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Analysing the sensitivity of a flood risk assessment model towards its input data

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Abstract. The Small Island Developing States are characterized by an unstable economy and low-lying, densely populated cities, resulting in a high vulnerability to natural hazards. Flooding affects more people than any other hazard. To limit the consequences of these hazards, adequate risk assessments are indispensable. For the case study of Annotto Bay, Jamaica, a flood damage assessment model was created. This model generates a damage map for the region based on the flood extent map of the 2001 inundations caused by Tropical Storm Michelle. In this study, a methodology was developed and evaluated to test the sensitivity of the flood model towards its input data. Three damages were taken into account: building, road and crop damage. Twelve scenarios were generated, each with a different combination of input data, testing one of the three damage calculations for its sensitivity. One main conclusion was that population density, in combination with an average number of people per household, is a good parameter in determining the building damage when exact building locations are unknown. Furthermore, the importance of roads for an accurate visual result was demonstrated. Finally, the accuracy of raster input data, based on satellite imagery, was proven to be lower than vector data.

Keywords: *SIDS, flooding, risk assessment, damage map, sensitivity analysis*

1 Introduction

Natural hazards have a great economic impact on countries worldwide. The losses as a result of earthquakes, cyclones, landslides, flooding and tsunamis are estimated at up to 300 billion USD per year (UNISDR, 2015). Natural hazards do not only cause economic but also human losses. Between 1975 and 2008, over 2.2 million people died due to natural hazards worldwide (ISDR, 2009). Floods affect more people worldwide than any other hazard (UNISDR, 2015). Not only low-income countries suffer from severe inundations. The economic damages caused by flooding in the UK, for example, mount to an average of 250 million USD per year (Penning-Rowsell, 2014).

Low-lying, densely populated areas with unstable economies have little protection against natural hazards (UNESCO, 2014). Many of these areas can be found in the SIDS (Small Island Developing States), which are located in the regions of Latin America, the Caribbean, East Asia and the Pacific, and are expected to lose 20 times more of their capital stock in disasters

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each year than Europe and Central Asia (UNISDR, 2015). In Jamaica, for example, economic damage due to flooding was estimated at 1.5 billion USD over a period of four years (ODPEM, 2013b).

To limit the consequences of flooding, many governments revert to technical interventions, such as dams, levees and flood forecasting. These approaches, however, have shown limited success in several countries (Gall et al., 2011; Deckers et al., 2010), leading to new approaches that focus on flood risk management rather than flood control (Institute for Water Resources, 2009). One of these approaches is a quantitative flood risk assessment, indicating the high-risk areas by estimating the possible damage caused by a flood hazard. The output of this method can help decision makers in identifying the most vulnerable regions and allocating the right resources and funds to the right locations. The technocratic interventions, as mentioned before, can thus be applied more effectively and sensibly.

The use of such risk assessment models has been limited, due to questions about the uncertainty and reliability of the results (Merz et al., 2004). Since these methodologies are built on input data that each have their own accuracy and uncertainty, the output of the methodology has an uncertainty that is very difficult to quantify (Yu et al., 2013). Furthermore, an increase of the input data accuracy doesn't automatically imply a decrease of the output's uncertainty (Apel et al., 2009).

Especially in countries like the SIDS, where data availability is very limited, a thorough assessment of the data needed should be done. What are the minimum data requirements to build a reliable model? What is the sensibility of the model to the different datasets? These are the questions that need to be answered whilst keeping in mind that a certain degree of uncertainty is inherent to the methodology.

This paper investigates the different types of data used in a flood risk assessment for Annotto Bay, Jamaica, and their influence on the overall result by performing a sensitivity analysis on the risk assessment model with different combinations of input data. The output of every combination is tested on its accuracy based on the estimated total material loss and affected area and the geographic positions of high- and low-risk areas, compared to the benchmark output that uses all available data.

1.1 Sensitivity analysis

Data and methodology uncertainties are inherent to every risk assessment model (Carrington & Bolger, 1998). Since they can influence decision-making, these uncertainties have been quantified in several previous studies (Yu et al., 2013; Apel et al., 2004; Apel et al., 2008; Weichel et al., 2007). More and more exact data, however, does not always translate in a decrease of the uncertainty, since the influence on the final result differs for each input data set (Apel et al., 2008).

In many SIDS, geographic and statistical data availability is a major issue. Moreover, the data available has a questionable accuracy (Glas et al., 2015). It is therefore important to define the importance and influence of every input data set. With a sensitivity analysis, the influence of all input data on the overall result and its degree of detail is determined. When the sensitivity of a model towards its input is known, the minimum required data and the level of detail in order to get an accurate result, can be deduced. Although uncertainty analyses are frequently performed in the literature, sensitivity analyses to determine the necessity of the input data are rare. Nonetheless, this information is useful in setting up an uncertainty

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analysis. The impact of an input data set on the final result can serve as an indication of the impact of the uncertainty of this data set on the overall result and its uncertainty.

In this study, the input of a flood risk assessment performed for Annotto Bay, Jamaica (Glas et al., 2015), was used as case study for the sensitivity analysis, because in 2012 a lot of accurate data was collected for this town in the framework of another research program (ODPEM, 2013a). Since hydraulic and rainfall data is scarce in this region, and return periods of floods are unknown, this quantitative risk assessment focuses on material damage due to inundations caused by the Tropical Storm Michelle, in 2001 (WRA, 2002).

1.2 Study area

Annotto Bay is a small coastal town in the northeast of Jamaica. The town is vulnerable to several natural hazards, of which storm surges and riverine flooding are the most severe (ODPEM, 2013a). This is due to the high-risk location of the community. Not only is the town situated close to the coastline, but it is also enclosed by the Blue Mountains. This topography, together with the presence of four rivers traversing Annotto Bay, causes the rapid flooding of the community whenever perpetuation occurs in the mountains (WRA, 2002). Since the highest point of the town is only three meters above Mean Sea Level, Annotto Bay suffers severely from storm surges as well. There are about 5,500 inhabitants in the area, living mainly in concrete and wooden buildings (Statistical Institute of Jamaica, 2012). The land use in the study area and the locations of the rivers, roads and buildings is shown in Figure 1.

All damage calculations made in this study were based on the flood map of the inundations on both the 28th and the 29th of October, 2001, caused by Tropical Storm Michelle. The city of Annotto Bay was largely flooded for two days (Figure 2). Houses, infrastructure and crops were damaged, however, since the flow velocity was less than 0.3 m/s, there was only little severe structural damage (ODPEM, 2013a).

2. Methods

First, in order to perform a sensitivity analysis, a benchmark flood risk model was determined. This model was created using all available data. In this risk assessment, geographic information was combined with the replacement values of the elements at risk and with the damage factors. Replacement values represent the cost to rebuild an element when it is totally destroyed, while the damage factors are an estimate of the degree of destruction based on the flood level, in feet, at the location of the element at risk. Damage costs of buildings, crops and roads are thus calculated by multiplication of the replacement value by the damage factor to generate a damage map, indicating the total damage cost per square meter for the study area. The input data of this model is listed in Table 1.

This first assessment, the bench mark, is called Scenario 1 (S1). Eleven other scenarios, each with less or less detailed input data than S1, were tested and compared to this first one. Table 2 shows an overview of all scenarios, with the input data that was used and the data that was not used, in order to test the sensitivity of the model towards this data type.

For each scenario, four elements were compared: the spatial difference, the visual output, the total damage cost and the total damaged area. To test the first element, all damage maps were converted into raster maps with a resolution of 5 meters. Then, the value of every pixel was compared to the values of its neighbors. The spatial difference was defined as the probability that a pixel has a different value than its neighbor, as demonstrated in Figure 3. The value of the spatial difference is thus a tool to describe the level of detail of a damage map. Since the resulting damages are assigned to classes, this level of detail may be difficult to deduct from only the visual mode of representation. Together with the total damage cost and the total damaged area, the visual result and the spatial difference determine the influence of each type of data on the overall result.

All scenarios were modeled in ArcGIS 10.2 using Python. The methodology of the risk assessment was automated through a script written in the ArcPy module. Although small differences exist between the scenarios, caused by the use of different or less input data, the overall methodology remains the same.

3. Results

3.1 Bench mark map

The benchmark damage map shows the output of the flood risk assessment model for Annotto Bay. This model focuses on three types of damage: building, road and crop damage. The cost of these damages was calculated separately for each type and then combined to generate an overall damage map of the region, as shown in

Figure 4. Table 3 contains the three numeric elements on which the comparison of the scenarios is based: the total damage, the total damaged area and the spatial difference, as calculated for S1.

Building damage calculations were based on the exact GPS position of all of the buildings in Annotto Bay, as well as their building materials and the number of floors. By using average values for the material cost and the building surface area, a maximum damage value was determined per building. Subsequently, these maximum damage values were multiplied with a damage factor, based on the water levels as shown on the 2001 flood map. These calculated real damages were then summed up per land use polygon, in order to generate a clear view of the building damage.

The damage to roads was calculated using the road network dataset. This dataset divides the roads into four classes, each with their own properties, for example the width of the road. The line dataset was converted into polygons, based on the different widths. Using the average maximum road damage and the damage factors, the real damage was then calculated for all roads.

Finally, the crop damage map was generated. A difference was made between banana plantains and other crops, due to the different reaction to inundations and the different average cost of the crops. The duration of the flood is especially important for banana plants, since a two-day flood, as this was the case in 2001, causes 100 percent destruction of the plants. For the damage calculations of the other crops, an average was used of the damage factors of eight crop types. The maximum crop damage value was then multiplied with this damage factor to determine the crop damage cost. Since the damage factor for the banana plantains was 1, their real damage value was equal to the maximum damage value.

3.2 Building damage sensitivity

In the next four scenarios, the sensitivity of the flood risk model towards the data used to calculate building damage was investigated. In S2, the information concerning materials and number of floors was replaced by average values, while in S3, the location of the buildings was also eliminated, leaving only the number of buildings in the total study area as information. In this case, after testing the available data in and around the study area, including the exact building locations and the land use data, 90% of the buildings was presumed to be in urban areas and the other 10% in rural areas. Population information was used to determine the building damage in S4 and S5, based on the presumption that a household, one building, consists of 3 people (WRA, 2002). In the former scenario, the population density per statistical sector was used to calculate the number of buildings. In the latter, however, only the total number of people in the study area was known. Here, the same assumption was made as in S3 about the division of buildings between rural and urban areas.

Figure 5 shows the visual result of the four scenarios, while Table 4 shows the calculated damage, the damaged area and the spatial difference in comparison to the benchmark results of S1. Visually, no big changes can be observed in the indication of the high-risk areas. The slightly lower spatial difference in S3 and S5 does indicate a decrease in the level of detail. While S2 gives the result that is most similar to the result of S1, the table clearly shows an important difference in the calculation of the total damage. Although the visual result of S4 is less detailed than the benchmark, the spatial difference of 4.52% indicates a similar level of detail as in S1. Moreover, this scenario gives the best result towards the calculation of the total damage.

3.3 Road damage sensitivity

Scenarios 6, 7, 8 and 9 were used to assess the sensitivity of the risk assessment towards the road data. In S6, the road classes were presumed to be unknown, giving all roads the same average width. The seventh scenario does not take the roads into account. In S8, the location of the roads is presumed to be unknown and therefore, they are calculated as a percentage of the land use. After analysing the available data in and around the study area, the percentages are set at 5% in urban areas and 2% in rural areas. S9 only used the road network to divide the land use polygons, but does not take them into account in the damage calculations.

The road cost is only a small share of the total calculated damage. This is clear when comparing the total damage of the four scenarios to the damage of the benchmark in Table 5. S6, for example, generates almost identical numbers than S1. Visually, these scenarios are almost identical.

There is a significant difference in damaged area between S1 and S8. Since the threshold value for road damage is 0 feet and the road damage is spread over the entire study area in S8, all flooded areas have damage. Moreover, visually, S8 shows a different, less accurate, result than the other scenarios, as shown in Figure 6. The scenario has a low spatial difference of

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1.75%.

Although S7 clearly has a better visual result than S8, indicating the areas without any damage more accurately, the spatial difference of this scenario is even lower. Due to a larger damaged area in S8, more pixels are taken into account in the spatial difference calculations, increasing the possibility of having neighboring pixels with a different value. The level of detail is thus higher in S8, but the visual result shows large deviations from S1. The removal of the roads in S7 and S9 only has a small effect on the total damage and damaged area, but it does have an important influence on the level of detail, as proven by the spatial differences. The ninth scenario, nonetheless, does have a more accurate visual result then the other road scenarios, due to the use of the road network to divide the land use polygons.

3.4 Crops damage sensitivity

Scenario 10 tested the sensitivity of the model by assuming the difference between banana plantains and other crops is unknown. This was done by using an average maximum damage value and the damage factors for the other crops, since the damage factors of the banana plants are based on time and not water height.

Since the real damage value of the crops is rather small in comparison to building damage values, S10 only has a small effect on the result. Therefore, the visual view of the map is almost identical to the bench mark damage map. This can be seen in Figure 7. Furthermore, Table 6 demonstrates that the calculated total damage and damaged area differ only little from the values that were generated by the model used for S1.

3.5 Data type sensitivity

The last two scenarios looked into the sensitivity of the model towards the input data type. In the benchmark model, all input data was vector data. In areas with little data available, however, a lot of information will have to be gathered from satellite imagery. Therefore, all input data in S11 and S12 was converted to raster data with a resolution of 10mx10m for S11 and 30mx30m for S12. The former was chosen since several satellites provide images with a world coverage with these resolutions. SPOT, for example, is a commercial high-resolution satellite system that provides images with 10 meter resolution. The Landsat program uses the latter resolution. This enterprise has an online service, providing free images with a 30 meter resolution. The calculations for the building damage were based on population data. The same method was used as in S4. Therefore, S4 is also included in Table 7.

Although the two damage maps, as shown in Figure 8, visually do not differ a lot from the maps of S1 and S4, Table 7 shows that the total damage cost is substantially bigger than the cost in S1 and S4. The total damaged area is slightly larger, due to the conversion of the polygon flood map to a raster map. Since the input of the scenarios was raster data, every pixel has been calculated separately. Therefore, the level of detail, and thus the spatial difference, is higher than in S7, S8 and S9. When comparing S11 and S12, it can be stated that the spatial difference shows a growing decrease of accuracy as the resolution of the raster data increases. Moreover, the visual result is less detailed and gaps arise in the final map.

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In all scenarios, more than 90% of the total flood damage consists of building damages. Consequently, scenarios that test the models sensibility for building data show the largest deviations in the total damage. Figure 9 shows the deviation for every scenario to the total cost of S1.

When looking at the scenarios focussing on building damage, S4 has the best result, with a deviation of 6.58% in relation to the result of S1. This scenario has calculated the damage cost based on population density per statistical sector. In the case study of Annotto Bay, the bench mark study made use of the exact GPS locations of all buildings in the region. In many other areas in the SIDS, this detailed information is not available. Population data, however, exists for most regions free of charge. Since the results give a good result, visually as well as in the total damage cost, this scenario must definitely be investigated further.

When only relying on Figure 9**Fout! Verwijzingsbron niet gevonden.**, it could be stated that the model is not sensitive to road data at all. However, not only the total damage must be taken into account, but also the spatial impact and the total damaged area have to be included. In Figure 10, the last factor is given. It is clear that S8, the scenario where roads are taken into account as a percentage of the land use, is not a good simplification. Since buildings have a threshold value to be marked as ‘inundated’ of 1,5 feet, but roads are marked immediately as flooded, the total damaged area in S8 is a big overestimation of the reality. This is affirmed by the visual result, showing a lot of damaged area with a low cost per square meter.

Although S7 scores very well for the total damage as well as for the total damaged area, the result is a lot less accurate than the benchmark map. This becomes clear when looking at Figure 11, that visualizes the deviation of the spatial difference of all scenarios in relation to S1. In this figure, three scenarios that test the influence of road data have the highest deviation and thus show significantly less detail in their damage map. Although the roads are negligible for the total damage and the damaged area, they are, nonetheless, an indispensable part in creating a visually accurate map.

Visually, as well as in total damage and damaged area, the difference between crops and banana plantains has a small effect on the results, as shown in Figure 11. It must be stated that this is the case for this case study of Annotto Bay, where building damage is the major type of damage. When looking into other regions, where agriculture has a more important role, the difference between crops can be a lot more significant for the results. This has to be further investigated.

Finally, S11 and S12 have shown the sensitivity of the flood model towards the input data type. In this case, all input data was converted to raster data. Although the visual result was similar to the benchmark, there was a clear difference in total damage and damaged area. Therefore, vector data has the preference when working in a relatively small study area. When some input data is vector and other raster data, it should be considered to vectorise the last type in order avoid losing detail. This methodology will give the most accurate result.

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5. Conclusion

This sensitivity analysis of the Annotto Bay flood model is a first step in determining which data are indispensable in the risk assessment. To do so, a benchmark model was created, using all available data to generate a result as accurate as possible. The damage map of this scenario 1 was used to compare with 11 other scenarios, each with a different combination of data. By comparing the visual result and the total damage and damaged area, the sensitivity of the flood risk model towards the different data could be determined.

Since the 2001 flood especially hit the urban areas of Annotto Bay, the building data was the most significant type of data in this study. The best result with simplified data was retrieved from the scenario that uses population density as input data, as well as the estimation of 3 people living in one building. In the resulting damage map, the high-risk areas were correctly indicated and a good level of detail was achieved. The total damage cost was 7% more than the cost of S1, but in light of the significant share of building damage, this is still a satisfying result. Furthermore, the global availability of population data, in many cases for free, is an important factor to take into account when applying the flood risk model in other regions.

Furthermore, the importance of road data was proven in this study. Although the roads have a small effect on the overall cost, they do have a role in the visual end result. An accurate road dataset helps to divide the land use, and to determine the building damage more precisely. In this light, the possibility of using remote sensing images to create road datasets must be investigated, since many available datasets do not include all roads. When using satellite imagery, the road classes cannot be taken into account, but this has been proven to have little impact on the result. A complete dataset can definitely help in defining building damage, since every building must have access to a road and will thus be most likely be located close to this road. Combining this information with population data must definitely be investigated.

No conclusions could be made from the sensitivity analysis towards crop data, because, in this case study, the impact was too small. The results were very positive, showing little difference between S1, where crops and banana plantains were treated separately, and the scenario where an average cost was used. To further investigate the impact of crop data, a more rural area should be investigated. However, there can be concluded that the difference between crops and banana plantains can be eliminated in a study area where especially the urban areas are affected by flooding.

Finally, the data type plays an important role in the accuracy of the final result of a risk assessment. Using raster data, from satellite imagery for example, causes an overestimation in total damage and damaged area. Vector data should thus be used when possible. If some input data is vector and other raster, vectorising the raster data is opted to avoid losing information or detail.

This sensitivity analysis gives an indication to which data is indispensable and which data can be adapted, replaced or ignored in a risk assessment. However, more research should be done in other regions to validate the results of the sensitivity analysis and to investigate the impact to the damage types in different situations.

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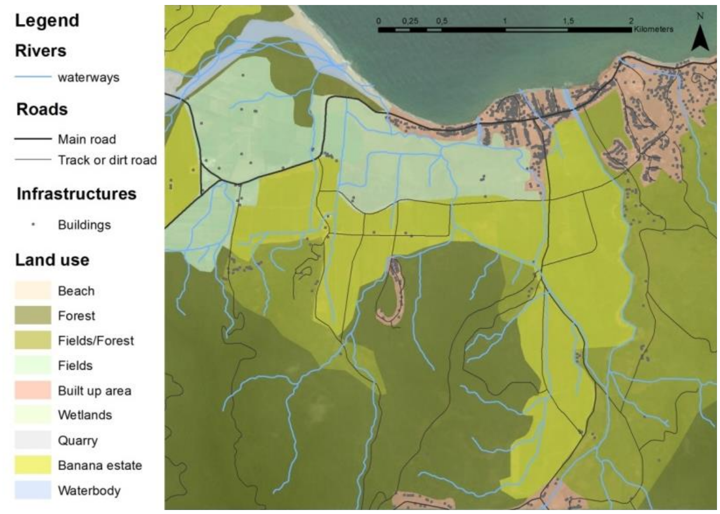

Figure 1: Situation map Annotto Bay, Jamaica (Glas et al, 2015)

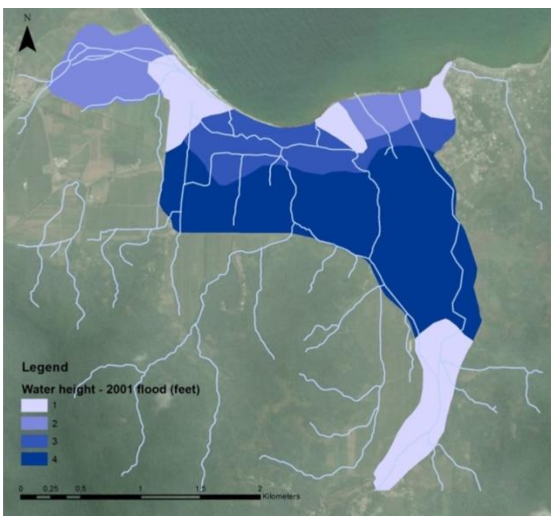

Figure 2: Flood extent of 2001 inundations caused by Tropical Storm Michelle in Annotto Bay, Jamaica (Glas et al, 2015)

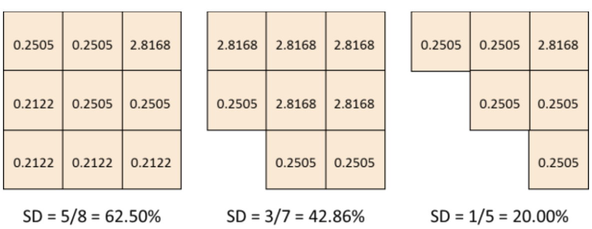

Figure 3: Calculation of the spatial difference (SD) of three center pixels with SD = {number of neighboring pixels with different value} / {number of neighboring pixels}

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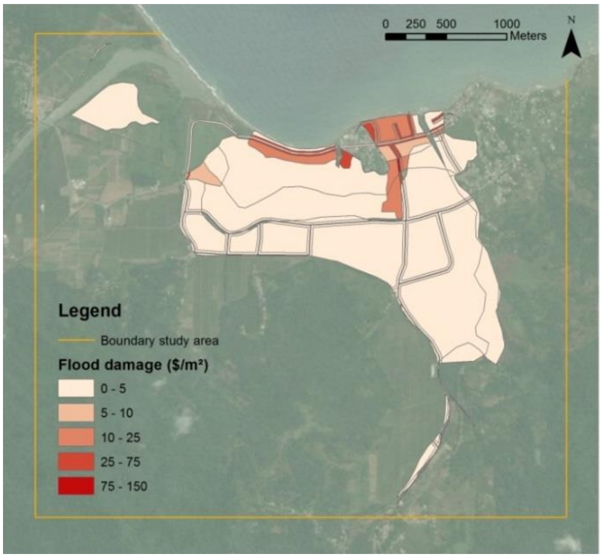

Figure 4: Scenario 1 (S1): Benchmark damage map of Annotto Bay, using all available input data

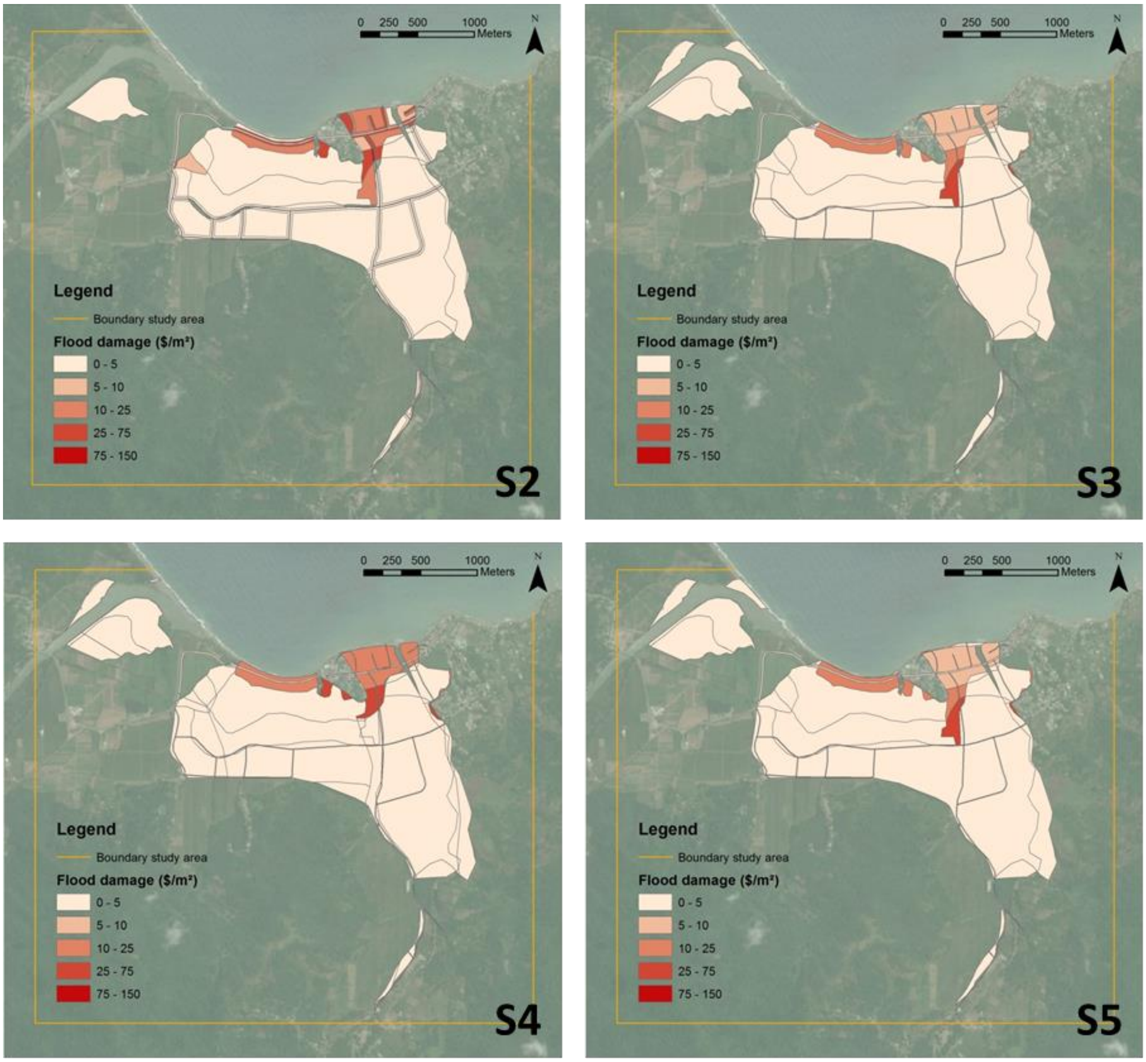

Figure 5: Damage maps for Annotto Bay for S2, S3, S4 and S5. (Top left: (S2) Building materials and number of floors unknown, Top right: (S3) Building locations, materials and number of floors unknown, Bottom left: (S4) Building density is calculated based on population density, Bottom right: (S5) Building density is calculated based on number of people in study area.)

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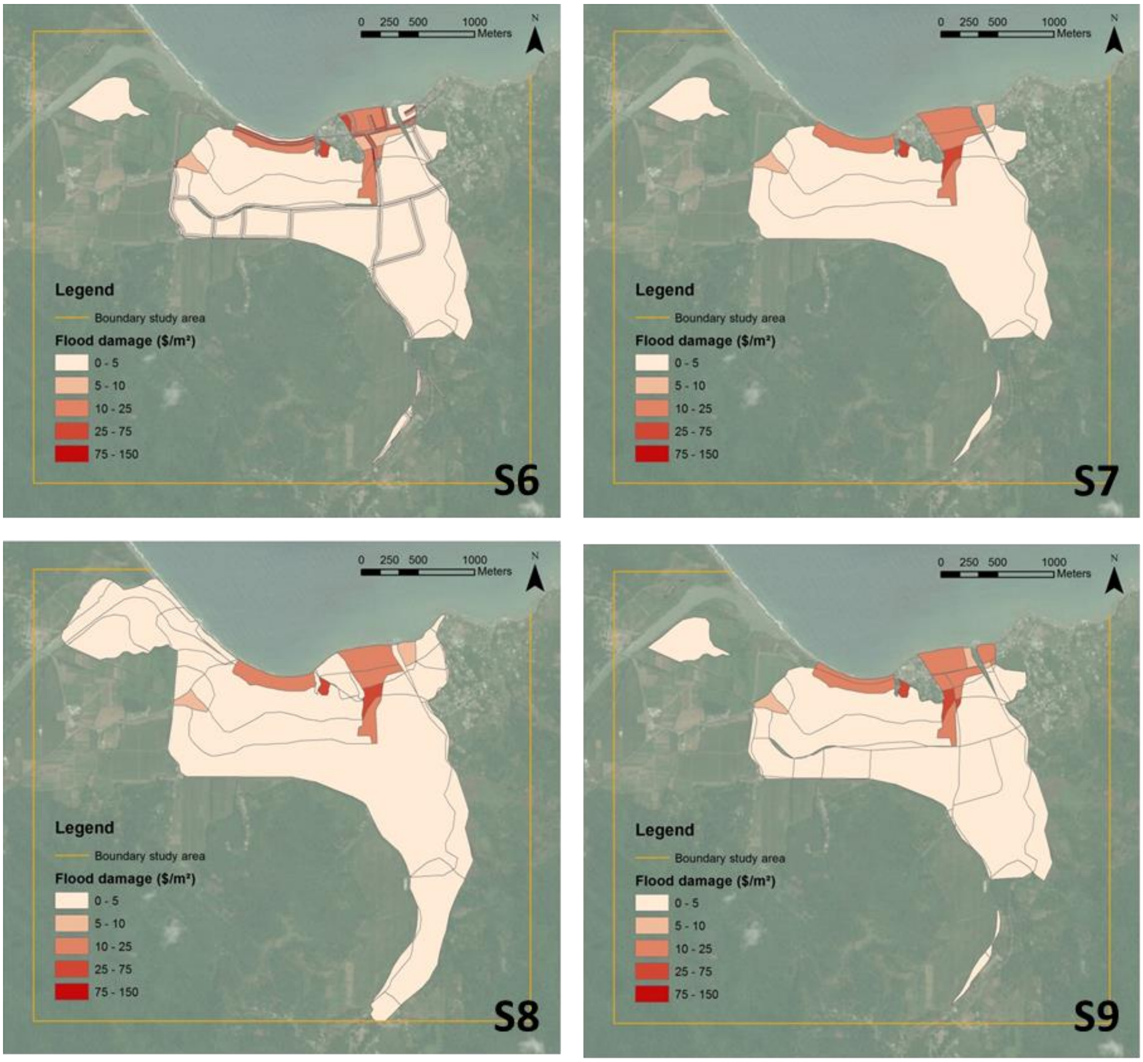

Figure 6: Damage maps for Annotto Bay for S6, S7, S8 and S9. (Top left: (S6) Road classes are unknown, Top right: (S7) All roads are unknown and not taken into account, Bottom left: (S8) All roads are unknown but taken into account as a percentage of land use, Bottom right: (S9) Roads are only used to divide land use polygons – no road damage.)

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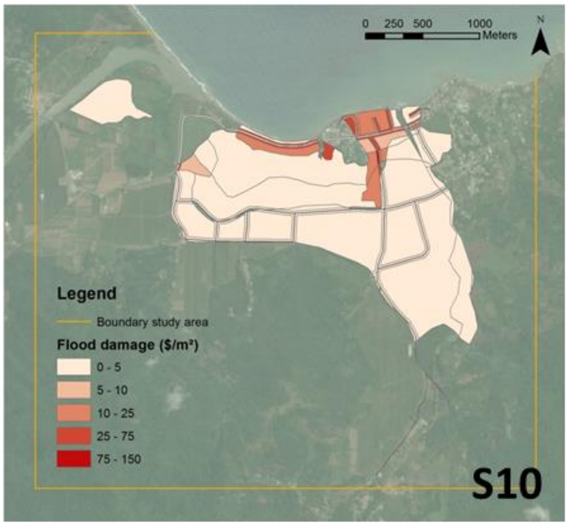

Figure 7: Damage map for Annotto Bay for S10 (Difference between banana plantains and other crops is unknown.)

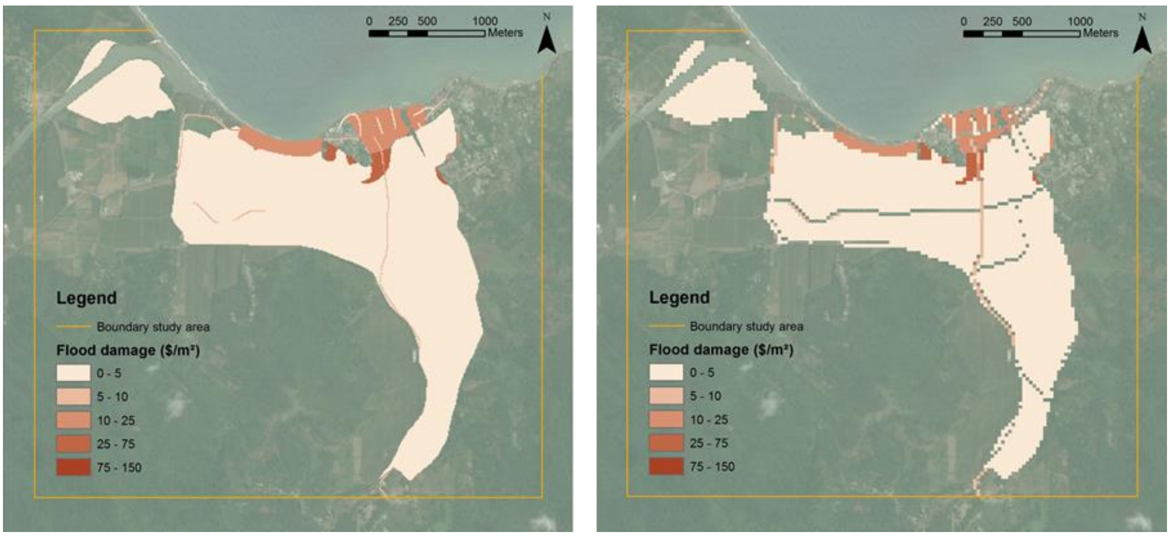

Figure 8: Damage maps for Annotto Bay for S11 and S12. (Left: (S11) Raster approach (10x10) based on population density, Right: (S12) Raster approach (30x30) based on population density.)

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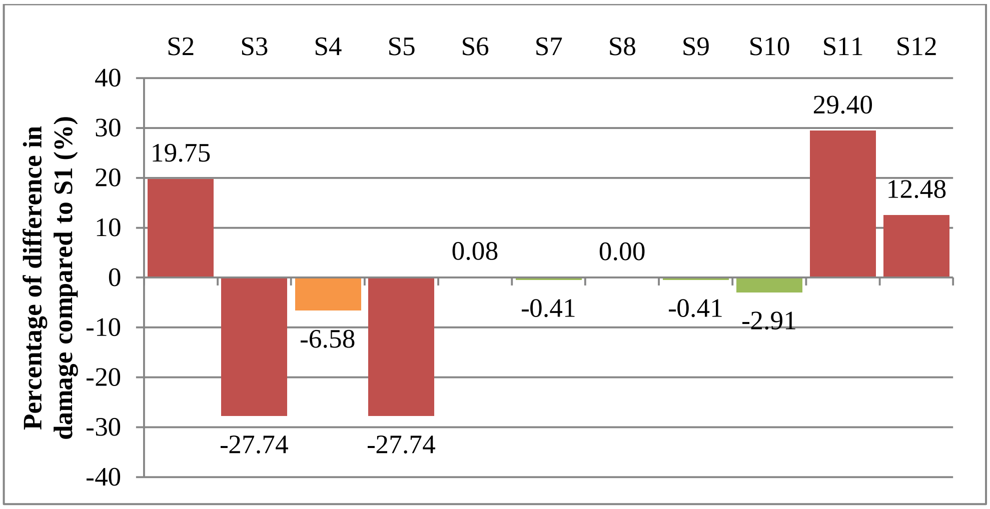
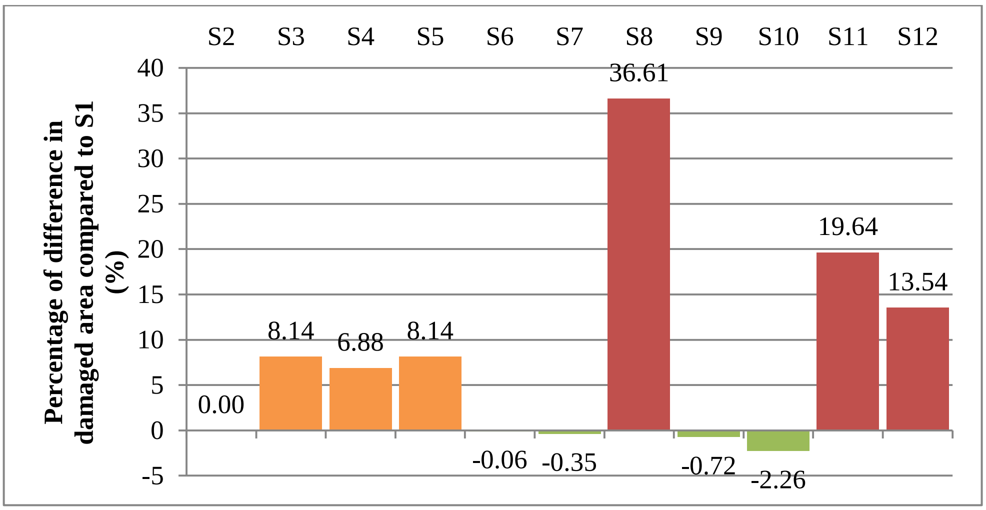


Figure 9: Deviation of total damage of all scenarios in relation to S1 (=0)



5 **Figure 10: Deviation of total damaged area of all scenarios in relation to S1 (=0)**

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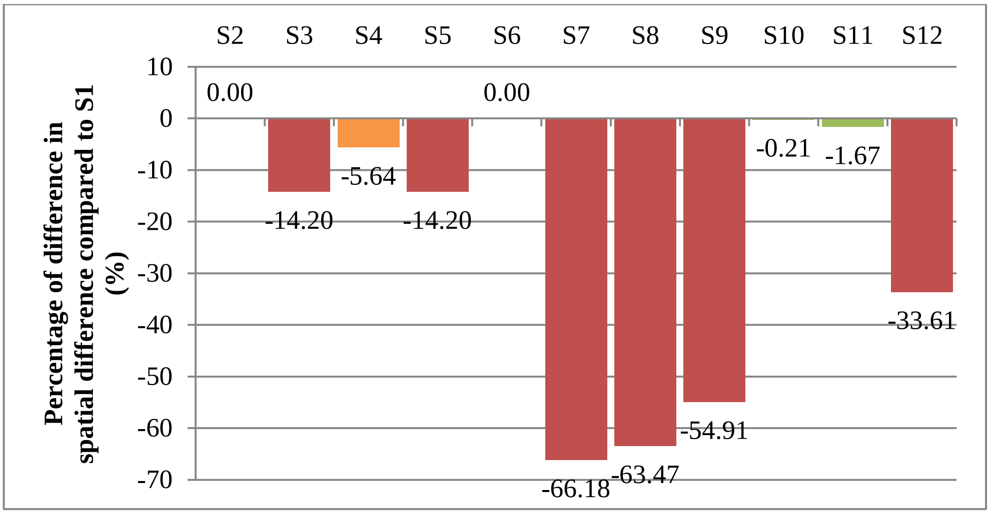

Figure 11: Deviation of spatial difference of all scenarios in relation to S1 (=0)

Table 1: Data used in the Annotto Bay flood risk assessment (Glas et al., 2015)

DATA	**TYPE**	**SOURCE**
Landuse	Polygon	NLA (2001) + update based on DigitalGlobe satellite imagery (2010)
Roads	Polyline	ODPEM (2013a)
Buildings	Point	ODPEM (2013a)
Population density	Polygon	Statistical Institute of Jamaica (2012)
Average crops values	Table	FAOSTAT (2014)
Average building values	Table	ODPEM (2013a)
Critical buildings	Point	ODPEM (2013a)
2001 Flood extent	Polygon	ODPEM (2001)
Damage functions	Table	Dutta et al. (2003)

Table 2: Overview of investigated scenarios in the sensitivity analysis

SCENARIO	**DESCRIPTION**	**USED INPUT DATA**
S1	**Detailed approach**	Land use data Roads (classes) – line 2001 flood data Building locations + materials + number of floors
S2	**Building materials and number of floors unknown**	building locations average material values average number of floors

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S3	**Building locations, materials and number of floors unknown**	number of buildings known presumed to be equally spread in the urban area
S4	**Building density is calculated based on population density (3 people per building)** Population density is used to determine number of buildings in statistical sectors	
S5	**Building density is calculated based on number of people in study area (3 per building)** Number of people in the study area is used to determine number of buildings	
S6	**Road classes are unknown** Average values for the width and the cost of the roads are used	
S7	**All roads are unknown and not taken into account** No roads data is used	
S8	**All roads are unknown but taken into account as a percentage of land use** (5% in urban areas, 2% in rural areas) No roads data is used, but the damage is calculated based on a percentage of land use	
S9	**Roads are only used to divide land use polygons – no road damage** Roads are used as a division tool, not to calculate damage	
S10	**Difference between banana plantains and other crops is unknown** In the damage calculations, the same damage factors and maximum costs are used to determine the cost of the crops and the banana plantains	
S11	**Raster approach (10mx10m) based on population density** All input data (vector) is converted to raster data with a resolution of 10 meters	
S12	**Raster approach (30mx30m) based on population density** All input data (vector) is converted to raster data with a resolution of 30 meters	

Table 3: Calculated total damage, total damaged area and spatial difference for S1

	TOTAL DAMAGE ($)	TOTAL DAMAGED AREA (m²)	SPATIAL DIFFERENCE (%)
S1	7 490 000	3 182 000	4.79

Table 4: Calculated total damage, total damaged area and spatial difference for S2, S3, S4 and S5 in comparison to S1

	TOTAL DAMAGE ($)	TOTAL DAMAGED AREA (m²)	SPATIAL DIFFERENCE (%)
S1	7 490 000	3 182 000	4.79
S2	8 969 000	3 182 000	4.79
S3	5 412 000	3 441 000	4.11
S4	6 997 000	3 401 000	4.52
S5	5 412 000	3 441 000	4.11

Table 5: Calculated total damage, total damaged area and spatial difference for S6, S7, S8 and S9 in comparison to S1

	TOTAL DAMAGE ($)	TOTAL DAMAGED AREA (m²)	SPATIAL DIFFERENCE (%)

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S1	7 490 000	3 182 000	4.79
S6	7 496 000	3 180 000	4.79
S7	7 459 000	3 171 000	1.62
S8	7 490 000	4 347 000	1.75
S9	7 459 000	3 159 000	2.16

Table 6: Calculated total damage, total damaged area and spatial difference for S10 in comparison to S1

	TOTAL DAMAGE ($)	TOTAL DAMAGED AREA (m^2)	SPATIAL DIFFERENCE (%)
S1	7 490 000	3 182 000	4.79
S10	7 272 000	3 110 000	4.78

Table 7: Calculated total damage, total damaged area and spatial difference for S11 and S12 in comparison to S1

	TOTAL DAMAGE ($)	TOTAL DAMAGED AREA (m^2)	SPATIAL DIFFERENCE (%)
S1	7 490 000	3 182 000	4.79
S4	6 997 000	3 401 000	4.52
S11	9 692 000	3 807 000	4.71
S12	8 425 000	3 613 000	3.18