MATS UTC

Integrated Data for Improved Asset Management

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Yawen Shen, Graduate Research Assistant, University of Virginia
Jonathan L. Goodall, Ph.D., P.E., Associate Professor, University of Virginia
Devin Harris, Ph.D., Assistant Professor, University of Virginia
Brian Smith, Ph.D., P.E., Professor, University of Virginia

Prepared by:

Department of Civil and Environmental Engineering
University of Virginia
351 McCormick Rd Thornton Hall
Charlottesville, VA 22904

Prepared for:
Virginia Transportation Research Council
530 Edgemont Road
Charlottesville, VA 22903

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Problem Statement

VDOT has made and continues to make significant investments in data collection. These efforts have resulted in a wealth of information that is used to support agency wide asset management and decision-making. However, to most effectively utilize these data it will be important to integrate data collected and maintained by individual divisions of the agency. Sharing data across divisions is often difficult and there are a variety of reasons for this difficulty. Despite the difficulty, there is significant potential that the agency would benefit in the long term from data integration efforts. Some of the potential benefits include (1) maximizing the value of often expensive data collection efforts, (2) reducing data collection costs by organizing cross-divisional data collection efforts, and (3) providing an integrated view of VDOT assets to support decision-making during day-to-day operations and critical event management. Furthermore, there is a high likelihood that integrating data resources across the agency will lead to innovative analytical tools that improved management and operation of VDOT assets. This high level of potential, and clear linkages to addressing sustainability issues ranging from critical event management required by more severe weather, to the enhanced management of assets in regions experiencing sea level rise, make an exploration of this topic ideal for the MATS UTC/VTRC partnership.

Research Objective

The objective of this research is to demonstrate the potential benefits for agency-wide data integration for VDOT asset management. This objective is achieved through an example application that requires information distributed across multiple databases both internal and external to VDOT to address. With effort, these data can be brought together into a single application, but doing so can be tedious and time consuming, limiting potential applications. Through this research, the goal is to demonstrate the potential benefit for integrated data for VDOT assessment management.

Approach

The example application focuses on a case study for the Hampton Roads region where data is integrated in order to identify bridge assets with high traffic volumes that are vulnerable to flooding for different return period rainfall events. Answering this question requires the integration of data from bridge databases, traffic databases, and hydrology-related datasets both internal and external to VDOT. Transportation infrastructure is facing increasing challenges due to climate change including more extreme rainfall events, so studies like this are critical to understanding data across VDOT departments can be leveraged to enhance decision making. This analysis provides an estimate of which bridge assets are vulnerable to flooding from extreme events, which of these bridges are most critical to the transportation network due to traffic volumes, and ultimately a mechanism that combines this information to help identify critical bridge assets vulnerable to flooding.

MATERIALS AND METHODS

Study Area

The study area for this research included the watersheds associated with the Blackwater, Norttoway, and Meherrin Rivers located within Hampton Roads District, VA (Figure 1). The bridge dataset displayed in Figure 1 was provided by VDOT's Hampton Roads district. This dataset contains the road elevation (deck elevation) attribute of each of the 475 bridges within this study area. There are only 11 stream gages in this region maintained by the US Geological Survey (USGS), which are mainly on the main stream and not on smaller tributaries. As a result, most of those bridges are located on streams with no nearby streamflow gage.

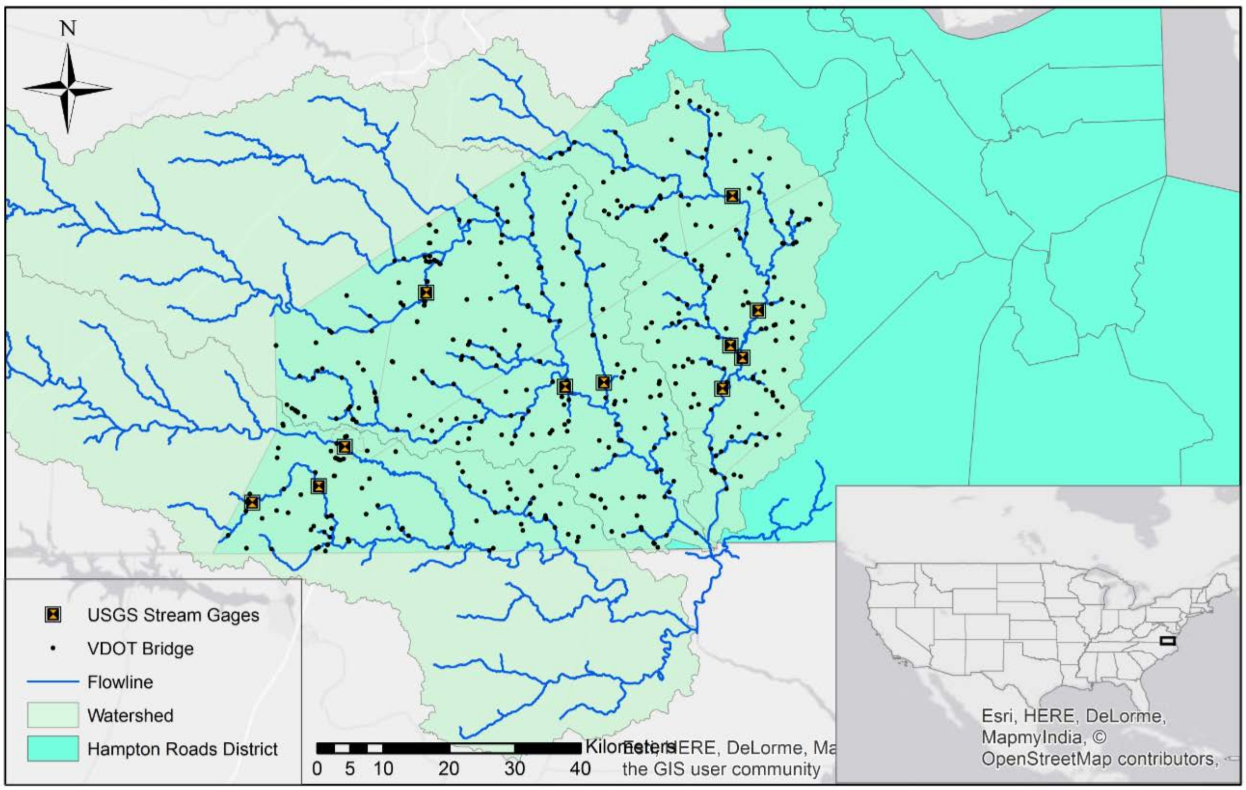


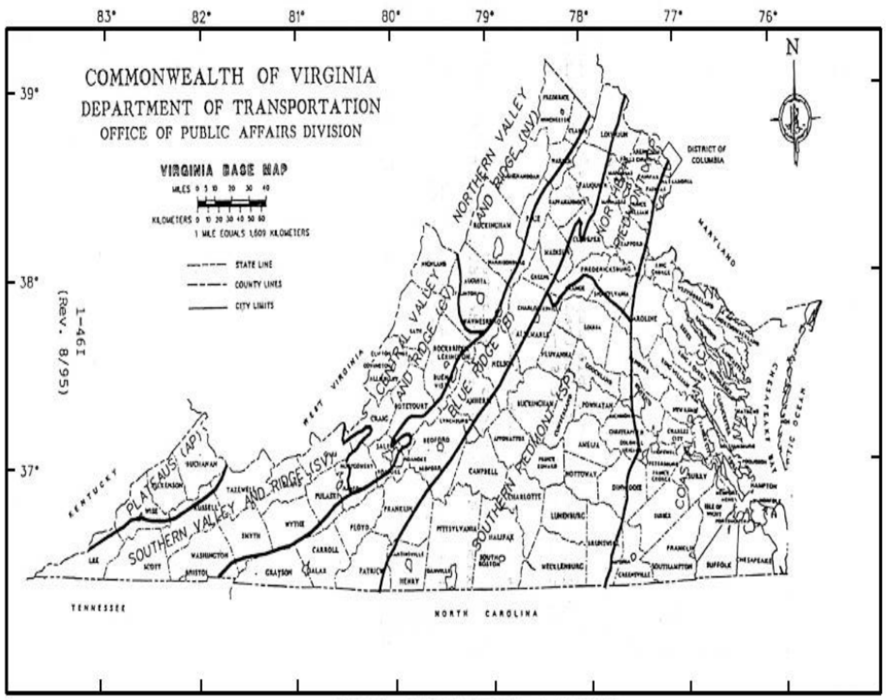
Figure 1. Study area including bridges and USGS stream gages within a portion of the Hampton Roads VDOT district

Estimate peak flow rate at bridge locations for different storm return periods

The peak flow in this study is estimated based on two methods: 1) using regression equations in the VDOT Drainage Manual [1]; 2) using the U.S. Geological Survey StreamStats application [2].

Regression equations in the VDOT Drainage Manual

In the VDOT Drainage Manual, the commonwealth is separated into 8 hydrologic regions (Figure 2). Each hydrologic region has regression equations based on the analysis of stream gage data that relate the size of a drainage area to flow rates for different return period storms. Our study area is located entirely within the Coastal Plain region, so these regression equations (Table 1) were used in the study.



PEAK - DISCHARGE REGIONS
(modified from Feeneman, 1938)

Figure 2. Hydrologic regions in VDOT drainage manual

Table 1. Drainage-area-only regional regression equations for estimating peak discharge

Regression Equation	Standard Error of Prediction (percent)	Equivalent Years of Record
Coastal Plain (C) – 29 Sites		
$Q_{(2)} = 57(A)^{0.589}$	55.8	1.4
$Q_{(5)} = 106(A)^{0.569}$	58.3	2.5
$Q_{(10)} = 153(A)^{0.555}$	62.1	3.5
$Q_{(25)} = 230(A)^{0.539}$	68.6	4.5
$Q_{(50)} = 302(A)^{0.528}$	74.1	5.2
$Q_{(100)} = 388(A)^{0.518}$	80.2	5.7
$Q_{(200)} = 489(A)^{0.509}$	86.7	6.2
$Q_{(500)} = 652(A)^{0.497}$	96.1	6.7

Regression equations in the USGS StreamStats system

StreamStats, like the VDOT Drainage Manual, applies multiple regression models to estimate peak flow for different return period storms. The regression equations are again geographically dependent (Figure 3) and relate the size of drainage area to peak flowrates (Table 2). The system has a Web interface (Figure 4) that allows for analysis at a single single point or batch processing where users upload a shapefile of points along the stream network and the system returns peak streamflow values for each point for different return period storms.

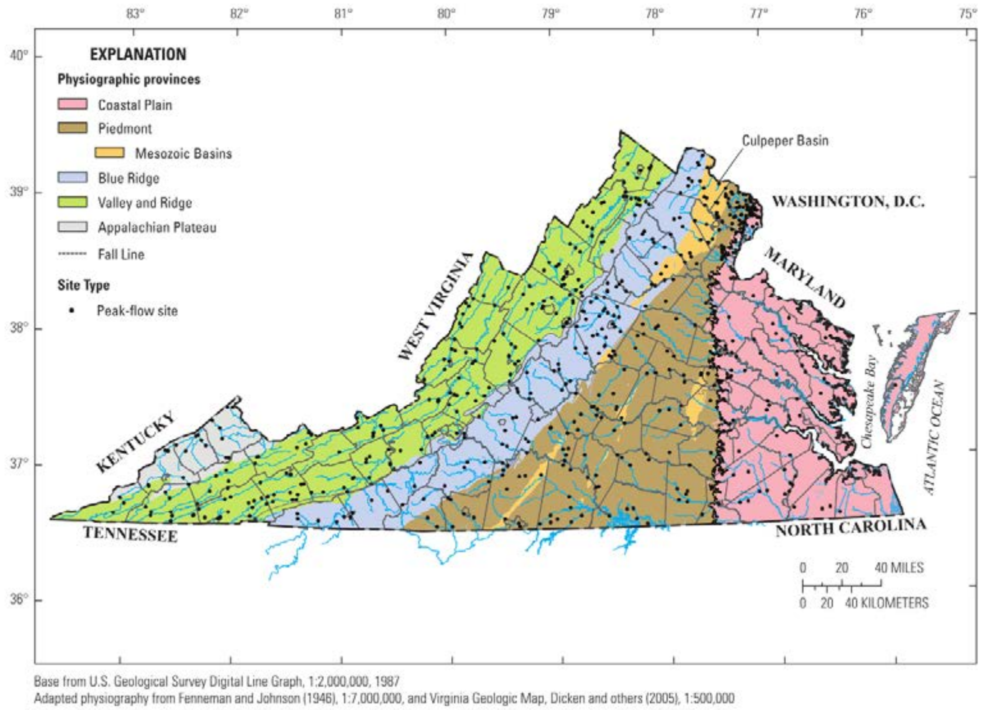


Figure 3. Physiographic provinces for application of peak-flow regional estimating equations

Table 2. Regional Regression equations for estimating peak flows of streams in Virginia

	Pseudo R-square[a]	Average standard error of prediction[a] (in percent)	Standard model error[a] (in percent)
Virginia basins in the Coastal Plain region			
Log10(0.2 peak) = 1.918 + 0.644 • Log10(DA)	0.91	48	44
Log10(0.1 peak) = 2.107 + 0.626 • Log10(DA)	0.90	51	47
Log10(0.04 peak) = 2.315 + 0.609 • Log10(DA)	0.88	56	51
Log10(0.02 peak) = 2.457 + 0.594 • Log10(DA)	0.86	60	55
Log10(0.01 peak) = 2.580 + 0.583 • Log10(DA)	0.84	65	58
Log10(0.005 peak) = 2.698 + 0.573 • Log10(DA)	0.82	71	64

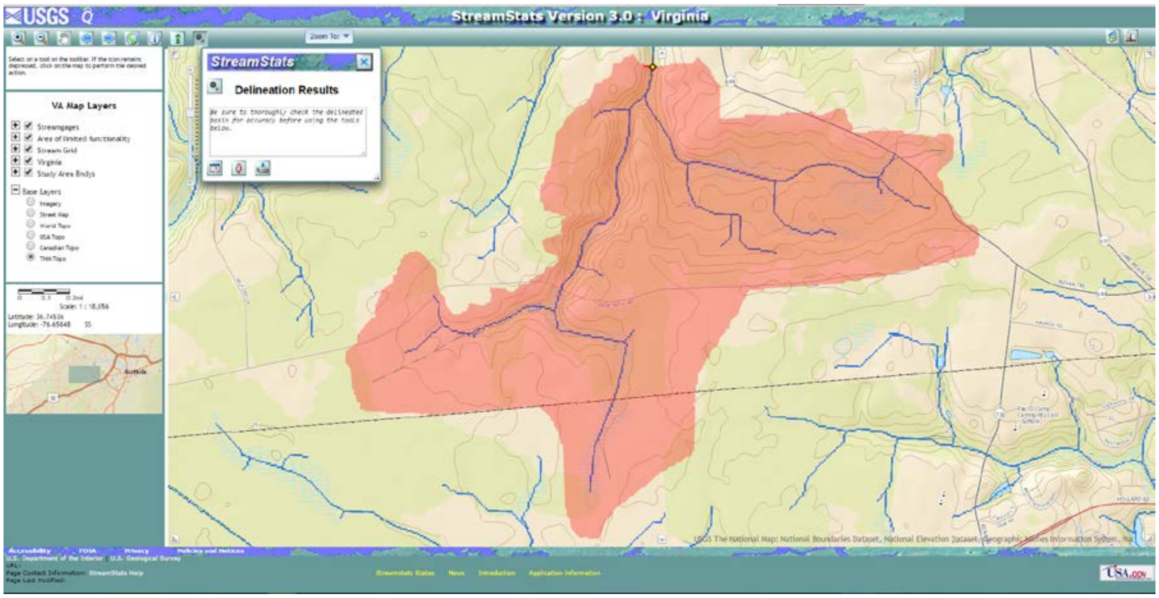


Figure 4. USGS StreamStats platform

Estimate river cross-section geomorphology at bridges

The National Hydrography Dataset (NHD) provides estimates of river centerlines flowline. This study used Version 2 of the NHD provided by the USGS [3] to identify the river that each bridge crosses. The method for relating bridges to rivers and then identifying the river cross-section at the bridge location follows. The FEMA 100-year floodplain map [4] was used to assist in this analysis as described below.

The first step was to find the nearest point on NHD flowline to each bridge and connect those points to corresponding bridges to create perpendicular lines from bridge to flowline. Those perpendicular lines determine the direction of cross section. Then this line was extended perpendicular from the two vertexes until it intersects with the boundary of 100-year floodplain. This perpendicular line was taken as the river cross sections used in this analysis (Figure 5).

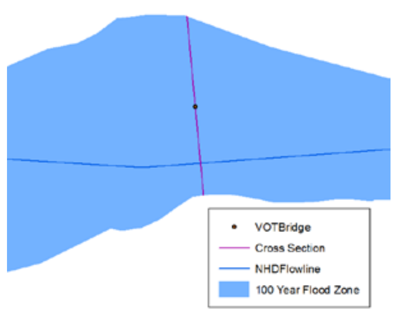


Figure 5. Identifying the river cross-section at a bridge location. This process was automated for all bridges within the study region.

Manning's roughness coefficient

Manning's roughness (n) is an important parameter for describing friction forces inhibiting river flow. The National Land Cover Database (NLCD) 2011 [5] was used to estimate Manning's roughness across each river cross section (Figure 6). Each land cover code has a definition that gives a description about the surface roughness based on the surface characterization. Each cell in the NLCD grid contains a land use code. Using this relationship, a Manning's n was assigned to each grid cell based on this code to create a Manning's roughness map. For example, the assigned Manning's n for land use code 24 is determined by an area weighted average where 80% of the area is assigned the value for concrete (0.013) and 20% is assigned the value for short grass (0.15), producing a calculated value of 0.0404. In this manner, the Manning's n values of all land cover were computed (Table 3).

Table 3. Manning's value used for NLCD map

Landcover	Description	Manning's n
11	waterbody	0.035
21	Developed, open space	0.0404
22	Developed, low intensity	0.0678
23	Developed, medium intensity	0.0678
24	Developed, high intensity	0.0404
31	Barren land	0.0113
41	Deciduous forest	0.36
42	Evergreen forest	0.32
43	Mixed forest	0.4
52	Shrub/srcub	0.4
71	Grassland/herbaceous	0.368
81	Pasture/Hay	0.325
82	Crop/vegetation	0.3228
90	Woody wetlands	0.086
95	Energent herbaceous wetlands	0.1825

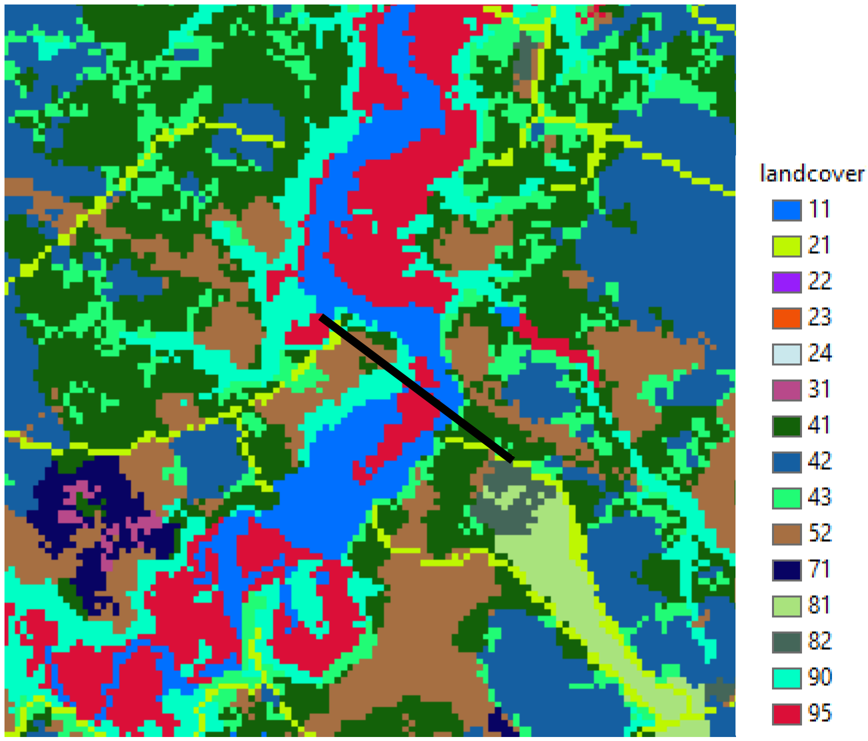


Figure 6. Cross-sectional profile and averaged Manning's roughness distribution

Elevation profiles

The National Elevation Dataset (NED) 1/3 arc-second DEM provided by USGS was used to determine the elevation profile for each river cross-section (Figure 7). This DEM has a resolution of 9.2 meters after it was projected. The steps taken to perform the analysis follow.

1) Find the vertexes of each cross-section. Interpolate 99 points between the vertexes of each cross-section to segment the cross-section into 100 equal intervals.
2) For every point along the cross section, use the "ReadAsArray" tool in the GDAL library to read the elevation from DEM map or roughness from Manning's roughness map. The array of elevations for each cross-section is the cross-section profile (Figure 8). Average the roughness along cross-section to get the overall Manning's n.

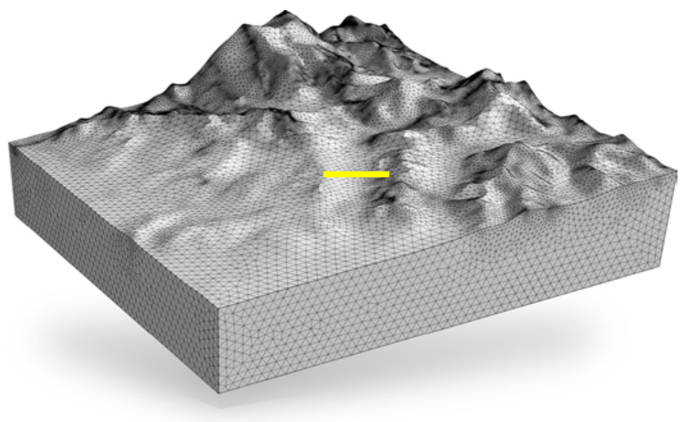


Figure 7. 3D representation of the DEM used to estimate the elevation profile for each river cross-section. The yellow line on the figure represents the river cross section with the elevation profile given in Figure 8.

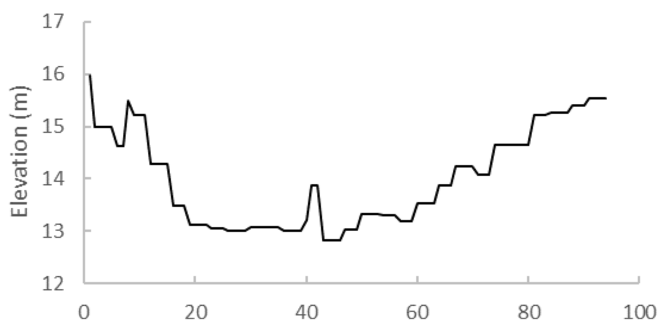


Figure 8. Example of an elevation profile for a river cross-section generated from the DEM (the yellow line shown in Figure 7).

Channel bed slope

Channel slope near bridges was estimated based on the data provided in the NHDPlusAttributes table. The slope of the closest flowline feature to each river cross section was assumed to represent the bottom channel slope of that river cross section.

Estimating peak water surface elevation at bridges

The peak flow rate (Q) of different return period floods, Manning's n, cross-section profile, and channel slope (S) are obtained from above steps.

Manning's Equation:

$$Q = VA = \frac{1}{n} A R^{\frac{2}{3}} S^{\frac{1}{2}} = \frac{1}{n} f(E) S^{\frac{1}{2}}$$

Where:

· V is the cross-sectional average velocity

· n is the Manning's coefficient

· R is the hydraulic radius

· S is the channel slope

· A is the cross-sectional area

· E is the surface water elevation

Both the cross-sectional area and hydraulic radius are functions of the water surface level. Therefore, in the Manning's equation, the only unknown is the surface water elevation. Given this, the following steps were used to estimate surface water level from Manning's equation.

1) Divide the cross section into 100 horizontal levels with identical interval
2) Calculate A and R under each level from cross-sectional profile, and Manning's roughness from Manning's roughness distribution
3) Compute Q using Manning's equation for every horizontal level
4) Compare this series of Q values with the discharge estimates from the USGS Streamstats and VDOT Drainage Manual regression equations. Find the closest Q and corresponding surface water elevation for both conditions.

The selected water surface elevations represent the tool's estimate of peak river stage for the flooding event.

Determining bridge deck elevation and average daily traffic

The surface water elevation predicted using the above method was then compared with the bridge deck elevation to estimate if the bridge would be overtopped. We simply assumed that, if the surface water elevation is higher than the road elevation, then the bridge would be flooded for that return period storm.

A dataset for Virginia roadways called "Annual Average Daily Traffic volumes with Vehicle Classification Data" was obtained from VDOT. These data included interstate highway, arterial and primary routes data, and AAWDT for the entire state from the years 1985 to 2014. The data was clipped to the Hampton Road's boundary to extract information for only the region being studied. Each bridge was intersected with the AADT value in order to estimate average traffic for each bridge.

RESULTS AND DISCUSSION

Bridge flooding risk

Performing this analysis across bridges in the study region resulted in an estimate of the bridges that would be impacted by 5, 10, 25, 50, 100 and 200 year storm events (Table 4).

Table 4. Number and percentage of bridge affected by flood of different return period

Method / Return Period	5 year		10 year		25 year		50 year		100 year		200 year	
USGS Streamstats	33	10.5%	45	14.4%	58	18.5%	76	24.3%	88	28.1%	95	30.4%
VDOT Draniange Manual	28	9.0%	36	11.5%	48	15.3%	58	18.5%	69	22.0%	76	24.3%

Note: the total number of bridge is 313

Figures 9 and 10 give the geographic location of bridges predicted to be impacted by storm return periods when using the USGS and VDOT stream discharge regression equations, respectively.

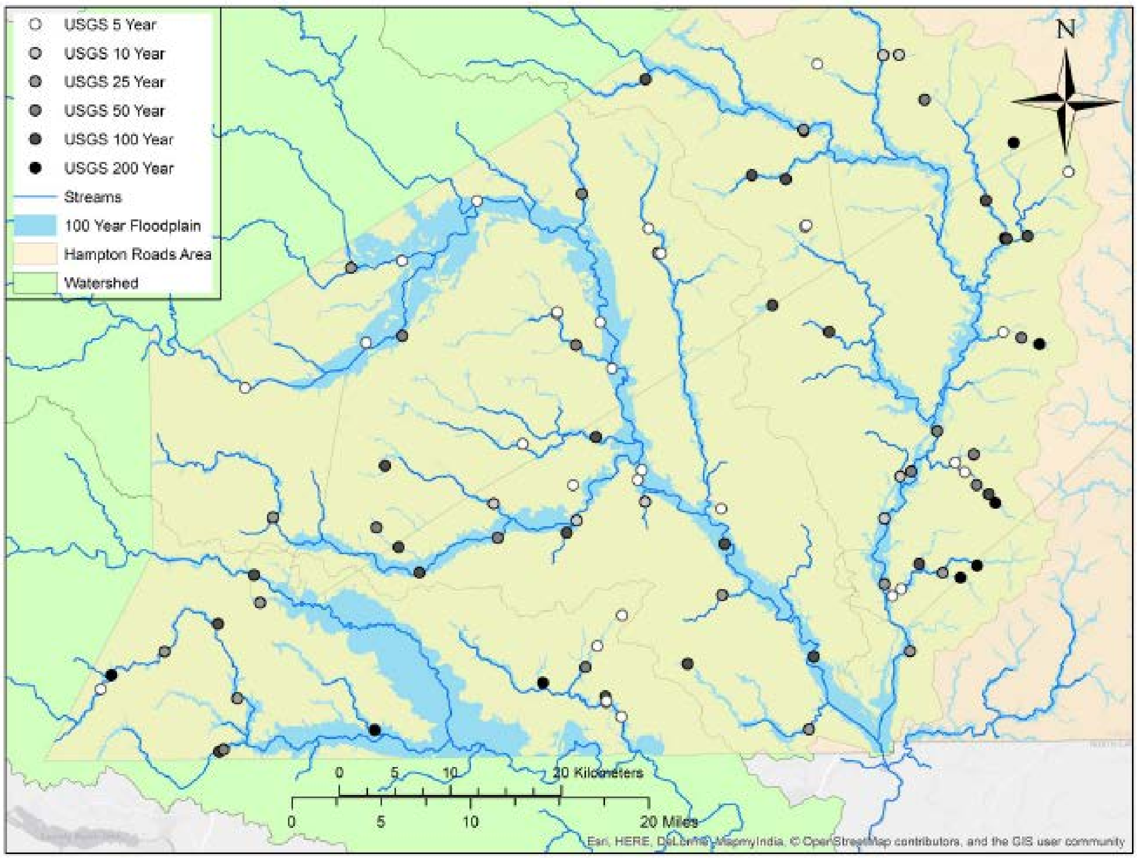


Figure 9. Bridges affected by flood of different return period using discharge estimated from USGS StreamStats regression equations

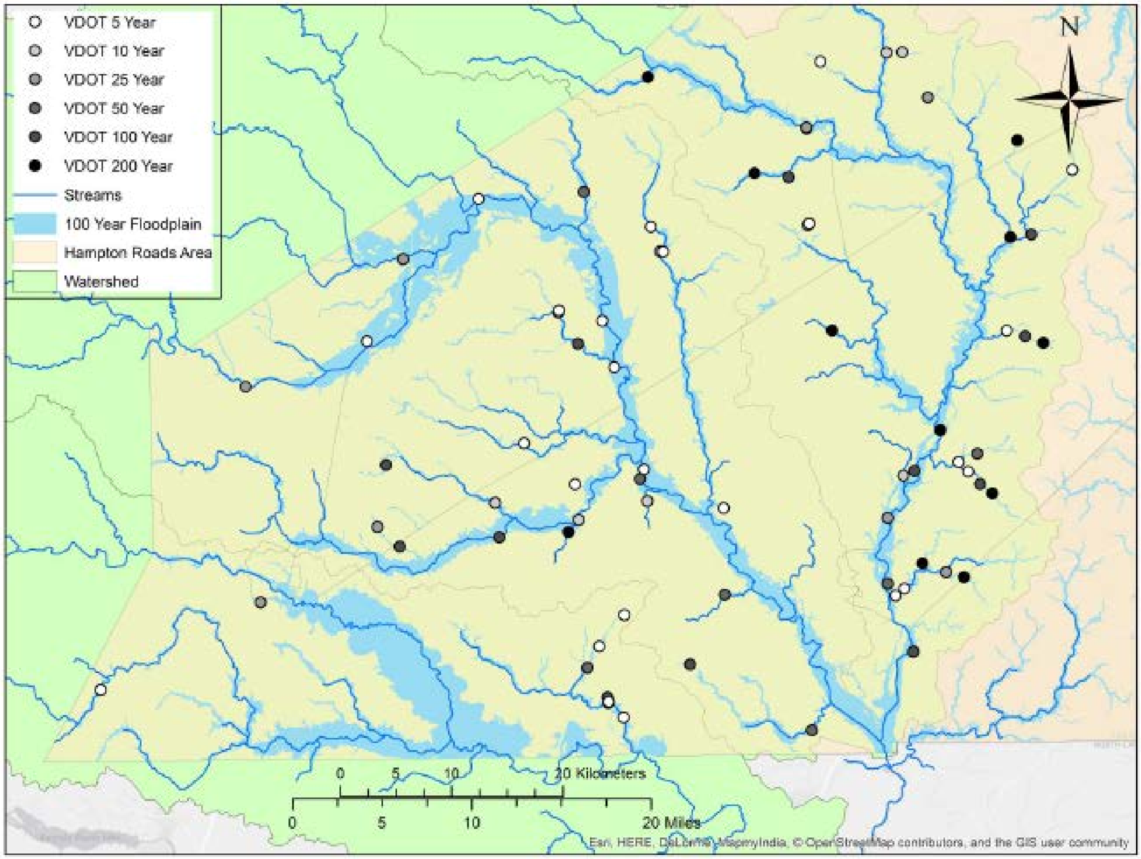


Figure 10. Bridges affected by flood of different return period using discharge estimated from VDOT Drainage Manual regression equations

Model evaluation

The results of this analysis were evaluated against limited river stage data available through the FEMA flood modeling effort. FEMA performs flood modeling in order to generate 100-year flood maps that are used for flood insurance purposes. These models are heavily time and resource intensive and not practical to implement across all rivers within the study region. Only select portions of major rivers within the study region (Figure 11) were modeled by FEMA using a sophisticated 1-D hydrodynamic model to estimate the peak river stage due to a 100-year storm event. These peak river stage estimates were then compared to river stage estimates generated through this study using regression and GIS-based analyses conducted for all bridges within the study region.

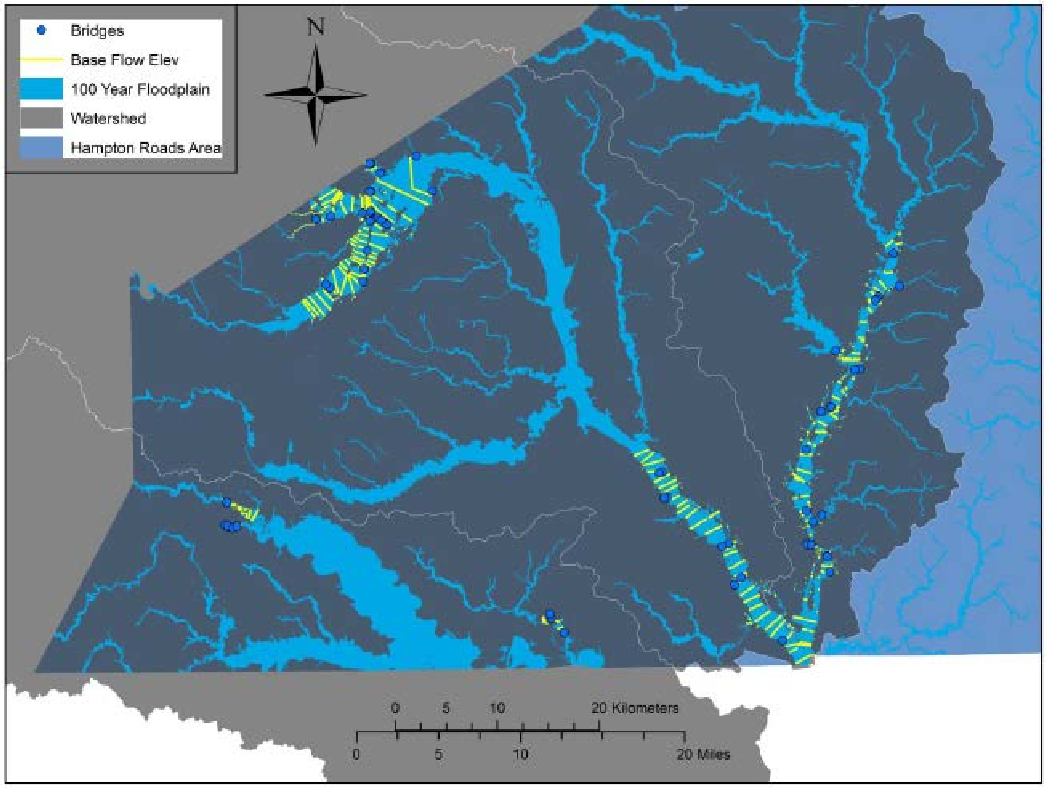


Figure 11. Location of FEMA flood model river cross sections used for verifying river stage estimates generated using USGS and VDOT regression curves.

The results of this model evaluation show that the analysis used in this study produced peak stage estimates inline with those generated through the more sophisticated 1D (Figures 12 and 13). The fit is arguably better when using the VDOT Drainage Manual regression equations, but both the USGS and VDOT regression equations are fairly equivalent.

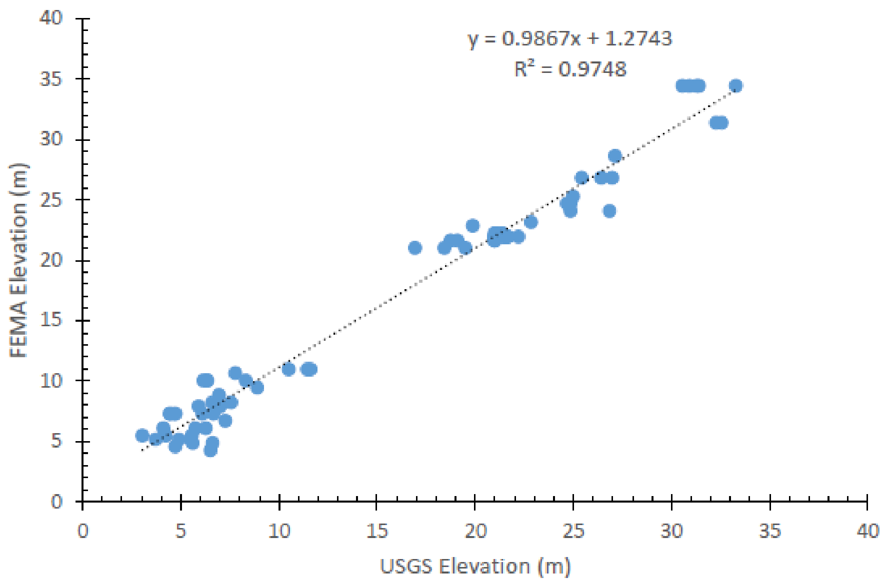


Figure 12. River stage estimated using the detailed FEMA flood models compared to river stage estimated using the USGS regression curves.

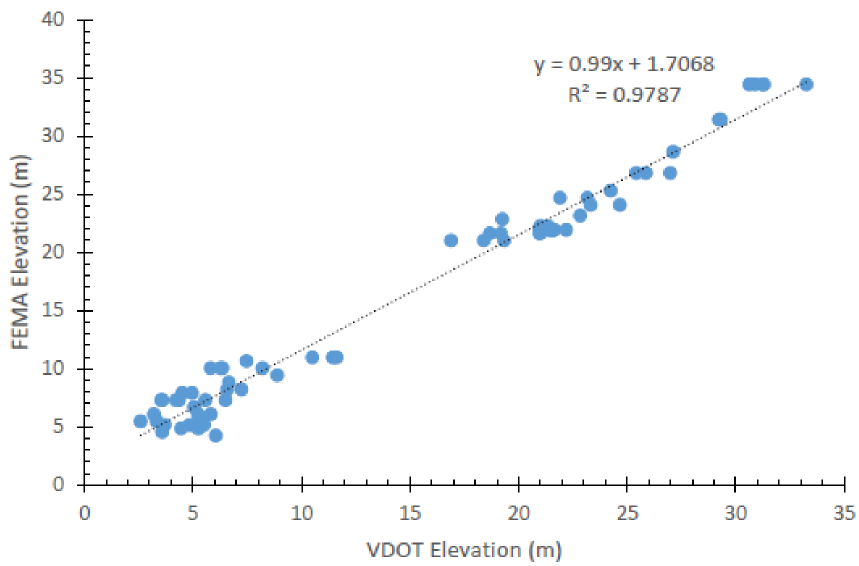


Figure 13. River stage estimated using the detailed FEMA flood models compared to river stage estimated using the VDOT regression curves.

Identifying flood risk of highly traveled bridges

When this data is combined with traffic information for each bridge, it helps to see the importance of each bridge within the transportation infrastructure in terms of the traffic that bridge typically carries (Figure 14). The analysis suggests that many of the bridges that would be impacted by smaller storm events (e.g., 5 year storms) do not carry significant traffic < 500 vehicles per day). However, there are some bridges that carry moderate traffic (>1000 vehicles per day) that, based on this analysis, could be impacted by 5-, 10-, or 25-year storm events. These bridges that carry heavier traffic loads and are at risk of flooding from more frequent flood events should be further investigated to better assess the potential risk due to flooding.

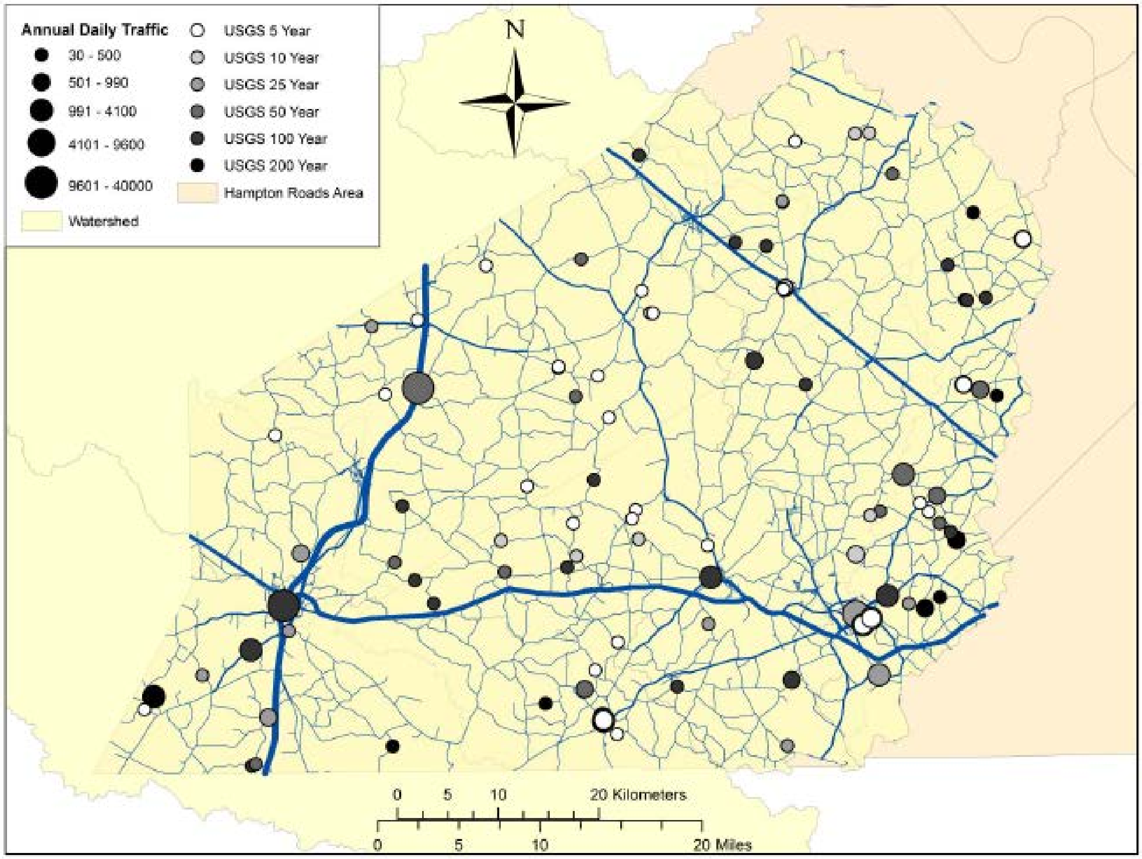


Figure 14. Annual daily traffic of vulnerable bridges

CONCLUSIONS

This analysis shows the power of integrating data across VDOT and other data providers in order to more comprehensively assess VDOT resources. Datasets used in the analysis include bridge, traffic, and hydrologic information from VDOT along with digital terrain, land use, hydrography, and floodplain data from the US Geological Survey and FEMA. Using these data together within a geographic information system (GIS), it was possible to provide a visualization and analysis of bridges in Hampton Roads that includes both the importance of that bridge to the transportation infrastructure system (measured using traffic data) and its flooding risk (measured through this study using hydrologic techniques and information from the bridge database).

This study could be extended in a number of ways that illustrate additional opportunities for data integration for VDOT asset management. (1) Rather than simply looking at traffic over bridges as a measure of the criticality of that bridge to the transportation network, further analysis could look at how trips would need to be altered if a given bridge is impacted due to flooding. For example, which of the bridges vulnerable to flooding from a 5-year storm event would have the greatest impact in terms of detour distance and impact? Do these bridges serve as a critical link for populations within the region that would otherwise have no or very limited access without that bridge? (2) How can future data collection efforts benefit integrated assets management? When bridges are inspected, is it possible for the bridge inspectors to also survey the river at the location with sufficient detail to feed into hydrologic analysis assessing flooding risk? Should bridge maintenance be prioritized due to their flooding risk to insure that debris is not impacting that bridge's hydraulic capacity?

Recommendations

(1) Expand this analysis to including more details on the transportation system to better quantify the importance of at risk bridges and the potential impact of service disruptions to mobility within the region. Certain bridges may have low daily average traffic, but may be critical in that their outage could result in isolating communities or very significant increases in travel time.

(2) Further investigate bridges identified in this study as being at risk from more frequently occurring flood events (e.g., 5-, 10-, and possibly 25-year storms), especially those with high traffic counts, to further verify the analysis results.

(3) For those bridges deemed to be vulnerable to flooding, consider more frequent inspection to insure debris is not impacting water flow through the bridge. Also consider installing real-time water surface and rainfall sensors that can be used to better refine the relationship between rainfall and river stage for that bridge.

(4) Expand this analysis to take further advantage of detailed bridge data available in the PONTIS and NBI databases. While this study used some information from these databases including location, bridge deck height, other information exists in these databases including operational, maintenance, and condition features that would enrich the current investigation. In addition to enriching this investigation, the corollary could yield enhancements to maintenance prioritization and pertinent supplemental data collection (e.g. stream slope or bed profile) during inspection for structures interfacing with water.

References

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