Developing First Floor Elevation Data for Coastal Resilience Planning in Hampton Roads

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BENJAMIN MCFARLANE	SENIOR REGIONAL PLANNER
ASHLEY GORDON	COASTAL ANALYST

DEVELOPING FIRST FLOOR ELEVATION DATA FOR COASTAL RESILIENCE PLANNING IN HAMPTON ROADS

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AUTHORS:
Ashley M. Gordon
Coastal Analyst

Benjamin J. McFarlane, AICP, CFM
Senior Regional Planner

ORGANIZATION NAME, ADDRESS AND TELEPHONE
Hampton Roads Planning District Commission
723 Woodlake Drive
Chesapeake, Virginia 23320
(757) 420-8300
http://www.hrpdcva.gov

ABSTRACT

This report describes the methodology used to develop a regional elevation certificate database and evaluate statistical approaches for estimating building first floor elevations. The regional elevation certificate inventory includes information from 10 Hampton Roads local governments and over 2,000 data points. Elevation certificate data were used to develop Random Forest models that predict first floor height for two case study communities, the City of Chesapeake and City of Hampton. The results of this analysis highlight the importance of detailed building foundation codes and additional field data collection. Both the elevation certificate geodatabase and estimated first floor elevations will support local and regional vulnerability assessments under various flooding scenarios.

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Virginia Coastal Zone
MANAGEMENT PROGRAM

NOAA
NATIONAL OCEANIC AND ATMOSPHERIC ADMINISTRATION
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Executive Summary

The first finished floor elevation (FFE) of a building provides critical information for understanding structural vulnerability to flood hazards and associated damage costs. In the Hampton Roads region of Virginia, FFEs have been identified as a major data gap. Although some localities have survey information or other data, the primary source of FFE information is FEMA National Flood Insurance Program elevation certificates. Less than 1% of structures within Hampton Roads have elevation certificates, and these certificates are typically only available as digital PDFs or paper copies by locality. To improve access to this information, the first objective of this project was to build a regional spatial database containing information from elevation certificates. The second objective was to use information from the elevation certificate database to develop a predictive statistical modeling approach for estimating FFEs, and then apply the resulting model to estimate FFEs for structures that do not have elevation certificates. The report also briefly reviews various approaches for estimating FFE and recommends practices for data management.

Elevation Certificate Data Collection, Assessment, and Processing

Elevation certificates were collected from ten Hampton Roads localities as digital pdfs. The property address, effective Flood Insurance Rate Map information, and building elevation values were recorded from the elevation certificates. A FFE was reported for each building based on the provided building diagram. The building's first floor height (FFH) [1] was also calculated to be consistent with the format required for FEMA's Hazus flood model. The elevation certificate information was then joined with parcels and building footprints to provide the data in a spatial GIS format. In total, information was recorded from 2,065 elevation certificates. This information is publicly available for download through the regional open data portal, HRGEO (www.HRGEO.org).

Analysis of Structure Data to Develop First Floor Elevations

In order to predict FFE for structures which currently lack elevation certificates, a predictive statistical model was developed for two test communities, Chesapeake and Hampton. These cities were selected because they had the largest number of elevation certificates available (over 500 for each city). The modeling approach, known as Random Forest, uses building attributes to predict FFH for residential structures. The resulting FFH value is then added to an estimate of the structure's lowest adjacent grade

[1] FFH is defined as the difference between a structure's FFE and lowest adjacent grade.

to obtain a final estimated FFE. The following variables were included in the model: foundation type, the year the structure was built, the current flood zone, the difference in grade (highest adjacent grade – lowest adjacent grade), and an estimate of the land elevation where the structure was located.

Foundation type was the most important variable for predicting FFH in both models. Year built was more important in the Hampton model than in the Chesapeake model, most likely because Hampton had a larger sample of elevation certificates for structures built prior to the first effective Flood Insurance Rate Map study. Both models showed an improvement in performance for estimating FFH relative to default values assigned using FEMA's Hazus reference tables.

Conclusions and Next Steps

While elevation certificates are the primary source of FFE information, this method of data collection can be costly in terms of both time and money. Assessments of alternative approaches to estimating FFE are needed to determine if more efficient data creation options are reasonably accurate and viable. The statistical modeling approach implemented in this project seems feasible and warrants additional research and testing. Foundation type was the most important variable for predicting FFE. Providing more detailed and standard foundation type information across locality assessor databases would further support FFE estimation approaches. This report marks the conclusion of the first phase of the regional FFE project. During the second phase, the elevation certificate database and modeling approach will continue to be expanded and refined. FFE estimates will also be applied to begin exploring structural vulnerability to coastal flood hazards.

I. Introduction

The Hampton Roads region of southeastern Virginia is surrounded by water and experiences recurrent flooding driven by high tides, storm surge, and precipitation events (Mitchell et al., 2013). With water levels in Hampton Roads rising more than one foot over the past 80 years, sea level rise and land subsidence further exacerbate flooding risk (Mitchell et al., 2013). The seventeen local governments of the Hampton Roads Planning District Commission[2] (HRPDC) have formally recognized through a resolution the need to account for recurrent flooding and sea level rise in planning and engineering design (HRPDC, 2018). While studies have been completed for the region to identify areas vulnerable to flooding or sea level rise (McFarlane, 2015), key data gaps exist that limit risk assessment accuracy.

A critical data need for assessing structural vulnerability to flooding and estimating associated damage is a building's first finished floor elevation (FFE). Hazus, the Federal Emergency Management Agency's (FEMA) integrated software package for estimating losses from natural hazards, includes a specific flood module that requires FFE estimates as an input (in terms of height above grade) (FEMA, 2017). The Hazus flood model uses building location, FFE, and flooding water level for a given scenario to determine the predicted depth of flooding by structure (FEMA, 2017). By applying this information to a depth damage curve, Hazus calculates an estimated loss value based on a percentage of the assessed value of the structure (FEMA, 2017). These estimates assist adaptation planning by allowing for comparisons of flood mitigation options in terms of losses avoided. The Hazus flood model was applied in the 2017 Hampton Roads Hazard Mitigation Plan using default FFE estimates; however, it is noted in the plan that the results may not accurately reflect the risk and exact FFE information would improve the flood damage vulnerability analysis (HRHMP, 2017).

The traditional method of collecting FFE data is the completion of an elevation certificate by a licensed surveyor. A national standard elevation certificate form is issued by FEMA through the National Flood Insurance Program (NFIP) (FEMA, 2015). These certificates provide elevation information that supports compliance with community floodplain management ordinances and insurance premium rate calculations (FEMA, 2015). Hampton Roads communities have identified the need for elevation

[2] The Hampton Roads region includes seventeen localities in southeastern Virginia: Chesapeake, Franklin, Gloucester County, Hampton, Isle of Wight County, James City County, Newport News, Norfolk, Poquoson, Portsmouth, Southampton County, Suffolk, Surry County, Town of Smithfield, Virginia Beach, Williamsburg, and York County.

certificates for structures in high risk zones, as well as for older structures that may pre-date the community's first Flood Insurance Rate Map (FIRM) and associated floodplain regulations (Stiff and Weaver, 2018). However, given that elevation certificates are completed on an individual structure basis, collecting FFE information through elevation certificates can be costly in terms of both time and money. Identifying methods of collecting FFE information that are more cost and time efficient than individual structural surveys are of interest to address the existing FFE data gap.

An alternative to elevation certificates for FFE data collection is side-scan mobile LiDAR, which uses a laser to generate a 3D point cloud from which FFE can be detected (Ibrahim and Lichti, 2012). Beginning in 2009, North Carolina conducted a statewide inventory of building FFEs using a combination of side-scan mobile LiDAR and laser inclinometer field data collection (Dorman, 2015). Building FFEs were stored in a spatial database as an attribute of building footprints and have been applied to improve estimated flood losses (Dorman, 2015). Although the North Carolina inventory approach provides accurate FFE measurements, the cost of these approaches can range between $18 -$40 per structure, creating challenges for large scale implementation (Koka, 2016).

In the City of Galveston, Texas, the Galveston Historical Foundation used an approach to estimating FFEs that combines Google Earth and Google Street View (Needham and McIntyre, 2018). For 479 structures in a particular section of the City, the vertical distance from the ground to the first habitable floor was measured in computer pixels using Google Street View. The structure's roof line was then measured in computer pixels in Google Street View, as well as in inches in Google Earth, to develop a pixel-to-inch conversion ratio. The vertical distance was converted from pixels to inches using the ratio to determine building first floor height above grade. Using 22 field observations, the Galveston Historical Foundation estimated this combined Google Street View and Google Earth approach produced an average estimation error of 0.33 feet. Although this methodology produces reasonably accurate results, it can be time consuming at an average estimation rate of 4 hours per city block. (Needham and McIntyre, 2018)

Within Hampton Roads, the U.S. Army Corps of Engineers (USACE) has completed a spatial building FFE database for the City of Norfolk and is currently developing a database for the City of Portsmouth. For residential structures built prior to the City of Portsmouth's first FIRM, USACE is using Google Street View and vehicle windshield surveys to estimate building FFEs. Using Google Street View imagery, USACE is recording the number of stairs leading to the structure's front door in a geodatabase. By assuming that each stair is a half foot in height, an estimate of the first finished floor height (FFH) can be calculated and added to the structure’s estimated lowest adjacent grade (LAG). Through vehicle windshield surveys, USACE is also recording counts of stairs and building foundation type through ArcGIS Collector App, which stores the data with the corresponding building footprint. For structures constructed after the City’s first FIRM within the Special Flood Hazard Area (SFHA), USACE is also estimating FFE based on the effective floodplain regulations at the time of construction. The estimated FFE for a post-FIRM structure would be equivalent to the Base Flood Elevation (BFE) and any additional freeboard in order for the structure to be in compliance.

The Google Street View and floodplain compliance methods were also applied by USACE in the City of Norfolk, in combination with information from elevation certificates and individual structural surveys where available. Old Dominion University has also obtained FFE estimates through laser inclinometer for a neighborhood within the City of Norfolk (Stiff and Weaver, 2018). Old Dominion University is also planning to investigate the use of geostatistics and machine learning to predict FFE in the City of Newport News in collaboration with the Virginia Department of Emergency Management, Virginia Institute of Marine Science, and the Commonwealth Center for Recurrent Flooding Resiliency (ODU, VIMS, VDEM, 2017).

The professional services firm Dewberry developed an FFE database for the City of Virginia Beach using predictive statistical modeling (Koka, 2016). Multivariate regression analysis uses observational data to produce an equation defining the relationship between predictor variables and a response (Hughes, 2012). Over 7,000 FFE data points sourced from city permit data were used to develop a regression model that predicts building FFH above grade from several building attributes, including year built and foundation type (Koka, 2016).

Apart from the completed FFE databases for the cities of Norfolk and Virginia Beach, and the work underway in Portsmouth, the only source of FFE information for Hampton Roads localities is elevation certificates. These certificates are completed on paper or through an editable PDF. Localities that have electronic PDF copies of elevation certificates often store them within individual building permit folders. To improve access to this information, the first objective of this project was to build a geospatial elevation certificate database with all recorded elevations joined to building footprints or parcels. The second objective of this project was to use information from the elevation certificate database to evaluate predictive statistical modeling approaches for estimating FFE and apply this model to structures which currently lack elevation certificates.

This report consists of five main sections. The first is a review of the methods to develop the regional elevation certificate database. The second section describes the selected statistical modeling approach for estimating FFE and evaluates the results for two test communities. The third section identifies the challenges associated with the statistical modeling approach and reviews alternative estimation methods. The fourth provides recommendations for management of elevation certificates and property attribute data. The final section recommends next steps for expanding the regional FFE inventory and applying the data to coastal hazard vulnerability assessments.

II. Elevation Certificate Data Collection, Assessment, and Processing

Elevation Certificate Collection and Review

To begin building the database, HRPDC staff contacted Hampton Roads localities regarding the availability of elevation certificate data. Ten Hampton Roads localities had digital copies of elevation certificates available, which were then shared with HRPDC staff. Table 1 summarizes the count of finished construction elevation certificates by locality, as well as the number of elevation certificates for residential structures. Approximately 85% of elevation certificates received corresponded with residential structures. Remaining elevation certificate building types included accessory structures, additions, and non-residential buildings, such as businesses and churches.

Table 1: Distribution of elevation certificates collected by locality. All elevation certificates are for finished construction.

Locality	Total Elevation Certificates	Residential Elevation Certificates
Chesapeake	593	556
Franklin	169	27
Hampton	651	631
James City County	177	170
Newport News	4	3
Norfolk	69	69
Portsmouth	75	57
Southampton County	32	NA
Virginia Beach	162	160
York County[1]	133	88
TOTAL	2,065	1,761

[1]York County inventory is not complete. County staff is continuing to share elevation certificates with HRPDC.
NA: Information regarding property type has not yet been obtained for Southampton County.

Each elevation certificate was reviewed and relevant information from the certificates was recorded in Excel. A brief summary of the information contained in these sections is provided in Table 2, and a complete list of attributes is provided in Appendix A. For older editions of elevation certificates, information that applied to the current format was recorded.

Table 2: Summary of information recorded from FEMA Elevation Certificate (2015 edition).

Elevation Certificate Section	Attributes Recorded
A) Property Information	Address, Building Use, and Building Diagram
B) Flood Insurance Rate Map Information	NFIP Community Number, Effective FIRM Panel Date, Flood Zone, and Base Flood Elevation
C) Building Elevation Information	Elevation Datum, All structural elevations (a-h), including Lowest and Highest Adjacent Grade
D) Survey, Engineer, or Architect Certification	Surveyor signature date

Although elevation certificates do not specifically designate the FFE, the selected building diagrams assist in identifying the FFE measurement. For example, elevation certificate Building Diagram 1A illustrates a slab-on-grade structure, while Building Diagram 8 models a building elevated on a crawlspace (Figure 1). Labels C2a and C2b indicate the location of the top of the bottom floor and top of the next higher floor respectively. In Diagram 1A, C2a represents the elevation of the FFE, whereas in Diagram 8, C2a represents the unfinished crawlspace and C2b represents the elevation of the FFE. For each of the 9 building diagram types, a general determination of the measurement (C2a or C2b) corresponding to the FFE was made. A list of building diagrams with summaries of the first floor elevation determination is presented in Appendix B.

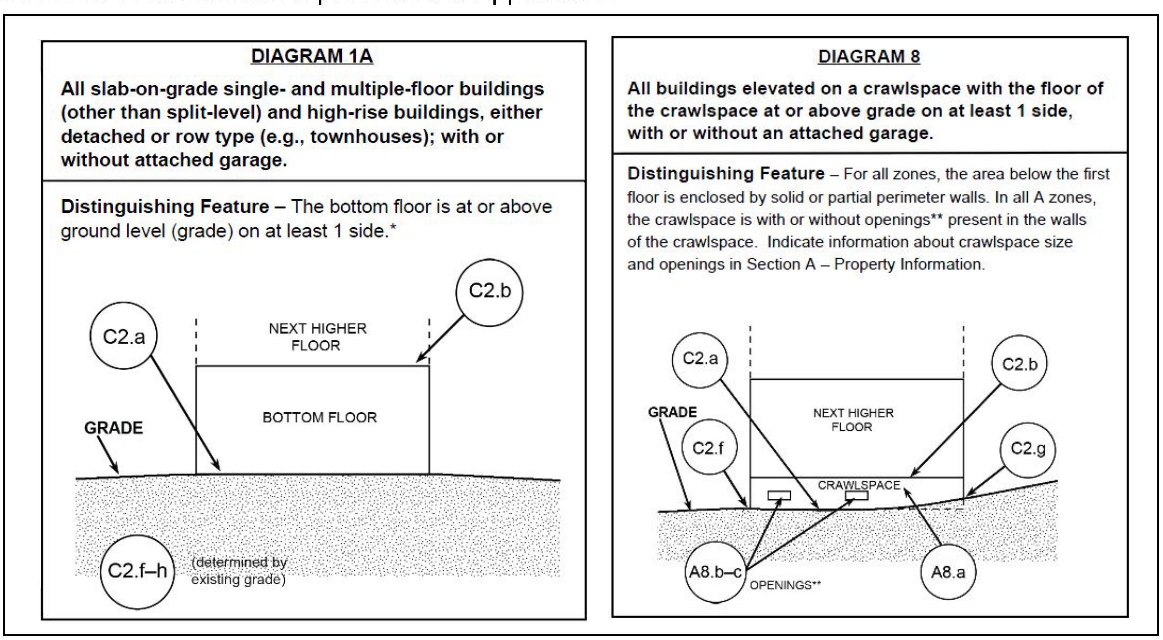

Figure 1: FEMA (2015) building diagram for slab-on-grade structure (Diagram 1A) and crawlspace structure (Diagram 8).

Geodatabase Development

The recorded elevation certificate information for each locality was transferred to a GIS format. Spreadsheets were matched to GIS parcel layers by locality through joining tables or geocoding. The information from all elevation certificates, including residential and non-residential certificates, is included in a regional parcels geodatabase[3] (Figure 2). The parcels information was spatially joined with building footprints available through the Virginia Geographic Information Network (VGIN) map service (VGIN, 2018). Due to the absence of building footprints in several parcels associated with elevation certificates, the building footprint geodatabase contains approximately 94% (1,933) of elevation certificates. The final regional elevation certificate information is available as both a parcel layer and building footprint layer on the Hampton Roads regional GIS portal (HRGEO, 2018).

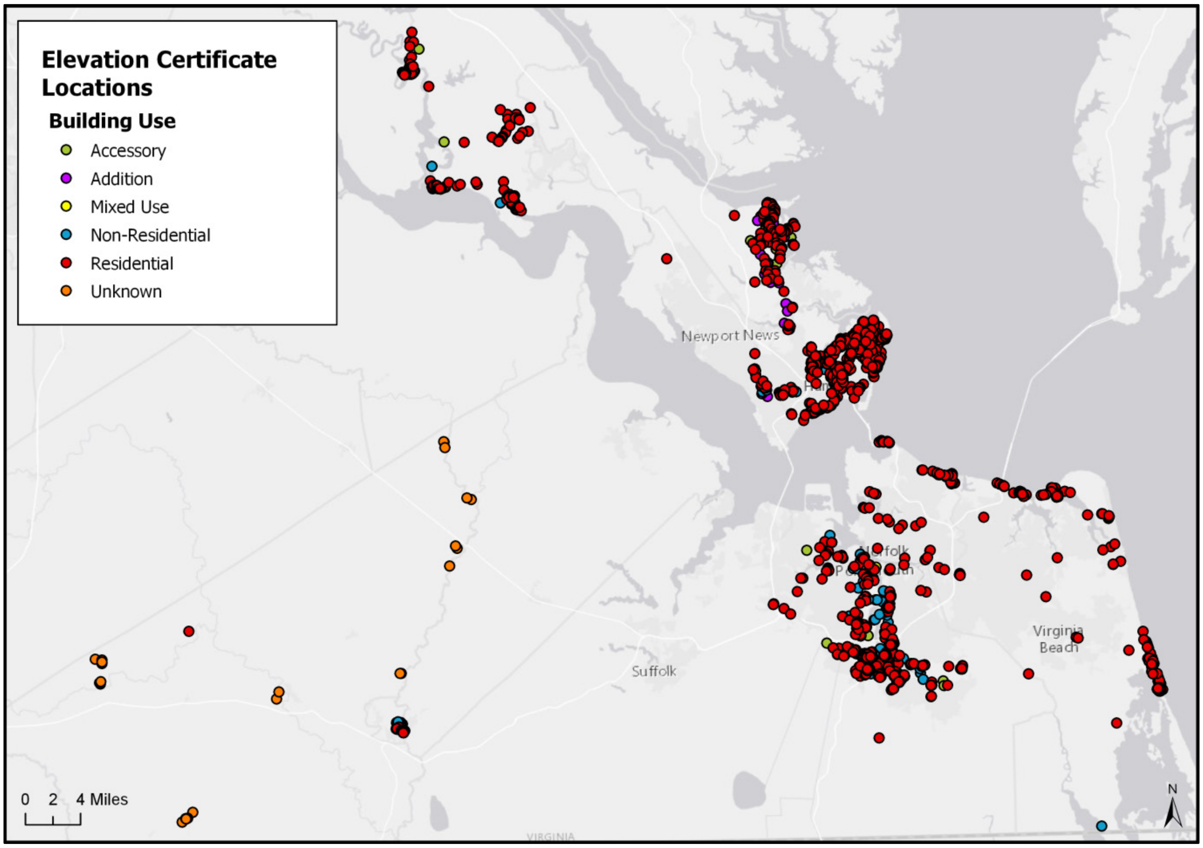

Figure 2: Distribution of elevation certificates across Hampton Roads displayed by building use type.

Upon request, localities provided additional parcel information from the tax assessment database. This included building attributes such as foundation type, year built, number of stories, and assessed value. Based on the building footprint locations, additional fields for the current effective

[3] A parcel is not available for one elevation certificate located in the City of Franklin; however, a building footprint is available. The total number of features in the regional parcels layer is 2,064.

highest risk flood zone, along with the associated BFE, were calculated for inclusion in the geodatabase. Flood zone designations were assigned by spatially joining building footprints and FEMA's National Flood Hazard Layer (FEMA, 2018). If a building footprint intersected multiple flood zones, a unique identifier developed to rank flood zones in descending order of risk was used to assign the flood zone of highest risk.

Using the year built feature, an additional attribute was created to distinguish a structure as built prior to (Pre) or after (Post) completion of the first FIRM study for each locality. Once the FIRM is effective, the NFIP requires the lowest floor elevation of new construction or substantial improvements occurring post-FIRM to be at least equal to the BFE of the effective flood zone (FEMA, 2000). Building completion years ranged from 1754 to 2018, while elevation certificate completion dates ranged from 1983 to 2018. Approximately 31% of structures were classified as Pre-FIRM (Figure 3). The City of Hampton had the greatest abundance of Pre-FIRM structures (274), followed by the City of Franklin (146) (Figure 3).

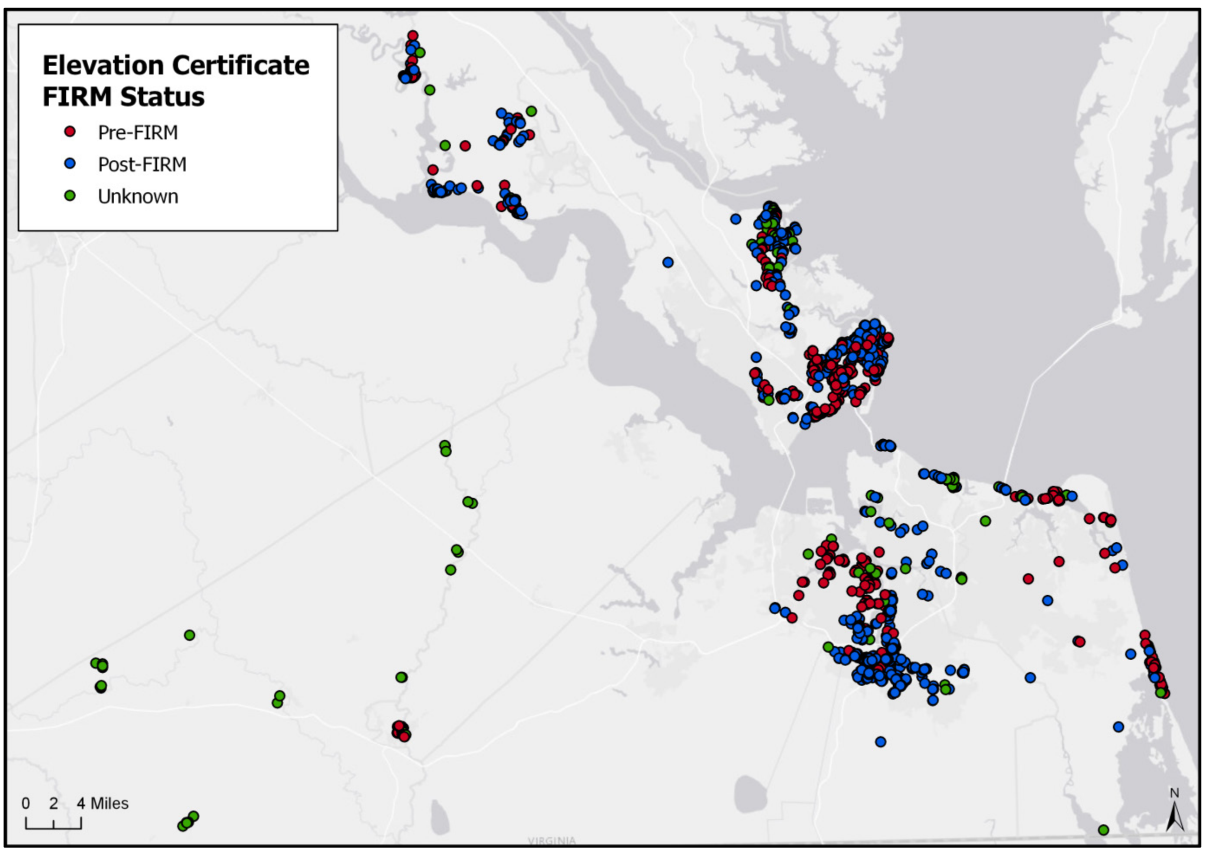

Figure 3: Distribution of elevation certificates across Hampton Roads displayed as Pre- or Post-FIRM.

Approximately 60% (1,256) of elevation certificates collected contained measurements completed using the previous vertical datum, National Geodetic Vertical Datum of 1929 (NGVD 1929), rather than the current North American Vertical Datum of 1988 (NAVD 1988). To provide a standardized measure of FFE across datums, the building's FFH was calculated as follows:

First Floor Height (FFH) = First Floor Elevation (FFE) – Lowest Adjacent Grade (LAG)

This is in agreement with the FEMA Hazus technical manual definition of first floor height as "the measurement of floor height from grade to the top of the finished floor." (FEMA, 2017, pg. 3-20).

A version of the elevation certificate database with all values reported in NAVD 1988 was also created. To convert elevations reported in NGVD 1929 to NAVD 1988, a conversion value must be obtained for each particular building location. The coordinates of the building footprint centroids (or parcel centroid if building footprint was unavailable) were entered into VERTCON v2.1 (NOAA NGS, 2018). The VERTCON program reports conversion values in meters. The conversion values were then converted to feet and applied as follows:

Elevation in NAVD 1988 = Elevation in NGVD 1929 (ft) + Conversion Value (ft)

The conversion factors are negative and are reported as an attribute in the feature class. A geodatabase with the four layers shown in Table 3 was shared with each locality for review.

Table 3: Summary of GIS layers included in the geodatabase distributed to each locality.

Spatial Layer	***Description***
Elevation Certificates with Parcels	Parcel polygons with building attributes and elevation certificate information reported in the original elevation certificate vertical datum (NGVD 1929 or NAVD 1988)
Elevation Certificates with Building Footprints	Building footprint polygons with building attributes, current flood zone, and elevation certificate information reported in the original elevation certificate vertical datum (NGVD 1929 or NAVD 1988)
Elevation Certificate Parcels reported in NAVD 1988	Parcel polygons with elevation certificate information converted to NAVD 1988
Elevation Certificate Building Footprints reported in NAVD 1988	Building footprint polygons with elevation certificate information converted to NAVD 1988

III. Analysis of Structure Data to Develop First Floor Elevations

Statistical Methods for Predicting First Floor Elevations

Although over 2,000 elevation certificates were collected, this represents less than 1% of the structures in Hampton Roads. Statistical modeling approaches provide a method of estimating FFE that uses sample data to inform predictions for thousands of structures. While elevation certificates are only available for a limited number of structures, building attributes, such as year built and foundation type, are widely available through each locality's tax assessor database. Statistical modeling techniques were used to identify the relationship between select building attributes and FFHs within the elevation certificate database. FFH was selected as the model output for two primary reasons. First, given that FFH is the difference between FFE and LAG, this eliminates additional error that is introduced through datum conversions. Second, FFH is consistent with the required input for FEMA's Hazus flood model. A final FFE can be obtained by adding the predicted FFH to an estimate of LAG. Based on the availability of elevation certificate data, Chesapeake and Hampton were selected as the two case study communities.

FEMA's Hazus technical manual and the previous analysis completed by Dewberry for the City of Virginia Beach identify several relevant building characteristics of interest for statistical analysis (FEMA, 2017; Koka, 2016). The Hazus technical manual provides estimates of FFH by building foundation type and whether a structure was built prior to or following a community's first FIRM (FEMA, 2017). Separate estimates of FFH are provided for riverine and coastal flood zones (Table 4). Dewberry's final regression model for Virginia Beach included building occupancy type, year built, foundation type, and difference in grade as predictor variables of FFH (Koka, 2016).

Referencing the variables identified by FEMA and Dewberry, the predictor variables of foundation type, year built, a structure's current highest risk flood zone, and difference in grade were evaluated during exploratory regression model development. Foundation type was tested as a predictor because building FFH is likely to differ by a foot or more between foundation types (Table 4). Year built was selected because it defines shifts in building construction standards. For example, the City of Hampton's first FIRM study occurred in 1984. If a structure was built prior to the community's effective FIRM date, the FFH is likely to be smaller because no floodplain building regulations existed. However following the FIRM, the lowest floor elevation of new construction buildings or substantial improvements must be at least equal to the BFE (FEMA, 2000). In 2014, Hampton passed 3 feet of freeboard within the SFHA, which requires a building's first floor to have a minimum elevation of 3ft above the BFE (City of Hampton, 2014). Therefore, year built and flood zone were tested as predictors because recent structures within the SFHA will likely have a larger FFH. Difference in grade was also tested as a predictor, and is defined as the difference between a structure's highest adjacent grade (HAG) and LAG. A large difference in grade indicates a structure was built on a slope and may consequently have a larger FFH.

Table 4: FEMA's default FFH values, defined as height from grade to top of finished floor, from the Hazus technical manual. Values reported in feet.

Foundation Type	***Pre-Firm FFH***	***Post-FIRM FFH (Riverine)***	***Post-FIRM FFH (Coastal A zone)***	***Post-FIRM FFH (Coastal V zone)***
Pile	7	8	8	8
Pier/Post/Beam	5	6	6	8
Solid Wall	7	8	8	8
Basement/Garden Level	4	4	4	4
Crawlspace	3	4	4	4
Fill	2	2	2	2
Slab	1	1	1	1

The building's assessed value and number of stories were also initially tested; however, they did not notably improve model performance. Occupancy type was excluded because the elevation certificate samples for Chesapeake and Hampton were predominantly single family residential homes. The Akaike Information Criterion (AIC) was used to identify the suite of final significant predictors for both case study communities (Table 5). AIC uses a backward selection process where predictor variables are removed to achieve a model that fits well and minimizes the number of parameters (Hughes, 2012).

Table 5: Predictor variables selected for inclusion in the final regression model.

Predictor Variable	***Predictor Type***	***Chesapeake Model***	***Hampton Model***
Foundation Type	Categorical	6 Types	3 Types
Year Built	Numeric Integer	1940 - 2018	1880 - 2018
Flood Zone	Categorical	AE, Shaded X, X	Special Flood Hazard Area (VE/AE/AO) Shaded X, X
Difference in Grade	Numeric	0 – 2.8ft	0 – 4.5ft

Although the same predictor variables were identified as significant for each test community, separate models were constructed for Chesapeake and Hampton because of differences in building attribute reporting. For example, Table 6 compares how foundation type is expressed by Chesapeake and Hampton's tax assessment offices. Given there are no common foundation codes between these localities, constructing separate models simplifies the analysis to test foundation type as a predictor of FFH. All exploratory regression analysis was completed in the statistical software package R, using the R-ArcGIS Pro Bridge for spatial data (Pobuda and Giner, 2017). The associated R script is attached in Appendix C.

Table 6: Foundation types as labeled in the tax assessment databases for the cities of Chesapeake and Hampton.

City of Chesapeake	***City of Hampton***
Brick Wall	None
Cinder Block	1/4 Crawl*
Concrete	1/2 Crawl*
Concrete Slab	3/4 Crawl*
Piers	Full Crawl
Stone Wall	Full Basement

*Foundation type was coded as partial crawl to simplify to 4 foundation types for Hampton's final regression model. Partial crawlspaces are calculated as a portion of a structure's total foundational area.

While multivariate linear regression is a useful tool for identifying structural relationships, the method imposes assumptions on the normality of the data and requires a linear relationship between the predictor variables and response (Hughes, 2012). Nonparametric statistical methods provide alternative predictive approaches with less stringent assumptions about the data structure (Hughes, 2013). Recursive partitioning is a nonparametric approach to regression analysis, where sub-groupings of similar responses are created based on the most relevant predictor variables (Hughes, 2013). The result is a regression tree that generates predictions. For example, Figure 4 shows a simple regression tree predicting FFH for the City of Hampton. The first branch of the tree is based on foundation type (Figure 4). Structures that are coded as “None” or “Partial Crawl” are directed to the left branch and estimated to have a FFH of 1.5 feet (Figure 4). Structures with a “Full Crawl” or “Basement” foundation type are grouped to the right, and then further subdivided by year built. In this sample regression tree, there are 5 possible FFH values a structure could be assigned.

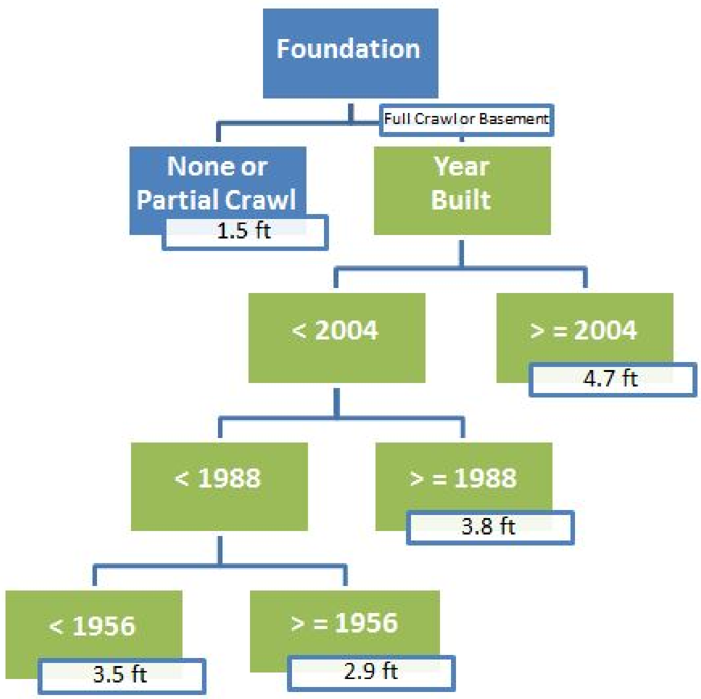

Figure 4: Simple regression tree example for the City of Hampton using foundation type and year built to predict first finished floor height (feet).

Random Forest is a method of recursive partitioning that generates and averages hundreds of regression trees, referred to as an ensemble, based on different randomly selected sub-sets of the sample data (Liaw and Wiener, 2002). When predicting values to a new sample, the Random Forest model considers results from the ensemble of decision trees to reduce overfitting that may result from a single tree (ESRI, 2018). Therefore, there are many possible prediction values, rather than only 5 as shown in Figure 4. Random Forest analysis can be conducted directly in ArcGIS Pro using the Forest-based Classification and Regression Tool within the Spatial Statistics toolbox.

The ArcGIS Pro tool also provides the advantage of using explanatory training rasters (ESRI, 2018). A Digital Elevation Model (DEM) with a resolution of 5 feet was included as an explanatory variable in addition to those previously mentioned (McFarlane, 2015). The DEM was selected as a predictor to reflect differences in elevation throughout the community and differences in risk within the SFHA. For example, the BFE for a given AE flood zone may be 8 feet. A structure located within this flood zone at an elevation of 3 feet would require an FFH of 5 feet to be in compliance with the NFIP, whereas a structure at an elevation of 7 feet would require a FFH of only 1 foot.

Prior to developing the Random Forest model, the elevation certificate databases for Chesapeake and Hampton were divided into randomly selected training and testing data sets, containing 80% and 20% of each locality's data, respectively. The purpose of the training data is to build the model, while the testing data set provides an independent sample of known FFH observations to evaluate model performance. Random Forest models with an ensemble of 500 trees were developed for Chesapeake and Hampton using their respective training data sets. The settings used in the ArcGIS Pro Forest-based Classification and Regression Tool are provided in Appendix D. The testing data set was selected in the tool as the set of features for which FFH predictions should be created.

Once predictions of FFH were obtained for the testing data sets of each locality, the absolute average error and Pearson correlation coefficients were calculated to assess model performance. The absolute error for each FFH prediction was calculated in GIS as the absolute value of the difference between the observed elevation certificate FFH and the Random Forest estimated FFH. The Pearson correlation coefficient measures the degree of linear association between two variables (Hughes, 2013). For example, if a model predicted each value in the testing data set exactly, the Pearson correlation coefficient would equal one. The Pearson correlation coefficient was calculated in R using the "cor" function (RDocumentation, 2019).

For each structure in the testing dataset, the recommended Hazus FFH value was also assigned in GIS based on the structure's foundation type, pre- or post-FIRM construction, and the highest risk flood zone (Table 4). The absolute average error and Pearson correlation coefficient were calculated for the Hazus FFH estimates relative to the observed FFH testing data. To assess how the Random Forest model performed relative to Hazus, the percent change in absolute average error between the Random Forest model and Hazus default FFH assignments was then calculated:

((Hazus Absolute Avg. Error – Random Forest Absolute Avg. Error) / (Hazus Absolute Avg. Error))*100

Once the models were established for Chesapeake and Hampton, they were applied to estimate the FFH of single-family residential homes across each locality. To develop the dataset for which the Random Forest models would predict FFH, single-family residential building footprints were selected for Chesapeake and Hampton. For a given parcel, multiple accessory structures may be present that are also labeled as single-family residential building types. Based on the assumption that the largest polygon is the primary residence, building footprints were additionally filtered by size so that only the largest structure within each parcel was retained. A summary of the distribution of single family residences by flood zone with complete attributes is presented in Table 7.

In order to obtain a FFE estimate, the predicted FFH must be added to the building's LAG. Estimates of each building's LAG within the predictive data sets were obtained using the DEM (McFarlane, 2015). The building footprints were first converted to line features. The minimum and maximum elevations, representing the LAG and HAG respectively, were extracted from the DEM along the building outline. The revised building footprints layer containing complete predictive attributes for each structure was then applied as the layer for which predictions would be created in the Forest-based Classification and Regression Tool.

Table 7: Summary of single family residential buildings by flood zone and test community. Building footprints last updated March 2, 2018 and August 22, 2018 for the Cities of Chesapeake and Hampton respectively.

	Within SFHA	***Within 500 year (Shaded X)***	***Area of Minimal Flood Hazard***	***Total***
Chesapeake	4,384	3,199	50,281	57,864
Hampton	8,340	5,295	24,892	38,527

Case Study Results: City of Chesapeake

The City of Chesapeake elevation certificate database contained 542 residential elevation certificate samples with complete building attributes that were used to support model development and evaluation. The training data set contained 434 observations (80%) randomly selected from the sample elevation certificate data. The remaining 20% of the data (108 observations) was reserved as the testing data set for model validation. The locations of elevation certificates used in the analysis are displayed in Figure 5, symbolized by training and testing data.

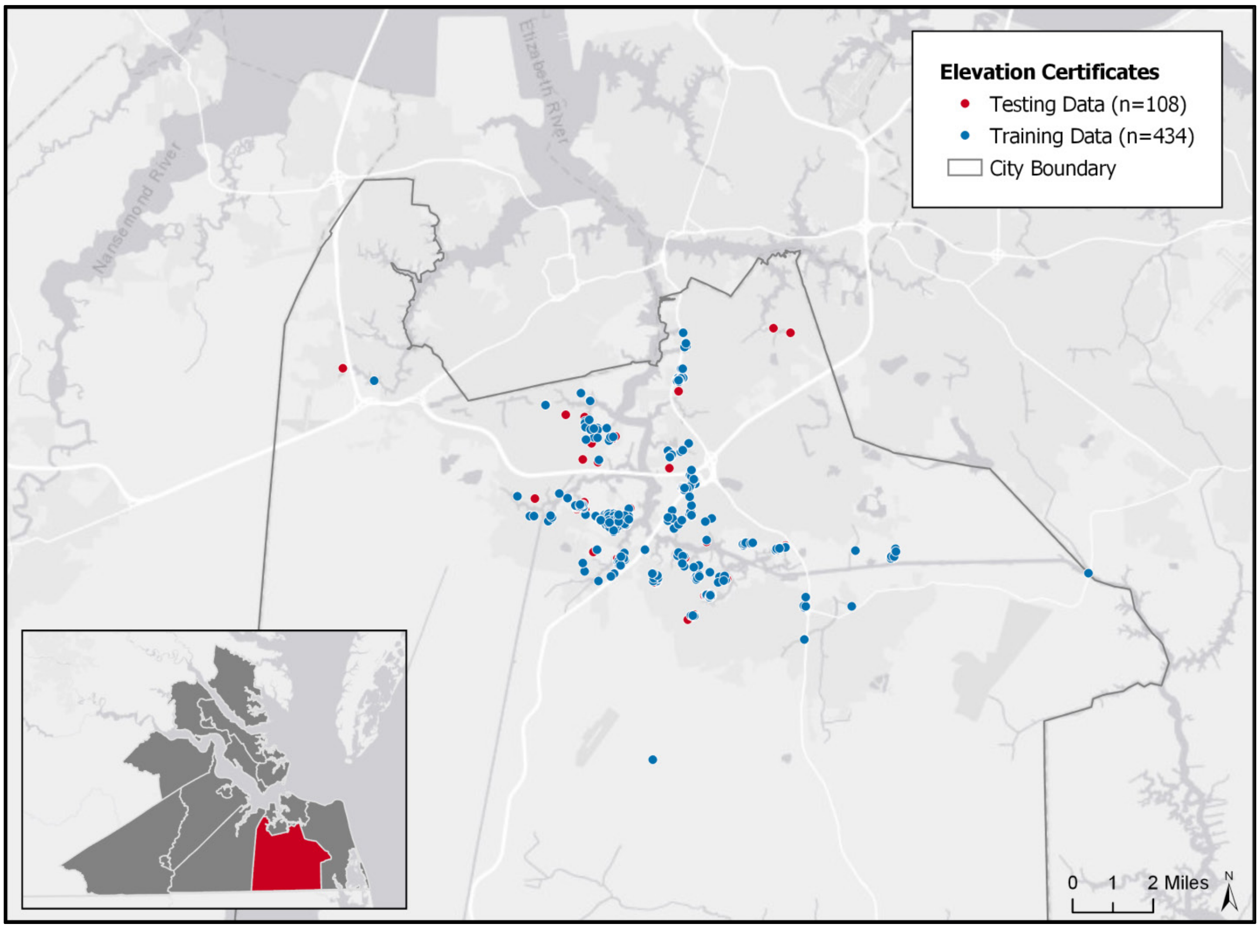

Figure 5: Distribution of elevation certificates used in Random Forest model development and evaluation for the City of Chesapeake.

Although Random Forest analysis eliminates several parametric regression assumptions about the data structure, outliers can negatively affect predictive ability. Outliers increase prediction error and can mask significant effects of predictor variables (Hughes, 2012). Five valid residential elevation certificates were flagged as outliers. Four of the five elevation certificates were homes of building diagram 6 or 7, which indicates an enclosure, such as a garage, below the primary living space (Figure 6).

If assuming the enclosure is unfinished, the resulting FFH is relatively high (9-11 feet) but is still categorized as brick wall or cinder block foundation type. The fifth elevation certificate removed represented a cinder block home with an unusually high FFH (15.3 feet). These abnormally large FFH values noticeably increase the variation within their foundation type categories, decreasing the usefulness of foundation type as a predictor. Given that these five structures are fundamentally different from other crawlspace structures, they were removed from the analysis.

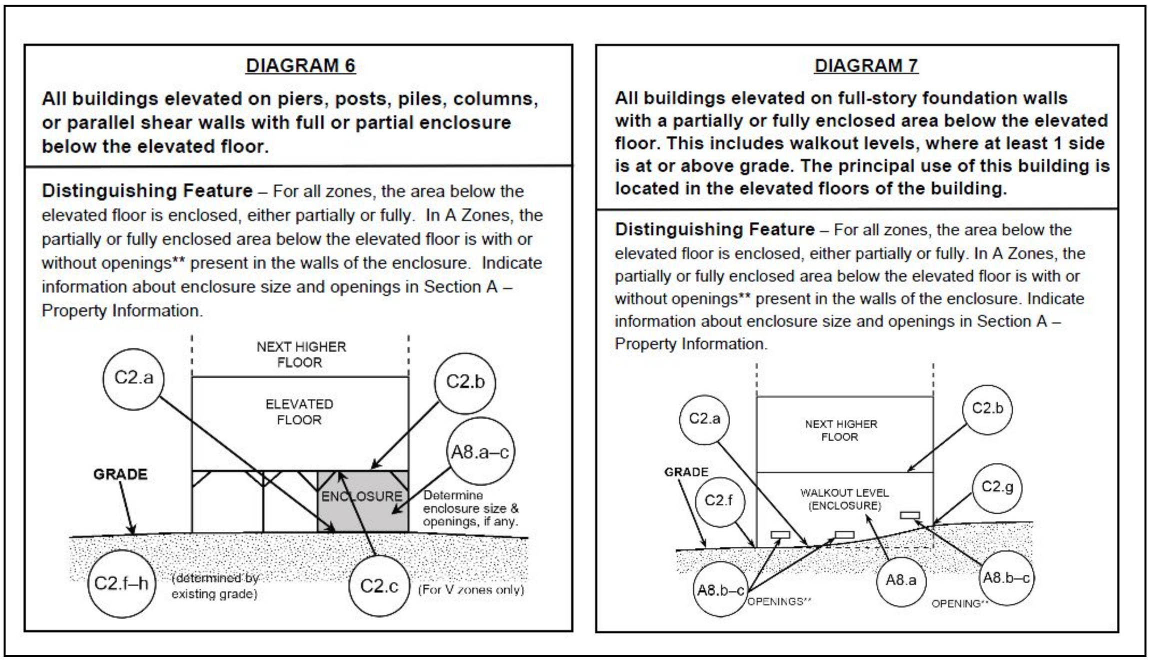

Figure 6: FEMA (2015) building diagram for structures elevated on partial or full enclosures at grade (Diagram 6) or partially below grade (Diagram 7).

The Random Forest analysis was conducted on the training data set of 434 observations with the predictor variables identified in Table 5 and the DEM value of each building footprint centroid (or parcel centroid if building footprint was unavailable). The ArcGIS Pro Forest-based Classification and Regression tool provides Out of Bag statistics to assess model accuracy. The Out of Bag Mean Squared Error (MSE) and percent of variation explained are calculated iteratively and averaged using the portion of the training dataset that is excluded from each subsample used to construct each tree in the forest (Esri, 2018). The resulting iteration indicated the model explained 69.46% of the sample variance with an MSE of 0.47. Taking the square root of the MSE allows for interpretation of the result in feet, the units of the response variable. The Random Forest model on average produces FFH estimates that are within 0.69 feet of the actual measured FFH. Foundation type was identified as the most important predictor variable, with a score representing 53% of all variable importance (Table 8). The importance score reflects the frequency of a variable creating a decision in the tree, or split, and the relative impact of that split divided by the number of trees (Esri, 2018).

Table 8: Summary of variable importance for the City of Chesapeake Random Forest model

Explanatory Variable	***Importance***	***Percent Importance***
Foundation Type	329.38	53%
DEM Value	140.84	22%
Difference in Grade	75.59	12%
Year Built	54.14	9%
Flood Zone	22.53	4%

The Random Forest model was applied to the testing data set of 108 features to generate predictions and evaluate model performance. Using the absolute value of difference between the observed and predicted FFH, 68.52% of the Random Forest predicted FFHs were within half a foot of the observed FFH (Table 9). Using the Hazus default values, 61.11% of the Hazus estimated FFHs were within half a foot of the observed value (Table 9). When compared to the testing data, the average absolute errors were 0.45 and 0.56 feet for the Random Forest and Hazus estimation approaches respectively. Overall, the Random Forest prediction approach resulted in a reduction of average error by 19.62% compared to Hazus (Figure 7).

Table 9: Summary of absolute average errors for the Random Forest Model and Hazus value estimates

Estimation Approach	***Within +/- 0.5 ft***	***Within +/- 1 ft***
Random Forest Model	68.52% (74/108)	93.5% (100/108)
Hazus Default Value	61.11% (66/108)	88.89% (96/108)

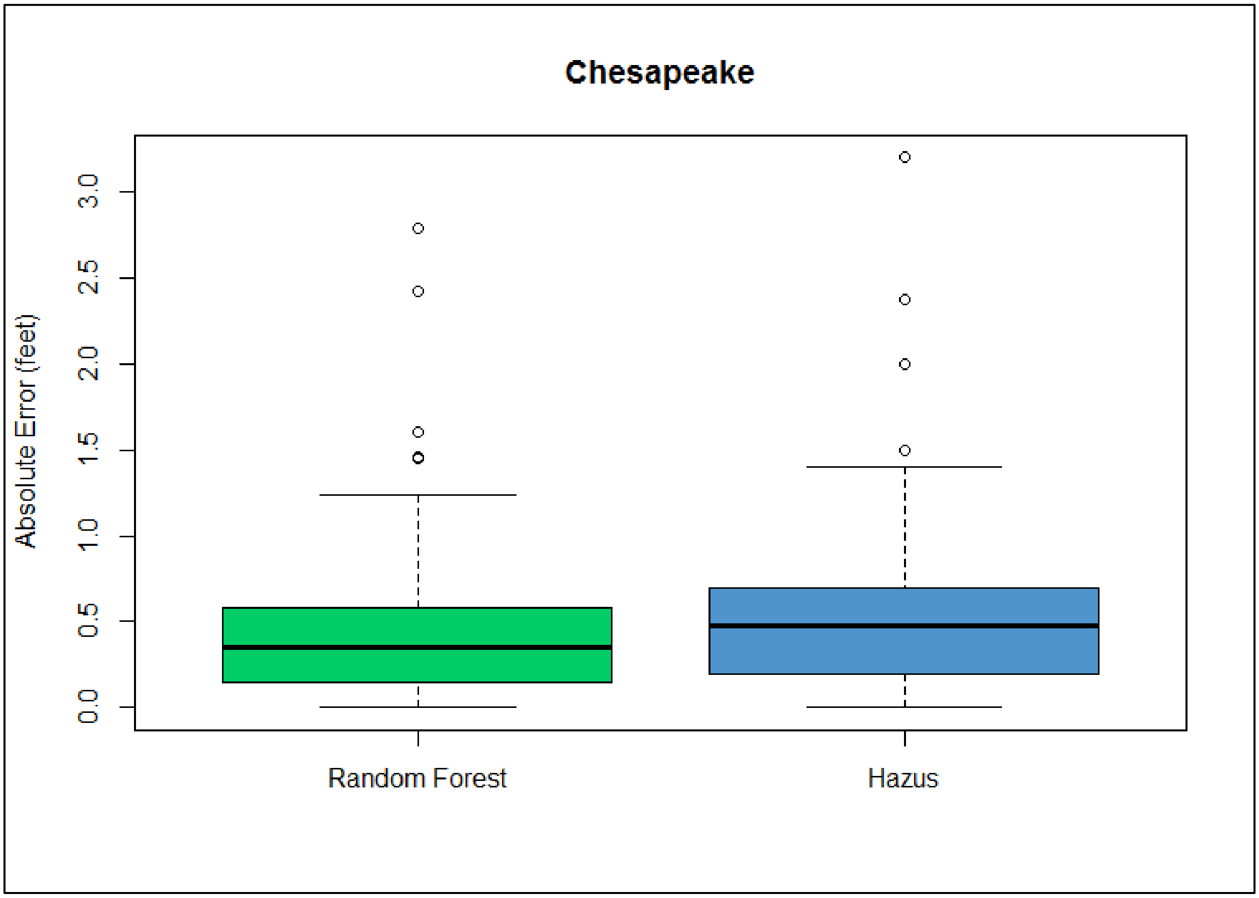

Figure 7: Comparison of absolute errors (Observed Elevation Certificate FFH – Estimated FFH) for the Random Forest model and Hazus default assignment method for Chesapeake.

The Pearson correlation coefficient for the Random Forest predictions relative to the observed FFH in the testing data set was 0.88 ($p<0.001$), and 0.82 ($P<0.001$) for the Hazus estimation approach (Figure 8). Given that a value of 1 indicates perfect correlation between observed and predicted values, the Pearson correlation coefficients further support that the Random Forest model improved prediction performance relative to the default Hazus values. In the Figure 8 scatterplot, points to the left of the diagonal reference line of perfect correlation represent overestimates of the observed FFH, and points to the right of the diagonal line indicate underestimates. The occurrence of over-predictions and under-predictions was fairly balanced for both estimation approaches, with approximately 49% of Random Forest and 48% of Hazus estimates underestimating the observed FFH.

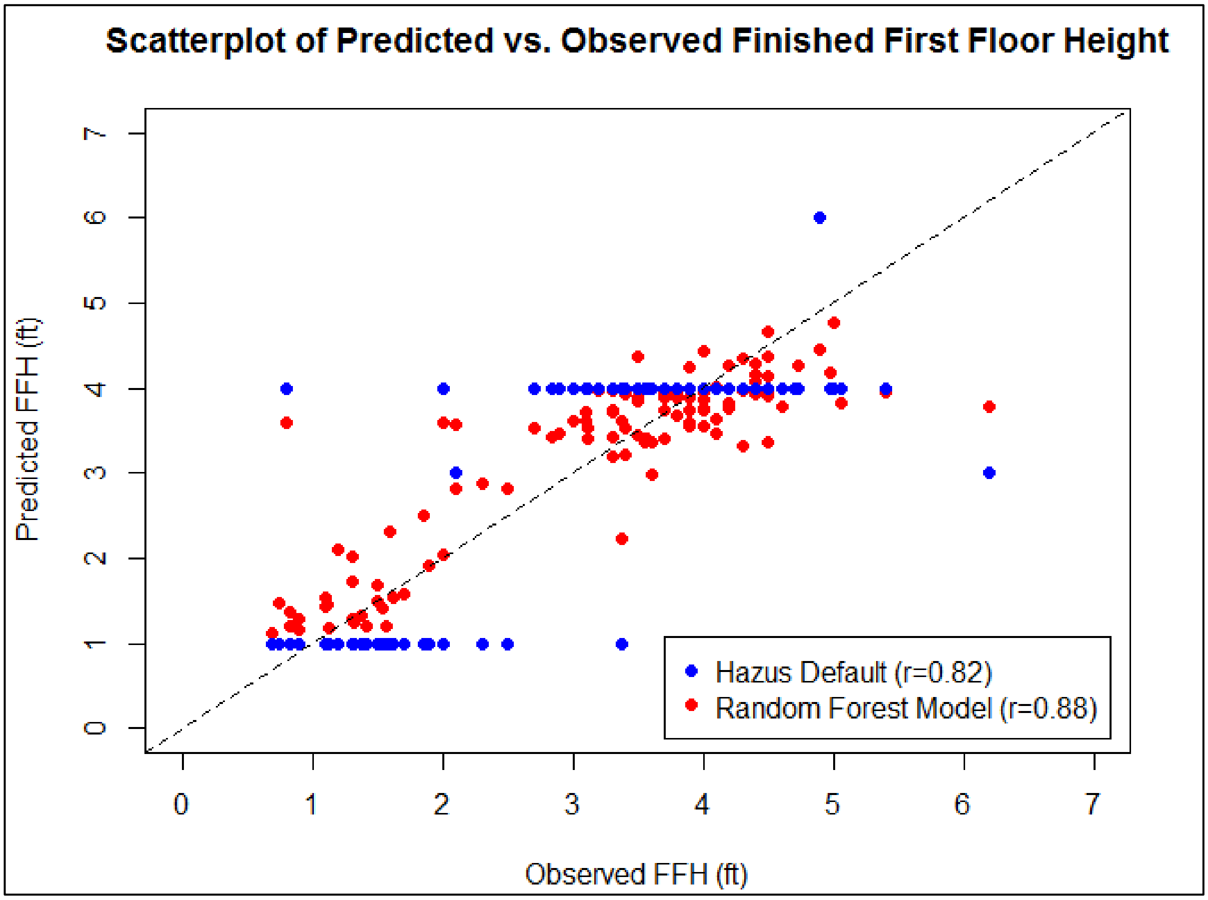

Figure 8: Comparison of the difference in predicted and observed first finished floor height (FFH) between the Hazus and Random Forest model predictions of the City of Chesapeake.

Case Study Results: City of Hampton

The City of Hampton elevation certificate database contained 614 residential elevation certificate samples, excluding multiple unit apartment complexes (17 elevation certificates). Of these elevation certificates, 52 structures were of building diagram 5, 6, or 7, representing an average first floor height of 8.87 feet (Figure 9). The City's assessment database currently classifies these foundation types as "None" or crawlspace; however, structures with a slab foundation type are also currently coded as "None" in the assessment database. Categorizing slab structures, pier structures, and structures which have the primary living space above a garage, as the same foundation type creates a large range of first floor heights within the "None" category and diminishes the value of foundation type as a predictor variable (Figure 10).

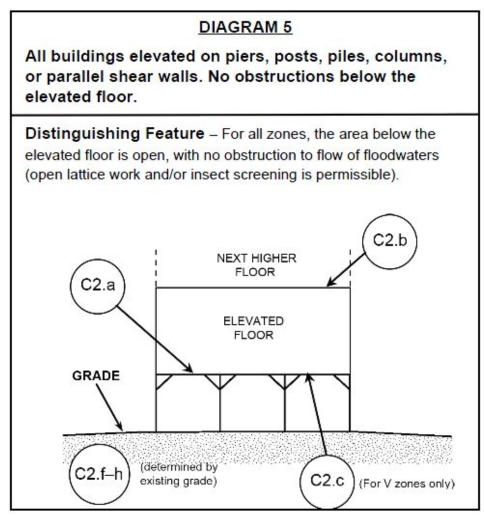

Figure 9: Building diagram for structure elevated on piers, posts, piles, columns, or parallel sheer walls.

For structures of building diagram 5, 6, or 7, 31 were coded as "None", 16 as "Full Crawl", 3 as partial crawl, and 2 as "Full Basement". After removing these 52 structures, along with 3 other outliers that appear to be elevated homes, the "None" category represents slab on grade and raised slab foundation type structures alone.

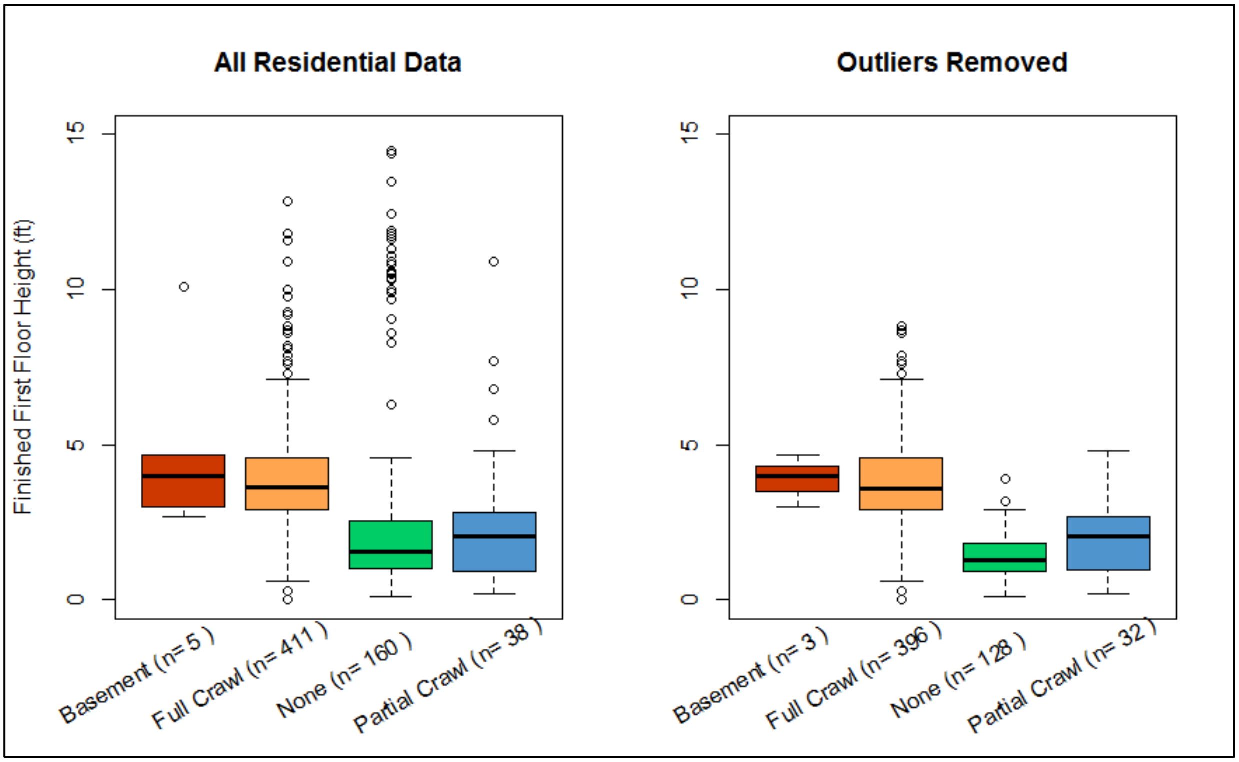

Figure 10: Comparison of first finished floor height distribution by foundation type before and after removal of building diagram 5, 6, and 7 outliers and elevated home outliers.

The final residential elevation certificate analysis sample contained 559 elevation certificates. Eighty percent of the sample data was randomly selected to create a training data set of 447 observations. The remaining 20% of the data (112 observations) was reserved as the testing data set for model validation. The locations of elevation certificates used in the analysis are displayed in Figure 11 and symbolized by training or testing data. The Random Forest analysis was conducted on the training data set using the variables identified in Table 5 and the DEM as explanatory variables. In order to use the difference in grade as a predictor variable, the HAG value was estimated for 65 structures because the HAG value was absent on the elevation certificate. The HAG values were estimated in NAVD 1988 using the DEM. For elevation certificates with values reported in NGVD 1929 (64 of 65), the estimated

NAVD 1988 HAG values were converted to NGVD 1929 using location specific conversion factors obtained through VERTCON.

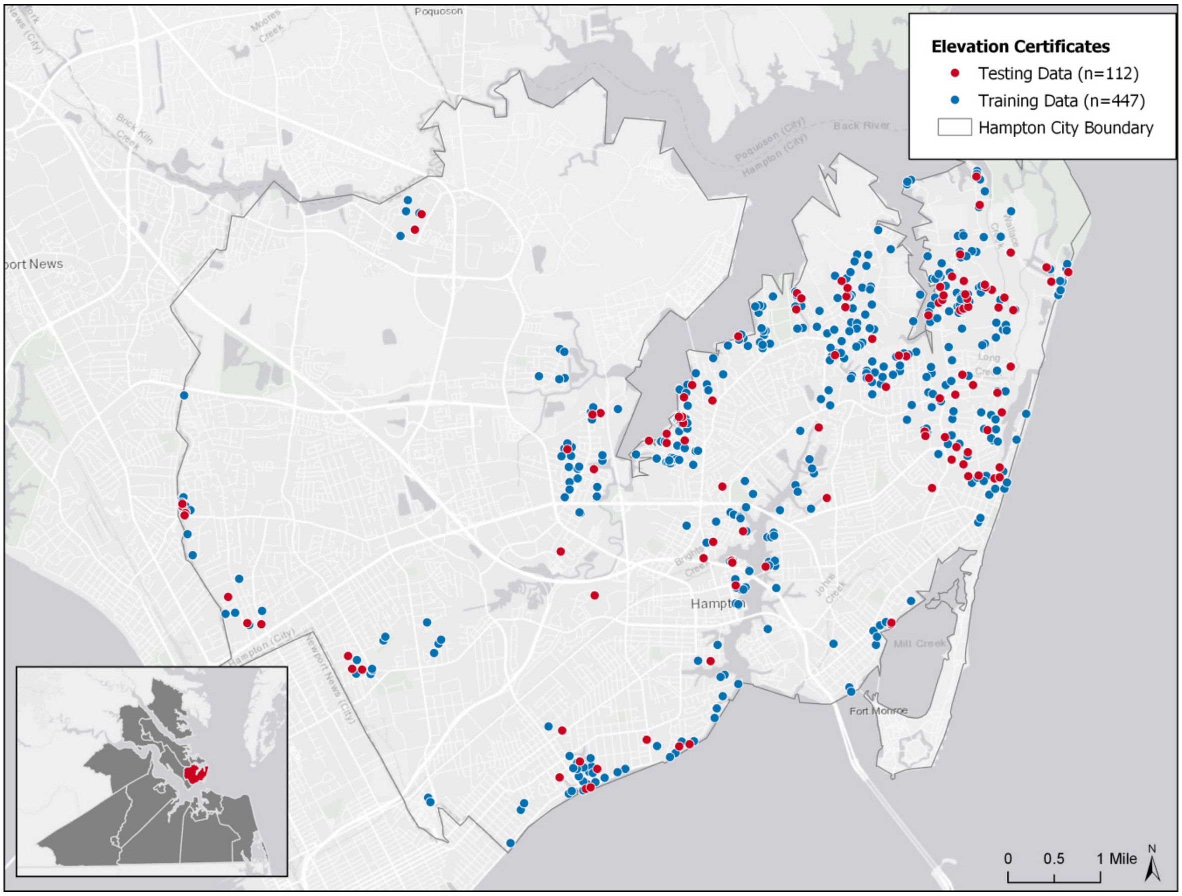

Figure 11: Distribution of elevation certificates used in Random Forest model development and evaluation for the City of Hampton.

The resulting Random Forest model out of bag errors indicate the model explained 61.97% of the sample variance with an MSE of 1.03. The Random Forest model on average produces FFH estimates that are within 1.02 feet of the actual measured FFH. Foundation type was identified as the most important predictor variable, with an importance score representing 38% of all variable importance (Table 10).

Table 10: Summary of variable importance for the City of Hampton Random Forest model

Explanatory Variable	***Importance***	***Percent Importance***
Foundation Type	415.16	38%
Year Built	270.49	25%
DEM Value	222.50	21%
Difference in Grade	148.43	14%
Flood Zone	23.17	2%

To assess the value of removing the 55 previously mentioned outliers from the model, a Random Forest model was developed using all available residential elevation certificate data and the same suite of predictors. The resulting Random Forest model had an average error of 2.07 feet and explained only 30.92% of the sample FFH variation. Foundation type was the second to last explanatory variable when ranked by importance. Thus removing the outliers substantially improved model performance and increased the value of foundation type as a predictor.

The Random Forest model was applied to the testing data set of 112 features to generate predictions and evaluate model performance. Using the absolute value of difference between the observed and predicted FFH, 52.68% of the Random Forest predicted FFHs were within half a foot of the observed FFH (Table 11). When using the Hazus default values, 42.86% of the Hazus estimated FFHs were within half a foot of the observed value (Table 11). The average absolute errors were 0.80 and 0.84 feet for the Random Forest and Hazus estimation approaches, respectively. Overall, the Random Forest prediction approach resulted in a reduction of average error by 4.76% (Figure 12).

Table 11: Summary of absolute average errors for the Random Forest Model and Hazus value estimates

Estimation Approach	***Within +/- 0.5ft***	***Within +/- 1 ft***
Random Forest Model	52.68% (59/112)	72.32% (81/112)
Hazus Default Value	42.86% (48/112)	71.42% (80/112)

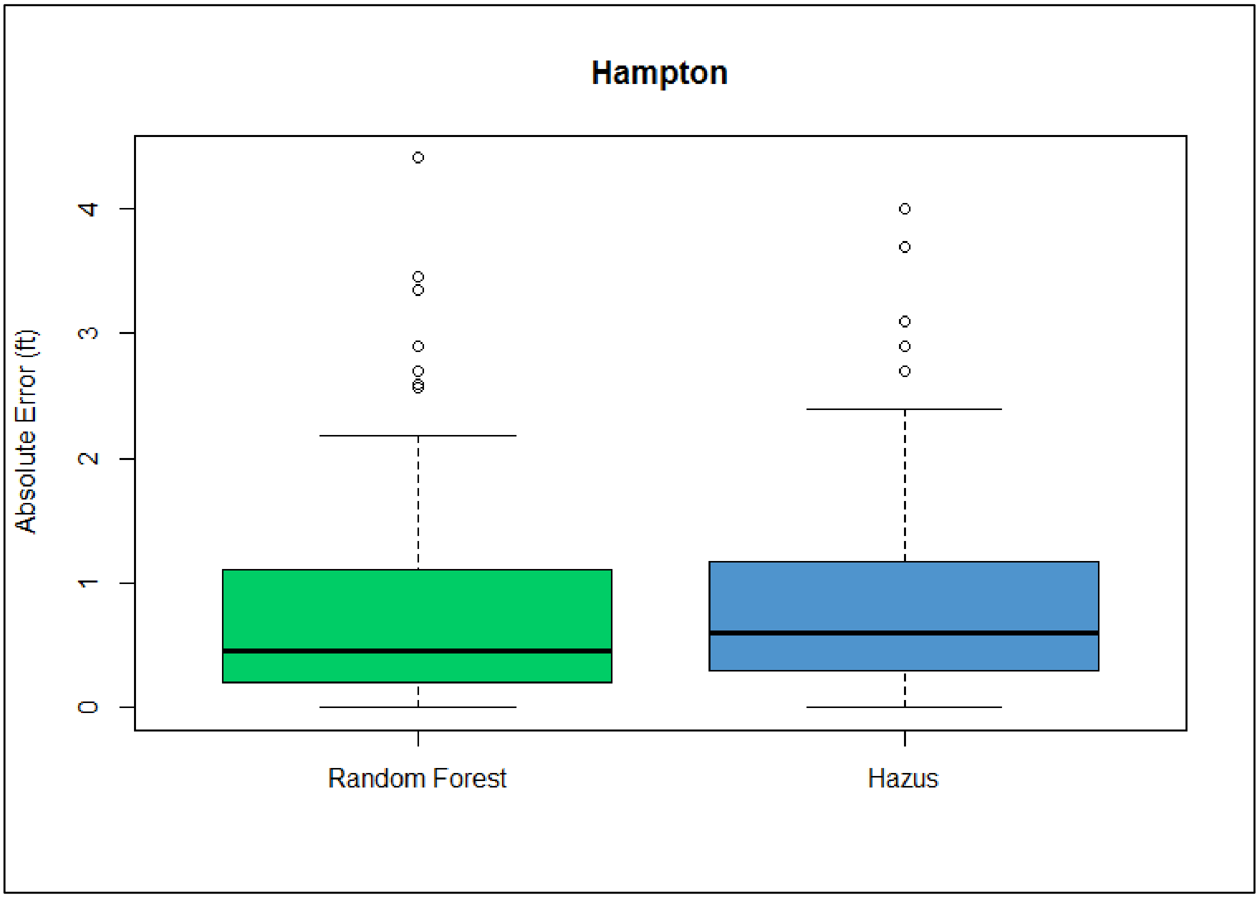

Figure 12: Comparison of absolute errors (Observed Elevation Certificate FFH – Estimated FFH) for the Random Forest model and Hazus default assignment method for Hampton.

The Pearson correlation coefficient for the Random Forest predictions relative to the observed FFH in the testing data set was 0.67 ($p<0.001$), and 0.63 ($p<0.001$) for the Hazus estimation approach (Figure 13). As observed in the Chesapeake Case study, the Random Forest model slightly improved estimations of FFH values relative to Hazus values. The occurrence of over-predictions and under-predictions was fairly balanced for both estimation approaches, with approximately 48% of Random Forest and 50% of Hazus estimates underestimating the observed FFH. For two homes in the testing data set, the Random Forest model underestimated the error by over 3 feet. After identifying images of these structures, one home appears to have been elevated while the other is a post-FIRM structure with an unusually high FFE in order to be in compliance with floodplain regulations. These structures reflect general categories of structures where the model likely performs poorly.

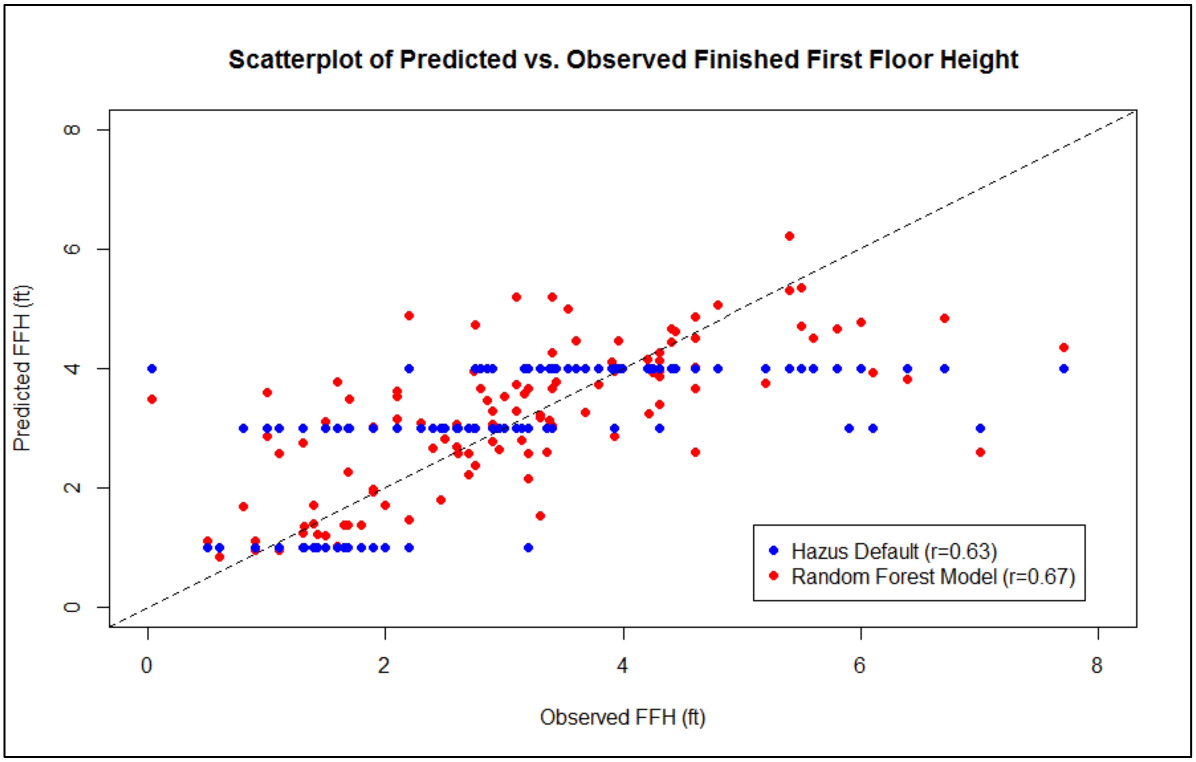

Figure 13: Comparison of the difference in predicted and observed first finished floor height (FFH) between the Hazus and Random Forest model predictions of the City of Hampton.

Case Study Comparisons and Limitations

When comparing the performance of the Random Forest models for Chesapeake and Hampton, the Chesapeake predicted values had a lower absolute average error and greater reduction in error relative to the Hazus estimates. Foundation type was identified as the most important variable for both the Chesapeake and Hampton models; however, foundation type accounted for a lower percent of the total variable importance for Hampton (38%) relative to Chesapeake (53%). This may be attributed to less overlap in the range of FFH between foundation type categories for Chesapeake (Figure 14). Year built was of greater variable importance for Hampton (25%) relative to Chesapeake (9%). Hampton had 197 Pre-FIRM structures relative to only 13 for the Chesapeake sample, creating greater variation in year built values. The average FFH for Pre-FIRM structures is 2.55 feet, compared to 3.56 feet for Post-FIRM structures. The FFH is expected to be lower for Pre-FIRM structures because they were constructed prior to the establishment of flood zones and compliance with the NFIP.

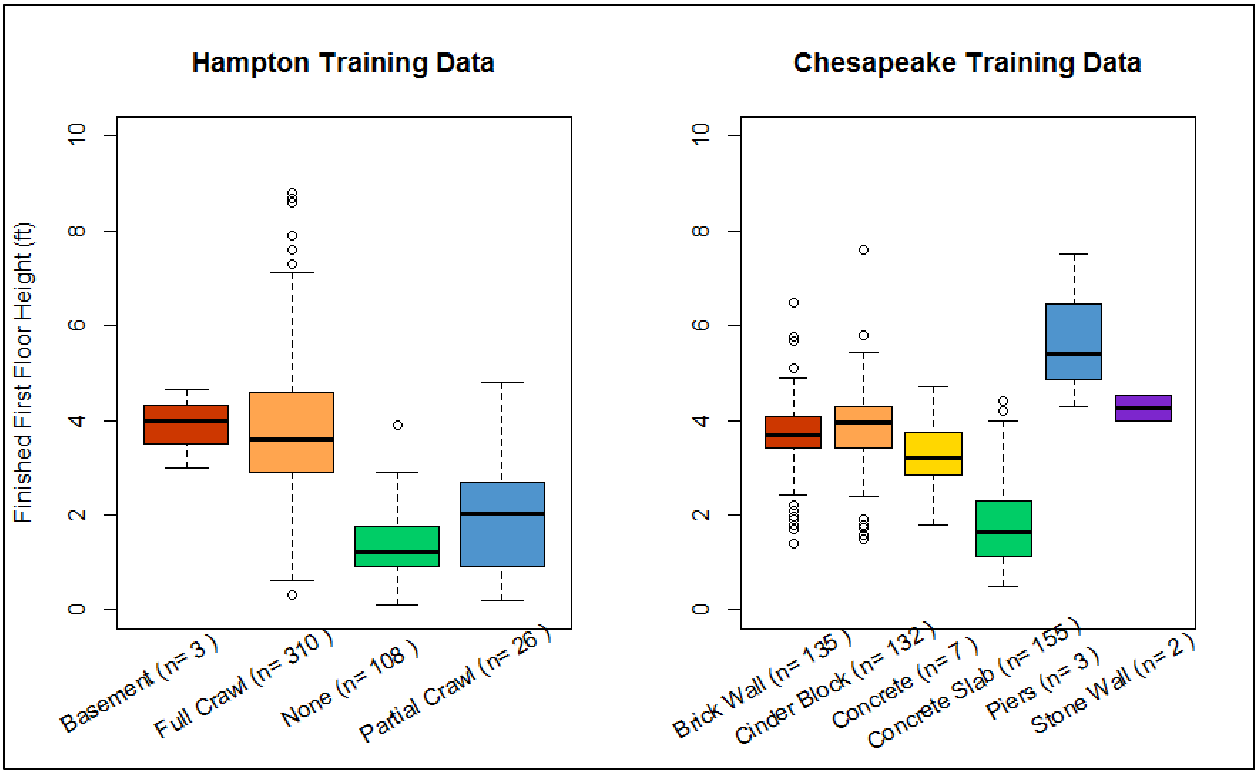

Figure 14: Boxplots comparing the range of first finished floor height values by foundation type between the cities of Hampton (left) and Chesapeake (right). The boxplots display only data used in the training data set for model development.

When comparing model performance by foundation type category with the testing data set, the Hampton model resulted in a reduction in absolute FFH prediction error (52.6%), relative to the Hazus default values, for only the "None" foundation category (n=20). For this category, a default Hazus value of 1 foot was selected, corresponding to slab foundation type. The Random Forest model likely shows an improvement in predicted FFH because it accounts for a larger range of values, including raised slab structures. The Random Forest model for Chesapeake reduced absolute prediction error relative to Hazus default values in all foundation type categories of the testing data set. Most notably this included a 30.5% reduction in absolute error for "Concrete Slab" (n=29), a 17.8% reduction for "Cinder Block" (n=42), and a 14.2% reduction for "Brick Wall" (n=30).

As previously noted, building diagrams of type 6 and 7 were removed from the analysis for the City of Hampton and Chesapeake to reduce variation within foundation type categories. A limitation of the Random Forest analysis approach is that the model is designed to predict only within the value range of the training data (ESRI, 2018). Thus the model prediction values likely underestimate the true FFH for these building diagram types. For example, the Hampton predictive model assumes all "None" foundation type buildings are slab on grade or raised slab. However, based on the elevation certificate data, some of these structures are of building diagram 5-7 and have a FFH greater than 10 ft.

It is also important to note that in addition to the error associated with the FFH prediction, the final FFE estimate also includes error from estimating the building's LAG value from the DEM. Using the building footprints associated with the training data set, the LAG was estimated from the DEM and subtracted from the observed LAG reported on the elevation certificate. The absolute average error was approximately 1 foot for Hampton and 2 feet for Chesapeake (Table 12). Given that the average error was positive for both localities, the DEM estimation approach tends to underestimate LAG elevation.

Table 12: Comparison of error, defined as the difference between the observed LAG on the elevation certificate and the estimated LAG from the DEM, for the Hampton and Chesapeake model training data sets. Only elevation certificates recorded in NAVD 1988 were used to avoid introducing additional conversion error.

Locality	*Abs. Average (ft)*	*Average (ft)*	*Abs. Median (ft)*	*Range (ft)*
Hampton (n=127)	1.00	0.97	0.62	-1.1 – 7.5
Chesapeake (n=77)	2.01	1.98	1.81	-0.95– 5.32

IV. Alternative Estimation Approaches

To apply the Random Forest estimation approach, a relatively large sample size is needed for model development. ESRI (2018) recommends training the model on at least several hundred features, which disqualifies localities with limited elevation certificate samples. In order to apply the random forest model to the other eight localities for which elevation certificates have been obtained, additional FFE samples are needed. These could be collected in the form of new elevation certificates or field surveys that provide an estimate of FFE and LAG. The Google Street View imagery approach applied by USACE also offers a relatively low-cost option for increasing FFE sample sizes. An accuracy assessment comparing approaches would be useful in determining the trade-off between cost and data quality.

The current database of elevation certificates and predictions could help inform strategic sampling of additional data collection. For example, the elevation certificate database can be used to identify neighborhoods where building diagram 5-7 structures are currently present and likely to occur. The predicted FFE can also be used to flag structures where the model may perform poorly. For example, structures that have a predicted FFE estimate below the BFE in the SFHA require further investigation. This is particularly important for Post-FIRM structures because an FFE below the BFE would not be compliant with the locality's floodplain management ordinance requirements. Post-FIRM structures with a predicted FFE estimate below the BFE likely indicate an error in the model performance and will require use of an alternative estimation approach.

Additional field data collection would also support an evaluation of the accuracy of elevation certificates. Elevation certificates several decades old may not reflect the current condition of the structure. Furthermore, nearly 60% of the elevation certificates in the geodatabase were recorded in NGVD 1929. When the elevations are converted to NAVD 1988, additional error is introduced; however, the VERTCON conversion program can be considered accurate within 2 cm (0.07 ft) (Mulcare, 2004). Surveying error may also result if the building diagram was incorrectly selected, or the surveyor misinterpreted the top of bottom floor classification. Collecting an independent sample of field measurements using a high-precision instrument, such as a laser inclinometer, of structures that have elevation certificates would allow for an estimation of existing error.

V. Recommended Practices for Data Management and Classification

All elevation certificates used for this project were collected as digital PDFs or image files. These digital copies are often stored in individual permit files. Creating and organizing digital copies of certificates in a single computer folder location, in addition to individual permit files, will help facilitate the process of future data entry. To streamline the process of importing data into GIS, it is recommended to include the address and Parcel ID in the elevation certificate PDF file name. For example, James City County includes Parcel ID in the filename for PDF copies of elevation certificates. The Python script in Appendix E loops through the PDF names and stores the output in an Excel table. This creates a common attribute field between the elevation certificates and spatial parcels layer to join the information in GIS. James City County also includes PDF copies of elevation certificates by parcel on their public property viewer (James City County, 2018). The elevation certificates can then easily be compared to the corresponding assessment data and building images.

As noted in the Chesapeake and Hampton case studies, localities have different schemes for coding foundation type. In some databases, a structure with a living space elevated above a garage cannot be distinguished from a slab on grade structure unless an image of the building is available, which creates a challenge for predictive modeling. A separate foundation type classification or additional attribute would be helpful. For example, York County denotes structures with the living space above the garage as “GAR/U”, and structures that have been elevated as “ELEV” (Figure 15). Based on the current elevation certificate sample for York County, structures with “GAR/U” foundation type have an average FFH of around 11 feet, and structures coded as “ELEV” have an average FFH of around 10 feet. These foundation types provide a critical distinction from slab structures, which often have an FFH around 1 foot. For new construction homes, localities should consider including an additional attribute or alter the foundation type code for structures with elevated living spaces.

Figure 15: House with foundation type coded as “GAR/U” (left) and house with foundation type coded as “ELEV” (right). Images obtained from York County Property Information portal https://maps.yorkcounty.gov/York/Account/Logon

VI. Conclusions and Next Steps

Building FFEs provide a critical piece of information when assessing structural vulnerability to flooding. Within Hampton Roads, the primary source of FFE information is elevation certificates. By compiling information from available digital copies of elevation certificates, a regional elevation certificate database was created with over 2,000 observations, now accessible on the Hampton Roads Regional GIS portal (www.HRGEO.org). Using elevation certificate information from two test communities, the cities of Chesapeake and Hampton, two predictive Random Forest models were created that estimate FFH for buildings that lack elevation certificates. The FFH prediction was then applied to an estimate of a structure's LAG to obtain a final predicted FFE. The models for both localities highlight the importance of foundation type as a predictive variable. Given the large number of Pre-FIRM structures within the Hampton database, year built was also identified as an important variable. Although the model performed with greater accuracy in Chesapeake than Hampton, both models improved FFH estimates relative to the current default Hazus FFH assignments. Further evaluation of spatial patterns in the resulting model error may help identify additional sources of error or priority areas for field data collection.

This report marks the conclusion of the first phase of the regional FFE database initiative. Funding has been awarded to continue the database development. The current inventory can be expanded by obtaining elevation certificates from communities which currently have only paper copies available. For example, York County is continuing to convert paper copies of elevation certificates into PDFs. Once all digital copies are obtained, there will likely be a sufficient sample size to test the modeling approach for York County. This will also allow for evaluation of model performance with a different foundation type coding scheme that includes a distinction for structures with a living space elevated above a garage. The existing database will also be updated with additional elevation certificates for new construction homes. A plan for long-term maintenance will likely include an annual or biannual data call for new elevation certificates.

The second phase of the FFE project will also involve applying the FFE database to test approaches for assessing structural vulnerability to coastal hazards, such as sea level rise, tidal flooding, and storm surge. Methodologies will be evaluated for pilot communities with the goal of providing vulnerability assessment techniques that could apply to local coastal hazard strategies, comprehensive plans, and the next update of the regional hazard mitigation plan. Continued coordination with both governmental and non-governmental entities, including academic institutions, will help ensure efforts are complimentary. By exploring and evaluating various methods for improving FFE data, the Hampton Roads region will continue to build the foundation of data necessary to understand and plan for the increasing risk of coastal hazards.

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VIII. Appendices

Appendix A: Elevation Certificate Database Attributes

Attribute Field	Description	Field Type	Source
EC_Street_Address	Street number and name as listed on the elevation certificate	Text	EC Sect. A2[4]
PSTLADDRES	Parcel postal address from HRGEO Parcels layer	Text	HRGEO Parcels[5]
City	City where applicable	Text	EC Sect. A2
County	County where applicable	Text	EC Sect. A2
State	State (Virginia)	Text	EC Sect. A2
PSTLZIP5	5 digit zip code from HRGEO Parcels layer or elevation certificate	Double	HRGEO Parcels
Exp_Date	Elevation certificate form expiration date. This refers to the format of the certificate, and does not mean the elevations reported are no longer valid if past the expiration date.	Date	EC Page 1
Bldg_Use	Building use (residential, non-residential, addition, accessory)	Text	EC Sect. A4
Bldg_Diagram	Building diagram number	Text	EC Sect. A7
DFIRM_ID	NFIP community number	Long Integer	EC Sect. B1
FIRM_Date	FIRM Panel Effective/Revised Date	Date	EC Sect. B8
EC_Flood_Zone	Primary flood zone (highest risk)	Text	EC Sect. B8
EC_Flood_Zone1	Additional flood zones on building property	Text	EC Sect. B8
EC_Flood_Zone2	Additional flood zones on building property	Text	EC Sect. B8
EC_BFE	Base flood elevation reported on elevation certificate	Double	EC Sect. B9
Elev_Datum	Elevation datum used for BFE and elevation certificate measurements	Text	EC Sect. C2
Top_BF	Top of bottom floor elevation	Double	EC Sect. C2a
Top_NHF	Top of the next higher floor elevation	Double	EC Sect. C2b
BLHM	Bottom of the lowest horizontal structural member elevation	Double	EC Sect. C2c
AT_GAR	Attached garage elevation	Double	EC Sect. C2d
Elev_Equip	Lowest elevation of machinery or equipment servicing the building	Double	EC Sect. C2e
LAG	Lowest adjacent (finished) grade next to building.	Double	EC Sect. C2f
HAG	Highest adjacent (finished) grade next to building.	Double	EC Sect. C2g

[4] EC Sect. abbreviates Elevation Certificate Section. Sections refer to the FEMA Elevation Certificate 2015 edition.
[5] HRGEO refers to the regional parcels layer on the Hampton Roads Regional GIS portal.

Attribute Field	Description	Field Type	Source
LowElev_Stairs	Lowest adjacent grade at lowest elevation of deck or stairs, including structural support	Double	EC Sect. C2h
Finished_First FloorElevation	See notes on Sheet 2 documenting first finished floor elevation determination.	Double	HRPDC Determination
Finished_FirstFloorHeight	Calculated as (Finished first floor elevation - Lowest Adjacent Grade)	Double	HRPDC Determination
Length_unit	Measurement unit used to record elevations.	Text	EC Sect. C2
Issue_Date	Date elevation certificate was signed by surveyor	Date	EC Sect. D
BuildingFootprint	Indicates if a building footprint is currently available for the structure (yes/no).	Text	HRPDC Determination
Notes	Notes about the specific structure where necessary	Text	HRPDC Determination
LowFloor 99	Elevation of lowest floor. Reported only for City of Franklin elevation certificates in 1999.	Double	EC Franklin 1999 edition
HighWater99	Elevation of high water mark. Reported only for City of Franklin elevation certificates in 1999.	Double	EC Franklin 1999 edition
FIPS	FIPS code	Text	FIPS
PARCELID	Parcel GPIN	Text	HRGEO Parcels
TAXMAPNO	Parcel Tax Map Number	Text	HRGEO Parcels
ZONING*	Locality Zoning District	Text	HRGEO Parcels
IMPVALUE*	Building Improvements Value	Text	HRGEO Parcels
LNDVALUE*	Land Value	Text	HRGEO Parcels
TOTVALUE*	Total Value	Text	HRGEO Parcels
RESYRBUILT*	Year Structure Built	Text	HRGEO Parcels
FIRM_Status*	Designates whether a structure is Pre or Post FIRM (Pre/Post)	Text	HRPDC Determination
FOUNDATION*	Structure foundation type as coded by locality	Text	Local assessment data
SRCAGENCY	Locality agency/dept. providing parcel information	Text	HRGEO Parcels
AGENCYURL	Locality agency/dept. URL	Text	HRGEO Parcels
PARCELS_LASTUPDATE	Date of last HRGEO update to parcels layer	Text	HRGEO Parcels

Attribute Field	Description	Field Type	Source
New_FLD_ZONE**	Highest risk flood zone of the current FIRM	Text	FEMA NFHL[6]
New_ZONE_SUBTY**	Description of current highest risk FIRM flood zone	Text	FEMA NFHL
New_STATIC_BFE_88**	Current highest base flood elevation in NAVD 1988	Double	FEMA NFHL
New_SFHA_TF**	Building currently located in the Special Flood Hazard Area (T/F)	Text	FEMA NFHL
FEMA_SOURCE_CIT**	FEMA study citation for current flood zones	Text	FEMA NFHL
STORY**	Number of stories	Text	Local assessment data
VGIN_LastUpdate**	Date of last VGIN update to building footprints layer	Date	VGIN Building Footprints[7]
VGIN_GEOID**	Identification number for building footprint from VGIN	Text	VGIN Building Footprints
Current_Datum***	Vertical datum that all elevations are reported in (NAVD 1988)	Text	NAVD 1988
Conv_FactorM***	Factor to convert from NGVD 1929 to NAVD 1988 reported in meters	Double	VERTCON Calculation[8]
Conv_FactorFt***	Factor to convert from NGVD 1929 to NAVD 1988 reported in feet	Double	VERTCON Calculation
LAT	Latitude of point used to determine conversion factor	Double	GIS Calculation
LON	Longitude of point used to determine conversion factor	Double	GIS Calculation

*Value not reported for accessory structures.

**Present in regional elevation certificate building footprints layer only.

***Present only in layers where all elevation values have been converted to NAVD 1988.

[6] Federal Emergency Management Agency's National Flood Hazard Layer. (2018)
[7] Virginia Geographic Information Network (VGIN) Building Footprint Map Service. (2018)
[8] NOAA National Geodetic Survey (NGS) datum conversion tool, VERTCONv2.1. (2018)

Appendix B: First Finished Floor Elevations by Building Diagram

Building Diagram[9]	First Finished Floor Measurement Label	Explanation[10]
1A	C2a	Slab-on-Grade
1B	C2a	Raised Slab-on-Grade
2A	C2b	Basement – Assumes basement is unfinished.
2B	C2b	Basement – Assumes basement is unfinished.
3	C2a	Split Level – Assumes partial slab-on-grade.
4	C2b	Split Level with Basement – Assumes basement is unfinished.
5	C2a	Elevated on pier, post, piles (etc.) with no obstructions below the elevated floor
6	C2b	Elevated on pier, post, piles (etc.) with full or partial enclosure below the elevated floor. Assumes enclosure is unfinished.
7	C2b	Elevated on full-story foundation walls with a partially or fully enclosed area below the elevated floor. Assumes enclosure is unfinished (i.e. garage).
8	C2b	Crawlspace
9	C2b	Sub-grade Crawlspace

[9] All building diagrams provided in FEMA National Flood Insurance Program Elevation Certificate and Instructions, 2015 Edition.

[10] Explanation provided by HRPDC to describe how first finished floors were generally assigned for database development. No official surveyor determination of first finished floor is required on the elevation certificate.

Appendix C: Exploratory Statistical Analysis Code

```
#Exploratory Regression Analysis for the Cities of Hampton and Chesapeake
#ESRI Resources: Go Deeper with Data Analytics Using ArcGIS Pro and R, Introduction to Regression Analysis Using ArcGIS Pro

#Load necessary packages
library(arcgisbinding)
arc.check_product()
library(rgdal)
library(rpart)

#Load Hampton elevation certificate feature layers
HA_gis_data_AllRes <-arc.open(path =
'K:/PHYS/PROJECTS/FFE/Hampton/HamptonFFEgdb.gdb/Hampton_ElevCert_Parcels_AllRes')

HA_gis_data_OutliersRemoved <-arc.open(path =
'K:/PHYS/PROJECTS/FFE/Hampton/HamptonFFEgdb.gdb/HA_REG_POINTS_FINAL')

#Convert feature layers to data frames
HA_all <- arc.select(HA_gis_data_AllRes)
HA_reg <- arc.select(HA_gis_data_OutliersRemoved)

#Load Chesapeake elevation certificate feature layers
CH_gis_data_OutliersRemoved <-arc.open(path =
'K:/PHYS/PROJECTS/FFE/Chesapeake/ChesapeakeFFE.gdb/CH_REG_POINTS_FINAL')

#Convert feature layers to data frames
CH_reg <- arc.select(CH_gis_data_OutliersRemoved)

#Create training and testing data subsets for Chesapeake and Hampton analysis
#80% training data and 20% testing. Determine number of observations needed for training dataset
smp_sizeHA <- round(0.80 * nrow(HA_reg), digits=0)
smp_sizeCH <- round(0.80 * nrow(CH_reg), digits=0)

#Randomly select observations for training data sample.
trainHA <- sample(seq_len(nrow(HA_reg)), size = smp_sizeHA)
trainCH <- sample(seq_len(nrow(CH_reg)), size = smp_sizeCH)

#Subset the original data based on the randomly selected observations above.
HA_train <- HA_reg[trainHA, ]
CH_train <- CH_reg[trainCH, ]

#Create spatial objects for the subset data frame in order to create GIS layer.
sp_HA_train <- arc.data2sp(HA_train)
sp_CH_train <- arc.data2sp(CH_train)
```

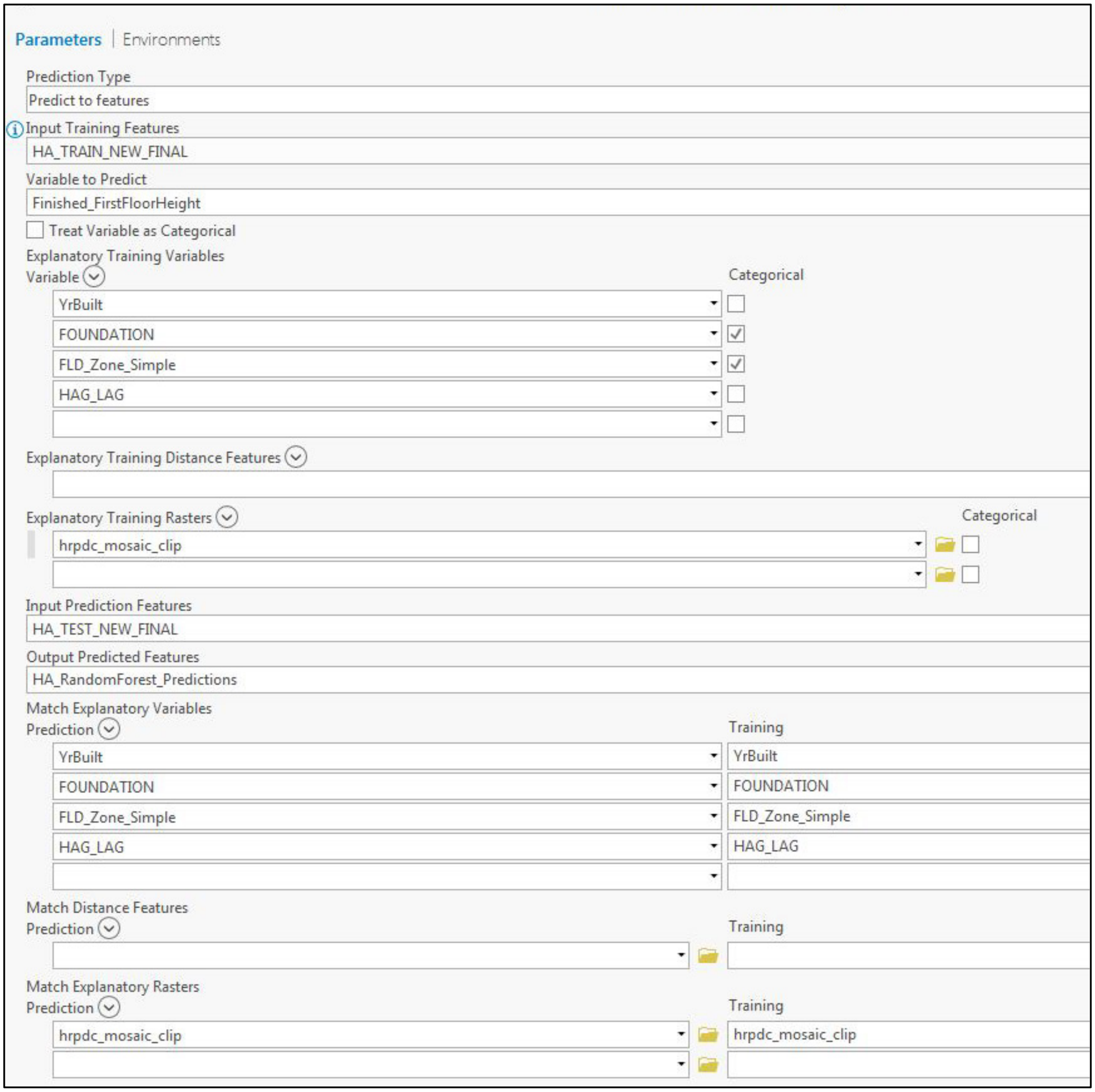
```
#Create testing data set using remaining 20% of observations that were not included in the training dataset.
HA_test <- HA_reg[-trainHA, ]
CH_test <- CH_reg[-trainCH, ]

#Create spatial objects for the subset data frame in order to create GIS layer.
sp_HA_test <-arc.data2sp(HA_test)
sp_CH_test <-arc.data2sp(CH_test)

#Write output of testing dataset as a shapefile for analysis in GIS. Ensure package Rgdal is loaded.
writeOGR(sp_HA_test, "K:/PHYS/PROJECTS/FFE/Hampton", "HA_TEST_RF_Final", driver="ESRI Shapefile")
writeOGR(sp_HA_train, "K:/PHYS/PROJECTS/FFE/Hampton", "HA_TRAIN_RF_Final", driver="ESRI Shapefile")

writeOGR(sp_CH_test, "K:/PHYS/PROJECTS/FFE/Chesapeake", "CH_TEST_RF_FINAL", driver="ESRI Shapefile")
writeOGR(sp_CH_train, "K:/PHYS/PROJECTS/FFE/Chesapeake", "CH_TRAIN_RF_Final", driver="ESRI Shapefile")

#---DESCRIPTIVE STATISTICS: BOXPLOTS---

#Hampton comparison of first finished floor height by foundation type before and after outlier removal.

attach(HA_all)
par(mfrow=c(1,2))
b <-boxplot(Finished_FirstFloorHeight ~ FOUNDAT,plot=0, xaxt="n")
boxplot(Finished_FirstFloorHeight ~ FOUNDAT, ylab="Finished First Floor Height (ft)", main="All Residential Data",
xaxt="n", ylim=c(0,15), col=c('orangered3','tan1', "springgreen3", "steelblue3"))
text(x=seq(0.5,3.5, by=1), par("usr")[3]-1.1, labels=paste(b$names,"(n=",b$n, ")"),srt=30, pos=1, xpd=TRUE)
detach(HA_all)
attach(HA_reg)
b <-boxplot(Finished_FirstFloorHeight ~ FOUNDATION,plot=0, xaxt="n")
boxplot(Finished_FirstFloorHeight ~ FOUNDATION, main="Outliers Removed", xaxt="n", ylim=c(0,15),
col=c('orangered3','tan1', "springgreen3", "steelblue3"))
text(x=seq(0.5,3.5, by=1), par("usr")[3]-1.1, labels=paste(b$names,"(n=",b$n, ")"),srt=30, pos=1, xpd=TRUE)
detach(HA_reg)

#Comparison of Hampton and Chesapeake training data first finished floor height by foundation type
attach(HA_train)
par(mfrow=c(1,2))
b <-boxplot(Finished_FirstFloorHeight ~ FOUNDATION,plot=0, yaxt="n", xaxt="n")
boxplot(Finished_FirstFloorHeight ~ FOUNDATION, names=paste(b$names,"(n=",b$n, ")"), ylim=c(0,10), xaxt="n",
main="Hampton Training Data", ylab="Finished First Floor Height (ft)", col=c('orangered3','tan1', "springgreen3",
"steelblue3"))
text(x=seq(0.5,3.5, by=1), par("usr")[3]-.7, labels=paste(b$names,"(n=",b$n, ")"),srt=30, pos=1, xpd=TRUE)
detach(HA_train)
attach(CH_train)
b <-boxplot(Finished_FirstFloorHeight ~ FOUNDAT,plot=0, yaxt="n", xaxt="n")
boxplot(Finished_FirstFloorHeight ~ FOUNDAT, names=paste(b$names,"(n=",b$n, ")"), ylim=c(0,10), xaxt="n",
main="Chesapeake Training Data", col=c('orangered3','tan1', "gold", "springgreen3", "steelblue3","purple3"))
text(x=seq(0.5,5.5, by=1), par("usr")[3]-.7, labels=paste(b$names,"(n=",b$n, ")"),srt=30, pos=1, xpd=TRUE)
detach(CH_train)
```

```
#---EXPLORATORY REGRESSION---

#Code for Akaike Information Criterion (AIC) variable selection for multivariate regression
#Run AIC with all potential predictors to assess best model fit.
#Hampton variable selection:
attach(HA_train)
mlrfit_HA <- lm(Finished_FirstFloorHeight ~ FOUNDATION + YrBuilt + FLD_Zone_Simple + HAG_LAG + STORY +
DwlgVal1)
#Note that 'Split' for story was coded as 1.5 to create numeric value.
summary(mlrfit_HA)
step(mlrfit_HA, direction = "backward")
detach(HA_train)

#Chesapeake variable selection:
attach(CH_train)
mlrfit_CH <- lm(Finished_FirstFloorHeight ~ FOUNDAT + YEARBUILT + FLD_ZONE + HAG_LAG + STORY+ IMPVALUE)
summary(mlrfit_CH)
step(mlrfit_CH, direction = "backward")
#IMPVALUE retained by AIC; however including it in the model only reduces standard error by 0.04ft. Not included
in final model.
detach(CH_train)

#Simple Regression Tree Demo. Ensure rpart package is loaded.
attach(HA_train)
par(mfrow=c(1,1))
treeSimple <- rpart(Finished_FirstFloorHeight ~ YrBuilt+FOUNDATION, data=HA_train)
plot(treeSimple)
text(treeSimple)
print(treeSimple)

#---Random Forest Model Evaluation: Pearson Correlation Test---
#Load Random Forest model and Hazus predictions for testing datasets for Hampton and Chesapeake
HA_gis_data_Predict <-arc.open(path =
'K:/PHYS/PROJECTS/FFE/Hampton/Hampton_FirstFloorElevations.gdb/Hampton_ElevCert_TEST_NEW_Predictions
_AllAtt')

CH_gis_data_Predict <- arc.open(path =
'K:/PHYS/PROJECTS/FFE/Chesapeake/ChesapeakeFFE.gdb/CH_Testing_NEW_Predictions_FINAL')

#Convert feature layers to data frames
HA_predict <- arc.select(HA_gis_data_Predict)
CH_predict <- arc.select(CH_gis_data_Predict)

#Hampton Data
attach(HA_predict)
```

```
#Run Pearson Correlation Coefficient Test for Random Forest predictions
RF_HA<- cor(PREDICTED,Finished_FirstFloorHeight, method="pearson")
cor.test(PREDICTED,Finished_FirstFloorHeight, method="pearson")

#Run Pearson Correlation Coefficient Test for Hazus estimations
Hazus_HA<- cor(HAZUS_FFH, Finished_FirstFloorHeight, method="pearson")
cor.test(HAZUS_FFH,Finished_FirstFloorHeight, method="pearson")

#Plot Ranodm Forest and Hazus estimations relative to observed first finished floor height
plot(PREDICTED~Finished_FirstFloorHeight, col='red', pch=16, ylab="Predicted FFH (ft)", xlab="Observed FFH (ft)",
ylim=c(0,8), xlim=c(0,8))
points(HAZUS_FFH~Finished_FirstFloorHeight, col='blue', pch=16)
abline(c(0,1), lty=2)
legend("bottomright",inset=.05,legend=c("Hazus Default (r=0.63)","Random Forest Model (r=0.67)"),pch=16,
col=c("blue","red"))
title(main="Scatterplot of Predicted vs. Observed Finished First Floor Height")
detach(HA_predict)

#Chesapeake Data
attach(CH_predict)

#Run Pearson Correlation Coefficient Test for Random Forest predictions
RF_CH<- cor(PREDICTED,Finished_FirstFloorHeight, method="pearson")
cor.test(PREDICTED,Finished_FirstFloorHeight, method="pearson")

Hazus_CH<- cor(HAZUS_FFH, Finished_FirstFloorHeight, method="pearson")
cor.test(HAZUS_FFH,Finished_FirstFloorHeight, method="pearson")

#Plot Random Forest and Hazus estimations relative to observed first finished floor height
plot(PREDICTED~Finished_FirstFloorHeight, col='red', pch=16, ylab="Predicted FFH (ft)", xlab="Observed FFH (ft)",
ylim=c(0,7), xlim=c(0,7))
points(HAZUS_FFH~Finished_FirstFloorHeight, col='blue', pch=16)
abline(c(0,1), lty=2)
legend("bottomright",inset=.02,legend=c("Hazus Default (r=0.82)","Random Forest Model (r=0.88)"),pch=16,
col=c("blue","red"))
title(main="Scatterplot of Predicted vs. Observed Finished First Floor Height")
detach(CH_predict)
```

Appendix D: Random Forest Tool Settings

Settings applied to the "Forest-based Classification and Regression" tool in ArcGIS Pro 2.2.0. This tool is included in the Modeling Spatial Relationships toolset of the Spatial Statistics toolbox.



The following modifications were also made to the Advanced Forest Options setting:

Setting	***Selected Value***	***Default Value***
Number of Trees	500	100
Number of Randomly Selected Variables	2	Not defined
Training Data Excluded for Validation	0	10%

Appendix E: Python Script for Organizing Elevation Certificates

```
#Script to extract parcel ID from multiple elevation certificate filenames and store in Excel.
#Hampton Roads Planning District Commission, January 2019

#Import modules
import sys, os
import pandas as pd

#Set relative paths
scriptDir = os.path.dirname(sys.argv[0])
rootDir = os.path.dirname(scriptDir)
dataDir = os.path.join(rootDir, "FFE\\ElevationCertificates”)

#Extract parcel ID from each elevation certificate filename and store in a dictionary
pathList = os.listdir(dataDir)
ecData = {}
ecList = []
for path in pathList:
   ecData['Filename']= path
   ecData['Parcel Number'] = path[17:-4]
   ecList.append(ecData.copy())
outfile = rootDir + '\\' + 'FFE\ElevationCertificates\\ElevationCertificatesID.csv'
#Convert parcel id list to a data frame and store as a csv
dfFinal = pd.DataFrame.from_records(ecList)
dfFinal.to_csv(outfile)
```