

# CHARACTERIZATION OF UNCERTAINTY IN INUNDATION MODELS AND WATERSHED HYSOMETRY FOR IDENTIFICATION AND ASSESSMENT OF NON-LINEAR IMPACTS OF SEA LEVEL RISE

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## Abstract

Sea level rise is a major concern for coastal Virginia which ranks 10th in the world in value of assets exposed to increased flooding. Inundation models are foundational to the analysis of the impacts of sea level rise. Uncertainty in analysis results from the accuracy of elevation data. This potential error may cause the inundation zone to fluctuate landward or seaward. Assessment of the impacts of vertical error was accomplished by conducting Monte Carlo simulation on one watershed in Norfolk, VA. Levels of uncertainty of the source elevation model were determined. 100 permutations were created using a pseudo-random number generator and the bounds of potential error. Means and standard deviations were calculated for all permutations to verify each was within the realm of possible error. Inundation modeling was performed on each permutation and differences were recorded. The cumulative confidence of all simulations was calculated by tallying the number of runs that resulted in each cell being inundated. Grid cells were shaded proportionally to the number of simulations that produced flooding, more precisely delineating potential error and flood vulnerability. Monte Carlo analysis of inundation variability using error modeling suggests broad fidelity of inundation zones while highlighting areas of moderate uncertainty.

## INTRODUCTION

### Sea Level Rise in Hampton Roads

The rate of relative sea level rise ( $\Delta$ RSL) for Hampton Roads is approximately double that of the rate of estimated global sea level rise ( $\Delta$ SLRG) and is increasing. The fundamental hazard posed to our community by the rising sea is best understood by examining the spatial relationship between the upper limits of ocean-connected waters and the geographic/topographic positioning of critical natural and societal assets. A multitude of studies have been performed to both quantify and identify the underlying causes of global and regional sea level rise.

In 2012, Boon's analysis of monthly mean sea level measurements at tide stations along the Atlantic seaboard revealed "statistically significant acceleration in sea level rise." Further analysis by Ezer and Corlett (2012) confirmed positive sea level rise acceleration in the Chesapeake Bay with rates nearly double those of 60 years prior. Sallenger et al. (2012) provided additional confirmation by identifying a 1000 km long hotspot of sea level rise acceleration on the mid-Atlantic coast north of Cape Hatteras which they found to be consistent with a slowdown of the Atlantic Meridional Overturning Current (AMOC).

Atkinson et al. (2013) explained that  $\Delta$ RSL in the mid-Atlantic is higher than

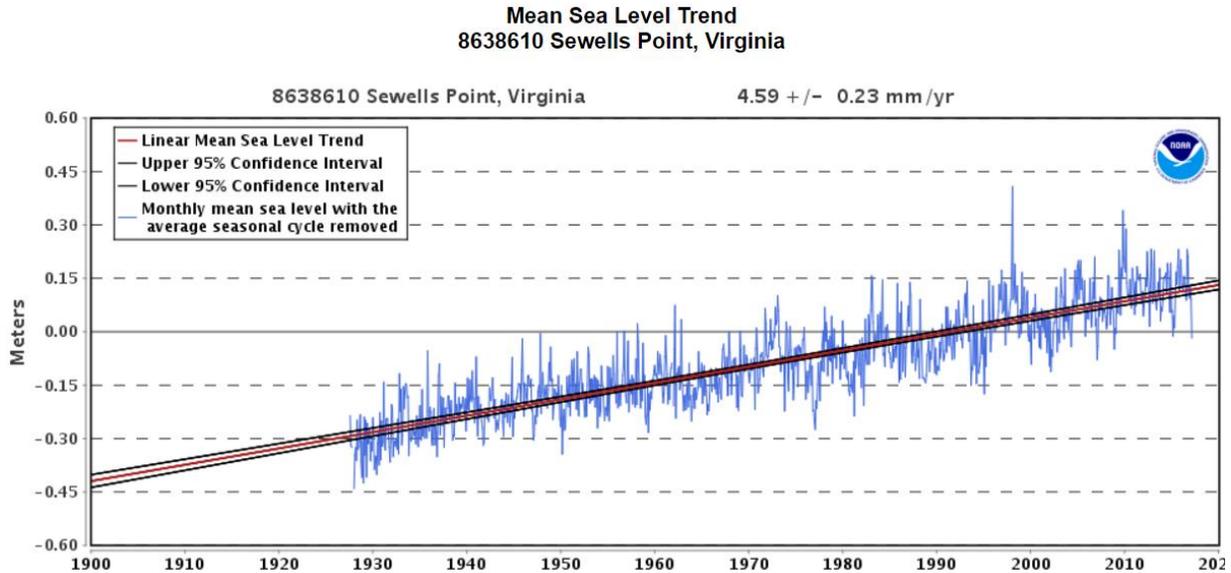


Fig. 1. Water level at the Sewells Point tide station in Norfolk. The total sea level rise since 1928 has been about 1.45 feet and the current rate is 4.59 mm/yr. (adapted from NOAA, 2010)

$\Delta$ SLRG for several reasons including: local subsidence from groundwater withdrawal and settling of sub-structural fill, regional subsidence resulting from glacial isostatic rebound, and changes in ocean surface elevation related to ocean circulation dynamics and weakening of the Gulf Stream current.

As Atkinson et al. (2013) point out, our best gauge of local  $\Delta$ RSL is the Sewells Point tide gauge at the Norfolk Naval Base which has been making measurements since 1927 (Figure 1) and is one of the longer records in the United States.

Examination and understanding of the natural and societal impacts caused by the location specific combination of these  $\Delta$ RSL-influencing factors necessitates a highly localized analysis. The study area for this research is the Lafayette River watershed in Norfolk, Virginia.

The Lafayette River watershed, shown in Figure 2, is the largest watershed in Norfolk, spanning approximately 9436 acres of mixed-use urban environment.

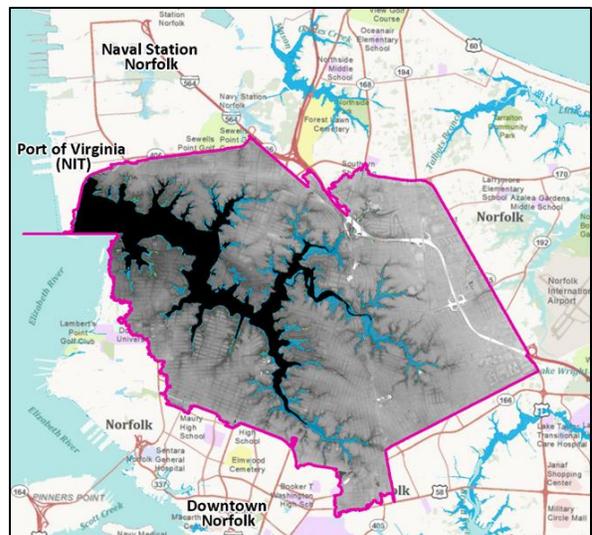


Fig. 2. Lafayette River watershed area

It contains large residential areas and critical transportation corridors which service Naval Station Norfolk, the Port of Virginia, and the downtown Norfolk central business district. It is also home

to Virginia Zoological park, Old Dominion University, the Hermitage Museum, and many other buildings of cultural and historical significance.

In one recent study of the Lafayette River basin, Fugro (2016) reported that Norfolk’s relatively low elevation and drainage gradients result in a significant percentage of the city being prone to tidal flooding and storm surges. The level of risk caused by this inherent condition is exacerbated by increasing local RSL.

Anecdotal reports of recurrent tidal flooding, often called “nuisance” flooding, in the Lafayette River basin and other areas of Norfolk have been increasing. Nuisance flooding is defined as a water level measured by NOAA tide gauges above the local NOAA National Weather Service (NWS) threshold for minor impacts established for emergency preparedness (Sweet and Marra, 2016). Fugro’s study (2016) provides support for these claims by indicating that tidal flooding in the Lafayette River area is frequent and is expected to worsen over time as “mean sea level” rises. Atkinson et al. (2013) have provided an extrapolation of higher tides into the future which shows that by the year 2050 a major transportation corridor, Hampton Boulevard, in the Lafayette River watershed will be flooded at every high tide.

Well before 2050, it is expected that the number of days of tidal flooding will increase apace with rising RSL. In 2016, Sweet and Marra (2016) calculated the “nuisance flooding” level for Norfolk, VA to be 0.53m above MHHW and predicted an accelerating trend of tidal flooding days per year (Figure 3).

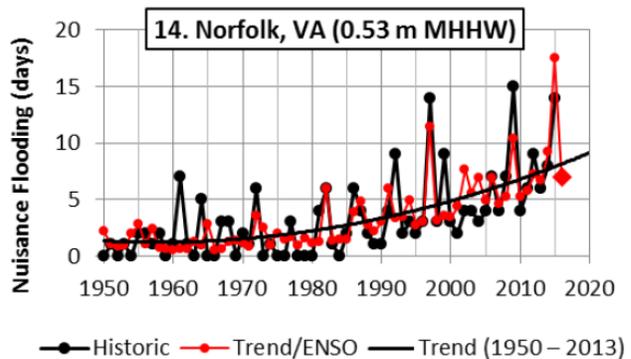


Fig. 3. Annual flood frequencies (black circles) with 1950-2013 quadratic trends in Norfolk and bivariate regressions including ENSO effects and 2016 Outlook (adapted from Sweet and Mara, 2016)

#### Elevation Uncertainty

Digital elevation data and inundation models are foundational to the analysis of the impacts of sea level rise. Uncertainty in the model analyses results, in large part, from the accuracy of elevation data. Positional error in inundation modeling relates to this uncertainty in vertical measurements and to issues of datum conversion, projection, and interpolation methods. This potential error may cause the inundation zone to move either landward or seaward. Consequently, Titus and Cacela (2008) note that estimates of flooded areas under any particular scenario of sea level rise can be expressed as a range of plausible values.

Multiple studies have affirmed the critical importance of elevation data for the modeling of sea level rise and flooding (Cooper et al., 2013; Gesh, 2009; Merwade et al., 2008; Mitchel et al., 2013). In Figure 4, Gesh (2009) illustrates how the uncertainty of elevation data affects the delineation of coastal elevation zones.

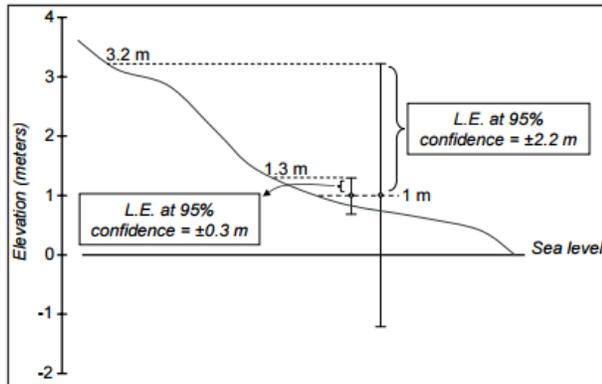


Fig. 4. In this example, a sea-level rise of 1 meter is mapped onto the land surface against two elevation datasets with differing vertical accuracies ( $\pm 0.3$  meters and  $\pm 2.2$  meters). The more accurate elevation model results in a delineation of inundation zones with much less uncertainty. (Adapted from Gesh, 2009)

Gesch (2012) stipulates that input elevation information is a primary contributor to the uncertainty associated with inundation hazard assessments and that, because these data are such a critical component in coastal hazard assessments, the vertical accuracy strongly influences the reliability of the results. Mitchel et al. (2013) provide the following concise affirmation, “The key factor for all of these (flooding) analyses is the accuracy of the underlying elevation data.”

Digital elevation data are produced using a variety of methods including: photogrammetry, radar, digitization from analog topographic maps, point surveys, and lidar. For the purpose of sea level rise assessments, Gesh (2009) found that lidar-derived elevation data are substantially better than non-lidar elevation datasets. Utilization of “best available” lidar having both high spatial resolution and accuracy is preferable. A key descriptive metric of the accuracy of

digital elevation data is fundamental vertical accuracy which describes vertical accuracy at the 95-percent confidence level in open terrain where errors should approximate a normal error distribution (Heideman, 2014). The fundamental vertical accuracy (FVA) for the current best available LiDAR data for the Hampton Roads study region was reported as  $\pm 0.129$  m (Dewberry & Davis LLC, 2014).

## MODELING METHODS

Assessment of the impacts of positional error in lidar-derived elevation models was accomplished through iterative Monte Carlo error distribution modeling. The process is detailed below.

### Study Area Delineation

The Lafayette River watershed boundary was delineated using GIS hydrology tools and the best available lidar data. The LiDAR-derived digital elevation model for Hampton Roads was clipped to the watershed boundary. All analyses and modeling were performed within this clipped study region.

### Hydrocorrection

As the accuracy and success of any flood modeling depends critically on the quality of study area elevation data, the DEM for the Lafayette River watershed was carefully examined for obvious errors in hydrological connectivity. Several possible errors were present wherein the extent of streamflow into the Lafayette basin was artificially curtailed by failure of the DEM to capture culverts and open bridges beneath which water flows freely (Figure 5).

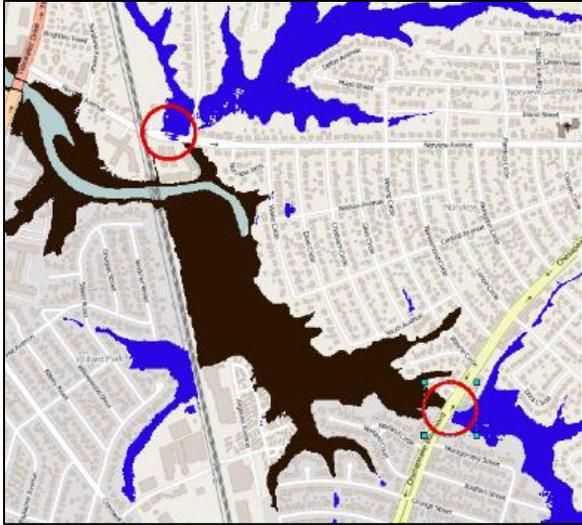


Fig. 5. Example of errors in hydrological connectivity observed in the LiDAR DEM. Black areas are open water. Blue are incorrectly disconnected water areas.

Field examination of points of concern revealed multiple locations where water flowed freely beneath bridges yet did not appear connected in the DEM (Figure 6).



Fig. 6. Example location where water passes freely beneath bridge opening, not represented accurately in the DEM

Accordingly, hydrocorrections were applied to the DEM to ensure that all areas of open and flowing water were accurately represented in flood modeling. Hydrocorrection was achieved through a “stream-burning”

process whereby elevation values for DEM pixels in the disconnected problem areas are reassigned to the surface elevation value of the connected stream surface. This results in an accurate, contiguous, and connected water elevation surface.

Monte Carlo Modeling

A Monte Carlo technique was used to iteratively distribute potential error in the elevation surface during flood modeling.

A normally distributed raster was created considering the FVA (+/- 0.129 m) of the LiDAR DEM. Figure 7 shows a histogram of values for this raster.

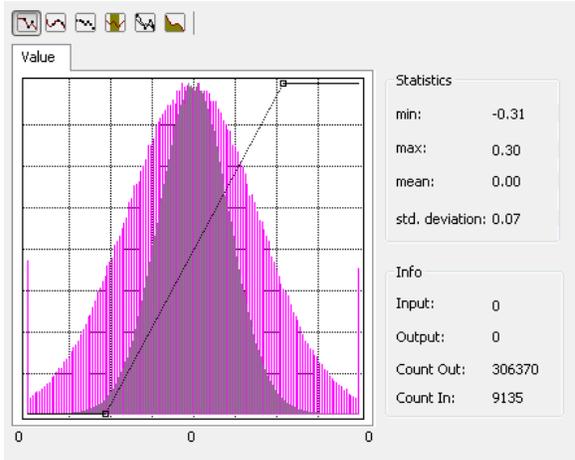


Fig. 7. Normalized raster histogram

This follows the current practice of sea level rise mapping which assumes that LiDAR vertical errors follow a normal distribution with zero bias (Cooper et al., 2013). Similar methods were used by Liu et al. (2007) for studying the effect of elevation error on shoreline position.

The values in the normally distributed raster provide corrections to the surface which account for potential error in the original DEM. The surface correction values, which range from -0.31 meters to +0.30 meters are added to the



layers represent recurrent tidal flooding with present-day sea level. These binary “flood” vs. “no flood” grids were created wherein flooded areas are represented by a value of 1 and non-flooded areas have a value of 0.

Each modeled flood surface is unique, resulting from variation in the normally distributed raster surfaces (Figure 10).

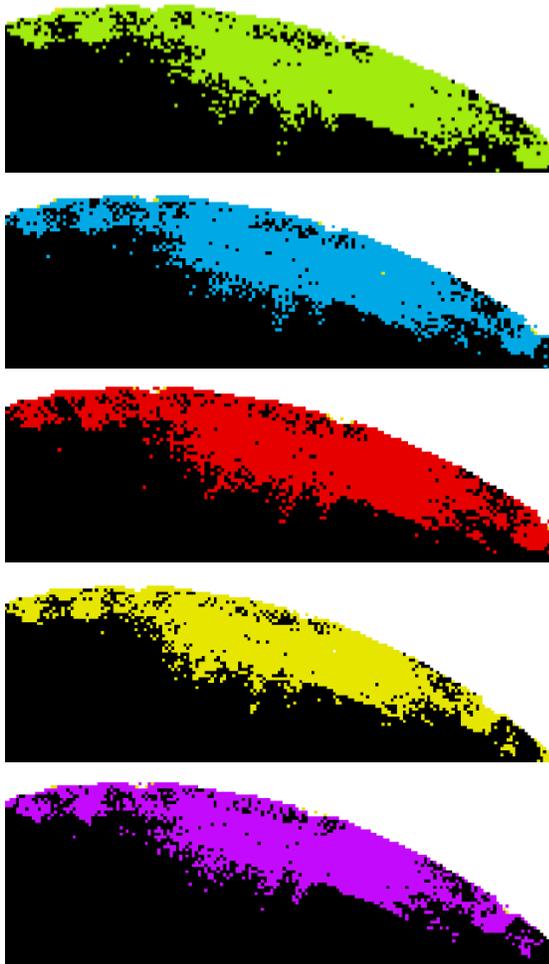


Fig. 10. Representations of the unique flood surfaces created by each model run.

These modeled flood surfaces are similar to many existing flood maps in that they present a single possible flooded area. However, when these outputs are summed, they provide a

modeled flood probability throughout the watershed. Grid cells were shaded in proportion to the number of simulations that produced flooding, providing more precise delineation of potential error and flood vulnerability (Figure 11).

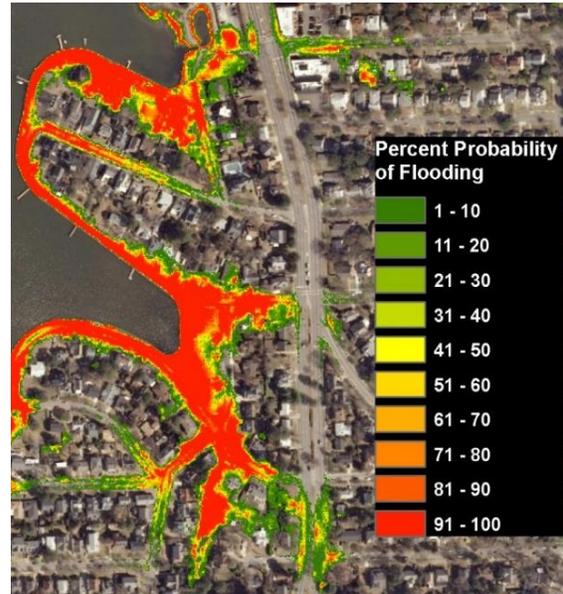


Fig. 11. Probabilistic flood map created by summing the outputs of individual flood model runs

In this manner, the cumulative confidence of all inundation simulations was calculated by tallying the number of runs that resulted in each data cell (ground area) being inundated. Using similar techniques, Bodoque et al. (2016) found the implementation of a probabilistic scheme for characterizing first floor elevation errors to be well suited for conveying the uncertainty inherent in spatially distributed errors.

## CONCLUSIONS

It was determined that approximately 189 acres within the Lafayette River watershed, equivalent to the entire

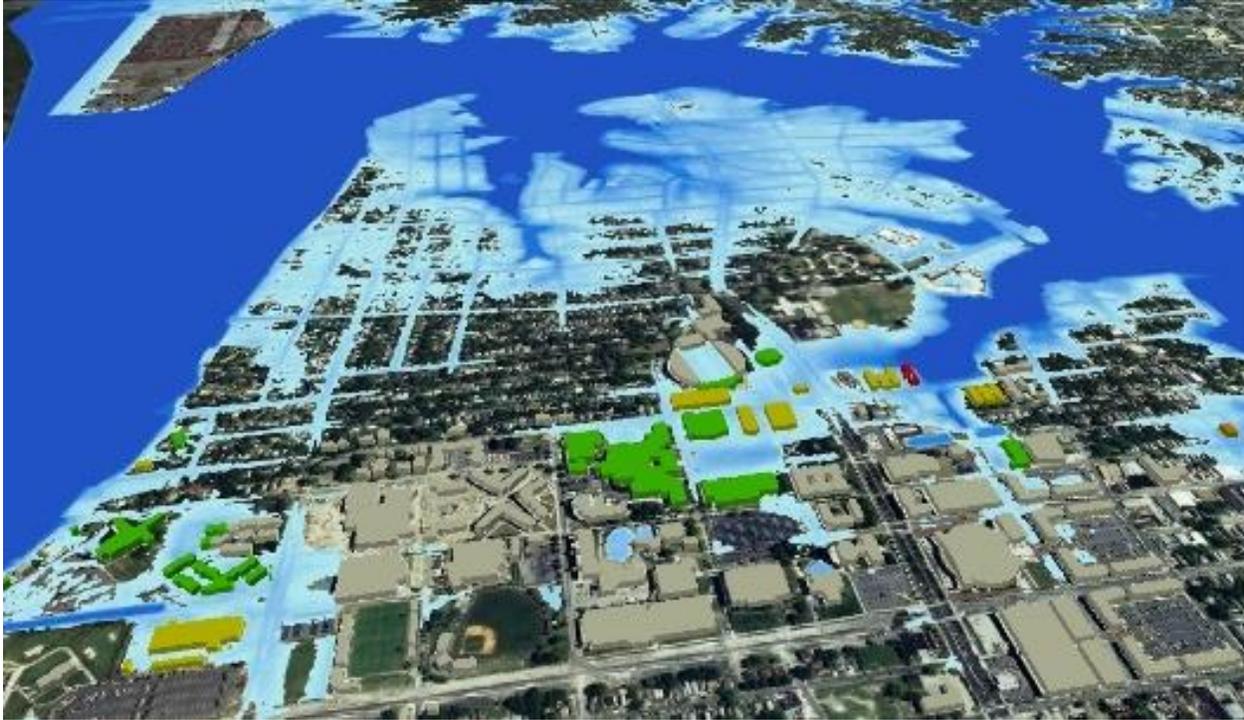


Fig. 12. Flooding of Lafayette River watershed shown with buildings in flooded areas symbolized according to probability of flooding.

financial district in New York City, have 90-100% probability of tidal flooding during extreme high tide events.

The creation of probabilistic flood maps provides vastly improved visualization of potential flood. Assignment of flooding probability to areas and co-located infrastructure (Figure 12) provides valuable information to emergency managers, elected officials, and the citizenry which will aid in prioritization of evacuation, mitigation, and/or response strategies.

Analysis of this type provides key insight into smaller-scale areas of vulnerability. Probabilistic flood modeling should be used to target regions which exhibit the highest vulnerability to sea level rise and tidal flooding. The coupling of probabilistic flood surfaces with other information, such as real estate records, transportation features, utilities, and

economic and business data can be invaluable for highlighting which areas and potentially critical potential failures must be addressed *before* they begin to feel the impacts of sea level rise.

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