COMMONWEALTH of VIRGINIA

Virginia ConservationVision
Watershed Impact Model
2022 Edition

Virginia Department of Conservation and Recreation
Division of Natural Heritage
Natural Heritage Technical Report 22-14
June 2022

Department of Conservation & Recreation
CONSERVING VIRGINIA'S NATURAL AND RECREATIONAL RESOURCES

Virginia ConservationVision
Watershed Impact Model
2022 Edition

Prepared by:

Kirsten R. Hazler and David N. Bucklin
Virginia Department of Conservation and Recreation
Division of Natural Heritage
600 East Main Street
Richmond, Virginia 23219

June 2022

Suggested citation:

Hazler, K.R. and D.N. Bucklin. 2022. Virginia ConservationVision Watershed Impact Model, 2022 Edition. Natural Heritage Technical Report 22-14. Virginia Department of Conservation and Recreation, Division of Natural Heritage, Richmond, Virginia.

Abstract

The purpose of the Virginia ConservationVision Watershed Impact Model is to help establish geographic priorities for conservation, restoration, or implementation of best management practices, where the goal is to maintain or improve water quality and/or aquatic ecological integrity. It is intended as a geospatial screening tool for assessing where activities on the land are expected to have the greatest impact on water. The model relies on multiple data sources representing conditions that drive the terrestrial influence on aquatic systems, including precipitation, geology, soils, topography, and hydrology. Although land cover also exerts a key influence on hydrologic flow and pollutant loads reaching streams, it is not used to calculate potential impact in this model. Instead, potential impact is calculated under a “worst case scenario” assumption of barren land. By leaving land cover out of the equation, the calculation of potential impact is robust in the face of land cover changes that can happen over very short time scales.

In addition to the model’s primary raster output representing potential impact, scored from 1 to 100, we provide several intermediate raster outputs that can be combined in various ways depending on end users’ needs. These include scores based on:

- potential for stormwater runoff
- potential for soil loss
- overland flow distance to surface waters
- prevalence of karst features
- soil sensitivity, a composite of stormwater runoff and soil loss potential
- landscape position, a composite of overland flow and prevalence of karst

This model is a contribution to the digital conservation planning atlas known as Virginia ConservationVision. It can be used in conjunction with other data to help prioritize conservation, restoration, and management efforts geared toward maintaining and/or improving the ecological health of aquatic systems and the quality of drinking water sources in Virginia.

Table of Contents

Introduction

As the state's lead natural resource conservation agency, the Virginia Department of Conservation and Recreation (DCR) has a mission to provide opportunities that encourage and enable people to enjoy, protect, and restore Virginia's natural and cultural resources (Virginia DCR Staff 2016). Natural areas and open space lands are increasingly threatened by encroaching development as well as population pressure, due to expanding human populations and demand for resources. The Virginia Land Conservation Foundation (VLCF) provides state funding to purchase or establish conservation easements on various lands of conservation concern (Virginia DCR Staff n.d.). Given limited funds, it is essential to have a means of prioritizing lands worthy of preservation. As part of its work, DCR's Division of Natural Heritage and its partners develop and maintain a suite of geospatial models intended to guide strategic land conservation and management decisions. This suite of models is known as Virginia ConservationVision. The models under the ConservationVision umbrella address a variety of conservation issues and priorities, including natural landscapes, agriculture, forestry, cultural resources, rare species richness, development vulnerability, outdoor recreation, and watersheds.

The purpose of the Virginia ConservationVision Watershed Impact Model is to help establish geographic priorities for conservation, restoration, and/or implementation of best management practices on land, when the goal is to maintain or improve water quality. The model does not estimate the quantities of pollutants entering water bodies within a given catchment, watershed, or other hydrologic unit; this problem is tackled by others (e.g., Ator 2019, Chesapeake Bay Program 2020, VADCR-DSWC n.d.). Instead, the model output is intended as a geospatial screening tool for assessing where activities on the land are expected to have the greatest impact on water.

Clean water is essential both for human health and for maintaining healthy populations of native species of plants and animals, especially those dependent on aquatic habitats. Point sources of water pollution, such as effluent from water treatment plants and industrial facilities, have been closely regulated in the United States since the 1970s, thanks to passage of the Clean Water Act (USEPA 2018). Nonpoint source (NPS) pollution results when rainfall, snowmelt, or irrigation water flows across or through the ground, picking up pollutants along the way and depositing them in surface or ground water. Nonpoint sources are diffuse rather than concentrated, and thus more difficult to control, but their influence on water quality is now reportedly greater than that of point sources (USEPA 1996, 2016). A national program to control NPS pollution was established in 1987, when Congress enacted Section 319(h) of the Clean Water Act. Through this program, states, territories, and tribes can obtain guidance and grant funding from the U.S. Environmental Protection Agency to implement their own projects and programs to control NPS pollution (USEPA 2016).

The top pollutants contributing to NPS pollution are nutrients (particularly nitrogen and phosphorus), suspended solids and sediments, and pathogens (USEPA 2016). To tackle the problem of NPS pollution, it is beneficial to apply a watershed approach that prioritizes protection of the most critical lands needed to protect water quality (Adamus and Bergman 1995, Randhir et al. 2001, Ernst 2004, Barten and Ernst 2004, Zhang and Barten 2009). Case studies have shown that the provision of financial incentives to upstream landowners to maintain, sustainably manage, and/or restore forests (i.e., “green infrastructure”) can be more cost effective for maintaining water quality than investments in “grey infrastructure” such as new water filtration plants (Hanson et al. 2011, Talberth et al. 2012).

The Safe Drinking Water Act, as originally enacted in 1974, focused primarily on water treatment to ensure safe drinking water at the tap, but following amendments in 1986 and 1996, the law now explicitly recognizes the importance of source water protection (USEPA 2004). Virginia developed its Source Water Assessment Program in 1999 in response to the 1996 amendment (VDH 1999, VDH-ODW n.d.). The purpose of the program is to encourage and facilitate the implementation of source water protection measures by waterworks across the state.

Soil type, topography, geology, precipitation, land cover, and hydrologic relationships interact in complex ways to determine the pollutant loads that ultimately end up in a body of water. Land cover is a major determinant of the types and amounts of pollutants originating from an area (USEPA 2016). In combination with soil type, slope, and precipitation, land cover also influences the rate of soil loss (erosion) and runoff volumes (Cronshey et al. 1986, Renard et al. 1997, Coastal Services Center 2014). Forested land cover, in particular, is highly valued for the watershed services it provides, including water flow regulation, erosion control, pollution filtration, and freshwater supply (Hanson et al. 2011).

Large volumes of stormwater runoff can transport high pollutant loads directly to water bodies, and this is exacerbated in areas with high rainfall volumes (Coastal Services Center 2014). On a parcel with soils prone to erosion and/or high volumes of stormwater runoff, a disturbance event such as forest clearing is expected to cause a greater reduction in water quality downstream than a similar event on an otherwise similar parcel with less sensitive soils. Similarly, restoration efforts to improve water quality are expected to yield a greater return on investment in areas with more sensitive soils, all else equal (Barten and Ernst 2004). This model prioritizes lands that are likely to have the most impact on water resources due to sensitive soils with high potential for soil loss and/or stormwater runoff.

Topography and geology influence the path and speed of water as it moves across the land or transitions to underground aquifers, as well as the distance it must travel to reach a stream or other concentration of water (Gallant and Wilson 2000). Vegetated buffer zones directly adjacent to streams and rivers are critical for filtering out pollutants before they reach the water's edge (Wenger 1999, Klapproth and Johnson 2009). Conditions along headwater streams are especially important because of their strong influence on downstream waters (Alexander et al. 2007). While flow paths of rainwater runoff across the land to surface waters can be derived from elevation data, flow paths in karst regions are more complicated. Sinkholes, caves, springs, losing streams, and underground drainage networks are characteristic of karst topography, which occurs in regions underlain by water-soluble, carbonate bedrock such as limestone or dolomite (Hubbard 2014, Weary and Doctor 2014). Sinkholes provide a conduit for surface waters, and any pollutants they may carry, to directly enter groundwater aquifers (VADCR-DNH n.d., Virginia Energy n.d.). Once underground, water follows unpredictable paths, and can move up to several kilometers per day, as indicated by dye trace studies in Virginia (VADCR-DNH n.d.). The direct connection between surface water and groundwater, combined with fast and largely unpredictable underground flow patterns, makes groundwater in karst regions especially vulnerable to pollution. This model prioritizes lands that are likely to have the most impact on water resources due to their position on the landscape relative to karst features, surface waters, and headwater zones.

The model described in this report replaces the edition released in 2017 (Hazler et al. 2018), known as the "Watershed Model", which in turn replaces the edition released in 2007

(Ciminelli and Scrivani 2007), known as the "Watershed Integrity Model". Significant differences in model inputs and methodology render direct comparisons between outputs from these model editions inadvisable. With the release of the current edition, the previous edition should be considered obsolete.

The current model relies on multiple data sources representing conditions that drive the terrestrial influence on aquatic systems, including precipitation, geology, soils, topography, and hydrology. Although land cover also exerts a key influence on hydrologic flow and pollutant loads reaching streams, it is not used to calculate potential impact. Instead, potential impact is calculated under a “worst case scenario” assumption of barren land. This can help identify, for example, where clearcutting a patch of forest would have the most devastating impact, or alternatively, where restoring native vegetation on denuded land could have the most beneficial impact on aquatic systems downstream. By leaving land cover out of the equation, the calculation of potential impact is robust in the face of land cover changes that can happen over short time scales.

Methods

In this model, a measure of the potential impact of terrestrial activity on water resources is derived from soil sensitivity and landscape position components (Figure 1). Our scoring of soil sensitivity, which reflects the potential for soil loss and stormwater runoff, relies heavily on the procedures described, equations provided, and references cited in the Technical Guide for OpenNSPECT (Coastal Services Center 2014), although we did not actually use the OpenNSPECT software. The landscape position component is based on overland flow distance to surface waters, location relative to headwaters, and the prevalence of karst. Numerous input datasets related to precipitation, soils, topography, hydrology, and geology were used to develop the model (Table 1).

ArcGIS Desktop (ESRI 2015) and ArcGIS Pro (ESRI 2020) software were used for all spatial data processing. As needed, input datasets were clipped to the area of interest, and reprojected to a common coordinate system to prior to processing. We used a template snap raster to set cell size and alignment for all raster processing and vector-to-raster transformations, and to limit processing to the relevant processing area. Unless otherwise stated, a pixel resolution of 10-m was used. We developed a set of custom Python scripts to carry out most of the input data preparation, modeling, and output finalization procedures. The repository containing these scripts is available on GitHub[1].

Model Components

Soil Loss Potential

To estimate the propensity for soil loss, we used a modification of the Revised Universal Soil Loss Equation (RUSLE; Renard et al. [1997]). The standard equation is:

$$A = R \times K \times L \times S \times C \times P$$

Equation 1

where:

A = average annual soil loss

R = rainfall/runoff erosivity factor (R-factor)

K = soil erodibility factor (K-factor)

L = slope length factor (L-factor)

S = slope steepness factor (S-factor)

C = cover management factor (C-factor)

P = supporting practices factor (P-factor)

The R-factor reflects the amount and rate of runoff associated with rainfall. We obtained a raster representing the R-factor with a pixel resolution of 800-m (NOAA-OCM 2013). The original dataset was downscaled to 10-m resolution to match other datasets, using bilinear resampling. The K-factor is a continuous numeric value measuring soil erodibility. Within the ArcMap interface, we used the statewide gSSURGO soil geodatabase for Virginia and surrounding states (Soil Survey Staff 2020), along with the "Create Soil Map" tool in the Soil Data Development Toolbox (NRCS 2017), to attribute soil map unit polygons with the K-factor for the whole soil down to a depth of 10-cm (dominant condition). Missing values for the K-factor were assigned a value of 0.30 following OpenNSPECT guidelines (Coastal Services

[1] https://github.com/VANatHeritage/ConsVision_WtrshdImpactModel

Center 2014). The polygons were then rasterized.

We obtained 1/3 arc-second elevation tiles provided by the 3D Elevation program (USGS 2017a). These were mosaicked and reprojected to produce an elevation raster covering the study area, with a horizontal resolution of 10-m. A raster representing percent slope was derived from the elevation raster, and an S-factor raster was then derived from the slope, θ, as follows (Renard et al. 1997):

where $\theta < 9\%$: $S = 10.8 \sin\theta + 0.03$

where $\theta \geq 9\%$: $S = 16.8 \sin\theta - 0.50$

Equation 2

The C-factor was obtained from a table of values associated with different land cover classes in the OpenNSPECT Technical Guide. Rather than using the C-factor associated with the actual classified land cover, we used the C-factor associated with what we considered a "worst case scenario", namely barren land with a C-factor of 0.7.

We omitted the P-factor because we did not have sufficient data to derive it. We also omitted the L-factor because it requires measurement of λ, the slope length, which is "best determined by pacing or measuring in the field" (Renard et al. 1997). Slope length is applicable to a particular expanse of land (e.g., a farm parcel on a slope viewed as a whole), rather than to an individual pixel (see Figure 1.1 in Renard et al. 1997). Thus, we calculated a modified estimate of soil loss potential by calculating the product of the R-, K-, S-, and C-factors; this product should be interpreted simply as a relative measure of potential soil loss under a worst case scenario, rather than an absolute volume of soil lost.

To produce a raster representing the Soil Loss Potential Score, we first calculated upper and lower truncation limits that were three standard deviations above and below the mean soil loss potential value, respectively. Original values below the lower truncation limit were set to 1, values above the upper truncation limit were set to 100, and values in between were rescaled with a positive linear function.

Runoff Potential

To estimate the runoff potential, we used the Soil Conservation Service (SCS) Curve-

Number Method (Cronshey et al. 1986), applying the following equations:

$$Q = \frac{(P - 0.2S)^2}{P + 0.8S}$$ **Equation 3**

$$S = \frac{1000}{CN} - 10$$ **Equation 4**

where:

Q = runoff (inches)

P = rainfall (inches)

S = potential maximum retention after runoff begins (inches)

CN = the SCS Runoff Curve Number (value from 0 to 100)

with the restriction:

if $P - 0.2S \leq 0$ or $CN = 0$, then $Q = 0$

For the amount of rainfall, in inches (*P*), we used probable maximum precipitation (PMP), which is a theoretical value defined as "the greatest depth of precipitation for a given duration that is physically possible over a given size storm area at a particular geographic location at a certain time of year" (Kappel et al. 2015). Within the ArcGIS Pro user interface, we used a customized PMP toolbox and associated data (Kappel et al. 2015) to calculate PMP for the entire state, specifying a 24-hour storm duration. We used the output points for a "general" storm, attributed with precipitation in inches. The point values were interpolated initially to a raster at 250-m resolution using the topographic algorithm in ArcGIS Pro, then downscaled to 10-m resolution to match other datasets, using bilinear interpolation, to produce a final rainfall raster. (Interpolation directly to 10-m resolution failed due to computer memory limitations).

The curve number (*CN*) depends on both the hydrologic soil group and the land cover class, and the OpenNSPECT Technical Guide provides *CN* values for all combinations of hydrologic soil groups and land cover classes. In the gSSURGO geodatabase, the hydrologic soil group is represented by a letter (A – D) indicating the soil's capacity to hold water. We used the Soil Data Development Toolbox to produce a vector dataset of polygons attributed with hydrologic groups. Following OpenNSPECT guidelines, letter values were converted to numeric values from 1 to 4. Compound letter values (e.g, A/D) were assigned to the latter group, and nulls were assumed to be group D (= 4). Instead of assigning curve numbers based on actual land cover, we assumed a "worst case scenario", namely barren land with *CN* ranging from 77 to 94 depending on soil type. (Although high-intensity developed land has slightly higher curve numbers, we wanted the worst case scenarios used for soil loss and runoff to be based on the same land cover type.) The soil polygons were then converted to a curve number raster.

A raster representing runoff, in inches, was produced using Equation 3 and Equation 4, with the curve number and rainfall rasters serving as parameters *CN* and *P*, respectively. To produce a raster representing the Runoff Potential Score, with values ranging from 1 to 100, we used the same truncation and rescaling procedure as for the Soil Loss Score.

Overland Flow

From the collection of NHDPlus High Resolution datasets (USGS 2018b), we downloaded raster files representing overland hydrologic flow direction for the ten 4-digit hydrologic units covering Virginia, along with vector data representing stream reaches (flowlines) and catchments. From each flow direction raster, we derived a flow length raster, representing the distance down to the nearest water body in the direction of flow (not straight-line distance). We mosaicked the individual flow length rasters to produce a single seamless flow length raster. The flowlines include a binary attribute indicating whether they are (1) or are not (0) headwater streams, and this attribute was attached to the corresponding catchments. For catchments without a corresponding flowline (i.e., sink catchments), the headwater attribute was set to 0. The catchments were rasterized to produce a headwaters indicator.

To produce the Overland Flow Score raster, values in the flow length raster were converted to scores by setting distances less than 50-m to a score of 100, distances greater than 500-m to a score of 1, and rescaling values in between with a negative linear function. The headwaters indicator raster was used to discount the scores in non-headwater areas to 90% of the original score. For example, if the original score based on flow length alone was 50, and the pixel was not within a headwater catchment, the final overland flow score would be 45.

Karst Prevalence

We downloaded a geodatabase containing polygon features representing karst geology throughout the United States (Weary and Doctor 2014). From this we derived a raster representing Euclidean distance (m) to the nearest karst geology polygon. Euclidean distances were converted to scores by setting values ≤ 100 to 100, setting values ≥ 5000 to 1 and rescaling values between these limits using a negative linear function.

We obtained a polygon shapefile delineating the locations of karst-related sinkholes (Hubbard 2014) from Virginia Energy. From this we generated a point feature class representing the centroids of the sinkholes. The sinkhole points were used in a kernel density analysis, using sinkhole area (m^2) as the population field, and using a search window of 5-km. We selected this search window based on the fact that only a single sinkhole point was > 5-km from a polygon in the karst geology layer. The output raster represented area-weighted sinkhole density (m^2/ha). To convert sinkhole density values to scores, we first calculated an upper truncation limit that was three standard deviations above the mean of non-zero raster values. Density values above the truncation limit were set to 100, and all other density values were rescaled to scores between 1 and 100 using a positive linear function. The scores based on sinkhole density and distance to karst were averaged to produce the raster representing the Karst Prevalence Score.

Composite Scores

From the model component scores based on soil loss potential, runoff potential, overland flow, and karst prevalence, we derived three composite scores. The Soil Sensitivity Score raster was produced by calculating the mean of the soil loss and runoff potential scores. The Landscape Position Score raster was produced by taking the maximum of the karst prevalence and overland flow scores. In effect, this means that a pixel outside of karst regions could get the highest possible score only by being directly adjacent to a headwater stream, whereas in karst regions a pixel would not need to be near surface waters to obtain the highest score. The Potential Impact Score raster was generated by calculating the mean of the soil sensitivity and landscape position scores.

Results

The primary output of the model is the Potential Impact Score (Map 1), a raster dataset with values ranging from 1 to 100, representing the relative potential for land-based impacts on water. Because the model focuses on the source of impacts, rather than on the target, open water areas are set to null (no data). The component raster datasets used to create the Potential Impact Score are also available, and these include:

- Runoff Potential Score (Map 2)
- Soil Loss Potential Score (Map 3)
- Overland Flow Score (Map 4)
- Karst Prevalence Score (Map 5)
- Soil Sensitivity Score (Map 6)
- Landscape Position Score (Map 7)

Like the Potential Impact Score, the component scores range from 1 to 100, with the value 100 representing the greatest potential impact. The data can be viewed online via the Natural Heritage Data Explorer[1] and a web mapping application hosted on ArcGIS Online[2]. For GIS users and analysts, the raster datasets can be downloaded from the model website[3]. Additional intermediate products may be available on request.

Discussion

Model interpretation

In the final model output, potential impact scores range from 1 to 100. Highest values indicate where land-altering activities are likely to have the greatest impacts on water quality, for better or for worse. A forest clearcut in high-scoring area is likely to have a greater negative impact than an equivalent clearcut in a lower-scoring area. Restoring native vegetation on a high-scoring bare field is likely to have a greater positive impact than equivalent restoration on a low-scoring but otherwise equivalent field.

Impact values should be considered in conjunction with current land cover, since the appropriate actions will differ depending on ground conditions. For example, high-scoring forested areas should be prioritized for protective action, such as establishing conservation

---

[1] https://vanhde.org/content/map; only the primary output data layer is available at this site
[2] https://arcg.is/1PCrv0; primary and component data layers are available at this site
[3] https://www.dcr.virginia.gov/natural-heritage/vaconviswater

easements, whereas high-scoring agricultural areas could be prioritized for restoring native vegetation and/or ensuring that best management practices are in place to reduce the amount of agricultural pollutants entering streams.

It is important to note that potential impacts are not accumulated in this model. The value of each cell represents the potential impact of that cell alone, not accounting for the accumulated influence of upstream cells.

Key model changes

For previous users of the 2017 model edition, we highlight some key differences between 2017 and 2022 editions. The new model has higher spatial resolution with a pixel size of 10-m, in comparison with the 30-m resolution of the previous edition. The derivation of the soil sensitivity component of the 2022 edition is more rigorous, employing standard equations for estimating soil loss and stormwater runoff, and the associated data needed for calculations. While the karst component of both editions utilized mapped sinkhole location, the 2022 edition also utilized a karst geology map, highlighting some areas of the Coastal Plain and Piedmont not previously included.

In the 2017 edition, source water zones of concern (based on data from the Virginia Department of Health, Office of Drinking Water) were incorporated into the landscape position component. This conflated prioritization based on natural phenomena (i.e., how water flows across the landscape) with prioritization based on human values (i.e., the desire to protect sources of drinking water). The 2022 edition does not include source water zones of concern, nor any other user-defined areas of importance. Instead, as illustrated in Figure 2, we intend for the model (upper left of diagram) to be used in conjunction with other spatial data representing the relative importance of different areas to the end user (upper right). Relative importance is driven by human values and spatial locations of specific aquatic resources of concern, whereas the Watershed Impact Model is driven only by site characteristics and hydrologic connectivity.

The 2017 edition incorporated land cover data reflecting conditions in 2011; this was the most current data available from the National Land Cover Database at the time. Related to this, the 2017 model produced three primary, mutually exclusive outputs, representing priorities for conservation, restoration, or urban stormwater management, depending on the land cover type. The 2022 edition does not incorporate land cover data. Instead, the primary model output, representing potential impact, is based on a "worst-case scenario" of barren land, and is intended to be used in conjunction with land cover data supplied by the end user. This prevents the model from becoming obsolete as land cover changes over time, and enables the user to use the best, most current land cover data available when formulating conservation, restoration, and/or management priorities.

The 2017 edition included a watershed integrity component that was based on attributes measured at the level of 12-digit hydrologic units, including percent cover of forests and wetlands, percent impervious cover, an index of biotic integrity, and pollution load estimates. There were two key problems with this. First, watershed integrity measures inevitably change with changes in land cover, and quickly become outdated. Second, the watershed integrity component was used in a rather subjective manner to adjust conservation, restoration, and stormwater management priorities. While any prioritization scheme requires some level of subjective judgement, our goal in the new edition was to eliminate as much subjectivity as possible, relegating such judgement calls to the end user. The watershed integrity component was eliminated from the 2022 edition, making the model more adaptable for a variety of users and more robust in the face of land cover change.

Model limitations

This model is intended as a geospatial screening tool to identify where land-altering activities are likely to have the greatest impact on water. It does not replace on-the-ground site assessments needed for specific projects, and it does not weight areas based on relevance to specific aquatic resources of concern. The model does not address current land cover conditions; it is assumed that the end user can supply a land cover dataset appropriate for their project area and time frame. Although the model incorporates empirical equations related to soil erosion and runoff, it does not calculate specific amounts of pollutants entering a watershed.

The output from this model is a raster dataset with 10-m resolution, which may or may not be sufficient for a particular application. This model, like any other, is limited by the quality of the data inputs as well as by the assumptions made and processes used in combining the inputs. All input datasets unavoidably have some spatial and/or attribute errors, which propagate to the final output. Users may or may not agree with how different inputs were scored and/or combined. No formal procedure for validating the model has been developed nor undertaken.

Model applications

We recommend a series of steps for applying this model to a particular project or end use. The first step is to identify a goal related to water quality. Example goals include:

- protecting drinking water sources from contamination
- maintaining healthy trout populations in popular fishing streams
- improving water quality in impaired stream reaches
- maintaining biotic integrity of healthy stream reaches

The second step is to delineate the area(s) relevant to achieving the stated goal. For example, if the goal is to maintain biotic integrity in healthy stream reaches, the land area draining to those reaches should be delineated as the area of interest. Optionally, within the delineated area of interest, relative importance may be scored at a more granular level. The next steps are to extract watershed impact scores and land cover in the area of interest. The final step is to combine resource importance scores, potential impact scores, and land cover data to derive priorities for action: protection, restoration, and/or best management practices. How these three elements (and possibly others) are combined is up to the end user. An example is provided in the use case below.

Example use case

In 2021, we developed a land prioritization map for maintaining the ecological integrity of healthy stream reaches, i.e., reaches identified as "healthy" or "outstanding" by the Virginia Healthy Waters Program (Neely et al. 2010). For each stream reach thus identified, we delineated the land area draining to it; the set of overlapping drainages defined the area of interest. Within the area of interest, we extracted potential impact scores from an earlier draft of the Watershed Impact Model, as well as land cover from the National Land Cover Database, representing conditions in 2019 (Dewitz and USGS 2021).

To assign relative importance scores within the area of interest, we made two assumptions:

- Catchments hydrologically closer to a healthy reach are more important than those farther away
- Catchments contributing to multiple healthy reaches are more important than those contributing to a single healthy reach

In addition to full drainages, we delineated drainages truncated at 2-, 3-, 5-, and 10-km upstream (Figure 3). Importance scores ranging from 1 to 100 were assigned to catchments based on hydrological distance to individual healthy reaches as well as the number of healthy reaches to which the catchments drain (Figure 4). Note that importance scoring is limited by sampling effort, as areas contributing to existing but undocumented healthy stream reaches do not contribute the score.

We multiplied potential impact scores by importance scores, and sliced the product into ten priority quantiles to produce a raster dataset with values ranging from 1 to 10, where 10 is the highest priority. Priorities were then split according to land cover type. Forest, wetland, scrub/shrub, and herbaceous cover classes were assigned conservation priorities. Agricultural lands, barren land, and developed open space were assigned priorities for restoration or rural best management practices. Low- to high-intensity developed areas were assigned priorities for urban stormwater best management practices. An overview of the process, and mapped section of the output, are shown in Figure 5. The output can be used to strategically target areas for conservation action geared toward maintaining documented healthy waters in Virginia.

Tables, Figures, and Maps

Table 1: Data sources and specialty toolsets used to produce the Watershed Impact Model

Dataset	Dataset Description	Data Source	Data Use
PMP	Probable maximum precipitation data and PMP toolbox	Virginia Dept. of Conservation & Recreation, Division of Dam Safety. Accessed May 28, 2020 from www.dcr.virginia.gov/dam-safety-and-floodplains/pmp-tool	Soil Sensitivity: runoff potential
gSSURGO	Soil geodatabase (FY 2020 Release) and Soil Data Management Toolbox for ArcGIS (version 5.0)	Natural Resources Conservation Service (NRCS). Soil data downloaded May 19, 2020 from http://datagateway.nrcs.usda.gov/	Soil Sensitivity: runoff and soil loss potential
R-factor	Rainfall-runoff erosivity factor for the conterminous United States	National Oceanic and Atmospheric Administration (NOAA). Accessed January 22, 2020 from https://coast.noaa.gov/data/digitalcoast/zip/R-Factor-CONUS.zip	Soil Sensitivity: soil loss potential
Elevation	1/3 arc-second digital elevation models	United State Geological Survey (USGS). Accessed October 3, 2019 from www.usgs.gov/core-science-systems/ngp/3dep/about-3dep-products-services	Soil Sensitivity: soil loss potential
NHDPlus-HR	National Hydrography Dataset Plus High Resolution: overland flow direction rasters, stream reaches, and catchments	United State Geological Survey (USGS). Accessed December 18, 2019 from www.usgs.gov/core-science-systems/ngp/national-hydrography/nhdplus-high-resolution	Landscape Position: overland flow
Sinkholes	Polygon feature class representing sinkhole locations.	Virginia Energy (formerly Department of Mines, Minerals, and Energy). Received January 2017. For more information, see energy.virginia.gov/geology/Sinkholes.shtml.	Landscape Position: karst prevalence
Karst geology	Polygon features representing karst geology	United States Geological Survey (USGS). Accessed February 11, 2016 from https://pubs.usgs.gov/of/2014/1156/	Landscape Position: karst prevalence

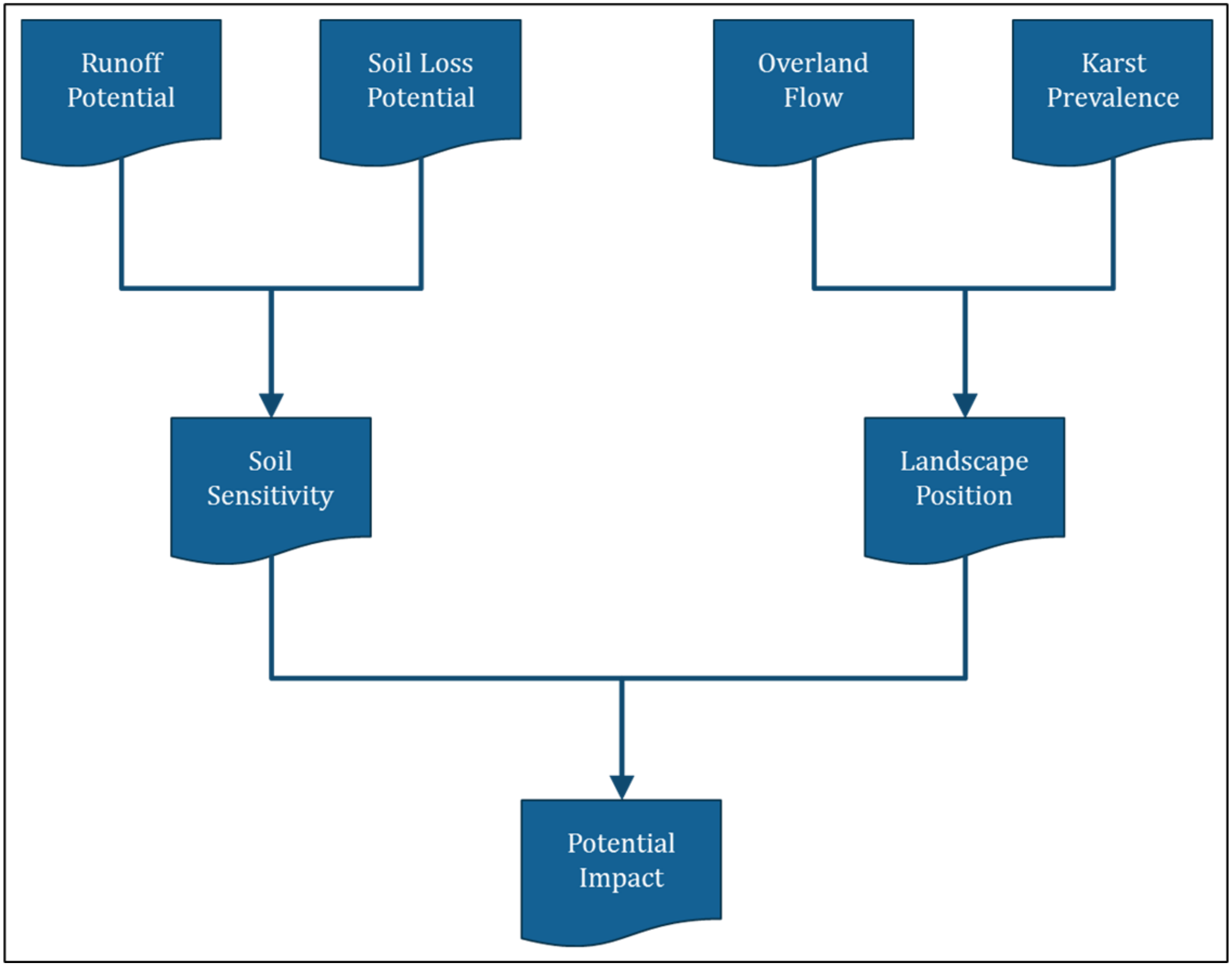


Figure 1: Components of the Watershed Impact Model

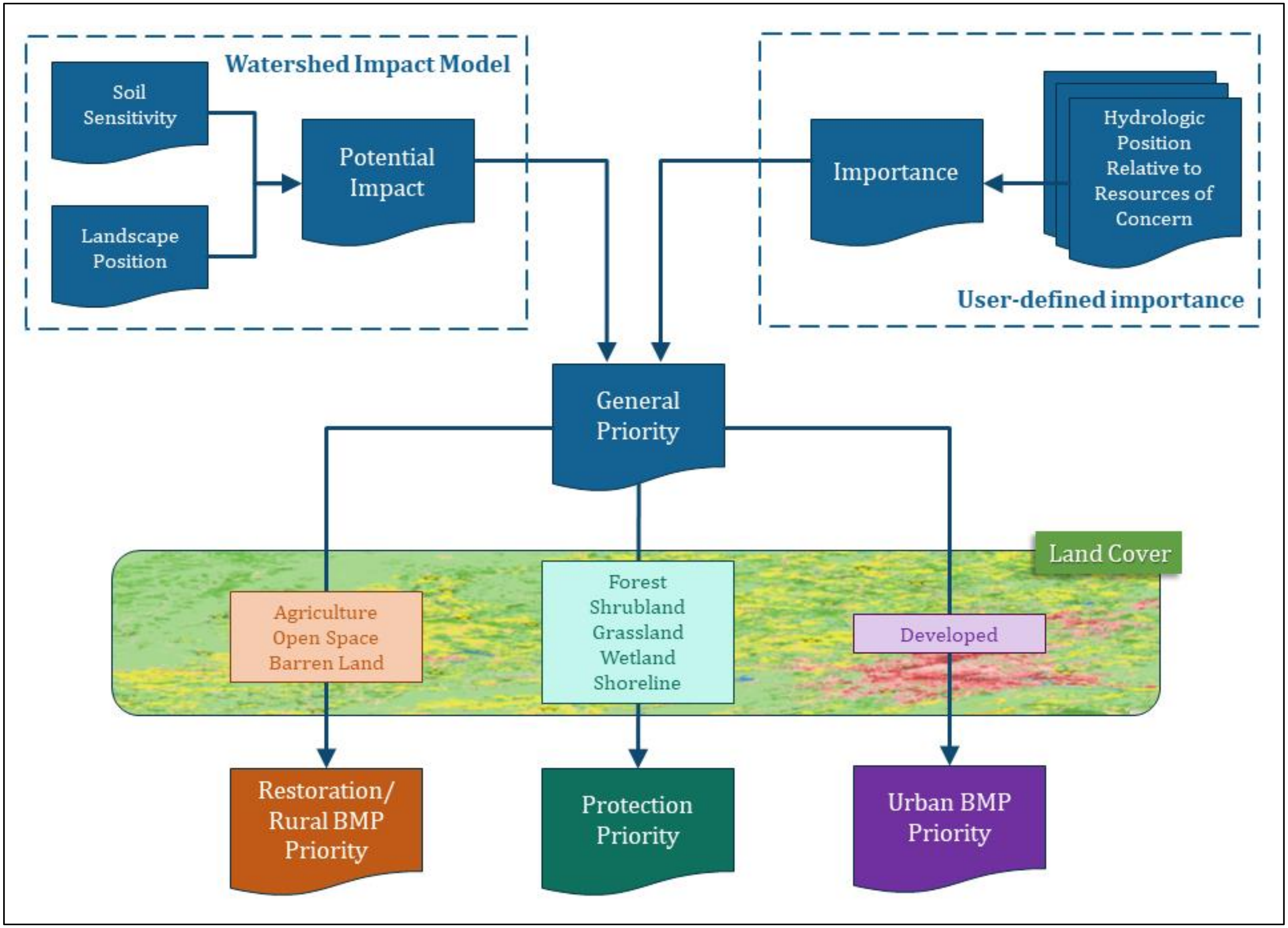


Figure 2: The Watershed Impact Model as an input to prioritization

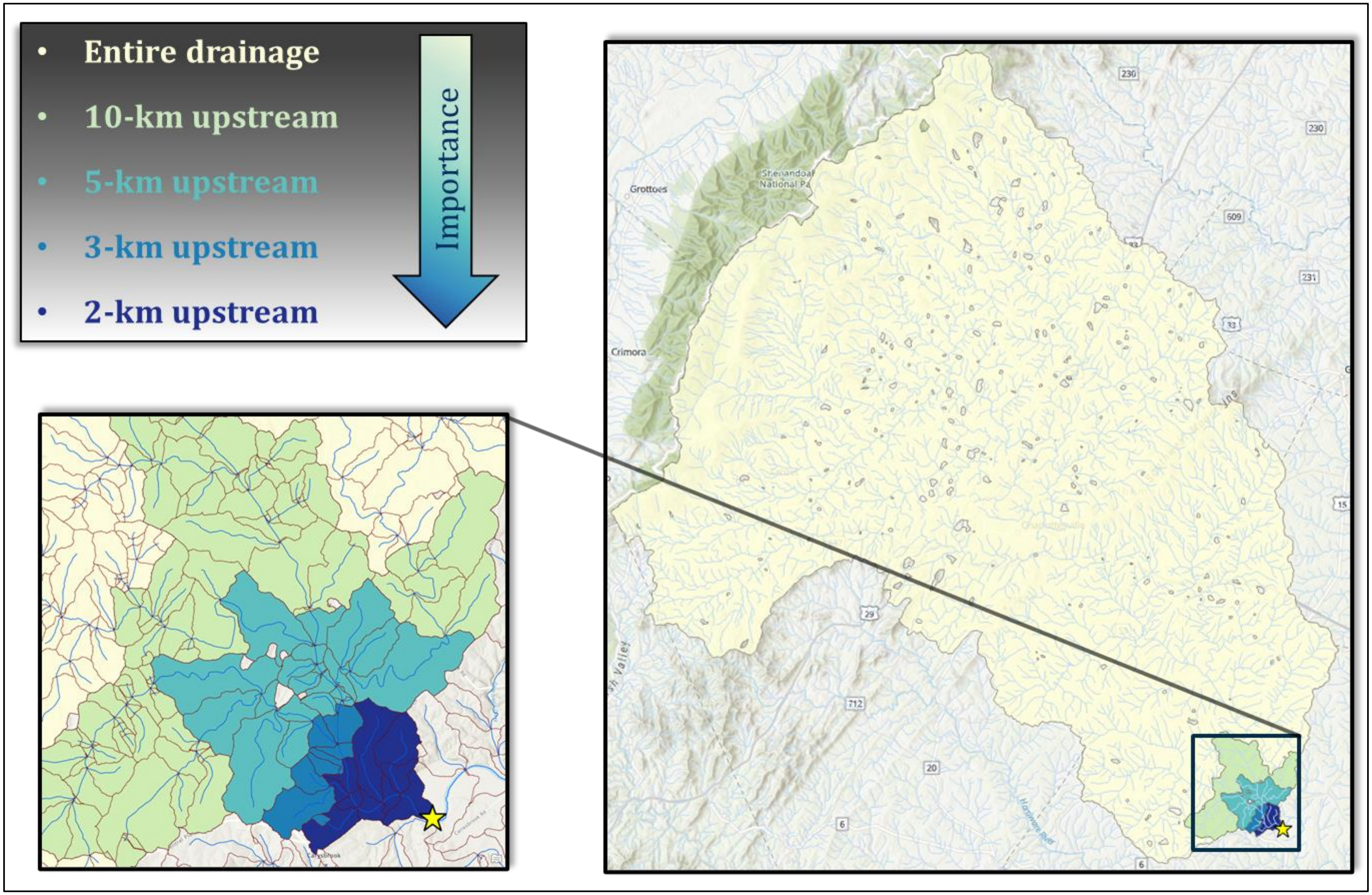


Figure 3: Drainage area of a healthy stream reach

The full drainage area of a healthy stream reach (site marked by yellow star) is shown in pale yellow, with truncated drainages, and corresponding relative importance, shown in shades of green to blue.

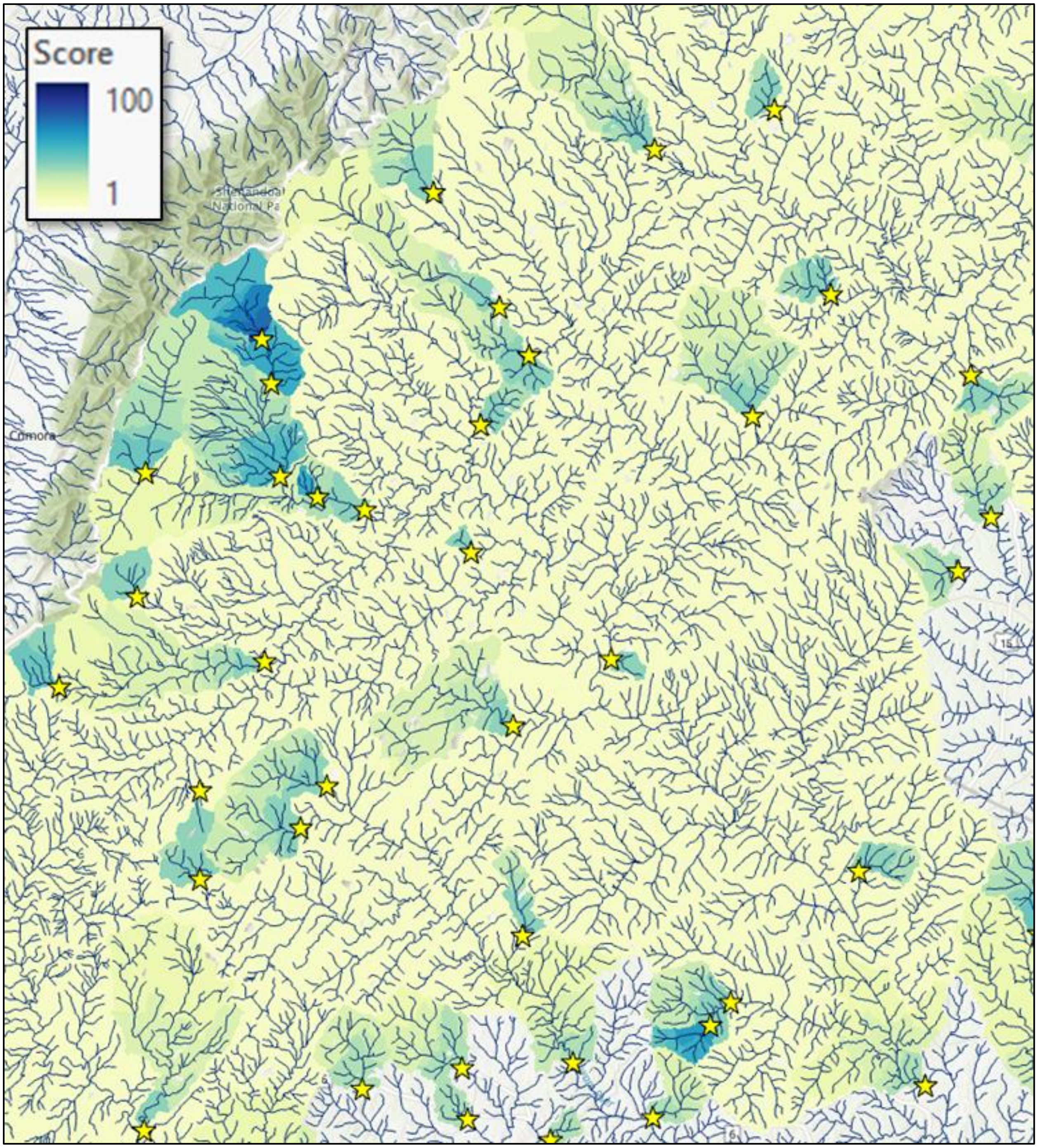


Figure 4: Relative importance for maintaining healthy stream reaches

A portion of the area draining to documented healthy stream reaches (marked with yellow stars) in Virginia is shown in shades from pale yellow to blue, indicating catchments' relative importance (scored from 1 to 100) based on hydrologic distance to healthy stream reaches and the number of healthy stream reaches to which they contribute.

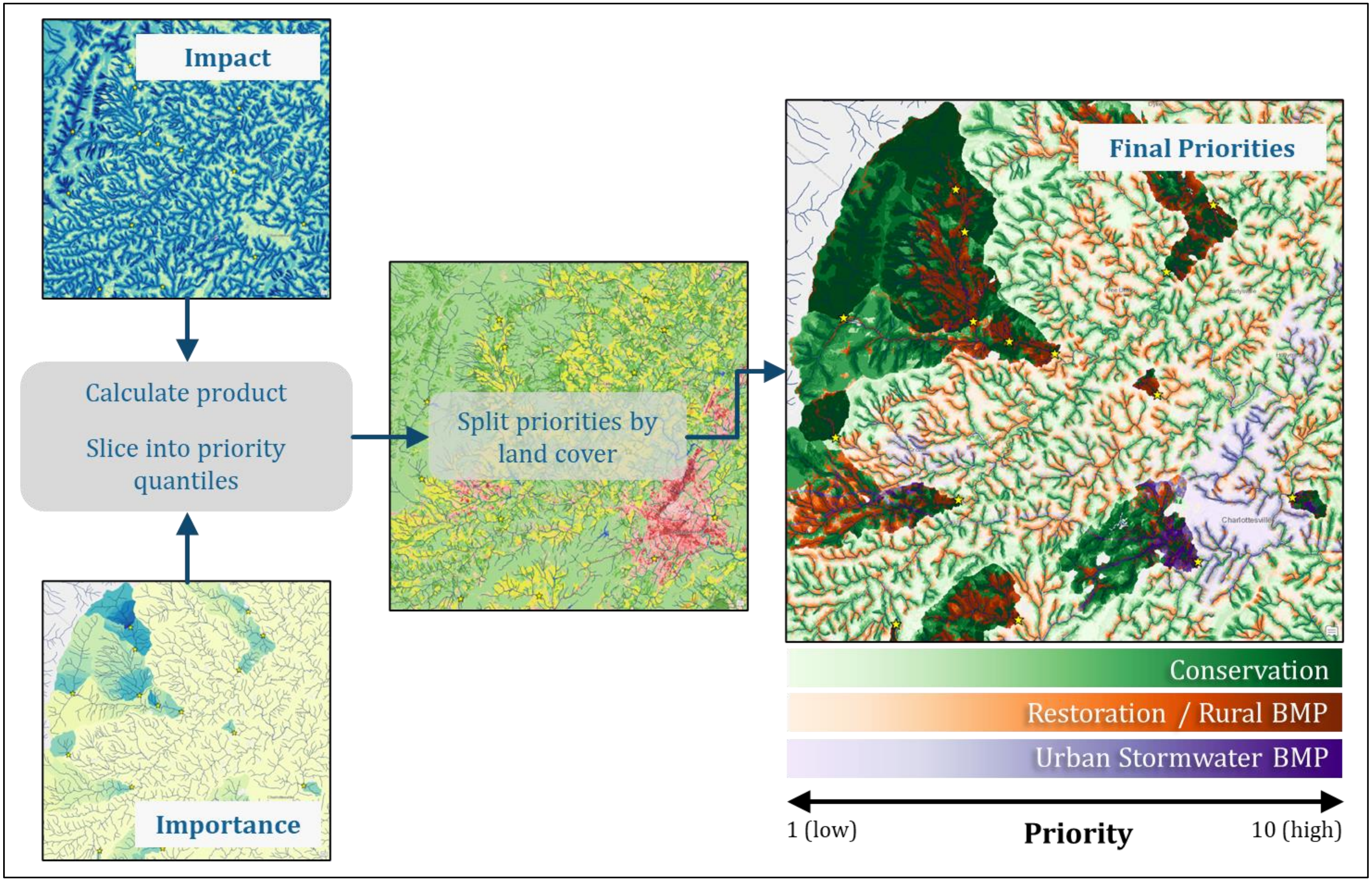
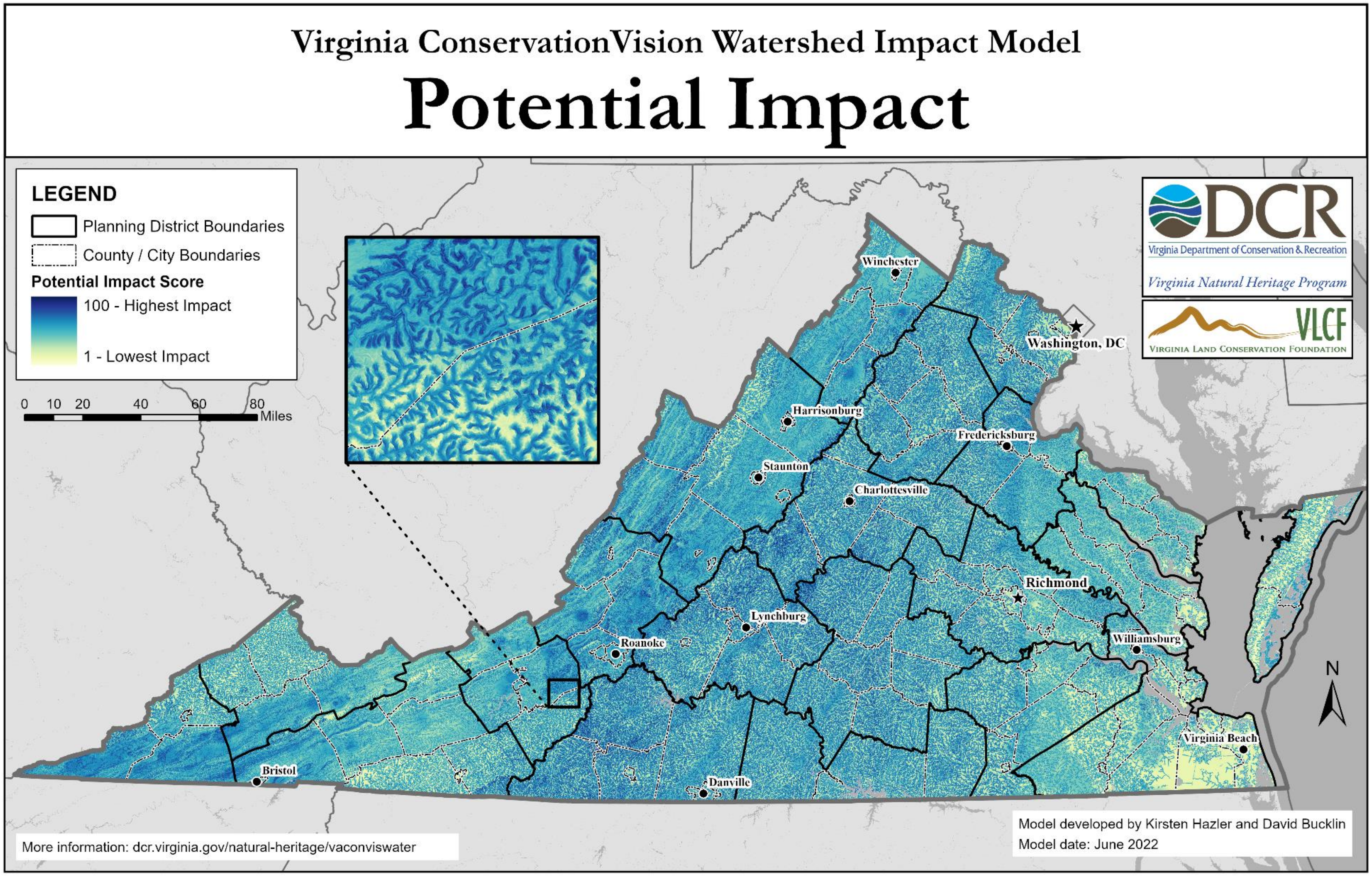
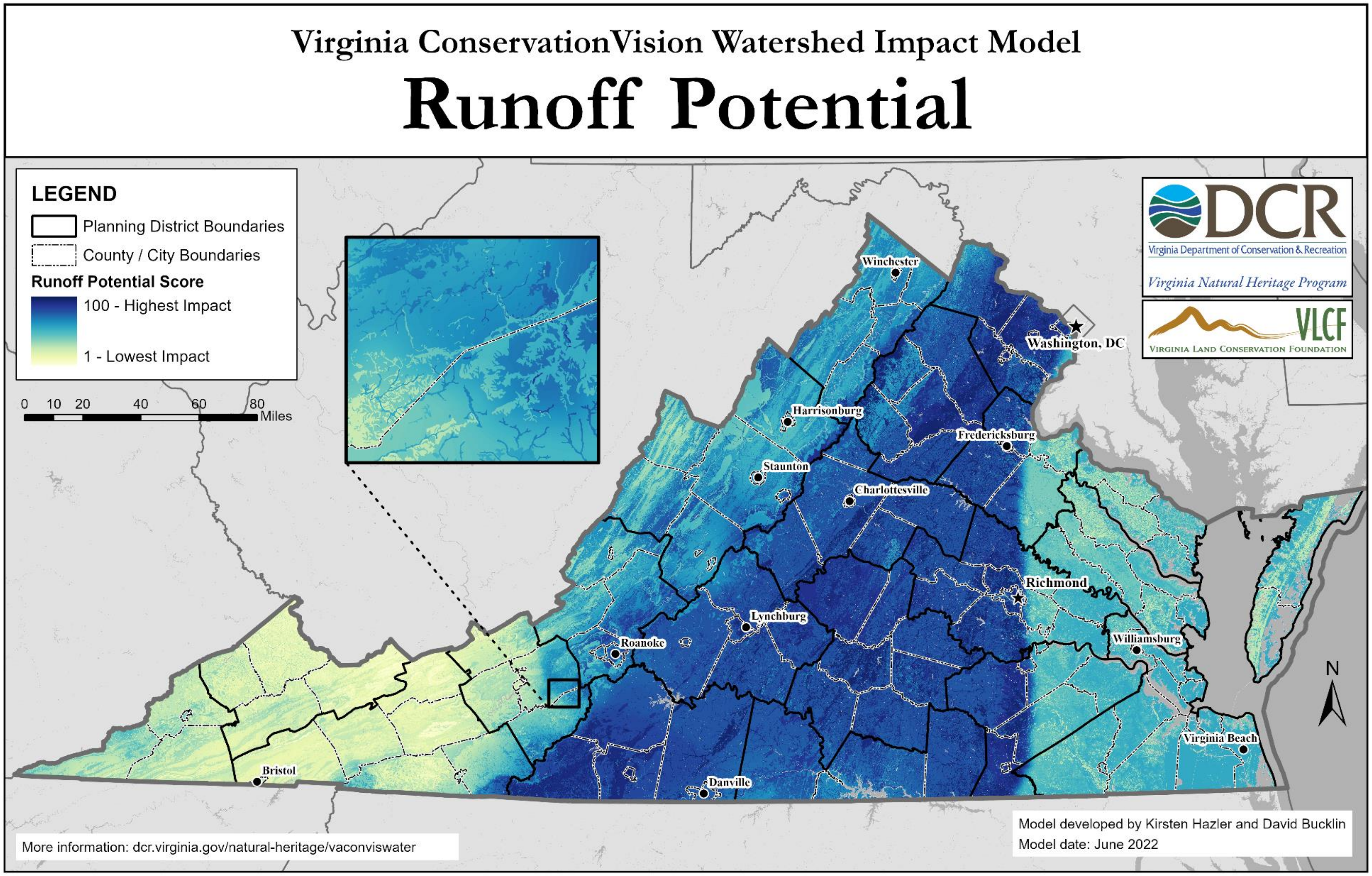


Figure 5: A prioritization model for maintaining Healthy Waters in Virginia

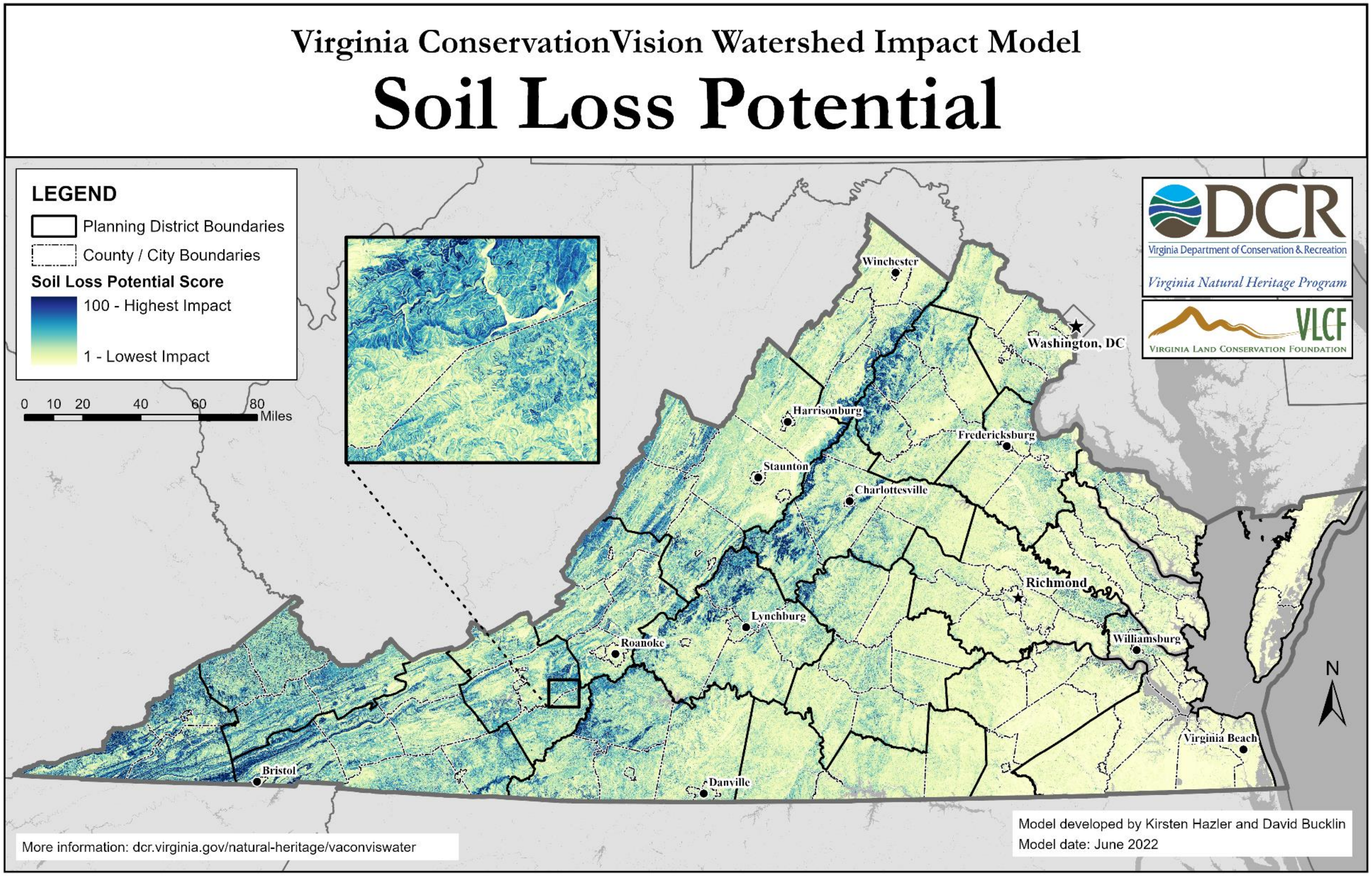
Map 1: Potential Impact Score



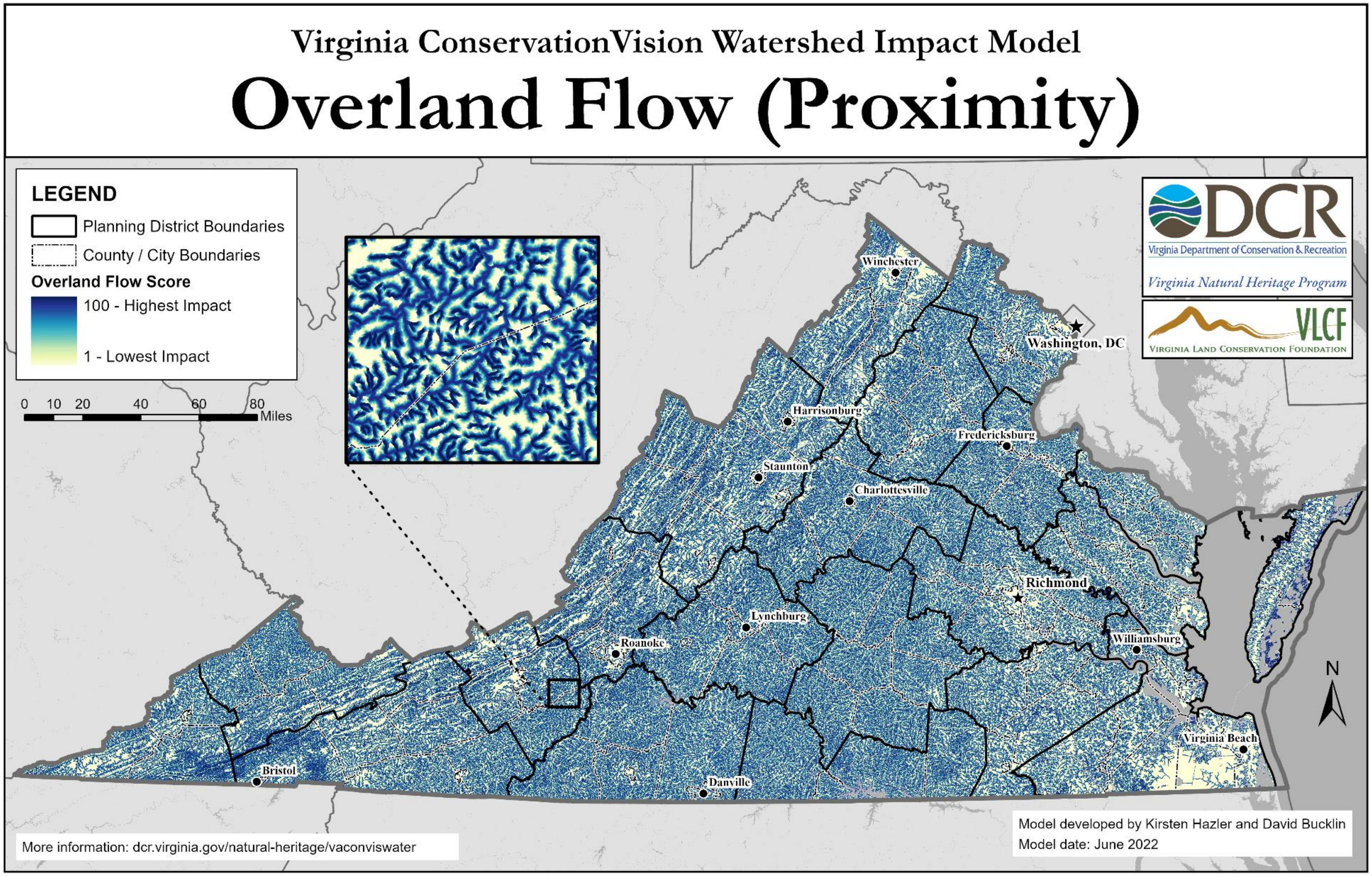
Map 2: Runoff Potential Score



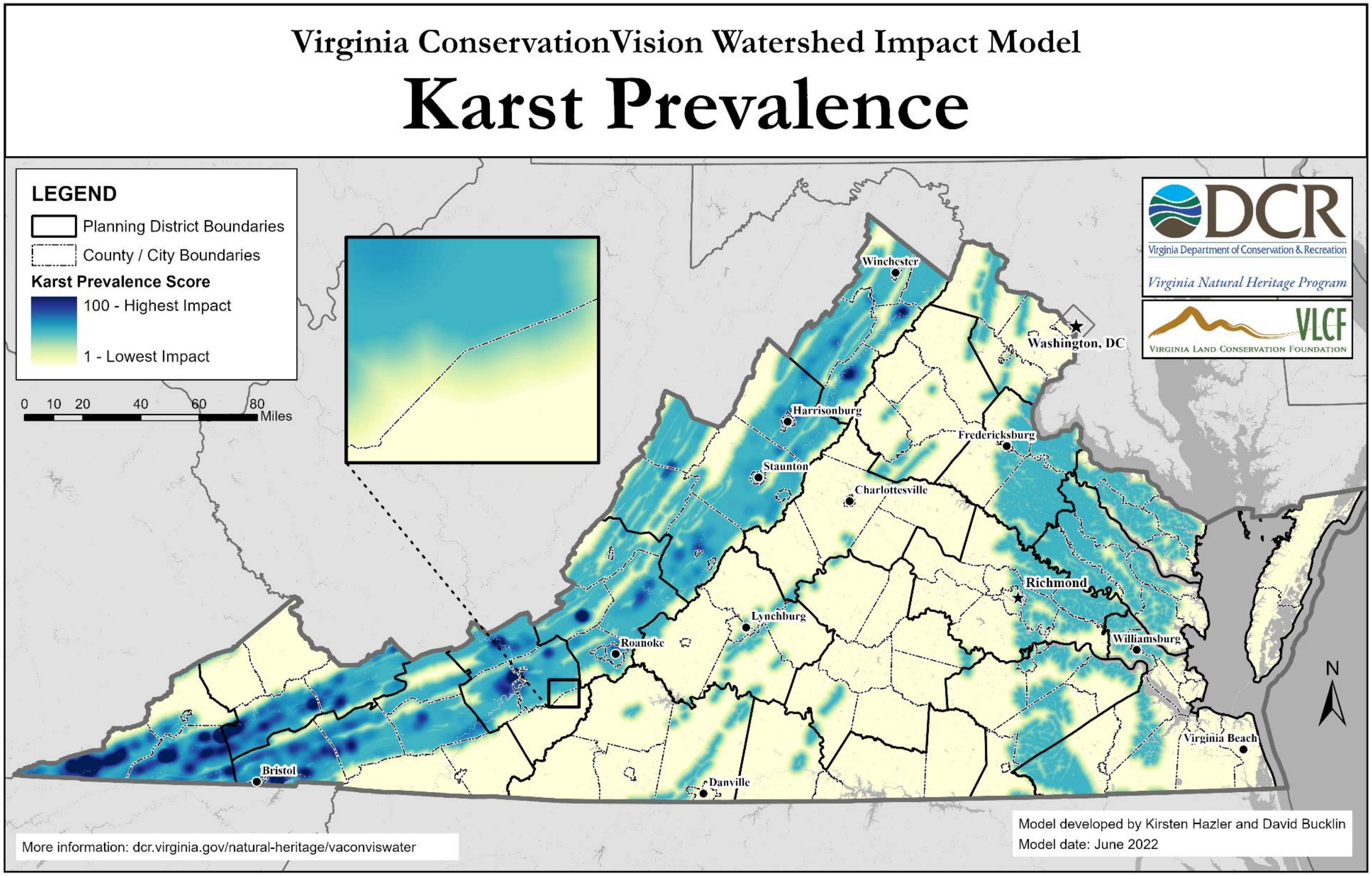
Map 3: Soil Loss Potential Score



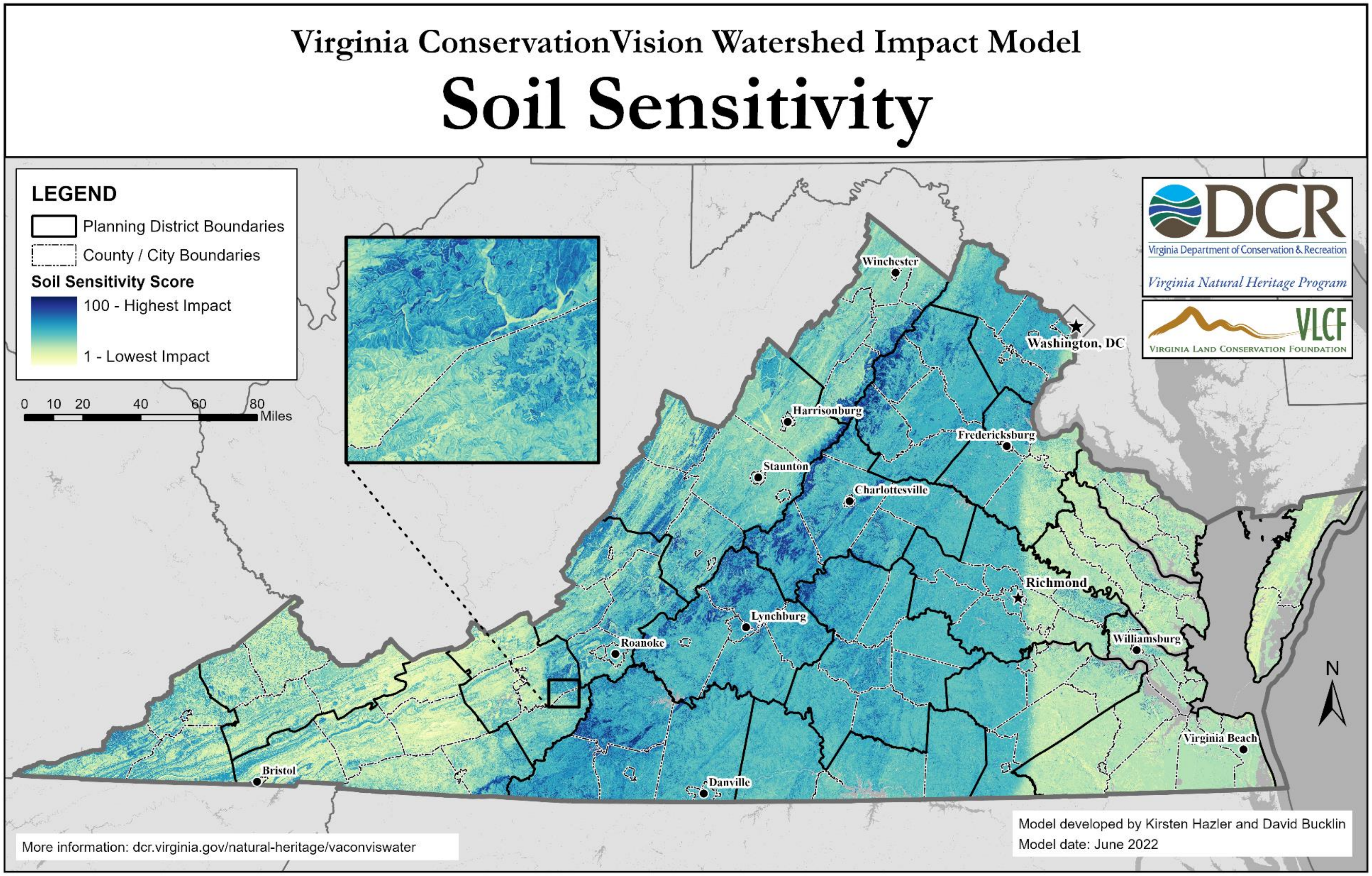
Map 4: Overland Flow (Proximity) Score



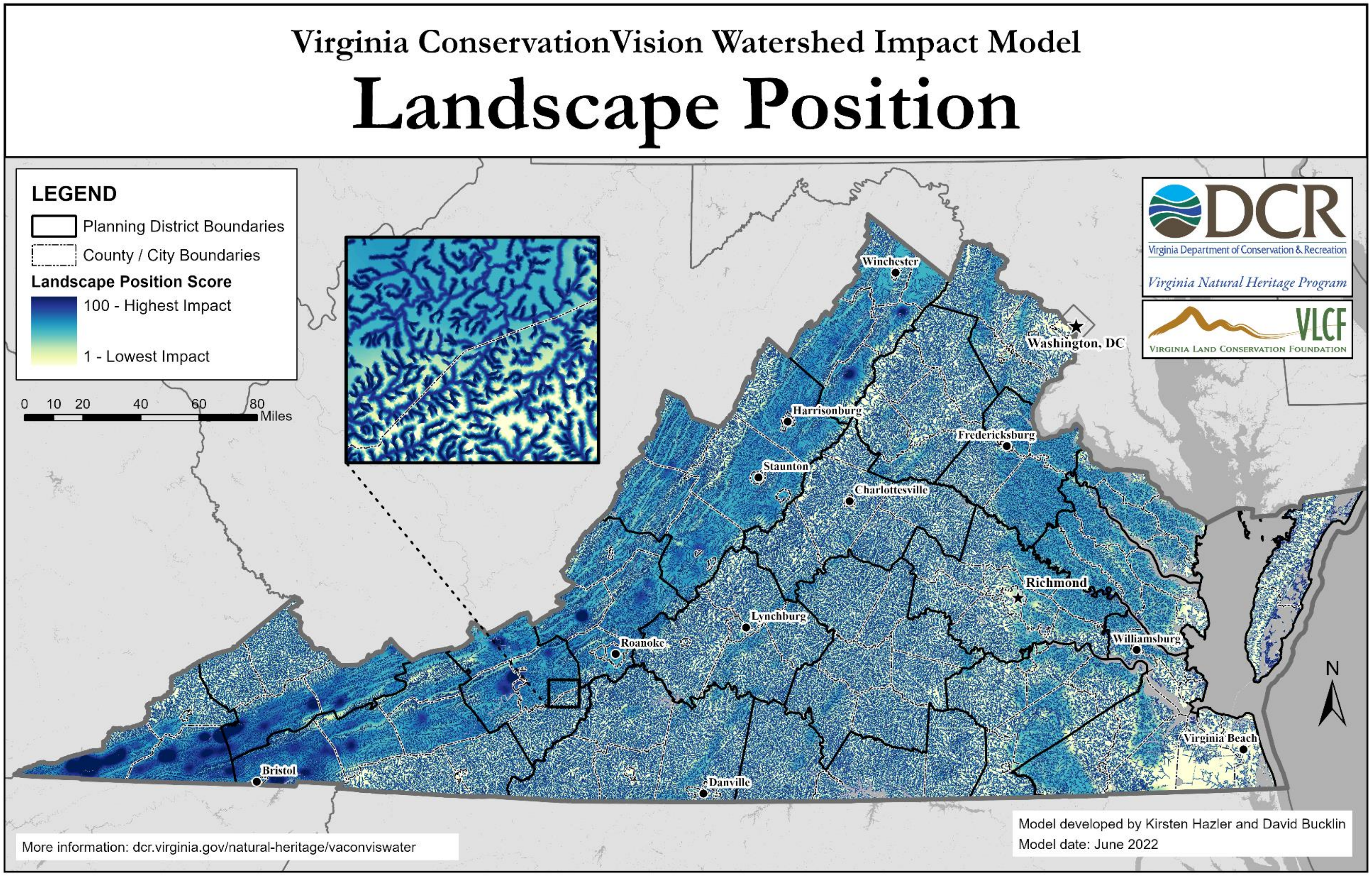
Map 5: Karst Prevalence Score



Map 6: Soil Sensitivity Score



Map 7: Landscape Position Score



Acknowledgements

We thank Karl Huber and Stu Blankenship for reviewing an earlier draft of this report.

References

Adamus, C. L., and M. J. Bergman. 1995. Estimating nonpoint source pollution loads with a GIS screening model. Journal of the American Water Resources Association 31:647–655.

Alexander, R. B., E. W. Boyer, R. A. Smith, G. E. Schwarz, and R. B. Moore. 2007. The role of headwater streams in downstream water quality. Journal of the American Water Resources Association 43:41–59.

Ator, S. W. 2019. Spatially referenced models of streamflow and nitrogen, phosphorus, and suspended-sediment loads in streams of the Northeastern United States. Scientific Investigations Report, U.S. Geological Survey, Reston, Virginia.

Barten, P. K., and C. E. Ernst. 2004. Land conservation and watershed management for source protection. Journal AWWA 96:121–135.

Chesapeake Bay Program. 2020. Chesapeake Assessment and Scenario Tool (CAST) Version 2019. https://cast.chesapeakebay.net/Documentation/ModelDocumentation.

Ciminelli, J., and J. Scrivani. 2007. Virginia Conservation Lands Needs Assessment: Virginia Watershed Integrity Model. Unpublished technical report, Virginia Dept. of Conservation and Recreation, Division of Natural Heritage; Virginia Department of Forestry, Richmond, Virginia.

Coastal Services Center. 2014. Technical Guide for OpenNSPECT, Version 1.2. National Oceanic and Atmospheric Administration.

Cronshey, R., R. H. McCuen, N. Miller, W. Rawls, S. Robbins, and D. Woodward. 1986. Urban Hydrology for Small Watersheds (2nd ed.). Technical Release, Natural Resources Conservation Service, U.S. Department of Agriculture.

Dewitz, J. and USGS. 2021. National Land Cover Database (NLCD) 2019 Products. U.S. Geological Survey.

Ernst, C. E. 2004. Protecting the Source: Land Conservation and the Future of America's Drinking Water. The Trust for Public Land and Amercan Water Works Association, Denver, Colorado.

ESRI. 2015. ArcGIS (Versions 10.2 - 10.3.1) [software]. Environmental Systems Resource Institute, Redlands, California.

ESRI. 2020. ArcGIS Pro (Version 2.7.x) [software]. Environmental Systems Resource Institute, Redlands, California.

Gallant, J. C., and J. P. Wilson. 2000. Primary topographic attributes. Pages 51–85 *in* J. P. Wilson and J. C. Gallant, editors. Terrain Analysis: Principles and applications. John

Wiley & Sons, Inc., New York.

Hanson, C., J. Talberth, and L. Yonavjak. 2011. Forests for water: Exploring payments for watershed services in the U.S. South. WRI Issue Brief, World Resources Institute, Washington, D.C.

Hazler, K., R. Gilb, and N. Knudson. 2018. Virginia ConservationVision: Watershed Model, 2017 Edition. Natural Heritage Technical Report 18-16, Dept. of Conservation and Recreation, Division of Natural Heritage, Richmond, Virginia.

Hubbard, D. A., Jr. 2014. Sinkholes. Fact Sheet, Virginia Energy, Charlottesville, Virginia.

Kappel, B., D. Hultstrand, J. Rodel, G. Muhlestein, K. Steinhilber, D. McGlone, and B. Lawrence. 2015. Probable Maximum Precipitation Study for Virginia. Applied Weather Associates, LLC, Monument, Colorado.

Klapproth, J. C., and J. E. Johnson. 2009. Understanding the science behind riparian forest buffers: Effects on water quality. Virginia Cooperative Extension Publication, College of Agriculture and Life Sciences, Virginia Polytechnic Institute and State University, Blacksburg, Virginia.

National Oceanic and Atmospheric Administration, Office for Coastal Management (NOAA-OCM). 2013. R-Factor for the Coterminous [sic] United States. National Oceanic and Atmospheric Administration, Office for Coastal Management, Charleston, S.C.

Neely, P., R. Hill, G. Garman, S. McIninch, J. Ciminelli, K. Hodge, and C. Rice. 2010. Healthy Waters: A new ecological approach to identifying and protecting healthy waters in Virginia. Brochure, Virginia Department of Conservation and Recreation, Richmond, Virginia.

Randhir, T. O., R. O’Connor, P. R. Penner, and D. W. Goodwin. 2001. A watershed-based land prioritization model for water supply protection. Forest Ecology and Management 143:47–56.

Renard, K. G., G. R. Foster, G. A. Weesies, D. K. McCool, and D. C. Yoder. 1997. Predicting soil erosion by water: a guide to conservation planning with the revised universal soil loss equation (RUSLE). Agriculture Handbook, U.S. Department of Agriculture.

Soil Survey Staff. 2020. Gridded Soil Survey Geographic (gSSURGO) Database for Virginia, Washington DC, Delaware, Kentucky, Maryland, North Carolina, Pennsylvania, Tennessee, and West Virginia (FY 2020 Release). United States Department of Agriculture, Natural Resources Conservation Service.

Talberth, J., E. Gray, E. Branosky, and T. Gartner. 2012. Insights from the field: Forests for water. WRI Issue Brief 9, World Resources Institute, Washington, D.C.

U.S. Dept. of Agriculture, Natural Resources Conservation Service (NRCS). 2017. Soil Data Management Toolbox for ArcGIS, version 5.0: User Guide. National Soil Survey Center, National Geospatial Center of Excellence.

U.S. Environmental Protection Agency (USEPA). 1996. Nonpoint source pollution: The nation’s largest water quality problem. EPA Fact Sheet 841-F-96-004A, U.S. Environmental

Protection Agency, Office of Water.

U.S. Environmental Protection Agency (USEPA). 2004. Understanding the Safe Drinking Water Act. EPA Fact Sheet 816-F-04-030.

U.S. Environmental Protection Agency (USEPA). 2016. National Nonpoint Source Program - a catalyst for water quality improvements. EPA Brochure 841-R-16-009, U.S. Environmental Protection Agency.

U.S. Environmental Protection Agency (USEPA). 2018. Summary of the Clean Water Act [web site]. https://www.epa.gov/laws-regulations/summary-clean-water-act.

U.S. Geological Survey (USGS). 2017. 1/3 arc-second Digital Elevation Models (DEMs) - USGS National Map 3DEP Downloadable Data Collection for Virginia [raster dataset].

U.S. Geological Survey (USGS). 2018. USGS National Hydrography Dataset Plus High Resolution (NHDPlus HR) for 4-digit Hydrologic Units in Virginia [geodatabase].

Virginia DCR Staff. 2016. Virginia Department of Conservation and Recreation Strategic Plan.

Virginia DCR Staff. (n.d.). Virginia Land Conservation Foundation [web site]. http://www.dcr.virginia.gov/virginia-land-conservation-foundation/.

Virginia Department of Conservation and Recreation, Division of Soil and Water Conservation (VADCR-DSWC). (n.d.). Nonpoint source pollution assessment and prioritization. https://www.dcr.virginia.gov/soil-and-water/npsassmt.

Virginia Dept. of Conservation and Recreation, Division of Natural Heritage (VADCR-DNH). (n.d.). Introduction to Virginia's Karst [powerpoint presentation].

Virginia Dept. of Health, Office of Drinking Water (VDH-ODW). (n.d.). Source Water Assessment Program [web site]. http://www.vdh.virginia.gov/drinking-water/source-water-programs/source-water-assessment-program/.

Virginia Dept. of Health (VDH). 1999. Virginia source water assessment program. Virginia Department of Health, Richmond, Virginia.

Virginia Energy. (n.d.). Sinkholes and Karst [web site]. https://energy.virginia.gov/geology/Sinkholes.shtml.

Weary, D. J., and D. H. Doctor. 2014. Karst in the United States: A digital map compilation and database. Open-File Report, U.S. Geological Survey.

Wenger, S. 1999. A review of the scientific literature on riparian buffer width, extent and vegetation. Public Service and Outreach Report, University of Georgia, Institute of Ecology, Athens, Georgia.

Zhang, Y., and P. K. Barten. 2009. Watershed Forest Management Information System (WFMIS). Environmental Modelling & Software 24:569–575.