Assessing and communicating erosion risk
An interdisciplinary case study in Bangladesh and the USA

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Assessing and communicating erosion risk
An interdisciplinary case study in Bangladesh and the USA

Master Thesis for the MSc Science, Technology and Policy

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Abstract

Climate change will increase the frequency and intensity of many natural hazards such as storms or fires. Governments and public officials have the duty to protect their citizens and to prevent these hazards from turning into disasters. To do so effectively, they first need a scientific assessment of the disaster risk, which they communicate to affected people in the second step. This thesis examined both steps, by assessing past events of riverbank erosion in Bangladesh using radar imagery, and by investigating how the resulting disaster risk information could aid in risk communication. I could show that analyzing radar imagery on the Google Earth Engine (GEE) can assess riverbank erosion shortly after the end of the monsoon, and hence earlier than it would be possible with optical imagery. I developed an interactive online tool allowing the user to explore where riverbank erosion has occurred along Jamuna River in the last five monsoon seasons (2015-2019). Further, the source code of this tool is made publicly available, providing an option to apply the algorithm in other geographical settings. This can be attractive for authorities in low resource settings, given that the GEE can be used free of charge. In the second part of this study, I conducted an online experiment in seven coastal US states to investigate how aerial photographs containing information on past events of coastal erosion can help to decrease framing effects inherent in disaster risk communication. I found no framing effects in a risky choice situation and a goal framing setup, casting doubt on the strength of framing effects in real world scenarios. Adding the aerial photographs to the textual description of the scenario made respondents more risk seeking and increased their stated behavioral intention to take preventive measures against coastal erosion. The overall awareness among respondents about the issue of coastal erosion was high, resulting in few risky choices and high levels of stated behavioral intentions. Further research is required on the nature of framing effects in more realistic scenarios and on how people read and interpret aerial photographs containing information on past disaster events. In addition, I will test the findings from the online survey in a large scale household survey in Bangladesh.
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<td>Bangladesh Water Development Board</td>
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<td>CBDRM</td>
<td>Community-based disaster risk management</td>
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<tr>
<td>CEGIS</td>
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<td>Synthetic Aperture Radar</td>
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<td>Strip Map</td>
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<td>VV</td>
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1 Introduction

In May 2020, the world holds its breath as it watches super cyclone Amphan approach the coast of Bangladesh and West Bengal in India, home to millions of people, amidst the global coronavirus pandemic. Amphan was the most powerful cyclone ever to form in the Bay of Bengal and even though it weakened before making landfall, it caused severe damages in both countries (Sud and Rajaram 2020). Shortly after the landfall, the Indian government estimated that Amphan caused at least $13 billion in damages in West Bengal alone (Sud and Rajaram 2020). While cyclones are not unusual in this region, their intensity and frequency has increased over the last decades (Wang et al. 2013). Partly, this increase can be attributed to rising sea surface temperature, which is a consequence of regional climate warming (Zhao et al. 2020).

Amphan illustrates that the debate around climate change should be shifted from its long-term, far-future effects to its impact on the climate of the present and the near future. Attribution studies are getting progressively more capable of estimating the extent to which single events (like cyclone Amphan) or weather extremes (like heat waves) are related to anthropogenic climate change (Bindoff et al. 2013). Additional climate related events that have gained a lot of media attention include the 2018 European heat wave and the 2019/20 Australian wildfires. In general, climate change will affect the intensity, duration and frequency of many atmospheric, hydrologic, geologic and biologic hazards1 (IPCC 2014, 2018; Faulkner and Ball 2007).

All these environmental hazards have in common that they impose a significant risk of material damage and human harm on affected societies. At the same time, governments have an economic interest and a humanitarian duty to prevent these hazards from turning into disasters2. To this end, disaster risk management is a systematic approach to identifying, assessing and reducing the risks of disasters. It operates on four stages: prevention and mitigation (avoiding or limiting adverse impacts of hazards), preparedness (knowledge and capacities to effectively anticipate, respond to and recover from the impacts of hazards), response (emergency services during or immediately after a disaster) and recovery (restoration of disaster-affected communities) (all definitions adapted from UN 2009).

For disaster risk management to be effective, communication between authorities and the public about natural hazards is imperative and hence it occurs at all four stages. However, the purpose of this communication varies from stage to stage, and it is especially different between stages one/two, which comprise the time period before the disaster strikes, and stages three/four, which cover the time during or after the disaster occurs. This thesis focuses on the first two stages, namely prevention/mitigation and preparedness to reduce the impacts of a natural hazard.

To effectively communicate the disaster risk before it materializes, warning systems are usually employed fulfilling two basic functions: assessment and dissemination. Assessment involves the formulation of a scientific forecast3 based on monitoring and/or modelling systems. Based on this forecast, a risk message is

1 A hazard is „a dangerous phenomenon, substance, human activity or condition that may cause loss of life, injury or other health impacts, property damage, loss of livelihoods and services, social and economic disruption, or environmental damage” (UN 2009).

2 A disaster is „a serious disruption of the functioning of a community or a society involving widespread human, material, economic or environmental losses and impacts, which exceeds the ability of the affected community or society to cope using its own resources” (UN 2009).

3 A forecast is „a definite statement or statistical estimate of the likely occurrence of a future event or conditions for a specific area” (UN 2009).
developed. Dissemination refers to actually communicating this risk message to the intended audience, either by the authorities directly or through the media (Nigg 1995).

The scientific assessment of disaster risk information, however, can be challenging, especially in resource-poor countries in the Global South: Both modelling and monitoring environmental changes are costly and/or require trained personnel, which might not be readily available. Consequently, forecasts might not be available at all or not early enough to warrant that the necessary/appropriate action is taken. Even if a forecast is available, it is of little value if it fails to specify the time, location, extent and probability of the anticipated event with sufficiently high precision.

Furthermore, even when a high-quality forecast is available early enough, its communication to the respective recipients poses additional challenges. Successful communication depends, among others, on the communication mode (e.g. text versus map) and on specific design features (e.g. cartographic design for the case of maps). In addition, recipients exhibit different biases in the way they perceive risk information (e.g. gain versus loss framing, relative versus absolute numbers). Further complexity is introduced when the message recipients are poorly educated as it is often the case in the Global South.

Summing up, both assessment and dissemination of disaster risk information are particularly demanding in countries with low resources and an overall low education level. This thesis addresses both challenges for the specific case study of riverbank erosion in Bangladesh (presented in more detail in the next chapter) by asking the following research questions:

1) How can the scientific assessment of riverbank erosion in Bangladesh be improved?
2) How can the scientifically obtained disaster risk information be utilized effectively in risk communication?

To address the first question, I examined whether radar satellite imagery can be used to assess the locations of riverbank erosion in the last monsoon season shortly after the end of the monsoon. Such information might be valuable to predict where erosion will most likely occur in the following monsoon season, and to warn potentially affected residents accordingly. I found that with radar data, erosion locations can be determined already one month after the end of the monsoon season, and hence earlier than using optical satellite images which depend on cloud free conditions. Further, I developed an interactive online tool allowing the user to explore where land and settlement has eroded in the monsoon seasons 2014/15 to 2019/20.

Turning to the second research question, I studied how the aerial photographs containing information on past erosion events, which I developed in the first part, could be useful to communicate erosion risk. Since I was not able to carry out a survey in Bangladesh due to constraints in time and money, I conducted an online survey experiment in the USA. I chose the USA since they are heavily affected by coastal erosion, which resembles riverbank erosion in many aspects. Specifically, I examined whether such aerial photographs can reduce framing effects inherent in disaster risk communication. However, I did not find framing effects in my experiment. Therefore, I could not formally test whether adding photographs reduces framing biases. However, I found that respondents who saw the photographs were both more risk seeking and more willing to take preventive measures than those who saw only a text, but no photograph.

The remainder of this thesis is structured as follows. Chapter 2 introduces the case study of riverbank erosion in Bangladesh. Chapter 3 presents the methodology and results of improving the monitoring of erosion using radar satellite imagery. Chapter 4 outlines how the resulting information about past erosion events could be used to improve disaster risk communication. Lastly, chapter 5 concludes the overall thesis.
2 The Case: Riverbank erosion in Bangladesh

Due to its topography and its location in one of the largest river deltas of the world, Bangladesh is among the countries most susceptible to the adverse effects of climate change (Kumari Rigaud et al. 2018). Already today, it is affected heavily by rising sea levels, increasing frequency of cyclones, and changing rainfall patterns (e.g. Sarker et al. 2012). Riverbank erosion is among the most drastic environmental processes in terms of yearly damage: Around 20 out of 64 districts in Bangladesh are prone to riverbank erosion, which consumes around 8.700 ha of land each year, affecting around 200.000 people (Alam 2017). Erosion has three main negative impacts: destruction of farmable land, housing, and infrastructure (e.g. streets, schools).

Riverbank erosion occurs in two distinct, but connected forms (Grove et al. 2013): First, the flow of water continuously removes small amounts of sediment from the riverbank (termed “gradual erosion”). Second, if large patches of land become unstable, “mass wasting” can occur whereby several hundred square meters of land can collapse into the river within short time. This mainly happens during the rainy monsoon season typically from June to October, when flooding increases the weight of the soil up to a point where it can no longer sustain itself.

In Bangladesh, mass wasting occurs primarily in a limited number of hotspot areas along the three major streams, Jamuna, Ganges and Meghna. Jamuna River is one of the largest braided river systems in the world, at a width of around 12 km. Since the 1970s, its bank line has shifted by around 20 km inland, continuously eroding the riverbank and creating new land (mainly in the form of islands).

Each year, the Bangladesh Water Development Board (BWDB) commissions an erosion prediction based on optical satellite imagery (e.g. CEGIS 2018). Based on this prediction, BWDB warns communities in the predicted hotspot areas. This warning happens, however, only a few weeks before the beginning of the monsoon season, that is in May, as the satellite images required for the forecast are only available in January each year. There is, thus, a need to improve the erosion prediction such that it is available earlier, which would give communities along the rivers more time to prepare.

Besides Bangladesh, riverbank erosion occurs along various major rivers worldwide (e.g. Mekong River, Yellow River, Mississippi River or Danube River). The findings of this study are thus relevant beyond the specific case study of Bangladesh.
3 Improving assessment of riverbank erosion with radar imagery

3.1 Literature review

In general, two distinct approaches exist to assess riverbank erosion quantitatively. First, the river system can be simulated using morphological numerical models. While such models were already developed in the 1980s and 1990s (e.g. Darby and Thorne 1996), their capacities increased significantly with the development of more powerful computers in the 2000s (Williams et al. 2016; Langendoen and Simon 2008; Luppi et al. 2009). Computing power is necessary since fluvial systems are highly complex due to the large number of processes, scales and dimensions involved. Darby et al. (2007), for instance, developed a numerical model to simulate the coupled effects of fluvial erosion and bank failure. Their study models one specific site for one specific event, and even within this limited scope, a significant number of input parameters is required (e.g. erodibility, hydraulic conductivity, soil water characteristic curve). Recently, models have also been applied to longer stretches and timespans, for example by Deng et al. (2019) for a 150 km reach of the Yangtze River for one hydrological year. In contrast to the meandering nature of the Yangtze, the Jamuna River is, however, braided into a large number of channels covering a total width of 12 kilometers. Applying a numerical model to the entire Jamuna River would thus be extremely difficult, if not impossible.

The second approach to assess erosion is remote sensing. Remote sensing can be defined “as the measurement of object properties on the earth’s surface using data acquired from aircraft and satellites” (Schowengerdt 2007). The data acquired is typically electromagnetic radiation, which can be registered by passive or active sensors. Passive sensors capture radiation that is emitted or reflected from an object, most commonly sunlight. Therefore, these systems are often called optical sensors (although there exist also active optical systems).

Passive optical systems are widely used and serve a variety of purposes. One important application is the classification of land cover, such as human settlements (Trianni et al. 2014), water bodies (Du et al. 2016; Rishikeshan and Ramesh 2018), river channels (Donovan et al. 2019) or crop and tree species (Immitzer et al. 2016). A second field of application is the monitoring of earth system processes. For example, optical images have been used to quantify and map riverbank erosion and accretion along the Ganges (Hossain et al. 2013), the Yellow River (Chu et al. 2006), the Mekong (Kummu et al. 2008) and the Jamuna and Padma River in Bangladesh (Islam 2009). Lastly, they can also help to generate hazard and risk maps, for instance, for landslide hazard in New Zealand (Joyce et al. 2009) or flooding risk in Egypt (El-Behaedi and Ghoneim 2018).

Their reliance on receiving reflected sunlight from the earth’s surface leads, however, to a significant drawback: Passive optical systems cannot generate data at night or under cloudy conditions. While the former is problematic mainly for rapidly occurring events such as floods or storms, the latter can affect any application since clouds can potentially occur anywhere at any time. For land cover classification or monitoring of slowly occurring phenomena such as glacier movement or land cover change, cloud coverage of individual images can usually be compensated by information from cloud free images obtained at earlier or later times. Yet, this strategy does not work if cloud coverage is continuous for a prolonged period. This is the case in Bangladesh, where cloud coverage is high during the monsoon season lasting for months.

Active microwave sensors, by contrast, are not limited to cloud free daylight conditions to collect data. They emit a signal themselves and measure the radiation that is reflected from the target. The two most common active systems are lidar and radar. While lidar emits ultraviolet, visible or infrared light, radar uses radio waves,
which have a longer wavelength. Today, the most important imaging radar technology used in remote sensing applications is Synthetic Aperture Radar (SAR) which provides high-resolution two-dimensional images independent from daylight, cloud coverage and weather conditions (Moreira et al. 2013).

In radar images, each pixel contains a complex number corresponding to an amplitude and a phase value. The amplitude value corresponds to the reflectivity of an area, such that targets with high backscatter appear as bright spots in the radar image and flat smooth surfaces as dark (Moreira et al. 2013). As such, amplitude values can for instance be used to classify land cover. The phase value, by contrast, contains information on the distance between the sensor and the ground, accurate to a small fraction of the radar wavelength. One powerful technique employing the phase value is SAR interferometry which compares for one scene the phase of two or more radar images acquired from different positions or at different times (Moreira et al. 2013). This enables interferometry to measure geophysical parameters such as surface topography or ground deformation and subsidence at high precision, with centi- or even millimetric accuracy. SAR interferometry could thus help to monitor erosion processes and provide input data for a (model-based) prediction of such processes.

Similar to optical systems, radar systems are employed in a wide range of applications. Examples include the extraction of shorelines (Al Fugura et al. 2011) and rivers (Sghaier et al. 2017) or land cover classification (Cable et al. 2014). On the topic of natural disasters, extensive research has investigated the use of radar for mapping the extent and depth of floods, for instance in the Amazon (Martinez and Le Toan 2007), the US (Townsend 2001), Taiwan (Chung et al. 2015) as well as for monsoon flooding in Bangladesh (Imhoff et al. 1987). Further, several studies used SAR data for fully automated flood detection to provide near-real time disaster information (Martinis et al. 2009; Martinis et al. 2015; Twele et al. 2016).

3.2 Scope and objective

To the best of my knowledge, no studies have employed radar imagery to assess riverbank erosion. Therefore, this thesis addresses the following research questions:

Is it possible to extract high-quality information on (specific) locations and the extent of past riverbank erosion events along the Jamuna River from radar imagery, where quality is assessed against the baseline of optical images?

If yes, how soon after the monsoon is this information available? At which spatial resolution?

A free and thus very attractive platform for analyzing remote sensing data is the Google Earth Engine (GEE). The GEE is a cloud-based platform providing access to a wide range of publicly available remote sensing data in connection with Google’s massive cloud computing resources (Gorelick et al. 2017). The platform can be accessed free of charge by scientists, practitioners, and other non-commercial users. Since its introduction in 2017, the GEE has been used for many remote sensing based (research) projects including applications close to the topical focus of this thesis (e.g. mapping floods (Liu et al. 2018) or wetland dynamics (Muro et al. 2019)) or geographic focus of this work (e.g. monitoring rice growth in West Bengal (Mandal et al. 2018) or Bangladesh (Singha et al. 2019)).

There are two main characteristics that make the GEE an appealing tool. First, it gives simple access to a vast amount of remote sensing data which do not have to be downloaded locally, but are processed in the cloud. Second, the GEE facilitates the combination of optical and SAR data, which generally yields an improved performance compared to using any of the two alone. Examples using both data types include land cover classification (Carrasco et al. 2019; Miettinen et al. 2019; Poortinga et al. 2019; Zhang et al. 2018), change
detection (Canty and Nielsen 2017; Celik 2018; Shimizu et al. 2019) and the derivation of river discharge for the Upper Brahmaputra River (Huang et al. 2018).

For the specific context of this study, it is further attractive that the GEE is relatively easy to use and that it does not require special software. Therefore, it can be applied in operational settings with limited resources, be it in terms of finances or trained personnel. Moreover, GEE code can be shared conveniently via one link. The algorithm developed in this study could thus be easily accessed and adapted by research institutes or government authorities in Bangladesh in case they are interested in using it.

For all these advantages, this study used the GEE as a tool to develop a technique to extract information on riverbank erosion from radar imagery. Due to its computing architecture, the GEE can process only the amplitude, but not the phase information of radar images. Therefore, the method presented subsequently works with backscatter coefficients only. In the future, it is intended to extend the analysis to interferometric techniques using the phase value as well.

3.3 Methods

3.3.1 Data and pre-processing

This study used publicly available satellite imagery from the European Space Agency’s (ESA) Sentinel mission (for more details see ESA 2020b). We obtained radar images from ESA’s Sentinel-1 mission launched in 2014, which collects C-band SAR images of the entire earth’s surface with a 6 day revisit cycle. Sentinel-1 has the objectives of monitoring land cover and climate change as well as emergency mapping support for natural disasters (ESA 2020b). Optical images were obtained from ESA’s Sentinel-2 mission launched in 2015, which has a revisit time of two to three days at mid-latitudes and has the purpose of monitoring variability in land surface conditions (ESA 2020c).

The Sentinel-1 SAR data used in this study was accessed through the GEE. The level-1 ground-range detected (GRD) scenes available in the GEE have already been pre-processed by the GEE following the steps from the Sentinel-1 toolbox (Veci et al. 2014; Google Developers 2020):

1) Application of orbit file (updates orbit metadata with restituted orbit file)
2) GRD border noise removal (removes low intensity noise and invalid data on scene edges)
3) Thermal noise removal (removes additive noise in sub-swaths)
4) Radiometric calibration (computes backscatter intensity using sensor calibration parameters)
5) Terrain correction (converts data from ground range geometry to take terrain into account using the SRTM 30 meter digital elevation model (DEM) or the ASTER DEM)
6) Conversion of the unitless backscatter coefficient to decibels (dB) to generate the Level-1 GRD scenes.

Since Sentinel-1 collects SAR data at a variety of modes, polarizations and resolutions, the pre-processed images provided by GEE were filtered before the analysis to create a homogenous subset of data:

- Acquisition mode: Sentinel-1 collects data in Interferometric Wide Swath (IW), Extra Wide Swath (EW) or Strip Map (SM) mode. IW mode was selected since it is the primary conflict-free mode over land. By contrast, EW and SM are appropriate for observations of the open ocean and small islands, respectively (ESA 2020a).
- Resolution: The IW images were filtered to keep only high-resolution images (pixel spacing of 10x10 m).
- Incidence angle: To reduce backscatter variation, only images with a look angle between 30° and 45° were kept.
- Look direction (ascending/descending): The look direction is relevant mainly for objects that have a specific and stable orientation. In the case at hand, this applies mainly to buildings and other man-made structures. Therefore, the influence of the pass type was tested for the detection of settlements. For the land cover classification, it is mainly important not to mix the two pass types. For this, the ascending orbit was chosen.
- Polarization: For the IW mode, VV and VH polarizations are available. Since VH is available only from 2017 on, all analyses were performed on VV images.

Fig. 1 gives an overview of the steps taken to develop the erosion detection algorithm. Methodological details are explained in the following sections. The full code used to develop the classifiers for land cover and settlements can be found here: https://code.earthengine.google.com/1583076e4360fb565e5ac1357f512ca2

3.3.2 Land cover classification

To get a visual impression of the backscattering characteristics of different land cover types, the average backscatter coefficient of five classes (settlement, trees, three fields, sand and water) was plotted for the period from January 2018 to April 2020. From visual inspection of this graph, November was defined as the beginning of the dry season since patches that had been flooded during the monsoon had returned to their dry season backscatter coefficient by November (cf. Fig. 3).
For each of the four land cover classes “water”, “sand”, “trees” and “agricultural fields”, ten patches of size 100x100 m were chosen based on visual inspection of the optical satellite images provided by the GEE. For each class, the ten patches were distributed along the length of the Jamuna River. The locations of the patches are shown in Fig. 30 in the appendix.

One common challenge of working with SAR images is the presence of speckle, which gives images a granular aspect with random spatial variations. Speckle occurs if one resolution cell contains several elementary scatterers which lead to a partially random path of the incoming radiation. There are two basic approaches that can reduce speckle: temporal averaging and spatial filtering. For temporal averaging, the data from several SAR images with a temporal baseline are averaged pixelwise. This has the advantage that spatial resolution is obtained, but several images are required. For spatial filtering, only one SAR image is used and each pixel is assigned a new value taking information from its neighboring pixels into account. Thereby, the resolution decreases. Two very common spatial filters are the boxcar and the Lee adaptive filter (Baghdadi and Zribi 2016).

There exists, thus, a tradeoff between keeping full spatial resolution and using only a few images. To predict riverbank erosion in Bangladesh, however, it would be ideal to use only a few images (to obtain the prediction as early as possible after the end of the monsoon season) while maintaining spatial resolution (to have a precise estimate of the erosion extent). Therefore, a compromise has to be found between sampling duration and spatial resolution. To explore the influence of these two parameters on the classification quality, the average backscatter as well as the standard deviation of all the pixels within each patch were measured for a range of configurations:

- To test the influence of the sampling duration on the recorded backscatter values, eight different sampling durations were tested: two weeks; 1 month; 2, 3, 4, 5, 6, 7 months. Each of these eight periods started on November 1st, 2018. All images within the respective period were averaged before the subsequent analysis.
- Seven different filters were tested: no filter; 3x3 refined Lee filter; 3x3, 5x5, 7x7, 25x25 and 50x50 boxcar filter. The filters were applied to the absolute backscatter values.

For a certain imaging configuration (sampling duration and filter type), the mean backscatter as well as the standard deviation of the pixels within each patch were calculated. Subsequently, these ten patch-specific mean and standard deviation values were averaged to yield one mean backscatter and one standard deviation value per land cover class and imaging configuration.

To classify pixels into one of the four categories, thresholds were defined between “water-sand”, “sand-fields” and “fields-trees”. The thresholds were calculated as $0.5 \times \left[ (\text{mean}_i + n \times \sigma_i) + (\text{mean}_j - n \times \sigma_j) \right]$ where i and j indicate the class with the lower and higher mean backscatter, respectively. n was chosen as the largest natural number such that $(\text{mean}_i + n \times \sigma_i)$ and $(\text{mean}_j - n \times \sigma_j)$ would not overlap. n could thus be different for each pair of classes for which a threshold was defined. For trees, an additional upper threshold was set at -2 dB to distinguish them from settlements. Pixels were then classified according to their backscatter value with respect to these thresholds. For instance, a pixel with a backscatter value larger than the threshold “water-sand”, but smaller than “sand-fields” was classified as “sand”. The quality of the classification was assessed visually with optical Sentinel-2 images as the baseline.
3.3.3 Settlement detection

Predicting the risk of riverbank erosion requires information about assets at risk of being eroded. Besides farmland, houses are an important asset in the Bangladesh context. Since houses in rural Bangladesh are typically surrounded by trees, they are not fully visible on satellite images. Moreover, they cover only small areas compared to water, sand or farmland. Therefore, they cannot be well detected with the classification approach presented in section 3.3.2 which involves spatial averaging.

To detect houses, I exploit the fact that unlike vegetation, houses do not move or change substantially over time. Due to this low temporal decorrelation, houses are treated as persistent scatterers (PS) (Ferretti et al. 1999). Detecting PS candidates in radar images usually implies analyzing phase coherence, which cannot be done in GEE where only amplitude information is available. However, Ferretti et al. (2001) show that phase dispersion can be estimated from the amplitude dispersion index $\sigma_A / m_A$ where $m_A$ and $\sigma_A$ are the mean and the standard deviation of the amplitude values, respectively. PS can then be selected by computing the dispersion index of each pixel from a stack of several SAR images of the same scene and keeping only those pixels exhibiting a low dispersion index. The typical range of threshold values for the dispersion index goes from 0.25 (Ferretti et al. 2001) to 0.4 (van Leijen 2014).

Houses are, however, not the only structures than can have a low dispersion index. Bare surfaces, for instance, might also be relatively stable over time. Therefore, I combine the dispersion criterion with an amplitude threshold: Pixels are selected as PS candidates and hence houses if they show a low dispersion index and a high absolute backscatter over a series of radar acquisitions.

Two implementations of the amplitude threshold were compared: First, following Kampes and Adam (2004), a pixel is selected as PS candidate if its normalized cross section $\sigma_0$ is above a threshold $N_2$ in at least $N_1$ images. These authors propose thresholds of -2 dB for $N_2$ and 0.65K for $N_1$, where K is the number of radar acquisitions. Second, the amplitude threshold was applied to the mean of all SAR images in the stack, instead of to the individual images.

The sensitivity of the settlement detection was tested for the following parameters:

- Thresholds: For the dispersion index, threshold values of 0.25 and 0.4 were tested. For the amplitude threshold, -4 dB, -2 dB and 0 dB were analyzed. These analyses were done for a sampling duration of six months starting Nov 1st, 2019.
- Sampling duration: Ferretti et al. (2001) recommend using at least 30 SAR images to apply the dispersion index threshold. To test the influence of the sampling duration on the classification result, sampling durations of six and twelve months were compared.
- Sampling year: To estimate how stable the classifier is with respect to which SAR images are used as an input, the classification was performed based on six months of data from the dry seasons 2017/18, 2018/19 and 2019/20.
- Look direction: Since the roofs of buildings typically have a specific orientation, they are likely to have a stronger backscatter for one of the two look directions “ascending” or descending”. Therefore, these two types were compared.
3.3.4 Erosion detection

In examining the impact of riverbank erosion on human livelihoods along the Jamuna River, I am interested in two effects, which are treated separately: erosion of land (farmland or trees) and erosion of houses. Land was identified as eroded in one specific monsoon season if it was classified as “field” or “trees” before the monsoon season and as “sand” or “water” afterwards. Erosion to sand and erosion to water were not differentiated further since in both cases, the land cannot be used for agriculture anymore, which is the main effect I am interested in this application. For classifying the land, a sampling duration of six months (November to April) was used for all years except for 2019/20, since these data are available for all years from 2014/15 to 2018/19. For 2019/20, only the images from November 2019 were used to simulate the case that the erosion detection has to be performed already in December after the end of the monsoon. A 7x7 boxcar filter was applied to create smooth and continuous erosion bands. The threshold discriminating sand/water from fields/trees was -13.2 dB and -12.7 dB for the case where six months and one month of data was used, respectively (cf. Table 11 and Table 12 in the appendix).

To detect eroded settlements, a similar strategy was followed: A pixel was selected as settlement eroded during a specific monsoon season if it was classified as “settlement” before the monsoon and as “sand” or “water” afterwards. The erosion detection was validated using optical Sentinel-2 images from before and after the respective monsoon season. The final algorithm to detect eroded land and settlement is schematized in Fig. 2.

Fig. 2: Flow chart of the final implementation to detect eroded land and settlement. THR = threshold.
3.4 Results and discussion

3.4.1 Land cover classification

The average monthly backscatter of seven patches is shown as a time series in Fig. 3. The settlement and tree patch are the most stable since they are neither affected by (rapid) vegetation growth nor by monsoon flooding. The river patch has mostly the lowest coefficient, which increases during the monsoon, potentially due to wind and rain disturbing the flat water surface. While fields generally have a backscatter coefficient close to that of trees, they can be seasonally flooded during the monsoon (field 2) or completely eroded (field 3). From the behavior of field 2, the dry season can be defined as the period between November and May of the following year (indicated by the vertical lines). The sand patch lies in between water and fields.

![Fig. 3: Mean monthly backscatter of different land cover types (the location of the patches is shown in Fig. 30 in the appendix) between January 2018 and April 2020. The vertical lines indicate the time window used to define the classification thresholds.](image)

The average backscatter of the ten sand patches is shown in Fig. 4 as a function of different sampling durations and filter configurations. For a given filter, there is no significant variation of the backscatter value with increasing sampling duration. For a given sampling duration, the average backscatter increases slightly with increasing filter size. However, this increase becomes statistically significant at the 95% level only for the largest filters (25x25 and 50x50 pixels). For such large filters (50x50 pixels corresponds to 500x500 meters), this is probably caused by other land cover classes with a higher backscatter value (e.g. fields) being included into the filter window.
Fig. 4: Average backscatter of ten sand patches for different sampling durations and filter sizes. The five filters for which only the size is indicated in the legend are all boxcar filters. Bars indicate the 95% confidence interval.

Fig. 5 presents the standard deviation of all pixels within one patch, averaged over the ten sand patches. For a given filter, the standard deviation decreases with increasing sampling duration. For a given sampling duration, it decreases with increasing filter size. These observations correspond to the two mechanisms for speckle reduction outlined in 3.3.2, namely temporal averaging and spatial filtering. The other three land cover classes “water”, “fields” and “trees” show similar tendencies for filter size and sampling duration, both for average backscatter values and standard deviations (cf. Fig. 31 to Fig. 36 in the appendix).

Fig. 5: Average standard deviation of the pixels within each of the ten sand patches for different sampling durations and filter sizes. The five filters for which only the size is given in the legend are all boxcar filters. Bars indicate the 95% confidence interval.
These findings allow me to define thresholds to separate the four classes in the land cover classification. As discussed above (see chapter 3.3.2), each combination of sampling duration and filter size has a certain advantage and a certain disadvantage. To illustrate this tradeoff, two extreme combinations are compared. If images are available only from two weeks, strong spatial filtering (25x25 pixels) reduces the standard deviation enough to separate all four classes even at the level of two standard deviations around the mean (Fig. 6, left).

If, by contrast, images are available from seven months, water, sand and fields can be separated even if no spatial filter is applied (Fig. 6, right). In this setting, fields and trees can be distinguished only at the level of one standard deviation around the mean (not shown in the graph).

In practice, a compromise between these two extremes seems more likely, meaning that some spatial resolution has to be given up when a slightly longer sampling duration is used. One example for such a compromise is presented in Fig. 7, for which images from one month have been filtered with a 3x3 boxcar filter.

The determination of the thresholds is illustrated in Table 1 for the case of one month sampling duration and a 3x3 boxcar filter. As can be seen in Fig. 7, the bars of fields and trees overlap if two standard deviations are used. However, they do not overlap if only one standard deviation is used. Hence, intervals with one standard deviation are used to determine the threshold between fields and trees. For “water-sand” and “sand-fields”, the intervals do not overlap even if three standard deviations are considered. Therefore, three standard deviations
are used to calculate the respective thresholds. The thresholds for the two configurations from Fig. 6 are contained in Table 9 and Table 10 in the appendix. The average backscatter values shown in Table 1, Table 9 and Table 10 compare reasonably well to reference values from the literature (Table 2).

Table 1: Determination of thresholds for a sampling duration of one month and a 3x3 boxcar filter. Values in bold are those that have been used to calculate the threshold indicated in the last column. All values are in dB.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std</th>
<th>Mean+Std</th>
<th>Mean-Std</th>
<th>Mean+2*Std</th>
<th>Mean-2*Std</th>
<th>Mean+3*Std</th>
<th>Mean-3*Std</th>
<th>Threshold</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>-24.4</td>
<td>0.9</td>
<td>-23.6</td>
<td>-22.7</td>
<td>-21.8</td>
<td>-21.8</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sand</td>
<td>-17.4</td>
<td>1.2</td>
<td>-16.2</td>
<td>-15.0</td>
<td>-13.8</td>
<td>-21.1</td>
<td>-21.5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fields</td>
<td>-9.5</td>
<td>0.8</td>
<td>-8.8</td>
<td>-8.0</td>
<td>-7.2</td>
<td>-11.8</td>
<td>-12.8</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trees</td>
<td>-6.1</td>
<td>1.7</td>
<td>-7.8</td>
<td>-9.4</td>
<td>-11.1</td>
<td>-8.3</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 2: Average backscatter values from Ulaby and Dobson (1989) for C-band at VV polarization for look angles of 30° and 45°.

Assuming the backscatter values in each class to be distributed normally around the mean, this approach allows an estimation of the accuracy of the resulting classification. In a normal distribution, 68%, 95% and 99.7% of all values lie within “mean ± one, two and three standard deviations”, respectively. As the thresholds “water-sand” and “sand-fields” are based on the interval with three standard deviations, we thus expect less than 0.15% of all water pixels to be incorrectly classified as sand pixels. The same percentage applies for sand pixels being incorrectly classified as water/field pixels and for field pixels being misclassified as sand pixels. For “fields-trees”, only one standard deviation has been used, and hence 16% of all field/tree pixels are expected to be falsely classified as tree/field pixels, respectively.

Trees and fields can thus not be well distinguished in this setup. This shortcoming is, however, negligible in the context of studying riverbank erosion. Here, the focus is on land covered by fields or trees being eroded and appearing as sand or water afterwards. Therefore, the most important threshold is the one between sand and fields, which yields higher accuracy.

The classification resulting from these three imaging configurations is depicted in Fig. 8 with an optical Sentinel-2 image as the baseline. If only two weeks are sampled with a 25x25 boxcar filter, the spatial resolution is largely lost (top right). If, by contrast, no filter is applied and six months are sampled, the classification remains very fine-grained (bottom left). However, the distinction between sand and water is not very accurate. The compromise – one month sampling duration and 3x3 boxcar filter (bottom right) – manages to preserve a large degree of spatial resolution while distinguishing well between the four classes. It thus seems the most appropriate of these three imaging configurations.
Fig. 8: Top left – Sentinel-2 image of a stretch of the eastern riverbank of Jamuna River, taken in November 2019. Image dimensions are ca. 4.5x6 km. Top right, bottom left and bottom right – Classification result for a sampling duration of two weeks/25x25 boxcar filter, six months/no filter and one month/3x3 filter, respectively. Blue – water, sand – sand, light green – fields, dark green – trees. The location of the patch is shown in Fig. 30 in the appendix (patch 1). Coordinates in this and all other maps are in “Gulshan 303 Bangladesh TM” (EPSG 3106).
3.4.2 Settlement detection

Fig. 9 illustrates the need to apply an amplitude threshold in addition to the dispersion index. If only the dispersion index is used to classify settlements, many vegetation pixels that happen to be stable over the sampled time window are misclassified as settlements. The influence of the dispersion index threshold and the amplitude threshold is shown in Fig. 10. For the dispersion index, a threshold of 0.25 (right panel) selects only very stable pixels as PS candidates. Accordingly, less pixels are selected than for a threshold of 0.4 (left panel). For the amplitude threshold, the effect is the opposite: Applying a threshold of -4 dB (red) selects more pixels as PS candidates than for -2 dB (blue) or 0 dB (orange). While the threshold of -4 dB thus seems to select more settlement pixels (e.g. upper left corner of the left panel), also the risk of misclassifying tree pixels as settlements rises. For this application, however, I am rather interested in detecting the rough location of settlements than in precisely distinguishing settlement and tree pixels. In fact, trees are often planted around houses, making them good indicators of settlements. As too few settlement pixels are detected in the right panel, I suggest a threshold combination of 0.4 and -4 dB for the dispersion index and the amplitude, respectively. Still, it is important to note that even with this combination (red pixels in the left panel), several pixels that appear as houses in the optical image are not detected. We should thus keep in mind that what the algorithm classifies as settlement is most likely indeed a settlement, but that it cannot detect all settlements, especially if they are covered by trees.

Fig. 9: Classification of settlements using the dispersion index only (blue) or the combination of dispersion index and amplitude threshold (orange). Thresholds: 0.25 (dispersion index), -2 dB (amplitude). Sampling duration: Six months. The location of the patch is shown in Fig. 30 in the appendix (patch 2).
Fig. 10: Influence of classification thresholds on settlement detection. Shown are dispersion index thresholds of 0.4 (left) and 0.25 (right) – the lower the threshold, the more stable a pixel has to be for it to be classified as a PS candidate. Colors correspond to different values of the amplitude threshold: -4 dB (red), -2 dB (blue), 0 dB (orange) – the lower the threshold, the higher the chance of classifying tree pixels as settlement pixels.
The impact of the sampling duration is presented in Fig. 11. All pixels that are classified as settlements for a sampling duration of twelve months (orange) are also detected with a sampling duration of six months (blue). However, several pixels are only detected with the shorter sampling duration. Applying the dispersion index threshold to a longer sampling duration corresponds to a stricter threshold since the probability of temporal decorrelation increases with increasing sampling duration. If available, it is thus recommended to use longer sampling durations if the classification accuracy should be high. However, also the short sampling duration seems to perform well from visual observation.

Fig. 11: Settlement detection for a sampling duration of six (blue) and twelve months (orange). Thresholds: 0.4 (dispersion index), -2 dB (amplitude).

Fig. 12 illustrates the settlement classification using data from three different years. While there are certain pixels that are classified only in single years (e.g. red spot in the top left corner), the overall overlap between the three years is good. Since buildings are not expected to move from year to year, one potential disturbing factor could be the vegetation surrounding the houses, which is much less stable. Alternatively, variations can occur if the SAR images are not perfectly geocoded. Again, however, I am not interested in a pixel-level precise estimate of settlements but only in their rough location. For this, the sampling year seems to be of minor importance.
Fig. 12: Settlement classification using SAR images from 2017 (red), 2018 (blue) and 2019 (orange). Thresholds: 0.4 (dispersion index), -2 dB (amplitude). Sampling duration: six months.

By contrast, the pass type exhibits a strong influence on the detected settlements (Fig. 13, left panel). The overlap between the ascending (orange) and descending orbit (blue) is small. This effect corresponds to the fact that each building has a specific orientation of its roof. Therefore, some roofs have a stronger backscatter in the descending orbit, while others reflect more in the ascending orbit. For maximum settlement detection, it is thus recommended to use SAR images of both pass types.

Lastly, it is important to note that the implementation of the amplitude threshold based on individual images fails in locations that are close to the border between two adjacent SAR imaging patches. In such a case, the amplitude threshold criterion applied above does not work since not all SAR images analyzed by the algorithm cover the location fully. An alternative criterion can be used for such locations, which requires that the pixel-wise average amplitude be larger than the threshold values (e.g. -2 dB). Both amplitude criteria yield largely comparable results (Fig. 13, right panel). Since the analyzed stretch of the Jamuna River is over 200 kilometers long and is thus not covered by one SAR imaging patch (cf. Fig. 37 in the appendix), I suggest applying the more robust criterion using the mean of all images in the stack.

To conclude, the recommended set of parameters to detect settlements is thus to use an amplitude and dispersion index threshold of -4 dB and 0.4, respectively, using images of both ascending and descending orbit. For the amplitude criterion, the more robust implementation using the mean of all SAR images in the stack should be preferred over working with individual images. Sampling duration and sampling year have a minor influence and should be chosen depending on data availability.
Fig. 13: Left: Settlement detection for ascending (orange) and descending (blue) orbit. Thresholds: 0.4 (dispersion index), -4 dB (amplitude). Sampling duration: six months. Right: Comparison of amplitude criteria requiring 65% of all images to be above-threshold (orange) or only the mean of all images to be above-threshold (blue). Thresholds: 0.4 (dispersion index), -2 dB (amplitude). Sampling duration: six months.
3.4.3 Erosion detection

Fig. 15 illustrates the result of the erosion detection (both land and settlements) for one specific site for the monsoon seasons 2018 and 2019. To evaluate the quality of the erosion detection, the detected erosion patches are mapped on optical images from before and after the monsoon. The focus of the project is on erosion occurring on the outer riverbanks of the Jamuna. Therefore, erosion happening on the sandbanks and islands in the river are omitted in the following discussion, which focuses exclusively on the long strip of eroded land in the center of the images. For both years, all that has been detected as eroded land has entirely been land before the monsoon (left column) and completely water after the monsoon (right column). For these examples, there is thus no type I error, i.e. classifying land as eroded when it is not.

There is, however, a type II error, i.e. eroded land that is not classified as such. This error tends to be small and thus negligible for the overall purpose of detecting sites where erosion occurred to a significant extent. Lastly, the algorithm can distinguish well between eroded land and eroded sand, as can be seen in the lower left corner of the 2019 image before the monsoon. Regarding the patches detected as eroded settlements (bright red), by far not all of the eroded settlement is detected. Again, this type II error is negligible given the purpose of detecting those sites that have seen erosion of settlements in general. For this, it is not necessary to detect every single house that has been eroded.

The erosion detection works for the monsoon seasons from 2015 to 2019, since Sentinel-1 images are only available from October 2014 onwards. Fig. 14 shows the sequential nature of erosion, which does not occur at random locations, but typically in sites which have already experienced erosion during the previous monsoon season(s). We can also see the highly dynamic nature of land accretion and erosion. For instance, an island had formed at the place where land had been before the 2015 monsoon. Part of this island has been eroded again in the 2019 monsoon season (orange patch overlaying the dark brown 2015 erosion band). Further, settlements have been eroded in all five monsoon seasons (blue dots). Fig. 16 shows where land was eroded in the 2019 monsoon along the entire Jamuna River. It can be clearly seen that erosion occurred all along the river, and to a large extent outside of the hotspot areas predicted by CEGIS (2018).

![Erosion detection result](image_url)

**Fig. 14:** Detected erosion for the monsoon seasons 2015 (dark red) to 2019 (light red). Blue: eroded settlements.
Fig. 15: Validation of erosion detection. Shown are eroded land (orange) and eroded settlements (red) for 2018 (first row) and 2019 (second row). Baseline: Optical Sentinel-2 images from before (left column) and after the monsoon (right column). The location of the patch is shown in Fig. 30 in the appendix (patch 3).
Fig. 16: Locations of land that was eroded during the 2019 monsoon (orange). The red rectangles are the locations for which CEGIS (2018) predicted severe erosion.
3.4.4 Final implementation

Finally, the learnings from chapters 3.4.1 to 3.4.3 were implemented in a tool that allows the user to explore where erosion of land and settlement has occurred during the past five monsoon seasons, 2015 to 2019. The tool contains the following information:

- Five layers for land eroded in the five monsoon seasons, 2015 to 2019
- Five layers for settlements eroded in the five monsoon seasons, 2015 to 2019
- One layer for the settlement detected in the beginning of 2020
- Three optical images from January 2018, 2019 and 2020 as a visual baseline
- The 14 “erosion hotspots” identified by CEGIS in their 2019 erosion prediction (cf. chapter 2)

The tool can be accessed here:

https://code.earthengine.google.com/3ea8f1fd5d771accc621550d744a914e?hideCode=true

To introduce users who are unfamiliar with the GEE into the application of this tool, I have recorded a short tutorial: https://youtu.be/_b9AAPDw7Wk

3.5 Outlook: Predicting erosion

After successfully detecting erosion events in the past, the next step will be to predict where erosion will occur in the coming monsoon season(s). There are different ideas how such a prediction could be produced:

- Manually: Large erosion events do not occur completely randomly, but they usually follow a pattern where erosion happens in one location for several years in a row (cf. Fig. 14). Exploiting this characteristic, one could look for locations where erosion has happened in the past years and then extrapolate manually in which zone erosion is expected to occur in the next monsoon season.
- Interferometry: SAR interferometry is capable of detecting land movement and subsidence in the range of millimeters or centimeters. One can hypothesize that land where erosion occurs on a large scale shows signs of instability, such as subsidence, already before the monsoon. If this were the case, an interferometric analysis of subsiding areas could yield a prediction of erosion in the upcoming monsoon. I will assess in the next steps whether this subsidence hypothesis holds.
- Modelling: The extent of erosion is determined – among other factors – by the strength of the monsoon. The stronger the monsoon, the more land is flooded and the more erosion is caused (Fig. 17). For each of the hotspot areas identified manually, one could establish a relationship between peak monsoon discharge and erosion extent. If there is a prediction on the strength of next year’s monsoon, this relationship could yield an estimate of the expected erosion extent. However, this strategy will be limited by the fact that Sentinel-1 SAR images are only available for the last five monsoon seasons, decreasing the strength of the established correlation.
- Machine learning: Potentially, erosion could also be predicted by a supervised or unsupervised machine learning algorithm. Such an algorithm could use past erosion events for training purposes. Again, this approach might be limited by the small amount of data available for training the classifier. This limitation could be overcome by merging the SAR data with optical data which is available for several decades.
Fig. 17: Annual rates of floodplain erosion at the right (west) and left (east) banks of the Jamuna River plotted against annual peak discharge. Graph taken from Sarker et al. (2014).
4 Improving communication of erosion risk

4.1 Scope and objective

The main products of chapter 3 are satellite photographs of the Jamuna River including information on where land and settlements have eroded in the past (cf. Fig. 14). Note that these photographs contain only information on past events, but no (explicit) prediction on where erosion might occur in the future. Implicitly, however, one can extrapolate past occurrences to future risk, assuming a linear, domino-like process. In any case, such scientific information is useful only if it is communicated effectively to decision makers and (potentially) affected people so that they can reduce the impact of the hazard. Therefore, I now turn my focus from the scientific assessment of erosion to disseminating the resulting information on past disaster occurrences (cf. chapter 1). Specifically, I investigate whether and how such aerial photographs can serve the goals of risk communication.

Risk communication can have different goals. Rowan (1991) discusses four common goals, namely creating awareness about the existence of important phenomena, enhancing understanding of complicated ideas, developing agreement about policy options, and motivating action. In communication pertaining to natural disasters, particular relevance is given to the last goal of motivating action, since adaptive measures on the side of affected individuals or households can significantly decrease material and human losses resulting from a disaster.

Adaptive measures can be classified according to the phases of the hazard life cycle (Lindell and Perry 2004): Mitigation measures are taken when the disaster threat is absent, e.g. building one’s house at a sufficient distance from the eroding riverbank. Preparedness measures are implemented shortly before the impact, e.g. evacuating one’s house before the peak monsoon flooding. Lastly, recovery measures support affected people in returning to a normal state, e.g. taking up an insurance against erosion-related losses.

Disaster risk communicators thus frequently have an interest in motivating behavioral change among the message recipients. Since disasters involve potential human and material losses, the corresponding risk messages are prone to be affected by framing effects. A frame is the way in which a certain situation is depicted, for instance whether the focus is put on what can be gained or on what can be lost. In the case of riverbank erosion, one option is to say, “If you build your house within 50 meters distance from the river, you have a 20 percent chance of keeping it safe over the next five years”. Alternatively, one could say, “If you build your house within 50 meters distance from the river, you have a 80 percent chance of losing it over the next five years”.

The actual information content is identical in both phrases. A rational decision maker should thus not be influenced by the way the information is presented. Still, humans perceive the erosion situation differently from the two phrases due to the phenomenon of loss aversion: Humans tend to prefer avoiding a loss over acquiring an equivalent gain. This deviation from the rationality postulate is called framing effect or framing bias (Tversky and Kahneman 1981; Kahneman and Tversky 1979).

Framing thus appears as an alluring option for policy makers to increase adaptive behavior at every stage of the hazard cycle. While such behavioral change is clearly desirable from an aggregate, societal perspective, manipulating citizens to change their behavior raises ethical concerns. Framing information to make risk messages more effective might not be consistent with truly informed decision making (Edwards et al. 2001; Edwards et al. 2002; Gigerenzer 2003). Informed decision making implies a “reasoned choice [...] made by a
reasonable individual using relevant information about the advantages and disadvantages of all the possible courses of action, in accord with the individual’s beliefs” (Bekker et al. 1999).

Enabling informed decision making in risk situations thus implies presenting the risk information in a way that does not push recipients to favor one option over the other simply by the presentation format. Different studies have examined ways to de-bias framing effects, for example, by making participants list advantages and disadvantages of both choice options (Almashat et al. 2008), by making participants describe the options in their own words (Simon et al. 2004), or by presenting information in visual format instead of text-only (Freihardt and Buchs 2019; Garcia-Retamero and Cokely 2011). These four studies pertain to the sectors of health and social dilemmas, for which framing has been studied extensively (Levin et al. 1998; Akl et al. 2011; Gong et al. 2013).

To the best of my knowledge, only one study has examined framing effects in the context of disaster risk communication, namely to enhance preparedness for earthquakes in New Zealand (McClure et al. 2009). No study, however, has investigated ways to de-bias framing effects in disaster risk communication. It can be debated whether it is actually desirable or not to use framing to motivate action that benefits the society as a whole. In this study, I posit that the goal of risk communication is to present the information such that the recipient is not pushed into one direction by the way it is presented. Focusing on sudden-onset natural disasters like riverbank erosion and the aerial photographs I produced in chapter 3, I posit the following research question:

Can aerial photographs containing information on past occurrences of sudden-onset natural disasters help to de-bias framing effects inherent in disaster risk communication aiming to motivate adaptive behavior?

4.2 Literature review

Risk communication has been defined as “the flow of information and risk evaluations back and forth between academic experts, regulatory practitioners, interest groups and the general public” (Leiss 1996). This definition contains two important aspects. First, it emphasizes the involvement of a variety of actors who might have divergent interests and perceptions. Second, the notion of “back and forth” implies a reciprocal instead of a one-way process.

In contrast, earlier approaches to risk communication had “assumed an ‘objective risk’ and an ‘ignorant public’ whose knowledge ‘deficit’ (compared with that of the experts) required that they are provided with simple information” (Barclay et al. 2008). Fischhoff (1995) depicts the historical evolution of risk communication styles as different stages that build upon each other by incorporating more and more psychological, social, cultural, economic and political factors.

This evolutionary development does not, however, imply that today’s risk communication is entirely two-way and iterative. Wardman (2008) distinguishes four conceptual models of risk communication along the two dimensions of co-involvement of different agents (i.e. one-way vs. two-way) and the implied driver of risk communication (i.e. normative vs. instrumental). Among these four, the one most utilized in communication studies and employed in practice is the risk message model.

The risk message model is based on the communication paradigm of the “encoder/decoder” model (Krauss and Fussell 1996). In this model, the message is encoded faithfully by the sender and transmitted via a communication channel to the receiver, who decodes and utilizes it. Information thus flows linearly from
sender to receiver, without any feedback loops. Under this paradigm, communication is successful if the message decoded by the receiver is identical to that encoded by the sender. The model assumes that the message is relevant to the receiver, who therefore has an interest to decode it correctly. Problems arise only if the message is incorrectly encoded by the sender or incorrectly decoded by the receiver.

In risk communication studies, much attention has accordingly been given to the identification of design features of the message to enable successful communication. One well-established phenomenon is that incidence rates expressed as a frequency (e.g., 3 out of 10 times) are often better understood than if they are expressed as a probability (e.g., 30%) (Ghosh and Ghosh 2005; Siegrist 1997; Visschers et al. 2009). Further, the mode in which the information is presented plays an important role. Burger et al. (2008) show that information uptake is improved by presenting it in various formats (text, table, map) instead of just a single one.

Several studies found that maps are perceived as more informative and persuasive than text-only descriptions (see Stieb et al. 2019 for a review). This also applies to flood risk maps, whereas understanding the underlying probabilities correctly remains a challenge (Strathie et al. 2017). In the specific context of flood risk, the authors recommend to present risk as cumulative probability over a number of years compared to the probability of a single event. As maps have such a prominent role in communicating spatio-temporal risks, a lot of research has studied the effect of different aspects of map design from a cartographic perspective (Stieb et al. 2019; Haynes et al. 2007; Dransch et al. 2010; Thompson et al. 2015).

Although widely applied, the risk message model has been criticized for its simplistic assumption that message receivers form their judgment only based on the message (Jaeger et al. 2001). Thereby, it ignores that risk perception, meaning the subjective assessment of the severity and relevance of a risk, is shaped by a variety of factors beyond the risk message. Notably, people cannot be viewed in isolation, but are part of complex social networks that heavily impact their perceptions (Wardman 2008). One approach to overcome this shortcoming is the “social amplification of risk” framework, which acknowledges that risk events are mediated by the interplay of individual psychological factors, influencing the capability to process the risk message, and social as well as cultural factors which can increase or decrease the public perception of risk (Kasperson et al. 1988; Pidgeon et al. 2003).

Rosenbaum and Culshaw (2003) describe four main components affecting the perception of risk messages about natural hazards: the actual quantitative risk level; personal experience of the hazard; whether the hazard seems controllable; and the horror, scale, and consequences of the hazard. Further, also the sources of the messages have been found to be important, with friends and family typically being the most trusted source (Eisenman et al. 2007; Haynes et al. 2008).

Another substantive criticism of the risk message model concerns its assumption of rationally acting message recipients: If the message gets transmitted and decoded correctly, the actors’ knowledge and understanding increases and they will act accordingly following the “rational actor paradigm”. This paradigm assumes that actors always choose the option that gives them the highest expected benefit. Since the 1950s, however, it became clear that humans deviate from rational decision making under certain circumstances. Herbert A. Simon coined the term “bounded rationality” to describe “rational choice that takes into account the cognitive limitations of the decision-maker” (Simon 1990). In the context of risk communication that tries to motivate adaptive behavior, assuming full rationality thus appears inappropriate given these cognitive limitations.

In their seminal paper, Tversky and Kahneman (1974) present different heuristics, or simple rules of thumb, that humans use to reach decisions under uncertainty. Such heuristics are usually effective decision aids, but
can lead to systematic errors. Whether information is processed heuristically or systematically depends on someone’s cognitive capacities, motivation, and available time (Visschers et al. 2009; Trumbo 1999). If any of these resources are missing, people tend to decide heuristically. When heuristics are used, the presentation format of the risk information has a larger influence than when it is processed systematically.

Different heuristics have been reported for the processing of risk information. First, respondents tend to estimate the probability of a risk based on the first number that is presented to them, ignoring numbers that are presented later (Visschers et al. 2009). This corresponds to the anchoring and adjustment heuristic. Second, respondents perceive risk as greater if it triggers fear in them, either because they have experienced the event themselves or because the risk communication manipulates their affect (Keller et al. 2006). It is, however, unclear whether this corresponds to the affect heuristic (affect is used to judge risks) or the availability heuristic (probabilities are judged depending on the ease to recall examples) (Slovic et al. 2007, 2013). In this context, Siegrist and Gutscher (2008) show that people without flooding experience underestimate the negative affect evoked by such an event. They conclude that motivating adaptive behavior could be more effective if the communication helps people imagine the negative feelings caused by such disasters.

Besides heuristics, another well-established cognitive bias is the framing bias introduced in the previous chapter. Levin et al. (1998) develop a typology to distinguish between three different kinds of valence framing effects, meaning effects where “the frame casts the same critical information in either a positive or a negative light”: risky choice framing, goal framing and attribute framing (see Table 3 for details on these three frame types). This work addresses both risky choice framing and goal framing.

<table>
<thead>
<tr>
<th>Frame type</th>
<th>What is framed</th>
<th>What is affected</th>
<th>How effect is measured</th>
</tr>
</thead>
<tbody>
<tr>
<td>Risky choice</td>
<td>Set of options with different risk levels</td>
<td>Risk preference</td>
<td>Comparison of choices for risky options</td>
</tr>
<tr>
<td>Attribute</td>
<td>Object/event attributes or characteristics</td>
<td>Item evaluation</td>
<td>Comparison of attractiveness ratings for the single item</td>
</tr>
<tr>
<td>Goal</td>
<td>Consequence or implied goal of a behavior</td>
<td>Impact of persuasion</td>
<td>Comparison of rate of adoption of the behavior</td>
</tr>
</tbody>
</table>

Table 3: Summary of methodological differences in risky choice, attribute, and goal framing (taken from Levin et al. 1998).

4.3 Theory

This work investigates the impact of aerial photographs on two types of framing effects, namely risky choice framing and goal framing. In a risky choice setting, respondents have to choose between two options, one of which is riskless and the other one is a two-outcome all-or-nothing option. The outcomes of these options are described either in terms of gains (positive frame) or in terms of losses (negative frame). Tversky and Kahneman (1981) were the first to show this setup leads to a “choice reversal” where participants in the positive frame prefer the sure option, whereas they prefer the risky option in the negative frame. They explain this finding with their prospect theory, which assumes an S-shaped subjective value function supporting risk aversion in the positive frame and risk seeking in the negative frame.
Most risky choice framing studies present respondents with a hypothetical, rather abstract situation. In this study, I translate the principle to a more real world setting in the context of erosion, where respondents have to choose between a risky and a riskless option concerning their own property. I therefore hypothesize that:

**Hypothesis 1 (risky choice framing effect):** Presenting a risky choice in the context of natural disasters with a focus on the gain makes respondents more risk averse, whereas a focus on the loss makes respondents more risk seeking.

The second type of framing studied here is goal framing. In goal framing, the impact of a persuasive message promoting a certain behavior depends on whether the message stresses either the positive consequences of performing the behavior or the negative consequences of not performing it (Levin et al. 1998). In an early review of goal framing studies, Levin et al. (1998) find that the negative frame generally has a stronger impact on changing behavior than the positive frame. They explain this difference by the phenomenon of loss aversion, meaning that people are more likely to perform a behavior to avoid a loss, than they are to obtain an equivalent gain.

Garcia-Retamero and Cokely (2011), however, present a more nuanced view: Whether the positive or the negative frame is more effective depends on the function of the promoted behavior. Positive frames are more persuasive if the promoted behavior is perceived as risk averse, meaning that it involves a low risk of an unpleasant outcome (e.g. it prevents the onset of health problems). If, by contrast, the risk of an unpleasant outcome is high (e.g. it detects a health problem), negative frames are more persuasive. This differentiation follows the same logic as the one for risky choice framing: Positive frames make people more risk averse, negative frames more risk seeking.

In the case of disaster risk communication promoting prevention behavior, there is a low chance that the behavior evokes a negative outcome for the actor. For example, planting vegetation that stabilizes the soil and reduces erosion would most likely not have a negative consequence for the actor, unlike the example presented by Garcia-Retamero and Cokely (2011) of a health screening that detects that the actor has a certain disease. I thus hypothesize that behavior preventing the negative outcome of a natural disaster is perceived as risk averse and that, consequently, the positive frame is more persuasive:

**Hypothesis 2 (goal framing effect):** Presenting disaster risk information promoting preventive behavior with a focus on the positive consequences of adopting the behavior makes respondents more likely to state that they would adopt preventive measures than presenting it with a focus on the negative consequences of not adopting the behavior.

In an earlier work, we show that depicting the two choice options in a risky choice situation using visual instead of as text-only form can alleviate the framing bias (Freihardt and Buchs 2019). In this study, we used an icon array to show either the number of people who would be saved (positive frame) or who would die (negative frame) if the respective option was chosen. Also for goal framing, visual aids can eliminate framing effects. Garcia-Retamero and Cokely (2011) show this in the health context by adding a bar chart illustrating the probabilities communicated in the information text. In this case, the graphic itself did not contain a frame, but only the accompanying text. They argue that visual aids improve the encoding of the relevant information such that the framing contained in the text gets overshadowed.

I hypothesize that appropriate visuals can help to alleviate framing effects also in a real world, natural disaster setting. Predicting the occurrence and extent of natural disasters is a complex problem involving many factors. Therefore, the resulting hazard and risk predictions typically involve a considerable amount of uncertainty
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(Reynolds and Seeger 2005). Communicating this uncertainty is challenging, especially in static, probabilistic maps (Thompson et al. 2015).

Instead of presenting uncertain predictions in a map, it is also possible to show past occurrences of the disaster and let respondents infer from this historical information to future risk. This is especially relevant for natural events that occur in a sequential, domino-like manner, as is the case for erosion processes. Saint-Marc et al. (2018) find that mapping past at-risk phenomena is useful to prepare against future risk. At the same time, depictions of past events are usually easier to produce than probabilistic predictions, making them an attractive tool for risk communication.

Further, it has been suggested that aerial photographs make it easier to locate and identify features than maps (Haynes et al. 2007): On a map, the cartographer filters certain information that she finds relevant, but that might not be relevant to the reader. With aerial photographs, by contrast, no information is filtered and spatial items are in their correct relative scale, allowing the reader to filter for the information relevant to her.

I accordingly posit that aerial photographs containing information on past erosion events could alleviate framing effects for both risky choice framing and goal framing:

**Hypothesis 3 (de-biasing risky choice framing using aerial photographs showing past events):** Presenting a risky choice in the context of natural disasters together with an aerial photograph showing past events reduces the framing effect compared to presenting the same information as text only. This means that the respondents presented with the aerial photograph are more risk neutral than those presented with the text only.

**Hypothesis 4 (de-biasing goal framing using aerial photographs showing past events):** Presenting disaster risk information aimed at behavioral change together with an aerial photograph showing past events reduces the framing effect compared to presenting the same information as text only. This implies that the difference in respondents stating that they would adopt preventive measures between positive and negative frame is smaller for those presented with the aerial photograph than for those presented with the text only.

I further contend that it is the actual risk information that decreases the framing effect and not the aerial photograph by itself. I base this claim on the fact that in all studies referenced above, where visual aids were used to alleviate framing effects, the applied visuals contained information on the risky situation. These studies did not, however, test explicitly whether other visuals not containing risk information would have been equally suited to decrease the framing effects. I therefore test the following hypothesis for the risky choice situation:

**Hypothesis 5 (influence of blank aerial photographs on risky choice framing):** Presenting a risky choice in the context of natural disasters together with an aerial photograph depicting the situation, but not showing past disaster events, does not reduce the framing effect compared to presenting the same information as text only.
4.4 Research design

Ideally, these hypotheses should be tested by collecting data from individuals residing along the Jamuna River in Bangladesh. However, due to constraints in time and money, I could not conduct a survey experiment in Bangladesh for my thesis. Therefore, I decided to carry out the experiment via an online survey in the USA since they experience erosion and since they have a population that can be accessed well online. To what extent the results from this online experiment can be transferred to the Bangladesh context will be discussed in chapter 4.7.

As the case for this online experiment, I chose coastal erosion in the USA since it is the natural phenomenon occurring in the USA that resembles most closely the case of riverbank erosion in Bangladesh. Coastal erosion causes around $500 million per year in coastal property loss in the USA, including damage to structures and loss of land (NOAA 2013). To mitigate coastal erosion, the US government spends an average of $150 million every year on beach nourishment and other shoreline erosion control measures (NOAA 2013).

To empirically test the above mentioned hypotheses, I implemented an online experiment on the platform Amazon Mechanical Turk (MTurk; see e.g. Berinsky et al. 2012; Follmer et al. 2017; Goodman et al. 2013 for an analysis of the characteristics of the MTurk population and a discussion on the drawbacks and advantages of this recruitment method). Due to the case study of coastal erosion, participation was possible only for MTurkers residing in seven coastal US states, namely California, Texas, and Florida in the first survey wave, and Georgia, New Jersey, North Carolina, and Virginia in the second wave. These states are all heavily affected by coastal erosion. By targeting them, I hoped to reach MTurkers living close to the coast who are familiar with erosion. I excluded mobile phones, as the photographs shown could not be seen well on a small screen.

The survey experiment consists of a two-stage scenario, namely a risky choice in the first and a goal framing setting in the second stage (Fig. 18). In the first stage, each respondent faces a hypothetical decision situation where she inherits a plot of land by the beach on which she wants to build a house to move there with her family. The beach experienced severe coastal erosion during three recent hurricanes. The respondent has to choose between two options for the position of the house: Right by the beach, where she can build a large house with a higher chance of being damaged by erosion, or at the rear of the plot, where she can build a smaller house with a lower chance of being damaged. The two options were presented either with a positive frame (“keeping your house safe”) or a negative frame (“losing your house”). The version with the positive frame is shown in Fig. 19.
Fig. 19: Decision situation of treatment 1 in the version shown to group 1.1 from Fig. 18 (text only, positive frame). It was randomized whether option A was the riskier or the low-risk option.

This decision situation resembles a risky choice, where the risky option is to build right by the beach, and the low-risk option is to build at the rear of the plot. Note, however, that the term “risky choice” usually refers to a situation where the probabilities of occurrence of all outcomes are known and hence, the expected value of the options can be calculated and compared. In the case of natural disasters like erosion, it is not possible to exactly quantify the probability of the hazard materializing. It is only possible to say that one option comes with a higher chance of being affected, while the other comes with a lower chance.

In the control group, the decision situation was described only as text, as shown above. In the first treatment group, respondents additionally saw an aerial photograph of the plot with the two options for building the house (Fig. 20). In the second treatment group, they saw the same aerial photograph, but also including bands indicating how much beach was eroded during three recent hurricanes (Fig. 21). This way of depicting erosion information is identical to the one employed in the final product of chapter 3 of this thesis. While the mentioned hurricanes have indeed caused severe erosion on Florida’s beaches, the extent of erosion depicted in the photographs is hypothetical.

After the respondent has chosen the location for her house, she is informed that two years after moving there, another hurricane caused widespread erosion, but not on the beach close to her house. This is followed by a list of measures she could take to mitigate erosion and to be prepared for the next erosion event (scenario adapted from McClure et al. 2009 who study the case of earthquake preparation messages; erosion control measures taken from Robertson 2010). These measures are recommended in either a positive or a negative frame (Fig. 22). The treatment group saw the same text, accompanied by an aerial photograph including erosion bands. The same photographs as in Fig. 21 were shown, but only the one for the option the respondent had chosen in treatment 1. Respondents were fully randomized between treatment 1 and treatment 2, meaning that some respondents saw the aerial photograph for the second time, and some for the first.
Formulating gain framing messages is complicated by the fact that both the action (“being well prepared” vs. “being poorly prepared”) and the outcome (“keeping your house safe from erosion” vs. “losing your house due to erosion”) can be phrased positively or negatively. This leads to four possible formulations of the same message. McClure et al. (2009) test all four formulations and find the largest framing effect if the action frame is positive and only the outcome frame is varied. Accordingly, I formulated the message in the scenario with a positive action frame and a positive/negative outcome frame: “If you are well prepared for a major erosion event you have a greater chance of keeping your house safe from erosion (…you have a lower chance of losing your house due to erosion).”
Fig. 22: Information provided in treatment 2 in the version shown to group 2.2 from Fig. 18 (text only, negative frame). The highlighted part in the first line was adapted according to the option chosen by the respondent in treatment 1.

The dependent variable of treatment 2 was the respondent’s attitude toward preparation for a major erosion event. This attitude was operationalized through two questions adopted from McClure et al. (2009): “How important do you think it is to be well prepared for a major erosion event?” (1 = not at all important, 7 = very important) and “How likely are you to actually take steps to prepare for a major erosion event?” (1 = very unlikely, 7 = very likely). These two questions were asked because they address different notions of the respondents’ attitude. While the first question describes a general attitude toward preparedness, the second one assesses the personal willingness to take preparatory measures, which is the central goal of such an information treatment.

A long-standing problem in survey research is that respondents might use ordinal scales such as the ones in this study in different ways. If this is the case, their responses on the 7-point scale are not comparable anymore. To correct for this incomparability, King et al. (2004) propose to have respondents assess, on the same scale as the self-assessment, the behavior of hypothetical individuals described in short vignettes. Subsequently, the respondents’ self-assessment can be recoded based on their relative position with respect to the vignettes. In my study, I designed the following two vignettes:
“Gary likes to create a safe and harmonious environment for his wife and three children. He has always liked engaging with local politics and contributing his share to protecting the environment.”

“Alison is annoyed that the state interferes too much in her private life. She has always dreamt of living right next to the ocean and wants to enjoy her present life without bothering too much about what might happen in the future.”

For each of these vignettes, respondents were then asked: “How likely is [Gary/Alison] to actually take steps to prepare for a major erosion event?” (1 = very unlikely, 7 = very likely). The vignettes are designed such that Gary has a higher likelihood to prepare than Alison. Based on this intended ordering of the vignettes, the respondents’ self-assessment was recoded following the methodology proposed by King and Wand (2007) (Table 4). Responses for which the recoded value could not be defined were excluded from further analysis. A co-benefit of this procedure is that it can potentially identify speeders who click randomly and might for instance assign a higher likelihood to Alison than to Gary. Recoding was done for both attitude questions according to Table 4. Afterwards, the two variables were averaged to form a measure of general attitude toward preparation (Cronbach’s alpha = 0.64).

<table>
<thead>
<tr>
<th>Survey responses</th>
<th>Recoded value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Self &lt; Alison and Self &lt; Gary</td>
<td>1</td>
</tr>
<tr>
<td>Self = Alison and Self &lt; Gary</td>
<td>2</td>
</tr>
<tr>
<td>Alison &lt; Self &lt; Gary</td>
<td>3</td>
</tr>
<tr>
<td>Alison &lt; Self and Self &lt; Gary</td>
<td>4</td>
</tr>
<tr>
<td>Alison &lt; Self and Gary &lt; Self</td>
<td>5</td>
</tr>
<tr>
<td>All other cases</td>
<td>Not defined</td>
</tr>
</tbody>
</table>

Table 4: Recoding of the attitudes towards erosion preparedness using two vignettes (Alison and Gary). Self = respondent’s self-assessment.

To check for balance between treatment groups, different covariates (Table 5) and demographic variables (age, gender, level of education, and state of residence) were included in the questionnaire. The full questionnaire, the raw data and the code used for the analysis are contained in the files submitted along with this thesis.
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<table>
<thead>
<tr>
<th>Covariate</th>
<th>Operationalization</th>
<th>Literature findings</th>
<th>Expected impact of higher covariate value on…</th>
<th>…choice of risky option</th>
<th>…attitude toward adaptive behavior</th>
</tr>
</thead>
<tbody>
<tr>
<td>Risk preference</td>
<td>Self-assessment on 10-point scale (10 – risk-seeking)</td>
<td>Risk-seeking individuals more likely to choose risky option (Weber and Milliman 1997)</td>
<td>More likely</td>
<td>Less likely</td>
<td>Less favorable</td>
</tr>
<tr>
<td>Familiarity with erosion</td>
<td>Heard about erosion</td>
<td>Individuals who have not yet experienced a disaster themselves underestimate the negative affect of being affected (Siegrist and Gutscher 2008; Keller et al. 2006)</td>
<td>Less likely</td>
<td>More favorable</td>
<td>More favorable</td>
</tr>
<tr>
<td></td>
<td>Seen erosion</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Affected by erosion (self or neighbors)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Distance from residence to coast</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Home ownership</td>
<td>Direct question (no/yes)</td>
<td>Home owners show higher levels of perceived risk than tenants (Kellens et al. 2013)</td>
<td>Less likely</td>
<td>More favorable</td>
<td></td>
</tr>
<tr>
<td>Trust in researchers</td>
<td>Self-assessment on 9-point scale (9 – high trust)</td>
<td>Risk messages more effective if source is trusted (Haynes et al. 2008)</td>
<td>(no expected impact)</td>
<td>More favorable</td>
<td></td>
</tr>
<tr>
<td>Personal responsibility</td>
<td>Self-assessment on 9-point scale (9 – high personal responsibility)</td>
<td>Adaptive behavior more likely if citizens see the responsibility for disaster protection with themselves instead of with the government (Lara et al. 2010; Terpstra and Gutteling 2008)</td>
<td>Less likely</td>
<td>More favorable</td>
<td></td>
</tr>
</tbody>
</table>

Table 5: Expected impact of covariates on dependent variables of the two experiments.
4.5 Results

4.5.1 Descriptive statistics

Demographics

In total, 1011 respondents participated in the study. Table 6 shows the number of respondents per group for the two sequential treatments. For treatment 1, the distribution of respondents according to demographic variables is displayed in Fig. 23. The respondents are mainly male (53% of the total sample), on average 41 years old, and more educated than the overall population with 69% having a Bachelor’s degree or higher. The distribution by states is largely according to the ratio of total population of these states. The corresponding demographic distribution for treatment 2 is presented in Fig. 38 in the appendix. Since the same respondents took treatment 1 and 2, the overall distribution is the same and only the share per group differs.

<table>
<thead>
<tr>
<th>Group</th>
<th>Treatment Frame</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1</td>
<td>Text Positive</td>
<td>166</td>
</tr>
<tr>
<td>1.2</td>
<td>Text Negative</td>
<td>164</td>
</tr>
<tr>
<td>1.3</td>
<td>Text + Positive</td>
<td>167</td>
</tr>
<tr>
<td>1.4</td>
<td>Text + Negative</td>
<td>172</td>
</tr>
<tr>
<td>1.5</td>
<td>Text + Positive</td>
<td>171</td>
</tr>
<tr>
<td>1.6</td>
<td>Text + Negative</td>
<td>171</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>1011</td>
</tr>
</tbody>
</table>

Table 6: Number of study respondents in each group.

Fig. 23: Distribution of respondents for treatment 1 by gender (upper left), age (lower left), state (upper right) and education (lower right). The vertical dashed lines represent the mean age. Treat 1A: aerial photograph without erosion bands, Treat 1B: aerial photograph with erosion bands.

Covariates

The distribution of the eight covariates described in Table 5 is shown in Fig. 24 and Fig. 25 for the groups of treatment 1 (see Fig. 39 and Fig. 40 in the appendix for the respective figures of treatment 2). Overall familiarity with the concept of coastal erosion is high, with 83% having heard of and 51% having seen coastal
erosion. Around 21% of the respondents indicated that they or neighbors/acquaintances of theirs had been directly affected by coastal erosion. 34% live less than 20 miles from the coast, with 54% living further than 40 miles from the coast.

The average trust in research is high at around seven on a 9-point scale. This is important for treatment 2 where the recommendations to take preventive measures are based on research findings. Further, respondents see it mainly as the personal responsibility of people living by the sea to take action against coastal erosion (mean value: seven on a 9-point scale). For risk preference, the distribution is more bi-modal, with peaks around two (risk averse) and six (slightly risk seeking) points on an 11-point scale (mean value: 4.1). Lastly, 58% own the house they are living in.

![Distribution of respondents for the six groups of treatment 1 for the four survey items assessing familiarity with coastal erosion.](image)

![Distribution of respondents for treatment 1 for the four covariates trust in research (upper left), risk preference (lower left), responsibility for erosion protection (upper right) and house ownership (lower right).](image)
Vignettes

The respondents’ assessment of the two vignettes used to correct for the fact that ordinal scales are used differently by different people is shown in Fig. 26. The average score of Anita is 2.5, and hence clearly lower than Gary’s score at 6.4. This corresponds well with the design of the vignettes depicting Gary as a person who likes to contribute to local politics whereas Anita likes to enjoy the present moment without caring too much about the future. 91% of the respondents assigned Gary a higher likelihood than Anita, as it was intended in the design of the vignettes (Fig. 27). For these respondents, recoding of the dependent variables of treatment 2 was possible. For the 6% who indicated that Gary and Anita have an equal likelihood, the ability to recode their response was possible only if their self-assessed likelihood was unequal to that of Gary and Anita. For the remaining 3% who gave Gary a lower likelihood than Anita, recoding was not possible. Overall, the dependent variables could be recoded for 95% of all respondents. The distribution of responses for the two dependent variables in original and recoded form is shown in Fig. 41 in the appendix.
Balance

To check the balance between treatment groups, I perform pair-wise joint orthogonality tests (see Hansen and Bowers 2008; McKenzie 2015). The output of the regressions are presented in Table 13 and Table 14 in the appendix for treatment 1 and treatment 2, respectively. I regress the treatment assignment (for instance being in the gain or loss frame for the control group) on all covariates and a constant. I test the joint hypothesis that all the coefficients of the covariates are zero. For treatment 1, the p-values of all models except model 5 are insignificant (p-value = 0.079). This means that the groups “control-gain” and “treat 1B-gain” are unbalanced at the 10%-level. The groups are unbalanced on whether respondents have or seen erosion and on where they see the responsibility for erosion protection.

For treatment 2, the p-values are insignificant for all models except model 1 (p-value = 0.059). This means that the groups “control-gain” and “control-loss” are unbalanced at the 10%-level. The groups are unbalanced on whether respondents have heard of or seen erosion and on where they see the responsibility for erosion protection.

4.5.2 Treatment 1: Risky choice framing

Fig. 28 presents the share of respondents choosing the risky option (i.e. building their house by the beach) in the six groups of treatment 1, with 95% confidence intervals. In the control group (left panel), 7.2% and 7.3% of the respondents chose the risky option in the gain and loss frame, respectively. Using a 2-sample proportion test, we cannot reject (p = 0.488) the null hypothesis that the proportion of risky choice in the gain frame is greater or equal to the one in the loss frame. Thus, I have to reject hypothesis 1 that respondents are more risk averse in the gain frame than in the loss frame.
Assessing and communicating erosion risk – an interdisciplinary case study in Bangladesh and the USA

Fig. 28: Share of respondents choosing to build their house close to the beach with 95% confidence intervals in the gain and loss frame, respectively, for the group that saw only text (left), text and the aerial photograph without erosion info (center) and text and the aerial photograph with erosion bands (right).

In the group that saw the aerial photograph without erosion information in addition to the text (central panel), 9.0% and 14.0% chose the risky option in the gain and loss frame, respectively. Hypothesis 5 states that showing the aerial photograph would not reduce the framing effect that is present in the control group. Since I found no framing effect in the control group, I cannot actually test hypothesis 5. If the aerial photograph alone was able to make respondents more risk neutral, we would expect that respondents get more risk seeking in the gain frame and more risk averse in the loss frame, as compared to the control group. Since the hypothesis is that the aerial photograph cannot reduce the framing effect, I test the opposite null hypotheses (Table 7). We can only reject the null hypothesis that the loss group in the control is larger or equal than the loss group that saw the photograph. This difference corresponds to an effect size of $d = 0.21$ for which I have a power of 63% (cf. Fig. 42 in the appendix). Additionally, I test whether the two frames in the photo group are equal, but cannot reject this null ($p = 0.152$).

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Tested null hypothesis</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1 (risky choice framing effect) control-gain ≥ control-loss</td>
<td>0.488</td>
<td></td>
</tr>
<tr>
<td>H5 (influence of blank aerial photograph on risky choice framing control-gain ≤ photo-gain</td>
<td>0.721</td>
<td></td>
</tr>
<tr>
<td></td>
<td>control-loss ≥ photo-loss</td>
<td>0.025*</td>
</tr>
<tr>
<td></td>
<td>photo-gain = photo-loss</td>
<td>0.152</td>
</tr>
<tr>
<td>H3 (de-biasing risky choice framing using aerial photographs showing past events) control-gain ≥ erosion-gain</td>
<td>0.059</td>
<td></td>
</tr>
<tr>
<td></td>
<td>control-loss ≤ erosion-loss</td>
<td>0.989</td>
</tr>
<tr>
<td></td>
<td>photo-gain ≥ erosion-gain</td>
<td>0.163</td>
</tr>
<tr>
<td></td>
<td>photo-loss ≤ erosion-loss</td>
<td>0.629</td>
</tr>
<tr>
<td></td>
<td>erosion-gain = erosion-loss</td>
<td>0.432</td>
</tr>
</tbody>
</table>

Table 7: Overview of null hypotheses tested to test the three hypotheses H1, H5 and H3 relating to treatment 1. Shown are p-values of two-sample proportion tests. * - significant at the 5% level.

These results show that presenting respondents with an aerial photograph of the plot significantly increases the share of risky choice in the loss frame, compared to when they only receive textual information. In the gain frame, this effect is also present, but not significant. Visually, Fig. 28 suggests that the aerial photograph introduces a framing effect, even though this effect is not statistically significant, as shown above. Overall, the
effect of the aerial picture seems to be an increase in risky choice, which is stronger in the loss than in the gain frame.

Considering the aerial photograph that also showed past erosion information (right panel), 12.3% and 15.2% of the respondents chose the risky option in the gain and loss frame, respectively. Hypothesis 3 states that showing the aerial photograph with erosion bands would reduce the framing effect that is present in the control group and in the group that saw the picture without the erosion information. Since I found no framing effect in the control group, I again cannot actually test hypothesis 3. Still, I test whether respondents who see the erosion information get more risk seeking in the gain frame, as compared to the control group and the blank photo group, as well as whether they get more risk averse in the loss frame. None of these effects is significant (Table 7). Lastly, I test whether the two frames in the group that saw the photo with erosion information are equal, and cannot reject this null (p = 0.432).

Visually, adding the erosion information increased the share of risky choice compared to the blank photo. This is the case for both frames. At the same time, the difference between gain and loss frame is smaller in the group that also saw the erosion information, suggesting that adding this information slightly reduced the framing effect.

Summing the effects of treatment 1 up, I cannot derive any conclusion on the influence of aerial photographs and erosion information on framing effects since there is no framing effect in the control group. Showing an aerial photograph of the plot increased the share of risky choice, especially in the loss frame. Adding erosion information to this photograph led to a further increase in the proportion of risky choice, but also to a decrease in the difference between gain and loss frame.

### 4.5.3 Treatment 2: Goal framing

Fig. 29 shows the average attitude towards taking preparatory measures against coastal erosion after recoding the original survey items with the vignettes (the attitudinal score before recoding is presented in Fig. 43 in the appendix). In the control group (left panel), the average attitude in the gain and loss frame was 3.91 and 3.85, respectively. In the treatment group, the corresponding attitude values were 3.94 and 4.04.

![Fig. 29: Average attitude (recoded with vignettes) toward taking preventive measures against coastal erosion with 95% confidence intervals in the gain and loss frame, respectively, for the group that saw only text (left) and text and the aerial photograph with erosion bands (right).](image)

Hypothesis 2 states that respondents in the positive frame indicate a higher likelihood to adopt preventive measures than those in the negative frame if they see the text only. If they see in addition the aerial photograph with erosion bands, we expect this difference between gain and loss frame to disappear (hypothesis 4). To test
these hypotheses, I run a linear regression of the recoded attitude score on frame and treatment (Table 8, model 1). Since the framing parameter is insignificant, I have to reject hypothesis 2. Since the treatment parameter is insignificant, I conclude that adding the aerial photograph does not increase the attitude score for respondents in the positive frame. In the negative frame, the attitude score is significantly higher in the treatment group than in the control group (p-value = 0.023 for Welch two sample t-test). This difference corresponds to an effect size of $d = 0.20$ for which I have a power of 73% (cf. Fig. 44 in the appendix). As there is no framing effect in the control group, I cannot formally test whether aerial photographs decrease the framing effect (hypothesis 4). Directly comparing gain and loss frame in the treatment group, I cannot reject (p-value = 0.130 for Welch two sample t-test) the null hypothesis that the means are equal.

I also test the robustness of these results by including those covariates for which I found an imbalance (chapter 4.5.1) as well as state-level fixed effects into the regression (Table 8, model 2). The effects of frame, treatment and their interaction remain insignificant. The attitude score was significantly higher if people had already heard about erosion and if they felt it was the personal responsibility of people living by the coast to take protective measures. This corresponds to my expectations (see Table 8 above). Further, the attitude score was significantly higher for certain states, as compared to the baseline of California. Lastly, I repeat these two regressions with the original attitude scale before recoding (Table 8, models 3 and 4). The results remain largely unchanged.

Summarizing the results from treatment 2, I could not find a goal framing effect in the treatment group and could hence not analyze whether adding aerial photographs could decrease the framing bias. Adding the photograph slightly increased the attitude score, but this was significant only in the loss frame.
### Table 8: Results of the linear regression for treatment 2 for the recoded attitude (models 1 and 2) and the original attitude score (3 and 4), both without (1 and 3) and with covariates (2 and 4).

<table>
<thead>
<tr>
<th></th>
<th>scale_recoded</th>
<th>scale</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Recoded attitude</td>
<td>General attitude</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Frame</td>
<td>-0.037</td>
<td>-0.025</td>
<td>-0.021</td>
</tr>
<tr>
<td></td>
<td>(0.069)</td>
<td>(0.068)</td>
<td>(0.079)</td>
</tr>
<tr>
<td>Treatment</td>
<td>0.023</td>
<td>0.029</td>
<td>0.034</td>
</tr>
<tr>
<td></td>
<td>(0.069)</td>
<td>(0.068)</td>
<td>(0.079)</td>
</tr>
<tr>
<td>Heard about erosion</td>
<td>0.138*</td>
<td>0.168**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.070)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Seen erosion</td>
<td>0.069</td>
<td>0.139**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.053)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Responsibility</td>
<td>0.056***</td>
<td>0.129***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Factor(Florida)</td>
<td>0.130*</td>
<td>0.132</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.075)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Factor(Georgia)</td>
<td>0.206**</td>
<td>0.242**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.094)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Factor(New Jersey)</td>
<td>0.245**</td>
<td>0.017</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.096)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Factor(North Carolina)</td>
<td>0.149*</td>
<td>0.183*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.089)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Factor(Other)</td>
<td>-0.164</td>
<td>0.063</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.152)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Factor(Texas)</td>
<td>0.078</td>
<td>0.050</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.076)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Factor(Virginia)</td>
<td>0.034</td>
<td>0.054</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.100)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frame:Treatment</td>
<td>0.139</td>
<td>0.119</td>
<td>0.072</td>
</tr>
<tr>
<td></td>
<td>(0.098)</td>
<td>(0.096)</td>
<td>(0.112)</td>
</tr>
<tr>
<td>Constant</td>
<td>3.912***</td>
<td>3.271***</td>
<td>6.370***</td>
</tr>
<tr>
<td></td>
<td>(0.048)</td>
<td>(0.134)</td>
<td>(0.056)</td>
</tr>
</tbody>
</table>

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Observations</td>
<td>968</td>
<td>968</td>
<td>1,011</td>
</tr>
<tr>
<td>R²</td>
<td>0.006</td>
<td>0.047</td>
<td>0.002</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.003</td>
<td>0.034</td>
<td>-0.001</td>
</tr>
<tr>
<td>Residual Std. Error</td>
<td>0.759 (df = 964)</td>
<td>0.747 (df = 954)</td>
<td>0.889 (df = 1007)</td>
</tr>
<tr>
<td></td>
<td>0.853 (df = 997)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>F Statistic</td>
<td>2.026 (df = 3; 964)</td>
<td>3.646*** (df = 13; 954)</td>
<td>0.666 (df = 3; 1007)</td>
</tr>
<tr>
<td></td>
<td>7.611*** (df = 13; 997)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Note:** *p<0.1; **p<0.05; ***p<0.01
4.6 Discussion

One important finding of this study is that I do not find a framing effect in either the risky choice situation or the goal framing scenario. This is surprising as framing effects are well established in the literature. In terms of risky choice framing, for instance, Freihardt and Buchs (2019) find a large difference between gain and loss frame of 35 percentage points with sample sizes similar to this study. In terms of goal framing, I closely reproduced the research design of McClure et al. (2009) who study earthquake preparation measures in New Zealand and find large differences in attitude scores between positive and negative frame. Various other studies have also identified significant and sizeable framing effects for both risky choice framing and goal framing (see Levin et al. 1998 and Piñon and Gambara 2005 for reviews).

Several reasons can potentially explain why I did not find framing effects. First, and foremost, my scenario differs strongly from the scenarios employed in most of the cited studies. Most risky choice studies (including my own one referenced above) replicate Tversky and Kahneman’s (1981) “Asian disease problem” involving a choice about human life or death. Schneider (1992), however, finds in her studies that framing effects are only strong if they involve decisions about human lives. In my study, the scenario was vastly different, with respondents having to choose the location of their house under the risk of a natural disaster occurring. Since this involves their personal property, the stakes are different from the “Asian disease problem” where the lives of other people are at risk.

Further, as Levin et al. (1998) note, choice situations only provide an indirect measure of the effect of framing on information processing. An individual forms her decision based on an interplay of the frame and the specifics of the decision situation. If an individual considers a risk as unacceptable for herself, she will most likely not react strongly to the framing, but choose the risk averse option irrespective of the frame. In my case, respondents seemed to consider coastal erosion as a severe risk, which could explain the dampening of the framing effect (discussed in more detail below).

Unlike most classical “Asian disease problems”, I could not assign quantitative risk levels to the two options. For most natural disasters, it is rarely possible to say whether a specific location is at an 80% or 50% risk of being affected by the disaster in the next X years. This is only possible for hazards where long time series of data are available, such as the risk of flooding for which return periods can be calculated. Coastal erosion occurs most severely during strong storms and hurricanes. Predicting the occurrence and severity of such events is challenging, and even more so in the light of climate change, which affects the frequency, intensity and duration of natural hazards. Therefore, I chose in this study to speak only of “higher” and “lower” risk. Respondents might interpret these terms differently, which further complicates the assessment of the effect of the frame itself.

Also in the goal framing literature, natural disasters have not been studied with the exception of the work by McClure et al. (2009). Most goal framing studies focus on health or marketing related topics. Following a similar logic as for risky choice framing, it could be that also goal framing effects are most prominent for messages related to human live or death. Further, it was found that goal framing effects are much less stable than risky choice framing effects (Levin et al. 2002; Levin et al. 2001). This unreliability of goal framing has been explained by the fact that behavioral intentions are formed not only based on the framed message, but

---

4 In this problem, respondents have to choose between two options to fight a disease that is expected to kill 600 people. If the first option is chosen, 200 people are saved for sure. In the second option, there is a one-third chance that all 600 are saved, and a two-thirds chance that no one is saved. In the negative frame, the same situation is described in terms of people “dying” instead of “being saved”.

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also based on various message-external factors, such as experience with the subject (Rothman and Salovey 1997), personal involvement with the issue (Hasseldine and Hite 2003) or the type of behavior promoted (Garcia-Retamero and Cokely 2011). I tried to account for these mediating factors through the covariates included in this study (e.g. familiarity with erosion, personal responsibility). Still, I did not find evidence for a goal framing effect. This could be due to the very high level of support for taking preventive measures (average score of 6.4 on a 7-point scale). If the overall support is so high, then framing single words in the message will most probably not be strong enough to create variations in attitude levels between frames.

With respect to framing, I thus conclude that its influence on risky choices or behavioral intentions might be limited beyond the typical, highly stylized scenarios that are mainly studied in the literature. In this study, I tried to construct a real world scenario in the context of natural disasters that resembles the “Asian disease problem”. How respondents decide in such a situation, might depend on various factors beyond the mere framing.

The second and main focus of this study was the influence of aerial photographs on framing effects. Since I do not find framing effects in the control groups of both treatments, I cannot evaluate whether photographs can help to decrease such framing effects. Irrespective of the size of the framing effect, I find an impact of adding the photographs in both treatments. In the risky choice, showing the aerial photograph without erosion information significantly increased the share of risky choice. This might be due to two particular features of the aerial photograph: First, the image shows a clear line between houses and beach, which can be interpreted as a wall protecting the houses from erosion. Second, all other houses in the photo are right by the beach, which might make respondents wonder why they should build at the rear of the plot if no one else does so. Within this group, we also see a clear difference between gain and loss frame, even though it is not statistically significant. Apparently, adding the contextual information contained in the image created a setting in which the framing in the accompanying text was effective. Ultimately, however, it is difficult to compare this effect to the control group since the photo contained additional information that was not transmitted in the text.

Adding the erosion bands to the photo made respondents even more risk seeking, although not statistically significant. Given that the rest of the photo remained unchanged, this implies that the erosion bands suggested a lower risk of being affected by erosion than the blank photo. This is counterintuitive given that the erosion bands are so wide that the distance between the houses and the water line is smaller than what has been eroded during any of the three hurricanes depicted. More research is thus needed to elicit how people read and interpret aerial photos containing information on past disaster events.

In the goal framing treatment, adding the photograph increased the attitude score. This is in line with my expectation that visualizing the imminence of the natural hazard would make respondents more willing to take preventive measures. However, the effect was small given that the baseline score in the control group was already very high.

With respect to the aerial photographs, I conclude that such photos contain contextual information that cannot be transferred in textual form and that might significantly alter respondents’ choices and behavioral intentions. At the same time, it remains unclear how people interpret information on past occurrences of a disaster if they are added to such aerial photographs.
The third and last point to discuss is the overall very high rate of risk averse choice in the first and of behavioral intention in the second treatment. This was not expected since I constructed the decision scenario as a tradeoff between the two options by contrasting “large house at high risk” versus “small house at low risk”. Thereby, I assumed that a large house was more desirable for most respondents than a small house. If this assumption is false, however, the tradeoff disappears and the two options occur to respondents as “house at high risk” versus “house at low risk” which would make most respondents choose the low risk option.

Also the average score in the goal framing part is much higher at 6.4 than the one in McClure et al.’s (2009) study (around 5.2). This is surprising since their study recommended low-investment measures such as buying a first-aid kit or re-arranging furniture in the house. My study, by contrast, promoted measures that involve a significant investment on the side of the respondents, such as taking out an insurance or building a sand fence on the beach.

One explanation for the very risk averse outcomes of both treatments could be that I only assess stated preferences: Respondents indicate what they would do in this hypothetical scenario. However, their actual behavior might differ if they were indeed in the situation of either choosing a location for the house or of taking preventive measures. This difference between stated and revealed preference is well known in the literature (Park et al. 2002; Murphy et al. 2005). In survey experiments, this can be overcome by giving respondents the possibility to invest part of their remuneration in one of the options from which they should choose. Combining stated and revealed preferences could then yield a more holistic picture of their preferences (Adamowicz et al. 1994). While assessing only stated and not revealed preferences is a clear shortcoming of my study, this in itself cannot yet explain why I find much higher attitude scores than McClure et al. (2009) who also used only stated preference questions.

Important drivers in risky choices and risk-related behavior are the respondents’ familiarity with the risk and their estimation of its severity (Rosenbaum and Culshaw 2003). In my study, respondents were overall very familiar with the phenomenon of coastal erosion, given that 83% had already heard about it and 51% had already seen it with their own eyes (cf. Fig. 24). Another indicator of the high relevance that many respondents assigned to the survey topic are the optional comments that respondents could enter at the end of survey. Over 90 of these comments (out of the 1011 respondents) referred explicitly to coastal erosion, covering various aspects mentioned in the study, such as the extent and speed of erosion:

“My family once had a cottage at a beach in N. Carolina. It was across the street from the beach when I was a kid (easy walk, but a house between it and the beach). It is now beachfront; no walk, no house in between (…).”

“I’ve seen places almost disappear over the past 10 years due to coastal erosion. The ocean is not something to mess around with”. 

the impact of hurricanes on shorelines:

“The NJ shore was a disaster after Sandy Hit.”

“My aunt and uncle owned a vacation home at Kure Beach near the ocean. They lived on third street, but it was actually the second street from the ocean. A storm or something had completely engulfed the first street at some time (…)”. 

“...”
measures to prevent erosion:

“"There are a lot of erosion fences and sand dune plantings nearby us, it's pretty cool to observe!""

“"After Sandy we saw how much beach erosion took place and while it is important for the homeowner to do their part, it has to be a partnership between the individual, the town, as well as the state. The homeowner can do some things but major things like sand replenishment will need significant infrastructure which has to be done by the town and the state. So we all have to do our part”,

and what respondents would actually do if they inherited such a plot of land:

“"Maybe provide an option to sell the plot of land for one further inland. I would not own a property that close to the ocean unless it were a second house.""

“I feel some people who live on the coast don't take coastal erosion seriously. To me living on the coast would be dangerous. I like to visit the beaches in NC, but I definitely would not live there.”

“I used to live near the beach in Ft Myers Fl. I moved to Central Fl (Orlando) for the very reasons discussed in the survey. In Fl. they say hide from the wind, run from the water. Erosion is a serious problem.”

Although anecdotal, these comments still provide evidence that residents of coastal states are mostly aware of erosion and consider it a severe problem. Consequently, building a house right next to an eroding beach is not an option for most of them, and they are very much willing to take measures that can prevent damage from erosion. This also reinforces the point raised above: If people have a very clear preference for one option, linguistic framing alone will hardly be able to shift their choice to the undesired option. In the current case, respondents’ preferences (building away from the sea, taking preventive measures) are in line with the larger societal goal of reducing human and material damage caused by erosion. In other cases, individual preferences might run contrary to the public interest, for instance regarding many climate-relevant behaviors (nutrition, mobility and others). In such situations, framing might seem like a promising option to nudge people into the direction desired from a societal point of view. This study raises doubt as to which extent this is possible if people have very strong preferences.

4.7 Future research and outlook

From the results of this study, two main areas emerge that require further research. First, it should be investigated more thoroughly to which extent the framing effects that have been established in various hypothetical scenarios are valid in real world decision-making situations. Although the present study also postulated a hypothetical scenario, still it was designed in a way that was more realistic than the classical “Asian disease problem”. As soon as the decision situation gets more realistic and tangible for respondents, various factors besides the mere information framing emerge that influence respondents’ choices. How effective frames can be constructed for such settings is an important question, given that for instance many climate change measures require rapid and drastic behavior changes at the individual level. Whether it is ethically acceptable to use such frames to nudge people is a normative question that requires a broader societal debate. Understanding if and how they work, by contrast, is a meaningful academic question.

Second, it will be beneficial for the area of risk communication to study in more detail how people understand and use maps and aerial photographs that present risk information not in a predictive manner, but only by showing the spatial extent of past risk events. Many climate related hazards occur in a spatially sequential way
– erosion of coasts and riverbanks being one example, desertification or salinization others. It can be scientifically challenging to predict the probability and extent of such events happening, and even if such probability information is available, it is even more challenging to communicate it to lay people (see Visschers et al. 2009 for a review). It is thus worth exploring whether people can more easily understand how imminent and threatening an environmental hazard is when they see where past events have occurred. In the present study, I find that such photographs make respondents more risk seeking, but we lack insight into the reasons for this shift.

A third field of research emerges not directly from the results of this experiment, but from the larger context of my research about riverbank erosion in Bangladesh. The overall goal is to study whether the maps developed in the first part of this thesis can be used to communicate the risk of riverbank erosion. The idea of the online experiment was to pre-test how people react to such maps or photographs. From the insights generated, I will develop a survey experiment to be included in a large household survey along the Jamuna River. The results of the US study are inconclusive with respect to the mechanisms behind the effects of the photos (e.g. why they make respondents more risk seeking). Moreover, the cultural and socioeconomic context of Bangladesh is vastly different from the US. Therefore, it might be necessary to perform a more qualitative, explorative pre-study to investigate how respondents in Bangladesh use and interpret such photographs.

### 4.8 Limitations

The main limitation of this research is that the discourse around framing and its use in risk communication largely follows the paradigm of the risk message model outlined in chapter 4.2: Scientists and experts have expert knowledge and use framing in their risk communication to nudge the lay public toward a desirable behavior. The limitations of this model have been discussed above and should not be repeated here. However, I would like to stress that in recent years, the need to include affected communities in every stage of the disaster risk management cycle has been more widely recognized. Different participatory tools have emerged to create partnership between scientists, authorities, and local communities (Cadag and Gaillard 2012; Ntajal et al. 2017). Community-based disaster risk management (CBDRM) emphasizes the value of local knowledge, local ownership, vulnerability and capacity assessments, acknowledging that local communities are the experts with respect to their environment and livelihood options (Barclay et al. 2008). It should thus be kept in mind that research about framing effects in risk communication is important to be aware about how a message might be received, especially in situations where community interaction is not possible due to time constraints like for emergency evacuation orders. Such communication cannot, nonetheless, replace more integrative communication strategies involving affected communities.

Two further, yet minor limitations arise. First, Stieb et al. (2019) point out that disaster risk communication with maps can have the unintended consequence of stigmatizing already disadvantaged communities. If certain areas are labelled as “risk zones”, this might create stress for residents, who are concerned about their perception by outsiders. While it is not clear whether this is relevant in the context of Bangladesh, it is important to keep this in mind. Second, using visuals to de-bias framed textual information might create a framing in itself, the so-called visual framing (Rodriguez and Dimitrova 2011). In my study, this became evident by the effect of adding the blank aerial photograph on risky choice in treatment 1. Visuals thus need to be chosen carefully and should be pre-tested in qualitative studies to elicit their effect before being applied in large scale.
5 Conclusions

This thesis had the overall goal of improving first the scientific assessment of riverbank erosion in Bangladesh and second the communication of the resulting disaster risk information. Both parts are essential elements of disaster risk management, yet both are especially challenging in settings that are low in resources and have an overall low level of education.

To improve the scientific assessment, I investigated whether the locations of past erosion events can be extracted from radar satellite imagery. To this end, I developed an algorithm to classify land cover, identify settlements and detect eroded land and settlements along the Jamuna River, Bangladesh. The algorithm can provide information on where land and settlements have been eroded during the last monsoon already one month after the end of the monsoon season, and hence earlier than using optical satellite images, which depend on cloud free conditions. This erosion detection can be achieved at sufficiently high spatial resolution. I could thus demonstrate the suitability of radar imagery to assess past erosion events using SAR imagery.

The analysis was performed on the GEE which gives access to massive amounts of satellite imagery as well as to Google’s cloud computing infrastructure. Further, resulting algorithms can be easily shared, making the results of this study potentially accessible and useable for government agencies or NGOs in Bangladesh. To share my results, I developed an interactive online tool allowing the user to explore where land and settlement have eroded along the Jamuna River in the monsoon seasons 2014/15 to 2019/20. This online tool as well as the underlying source code can be accessed and adapted free of charge, making it an attractive tool to use in low resource settings. Further work will attempt to improve this erosion detection algorithm by using the technique of SAR interferometry. In addition, I will explore how this assessment of past erosion events can be used as an input for modelling where erosion will occur in the next monsoon season.

Information on past occurrences of riverbank erosion might be valuable to predict where erosion will most likely occur in the following monsoon season, and to warn potentially affected residents accordingly. Even without an explicit prediction, the aerial photographs produced in the first part might be useful for risk communication purposes if recipients are able to extrapolate from past to future occurrences. For this to be the case, the risk information needs to be communicated effectively, which was the focus of the second part of my thesis.

Therein, I investigated whether such aerial photographs can reduce framing effects inherent in disaster risk communication. Framing effects mean that disaster risk information presented in a positive frame is perceived differently than if it is presented in a negative frame. I hypothesized that these framing effects occur if the information is presented as text only, but that they do not occur if an aerial photograph containing information on past erosion events is added to the text. Since I was not able to test these hypotheses with a survey in Bangladesh due to constraints in time and money, I conducted an online survey experiment in seven coastal states of the USA. I chose the USA since they are heavily affected by coastal erosion, which resembles riverbank erosion in many aspects.

Since I did not find framing effects in the control groups of my experiment, I could not formally test whether adding photographs reduces framing biases. These results cast doubt on the validity of framing effects in real world scenarios extending beyond the classical, stylized scenarios that have mostly been studied in the literature. Respondents who saw the aerial photographs were both more risk seeking and more willing to take preventive measures than those who saw only a text, but no photograph. We could, however, not elicit the mechanisms that caused these observed shifts in choices and behavioral intentions.
Overall, only few respondents chose the risky option of building their house by the sea and most of them stated very high intentions to take preventive measures. The covariates as well as qualitative comments given by several respondents suggest that many residents of coastal states are well aware of the phenomenon and risk of coastal erosion. In such a setting of strong preferences, framing might have a limited effect. The results also suggest that if people are aware of an environmental hazard and can choose where to build their house, they mostly choose the low risk option. Conversely, this implies that if people build their house in a high-risk location even though they are aware of the risk, they are either very risk seeking or they do not have any other choice than building in this location.

Investigating this hypothesis remains a subject for future research. It will be especially relevant to examine it in the context of Bangladesh where thousands of people live right next to the Jamuna River even though the area is well known for its high erosion rates. In general, it will be important to study how the findings from this study can be transferred and adapted to the context of Bangladesh. Further, more research is required about if and how framing can be effective in real world settings such as disaster risk communication and about how people read and interpret aerial photographs containing information on past disaster events.
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Appendix

Fig. 30: Left: Locations of the patches shown in Fig. 3 (symbols are larger than the patches). Center: Locations of the patches analyzed for the development of the land cover classification (symbols are larger than the patches). Right: Locations of the patches used to validate the land cover classification (patch 1), the settlement detection (patch 2) and the erosion detection (patch 3). Exact coordinates for all patches are contained in the GEE source code.
Fig. 31: Average backscatter of ten water patches for different sampling durations and filter sizes. The five filters for which only the size is indicated are all boxcar filters. Bars indicate the 95% confidence interval.

Fig. 32: Average standard deviation of the pixels within each of the ten water patches for different sampling durations and filter sizes. The five filters for which only the size is indicated are all boxcar filters. Bars indicate the 95% confidence interval.
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Fig. 33: Average backscatter of ten field patches for different sampling durations and filter sizes. The five filters for which only the size is indicated are all boxcar filters. Bars indicate the 95% confidence interval.

Fig. 34: Average standard deviation of the pixels within each of the ten field patches for different sampling durations and filter sizes. The five filters for which only the size is indicated are all boxcar filters. Bars indicate the 95% confidence interval.
Fig. 35: Average backscatter of ten tree patches for different sampling durations and filter sizes. The five filters for which only the size is indicated are all boxcar filters. Bars indicate the 95% confidence interval.

Fig. 36: Average standard deviation of the pixels within each of the ten tree patches for different sampling durations and filter sizes. The five filters for which only the size is indicated are all boxcar filters. Bars indicate the 95% confidence interval.
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Table 9: Determination of thresholds for a sampling duration of two weeks and a 25x25 boxcar filter. Values in bold are those that have been used to calculate the threshold indicated in the last column. All values are in dB.

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Table 10: Determination of thresholds for a sampling duration of seven months, unfiltered. Values in bold are those that have been used to calculate the threshold indicated in the last column. All values are in dB.

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Fig. 37: The studied stretch of the Jamuna River is not fully covered by one SAR imaging patch, but by several. Further, ascending (red) and descending (green) orbits do not overlap completely.
Table 11: Determination of thresholds for a sampling duration of six months and a 7x7 boxcar filter. Values in bold are those that have been used to calculate the threshold indicated in the last column. All values are in dB.

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Table 12: Determination of thresholds for a sampling duration of one month and a 7x7 boxcar filter. Values in bold are those that have been used to calculate the threshold indicated in the last column. All values are in dB.

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Fig. 38: Distribution of respondents for treatment 2 by gender (upper left), age (lower left), state (upper right) and education (lower right). The vertical dashed lines represent the mean age.

Fig. 39: Distribution of respondents for the four groups of treatment 2 for the four survey items assessing familiarity with coastal erosion.
Fig. 40: Distribution of respondents for treatment 2 for the four covariates trust in research (upper left), risk preference (lower left), responsibility for erosion protection (upper right) and house ownership (lower right).

Fig. 41: Distribution of respondents for treatment 2 for the two dependent variables in their original (first row) and recoded form (second row).
Fig. 42: Minimum detectable effect size (MDES) for treatment 1, as a function of the statistical power for a one-tailed test with 95% confidence intervals. Other parameters for this calculation are the probability of type I error, $\alpha = 0.05$, the proportion of units randomly assigned to treatment, $p = 0.5$, the number of covariates, $g = 0$, and the sample size, $n = 330$. 
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**Dependent variable:**

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<td>-0.028</td>
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<tr>
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<td>0.018</td>
<td>0.037**</td>
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<td>(0.018)</td>
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<td>-0.003</td>
<td>0.004</td>
<td>-0.014</td>
<td>-0.022^*</td>
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<td></td>
<td>(0.012)</td>
<td>(0.011)</td>
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<tr>
<td>Constant</td>
<td>0.336^*</td>
<td>0.562***</td>
<td>0.822***</td>
<td>0.480**</td>
<td>0.174</td>
<td>0.722***</td>
<td>0.672***</td>
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**Observations:** 330  
**R^2:** 0.044  
**Adjusted R^2:** 0.011  
**Residual Std. Error:** 0.498 (df = 318)  
**F Statistic:** 1.346 (df = 11; 318) (p = 0.198)

**Note:**  
*p<0.1; **p<0.05; ***p<0.01

Table 13: Pair-wise joint orthogonality tests between groups for treatment 1. The treat variable is binary. Model 1, 2 and 3 are comparisons gain/loss frame in the control group, Treat 1A group and Treat 1B group, respectively (treat = 1 for gain frame). Model 4 and 5 are comparisons control/Treat 1A group and control/Treat 1B group, respectively, in the gain frame (treat = 0 for control group). Model 6 and 7 is a comparison control/Treat 1A group and control/Treat 1B group, respectively, in the loss frame (treat = 0 for control group).
### Table 14: Pair-wise joint orthogonality tests between groups for treatment 2. The treat variable is binary. Model 1 is a comparison gain/loss frame in the control group (treat = 1 for loss frame). Model 2 is a comparison control/treatment group in the gain frame (treat = 1 for treatment group). Model 3 is a comparison control/treatment group in the loss frame (treat = 1 for treatment group). Model 4 is a comparison gain/loss frame in the treatment group (treat = 1 for loss frame).
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Fig. 43: Average attitude towards taking preventive measures against coastal erosion with 95% confidence intervals in the gain and loss frame, respectively, for the group that saw only text (left) and text and the aerial photograph with erosion bands (right).

Fig. 44: Minimum detectable effect size (MDES) for treatment 2, as a function of the statistical power for a one-tailed test with 95% confidence intervals. Other parameters for this calculation are the probability of type I error, $\alpha = 0.05$, the proportion of units randomly assigned to treatment, $p = 0.5$, the number of covariates, $g = 0$, and the sample size, $n = 485$. 