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Hypothetically Quantifying Flood Vulnerability in a Reservoir Tributary Employing 3-Dimensional Geomorphological Terrain Related Covariants, a Stochastic Iterative Quantitative Interpolator and a Space-time Global Circulation Model Paradigm

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Abstract

Deaths from flooding in the United States are preventable with the right planning maps and mitigation. This research is revolutionary as it forecast the most vulnerable flooding areas of higher population regions by incorporating future precipitation projections, soil classifications, a 3-dimensional (3-D) digital elevation model (DEM) and the Geographic Information System (GIS) kriging algorithmic iterative interpolation tool to determine the optimal geolocations where storm water drainage detention or retention and improvements should occur. Firstly, utilizing spatial tools and a global circulation models (GCMs), precipitation was mapped to determine high vulnerability areas for future potential flooding. A robust semi variogram, geospatial explanatory locations of precipitation were then parsimoniously constructed for a sample site in Hillsborough County, Florida. Overlaying this data on 3-D temporal geomorphological terrain related elevation models, high risk flooding areas were geolocated employing geospectrotemporal geospatial techniques. For this region, two-thirds of the precipitation occurs during the summer months; therefore, June, July and August were analyzed. Furthermore, just focusing on one month, e.g., August, would not take into account antecedent ecogeohydrology conditions which impact run off volume and flooding. Soil characteristics such as capillary action, permeability and drainage porosity were considered as some soils have a high water-holding saturation capacity and poor infiltration capability, increasing flooding. Finally, extracting forecasted slope coefficient from 3-D models were examined to determine if they were feasible to help extract geolocations where there is prevalent standing water during wet season.

Keywords: General circulation models; Elevation; Flood vulnerability; Interpolation; Semi variogram

Introduction

Flooding can have a devastating effect on whoever is in its pathway. Not only can flooding create a catastrophe as seen in 2005 Hurricane Katrina disaster in New Orleans where there were over 1100 fatalities, but areas of standing water invite nuisances and increase the spread of water-borne diseases [1-3]. Drayna et al. [4] study showed how for the four days after any rainfall in Milwaukee, pediatric emergencies significantly increased by 11% due to viral infections such as norovirus, rotavirus, calicivirus, enterovirus, and adenovirus. Another study by Carlton et al. [5] linked heavy precipitation events to cases of diarrhea, especially with heavy rainfall events following dry period. Children under 5 years of age were affected more than three times more than those over this age.

Preparing for the future by focusing mitigation on areas of greatest potential risk is imperative as it will alleviate some of the potential destruction to human life and the environment. The current flood maps and evacuation plans are all based on past precipitation and some using larger scale sub-basins. For example, Yahya, Devi and Umrikar [6] examine flooding in Mauritius by only using digital elevation model (DEM) and flood hydrographs to locate critical flood prone areas. While this technique provided an estimated idea of flooding by a coarse sub-basin zone, it did not take into account future hydrological conditions to see how precipitation will be dispersed at a more refined resolution. Jalayer et al. [7] identified flooding risk hotspots for urban and residential buildings corridors by using a maximum likelihood method and overlaying maps of urban and residential areas corridors and potentially flood-prone areas with geo-spatial census dataset. Whilst this method has some merit, it failed to consider future climate

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conditions or soil characteristics which could be susceptible to standing water and encourage waterborne diseases. Hardmeyer and Spencer [8] used Geographic Information System (GIS) and a risk-based approach to create a map to predict where and how often floods might occur in the future. Although this showed potential risk for structure damage if an average recurrence interval (percent chance of flooding) occurred, it failed to consider future precipitation patterns as well as optimal stormwater mitigation locations.

By utilizing spatial tools and a general circulation model (GCM), precipitation can be mapped by constructing robust semivariogram, geospatial locations, isolating high vulnerability areas for future potential flooding at a finer resolution. Pinpointing areas of risk using GIS models allows for more concise stormwater drainage planning and flood risk management. Flooding is a great concern for Tampa Bay, Florida (FL); therefore, it has been used as the case study. In 2005 it was rank 7th for economic average annual losses due to potential future flooding [9]. This is not surprising considering the region receives around 1.32 m of precipitation each year, with two-thirds of this occurring during a short

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timeframe, from June through September which is well above the US annual average of 0.760 m [10,11]. Additionally, Hillsborough County is almost homogenously flat and low lying with locations at sea level to only a few areas at 30 m above sea level, promoting standing water and a reduce runoff rate compared to areas with steeper topography [12]. Soil characteristics is also an important factor promoting flooding. Soils that are very poorly drained are more prone to standing water and flooding due to a slow infiltration rate versus a moderately well drained soils.

What renders this research revolutionary where others have fail, is that it utilizes future precipitation projections, GIS and statistics to modeling areas at greatest risk. Applying geospectro techniques, 3-dimensional (3-D) temporal geomorphological terrain related elevation models can better identify flood vulnerability high risk areas by overlaying precipitation and soil classes, and then focusing on these locations that are more densely populated.

Materials and Methods

Downscaling and bias-correction

GCMs are available from the World Climate Research Programme's Coupled Model Intercomparison Projects (CMIP) (Lawrence Livermore National Laboratory of the U.S. Department of Energy, http://www-pcmdi.llnl.gov/projects/pcmdi/). Since CMIP Phase 5 GCMs are created at a coarse resolution, around 250 and 600 kilometers (km), they are downscaled to support regional spatial resolution for hydrologic simulations required for water supply and management. There are multiple techniques but for this research it was performed using the Bias-Correction and Stochastic Analog as it is better fit for this study region [13,14]. The downscaled procedure also utilized Maurer's nationally available precipitation data for the biascorrection as it has been utilized by many researchers due to having a comprehensive data set as well as being gridded at 1/8 degree spatial resolution (about 12 km) supporting the required spatial scale. Beijing Normal University Earth System Model representative concentration pathway 4.5 (BNU_ESM_rcp45) was selected for this cases study. Representative concentration pathway (RCP) 4.5 is in the middle of the range for the emission scenarios as the radiative forcing are stabilized at around 4.5 W/m² before 2100 and extended concentration pathways concentrations are constant after 2150 (Figure 1) [14-16].

Precipitation from this GCM was downscaled to 172 locations in and surrounding the Tampa Bay region to provide better precipitation estimates for the Hillsborough County regions for 2017 through 2020 (Figure 2). Although these are predicted for a time series it is not expected to 100% match the exact year to the modeled, but rather capture the overall statistics for the record of interest. This time period, summers June 2017 to August 2020, was selected as an example for the case study. The reason for selecting multiple consecutive months was to account for antecedent hydrological conditions which impact runoff volume and flooding. For instance, if June and July had higher precipitation, soil storage in the vadose zone could be saturated promoting more run off than infiltration. On the other hand, if June and July were dry, more infiltration would occur as the soil would not be at its saturation point [13,17-20].

Kriging

The GIS Gaussian Ordinary Kriging technique was selected to map the GCM precipitation data. Ordinary kriging, a stochastic model that uses geostatistical techniques, depends on correlation between data points and the spatial structure to determine the weighting values to

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estimate a value at an unknown location [20]. It was selected as it has the ability to take localized measures of rainfall projects across an entire domain employing interpolation and distance weighting factors [21]. In literature, Rogelis et al. [22] researched the Kriging tool and displayed how there was no significant differences in performance between individual variogram interpolation with Ordinary Kriging, and Kriging with external drift and pooled variogram interpolation. Bayat et al. [23] applied a cluster method together with Ordinary Kriging and Bayesian maximum entropy techniques to determine spatial deviations of mean annual precipitation in a watershed. Arun [24] evaluated the use of DEM with kriging, ANUDEM, Inverse Distance Weighted, Nearest Neighbor, and Spline and determined that Kriging was superior. In general, Kriging is defined as [25-27]:

$$\hat{Z}(\mathbf{S}_{0}) = \sum_{i=1}^{N} \lambda_{i} Z(\mathbf{S}_{i})$$
⁽¹⁾

Where S_0 is the prediction location; λ_i =an unknown weight for the measured value at the ith location; $Z(S_i)$ is the measured value at the ith location; and N is the number of measured values. In this research, the unknown precipitation value $Z(S_0)$ was a random variable located in (S_0) , where the values of neighbor's samples $(Z S_i)$, i=1, ..., N. $Z(S_i)$ was also estimated as a random variable located in the interpolator S_i [20].

Digital elevation model and slope

The DEMs in this researched were Aster Global DEMs obtained from http://earthexplorer.usgs.gov/which have a WGS_1984 coordinate system and a spatial resolution of $0.0002777778 \times 0.0002777778$ degrees (ASTER GDEM is a product of METI and NASA). The purpose of the DEM was to extract slope coefficient to determine lowest elevation areas. Slope is the rate of change in the x and y direction of the elevation which determines the magnitude and direction of the steepest gradient for a topographic elevation. The local slope can be defined as [28,29].

$$S = \sqrt{\left(\partial_x h\right)^2 + \left(\partial_y h\right)^2}$$
(2)

Where a is the direction

$$\partial = \tan^{-1} \frac{\partial_{y} \mathbf{h}}{\partial_{x} \mathbf{h}}$$
(3)

S is the change in elevation per horizontal unit length (magnitude of the gradient); α is measured from west counterclockwise; and x and y axes represent the reference parallel and meridian.

Soil characteristics

Valuable information on permeability and whether locations are more prone to more standing water can be extricated from analysis of soils classifications and their structural compositions. Different soils have varied soil hydraulic conductivity, porosity, intrinsic permeability, saturation capacity. Understanding the types of soil and its permeability is vital to determining regions of possible flooding. Soil data was obtained from Florida Geographic Data Library, ftp1.fgdl.org [30]. Soils for the Hillsborough region comprise of Adamsville fine sand; Anclote fine sand, Archbold fine sand, Basinger fine sand, Braden fine sand, Candler fine sand, Cassia fine sand, Chobee loamy fine sand, Chobee sandy loam, Delray mucky fine sand, Duette fine sand, Eaton fine sand, Eaugallie fine sand, Felda fine sand, Floridian fine sand, Fort Meade loamy fine sand, Immokalee fine sand, Kesson fine sand, Malabar fine sand, Manatee loamy fine sand, Myakka fine sand, Ona fine sand', Pomello fine sand, Smyrna fine sand, Wauchula fine sand, Zolfo fine sand, arents, and astatula, among others. The dual hydrologic



groups are: A, A/D, B, B/D, C, C/D, and D. Soils of concern are 'poorly drained' and 'very poorly drained' soils in hydrologic groups A/D, B/D, C/D, and D.

Population

In order to prioritizing and focusing stormwater improvements, more densely populated regions with a population projections for regions greater than or equal to 500 people were selected. Furthermore, a 1×10^3 m buffer was added to these selected population locations since flooding can occur due to adjacent hydrologic conditions. The 2015 population data for this study was obtained from Southwest Florida Water Management District, http://data.swfwmd.opendata. arcgis.com[31].

3D modeling

Using DEM and soil statistics, a 3-D model of the study area was created using ArcScene, an extension of ArcGIS^{*}. Data exhibited in 3-D extract multiple structural perspectives and viewpoints by expanding the surface data viewpoint. Creating coherent visual displays magnify and project areas of concern through data visualization. Layers elevations were converted to scene units at a factor of 0.0005. Elevation from the surface was floated either on the DEM, soil or precipitation layer, with all layers remained at a zero elevation offset.

Results

The Slope coefficients were derived for Hillsborough County via extraction from a DEM. Slopes ranged between 0 to 66 degrees with a mean around 3.9 degrees (Figure 4). In order to isolate differences, slopes were separated at 0.1 increments for lower degrees due to small elevation differences and skewness in the probability distribution function (Figure 3).

Superimposing the precipitation over the DEM to find overlapping locations based on slope to isolate areas that are more susceptible to flooding was deemed not viable because the terrain is extremely flat (Figure 5). Without enough variability in elevations it is not a feasible approach to locate pockets of low lying regions surrounded by higher elevations that would capture water or identify zones with steep slopes that would promote higher runoff rates. Although this technique has been used for other regions to determine flooding, it was deemed not a suitable tool for this region due to the almost uniformly terrain [32-34]. Employing soil characteristics was found to be a more precise approach to improve selection of target flooding locations. For homogenously flat terrain, soil properties and permeability have a detrimental effect on standing water due to saturation and runoff mechanisms.

Figure 6 portrays locations of 'poorly drained' and 'very poorly drained' soils. The south east region of the county in zip codes 33567, 33594, and 33527 comprise of very poorly drained soils, which would be more prone to flooding. Poorly drained and well drained soils were located in many locations throughout the county. To further narrow down and isolate regions where stormwater mitigation should occur, a 3-D model was constructed to visually evaluate the relationships between population, precipitation and soils.

Figure 7 exemplifies how primary target flooding regions can be extricated from the intersection of very poorly drained soils and high precipitation that are also within a 1 km buffer of areas where populations are estimated to be greater than or equal to 500 people. Precipitation is the most crucial flooding factor. The semi variogram successfully summarized the spatial continuity of the precipitation for each month, providing feasible spatial interpolation results (Figure 8).

Furthermore, the regression model was able to effectively classify high and low areas of precipitation at and surrounding Hillsborough County per respective month (Figure 9). The highest cumulative monthly precipitation occurred in July 2020 with a maximum value around 284.6 mm and a mean of 213.8 mm. It trailed a very wet June with a mean precipitation of 209.7 mm, and was followed by a very dry August with 68.4 mm. If flooding was to strike, it would more than likely occur during July since soil conditions would have been saturated or near saturation from high June precipitation. On average, the wettest month was August 2017 with a maximum of 246.9 mm and a mean of 226.9 mm (Table 1). Majority of the highest precipitation was seen in the eastern half of the county in zip codes 33572, 33573, 33578, 33579, 33584, 33592, 33594, 33596, 33598, 33617, 33619, 33637, and 33647. This followed a June and July with mean precipitation of 112.2 mm and 104.7 mm, respectively (Table 1).

It is feasible that flooding would happen in August since the amount of precipitation is well above the mean, plus it is probable that soil could be at or near saturation due to the precipitation conditions of prior months. Other instances where the mean precipitation was above 200

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	2017			2018			2019			2020		
Units: 10 ⁻³ m	June	July	Aug	June	July	Aug	June	July	Aug	June	July	Aug
Min	85.2	95.0	186.4	183.1	192.0	63.2	183.5	110.4	27.5	132.9	189.9	63.4
Max	133.0	118.6	246.9	229.1	243.3	100.3	248.6	179.3	53.5	201.9	284.6	79.3
Mean	112.2	104.7	226.9	209.7	224.0	82.6	213.4	126.1	42.9	165.0	213.8	68.4
Standard Deviation	14.4	6.6	18.9	8.7	14.3	9.7	20.4	15.8	7.6	15.0	19.9	3.0

Table 1: Precipitation statistics by month for all interpolated locations.



Figure 10: Estimated precipitation over Hillsborough County based on 1km buffer around areas where the population is greater than 500 people and where soil type is poorly draining or very poorly draining (June, July and August from 2017 to 2020).

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mm were June and July, 2018; June 2019; and July 2020 which are visually displayed in Figure 9. The last step of this process was to combine soils, precipitation by month, and population with a 1 km buffer to extricate prioritized areas for focusing storm water mitigation efforts. Figure 10 provides areas of concern for each month. For six out of the 12 months, summers June 2017 thru August 2020, zip code 33647 had estimated precipitation greater than 200 mm per month and soil was either poorly draining or very poorly draining. Due to this higher rate, this would be considered the first primary target for mitigation. Following this, there were four zip codes with these same precipitation and soil criteria that occurred in five of the months. These were 33578, 33579, 33598, and 33619. Additionally, zip codes 33511, 33544, 33559, 33569, 33572, 33573, 33584, 33592, and 33637 met these criteria on four occasions. Budget depending, these locations could be prioritized accordingly. Figure 11 is an example extracted from Figure 10 to provide a closer visual of one of the month results. The locations west of Hillsborough Bay in red have the highest cumulative monthly precipitation, greater than 225 mm. Furthermore, these high precipitations fall over zip codes 33567, 33594, and 33527 which have very poorly drained soils and are more prone to standing water and flooding. Areas in bright purple have monthly precipitation between 200 to 225 mm, and locations in yellow are between 175 to 200 mm. Unshaded locations within the 1 km Population buffer are where soils do not match the criteria and where planning efforts should not be focused.

Conclusion

Using a combination of predicted precipitation over a time period, soil characteristics and population provided a feasible approach to determine locations of potential concern. In this study, a prioritized zip code list where drainage improvements should occur were evaluated; however, it is also plausible to extract locations at the street level. Locations of probable future flooding were successfully isolated which can be used to promote improved management of funding and available resources. To isolate smaller locations, reduced population and buffers can be employed as well as longer periods of record. Finally, for predominately homogenous terrain slope coefficients was not the ideal tool to determine locations of flood vulnerability to target storm water mitigation.

As with any study, there were limitations. Since the GCM was supplied, there were not as limited downscaled and bias-correction precipitation data for locations south and east of Hillsborough County. Furthermore, to create an even more robust and refined model, potentiometric surface parameter, a larger time period, impervious versus non-impervious surfaces and evaluation of other GCMs with alternate RPCs can be added to provide enhanced predicted results. Additionally, the rate of precipitation was not considered but could be added to future studies.

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