.1016/J.OCEMOD.2019.101526>, 2020.

Ye, F., Huang, W., Zhang, Y. J., Moghimi, S., Myers, E., Pe'eri, S., and Yu, H. C.: A cross-scale study for compound flooding processes during Hurricane Florence, *Nat. Hazards Earth Syst. Sci.*, 21, 1703–1719, <https://doi.org/10.5194/NHESS-21-1703-2021>, 2021.

Yunus, A. P., Avtar, R., Kraines, S., Yamamuro, M., Lindberg, F., and Grimmond, C. S. B.: Uncertainties in Tidally Adjusted Estimates of Sea Level Rise Flooding (Bathtub Model) for the Greater London, *Remote Sens.* 2016, Vol. 8, Page 366, 8, 366, <https://doi.org/10.3390/rs8050366>, 2016.

Zambrano-Bigiarini, M.: Goodness-of-Fit Functions for Comparison of Simulated and Observed Hydrological Time Series [R package hydroGOF version 0.4-0], 2020.

Zhang, J. and Liu, H.: Modeling of waves overtopping and flooding in the coastal reach by a non-hydrostatic model, in: *Procedia IUTAM*, 126–130, <https://doi.org/10.1016/j.piutam.2017.09.019>, 2017.

Zhang, Y., Chiew, F. H. S., Li, M., and Post, D.: Predicting Runoff Signatures Using Regression and Hydrological Modeling Approaches, *Water Resour. Res.*, 54, 7859–7878, <https://doi.org/10.1029/2018WR023325>, 2018.

Zhong, L. and Li, M.: Tidal energy fluxes and dissipation in the Chesapeake Bay, *Cont. Shelf Res.*, 26, 752–770, <https://doi.org/10.1016/J.CSR.2006.02.006>, 2006.

Zijl, F., Verlaan, M., and Gerritsen, H.: Improved water-level forecasting for the Northwest European Shelf and North Sea through direct modelling of tide, surge and non-linear interaction, *Ocean Dyn.*, 63, 823–847, <https://doi.org/10.1007/s10236-013-0624-2>, 2013.