Spatial Analysis of Ecosystem Service Intensity in the Snohomish Basin, Washington

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1. Recommended Course of Action

The objective of this report is to explore an analytical framework that is hoped to make a meaningful contribution towards the multi-disciplinary approach being applied to the study of ecosystem services in the Snohomish Basin of Washington state. Snohomish Basin is currently the focus of a sustained scientific effort within the Regional Open Space Strategy (ROSS), an initiative coordinated by a vibrant alliance of government agencies, research institutions, non-profit and private organizations to achieve a multi-dimensional, integrated set of priorities and tools for planning and stewardship in the greater Puget Sound region. An essential part of the ROSS vision is working across existing jurisdictional boundaries at scales that form more natural units of analysis, such as watersheds. While significant research has been conducted for watersheds encompassing the traditional Seattle urban core, more distant areas like the Snohomish Basin, which is so large that it spans two counties, are only now beginning to receive proper attention for their importance in terms of ecosystem service provisioning. The impetus for these efforts has a lot to do with the rate of development in Puget Sound, as growing populations and increasing demand for resources create significant pressures on the landscape. Though our project faced considerable limitations in terms of time availability along with certain aspects of the methodology, we remain confident that the ideas presented in the following pages can inform future research effort by ROSS and/or other initiatives towards obtaining truly comprehensive results.

2. Introduction

The study of ecosystem services with their associated stocks and flows is an integral component of the framework seeking to address what has been termed the "central challenge of sustainability science" (Kates et al. 2001). At its heart, this challenge refers to the seemingly irreconcilable goals of securing society's use of resources for the most fundamental human needs while at the same maintaining ecosystem function and services (Blumstein and Thompson 2015). By the simplest definition, ecosystem services are the benefits people obtain from ecosystems (Millennium Ecosystem Assessment [MEA] 2003). Because these services are produced in bundles everywhere on the planet, the ability to locate, quantify and qualitatively assess the synergistic effect of multiple ecosystem services is essential to fully understanding changes in ecosystems and their impacts on human well-being.

To aid with their study, ecosystem services are classified along functional lines into four categories: regulating services, provisioning services, cultural services and supporting services (MEA 2003). Taken together, these are responsible for providing every attribute needed to sustain life and ecological well-being throughout all biomes. They are associated with the maintenance of all natural systems, soil, air, water, and organisms. Additionally, they underlie the production of much of the planet's human wealth.

According to the National Wildlife Federation, a regulating ecosystem service is "the benefit provided by ecosystem processes that moderate natural phenomena" (NWF 2015). Regulating services produce a sustainable balance in natural systems and usually operate at large spatial scales. They include climate regulation, air quality maintenance, water regulation, erosion control, waste treatment, disease regulation, storm protection, biological control and pollination (MEA 2003). As long as existing services remain intact, ecological threats are less likely to cause lasting degradation of biodiversity. Regulating services make ecosystems more resilient to stressors, but many anthropogenic activities are detrimental to the foundational components that maintain the functional equilibrium of an ecosystem, such as the degradation of pollinators by pesticides.

Provisioning services are the indispensable products obtained directly from ecosystems. They include fresh water (through processes of purification), food and fiber, fuel, genetic resources, biochemical and pharmaceutical agents, and ornamental resources - the latter being an example of a service that is considered a linkage as it can go in multiple categories (MEA 2003).

Cultural services are not specifically linked with ecological fitness, but refer to non-material benefits humans derive from contact with nature and participation in recreational activities. They include cultural diversity, spiritual and religious values, knowledge systems, educational values, aesthetic values, social relations, cultural heritage and recreation and

ecotourism (MEA 2003). Cultural services are a critical factor in building salience and support for sustainable management of all ecosystem services. These services include have a considerable influence on regional economic development, particularly in areas of rapid urban expansion, and are increasingly addressed in land use planning and natural resource management.

Supporting services refer to the complex and long-term biophysical interactions that are foundational to all other ecosystem services and to the existence of life on Earth. These services maintain the fundamental attributes of ecosystems by functioning at large scales, many times globally, as well as over very long periods of time with impacts that are not immediately obvious to human populations (MEA 2003). Supporting services include photosynthesis and the production of atmospheric oxygen, nutrient cycling, the hydrologic cycle, primary production, soil formation and provisioning of habitat (NWF 2015). Many of these can also serve as linkages between the other ecosystem services.

Finally, the concept of biodiversity must be mentioned in relation to ecosystem services. Biodiversity is defined by the Convention on Biological Diversity as "the variability among living organisms from all sources including terrestrial, marine and other aquatic ecosystems and the ecological complexes of which they are part; this includes diversity within species, between species and of ecosystems" (MEA 2003). Diversity can therefore be interpreted as a structural feature of ecosystems, and variability among ecosystems is an element of biodiversity.

This project was developed in collaboration with the Regional Open Space Strategy (ROSS) initiative. ROSS is a Puget Sound-based project dedicated to promoting sustainable management of rural and urban open space resources for a variety of uses and functions. ROSS is unique in their use of integrated planning. They utilize experts from a wide variety of technical fields and collaborate with a diverse range of public and private partners to obtain a wide angle perspective on regional ecological interactions. By analyzing ecosystem services using a wide variety of criteria, ROSS is able to identify nuanced, synergistic activity among the variety of species and process that make up a given biosphere. This approach provides a complimentary perspective to the often narrow set of priorities governing the agenda of any single institution (ROSS 2015).

For this project, we were tasked by ROSS to perform an analysis of ecosystem services in Snohomish Basin, with an emphasis on the spatial distribution and intensity of services in relation to urban areas and land cover. The Snohomish Basin extends from the Cascade Mountains to the Puget Sound in the state of Washington; this vast landscape spans King and Snohomish counties and drains northwest into the Puget Sound. It ranges in elevation from sea level to approximately 2,400 meters. The total drainage area of the watershed is 4,945 square kilometers (WA DOE 2015). The predominant land cover of the region is evergreen forest and grassland, along with mixed forest and shrub. For the purposes of this project, the boundaries of

the Snohomish Basin are considered to be identical to those of the Water Resource Inventory Area (WRIA) 7, as classified by the Washington Department of Ecology.
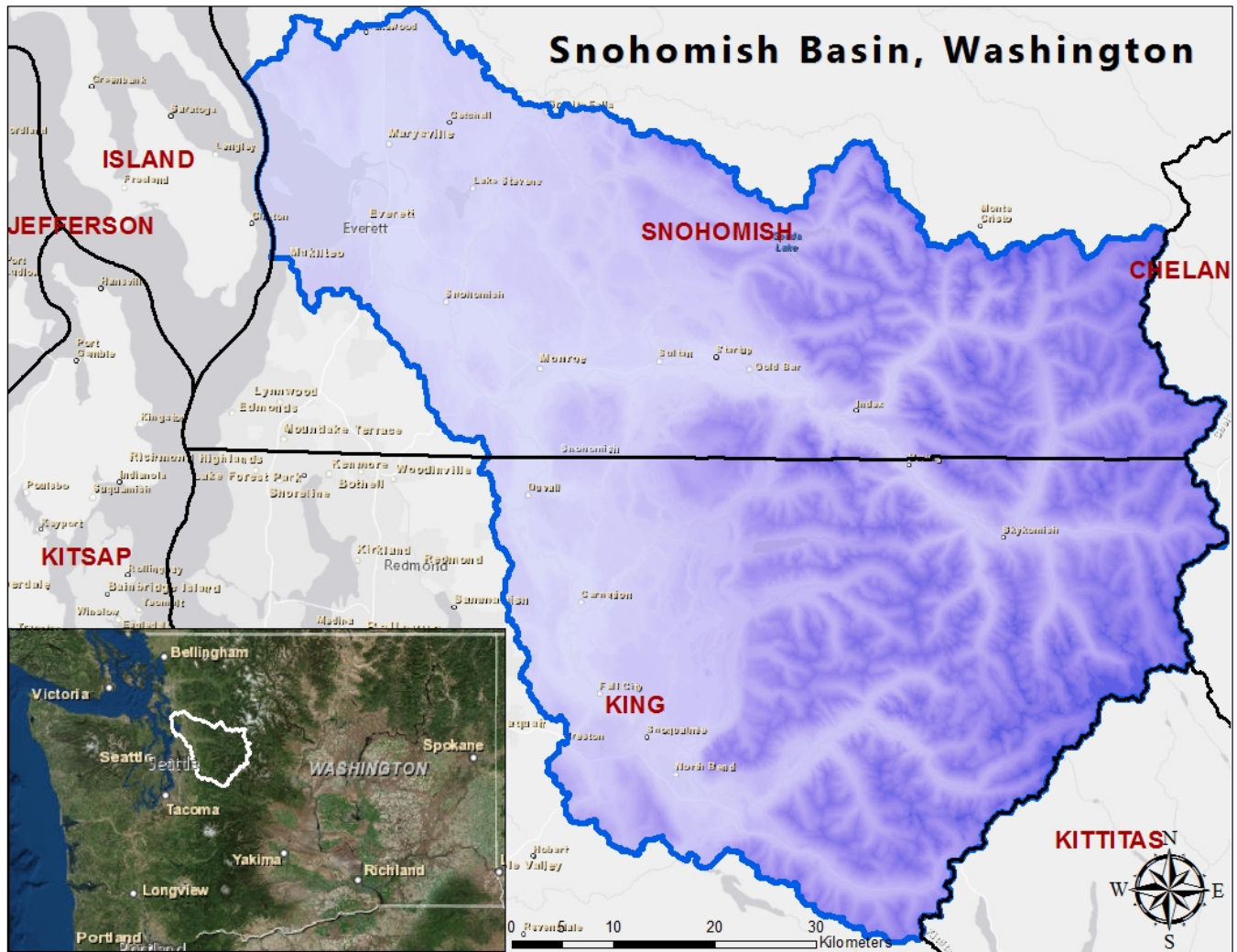
Figure 1: Reference Map for Snohomish Basin, Washington

The greater Seattle urban area relies heavily on the ecosystem services provided by the natural lands of Snohomish Basin, from drinking water to carbon storage to recreation. It is estimated that this watershed: 1) provides more drinking water than any other in the state of Washington; 2) functions as one of the primary producers of salmon in the Puget Sound region; and 3) captures more carbon stock than any other basin in the Puget Sound. With over 600,000 acres of protected lands, Snohomish Basin is one of the most popular recreation destinations for the largest metropolitan area in the state (Alberti et al. 2013).

The basin also contains one of the fastest growing urban areas in the state, concentrated primarily around the city of Everett in Snohomish County. Major employers, including Boeing, Providence Regional Medical Center and Microsoft, drive population growth and the

corresponding land development. Over the last half century, the basin has shifted from supporting a largely rural population to an urban population, and along with this change it has seen dramatic transitions in landscape character, resource consumption and governance (Alberti et al. 2013). Some of the aspects defining the challenge of meeting human resource demands with preservation of ecosystem services are outlined as a social-ecological systems matrix in Table 1 below.

Conceptual Scale	Unit Scale	Carbon	Water	Biodiversity	Social Aspects
Landscape (Above)	Puget Sound	Regional average of stored carbon is useful for calculating net carbon emissions at a regional scale. The net carbon emissions of Puget Sound may tie the region to a National or global carbon management scheme.	Puget Sound suffers consistent overloading of nitrogen and phosphorus. Removal of these nutrients using conventional treatment is costly. Source reduction is easily justifiable in terms of equity.	ROSS specializes in integrating a variety of biological suitability and threat data over a broader landscape scale. The most accurate representation of a biophysical domain involves consideration of many interactions across the spatial range in which the interactions occur.	A multi-disciplinary effort is underway to manage the rapid growth of the Puget Sound region. Land use, water and transportation planning has failed to keep pace with urban and suburban expansion. The cultural identity of the region is dependent upon clean air, land and water.
Focal	Snohomish Basin/WRIA7	Land use plays a large role in a landscape's carbon storage capacity. Watershed scale carbon management plays an important role in reducing global carbon surplus.	Water quality throughout the focal area provides a snapshot of how land use, transportation and water planning impact aquatic resources.	Compare land use management of the region to the overall biodiversity, continuity of plant association groups, and area of sensitive habitats.	Population growth, especially in and around urban growth areas and provisioning activities such as agriculture, forest product and marine harvest apply increasing strain on ecosystem services within Snohomish Basin.
Detailed (Below)	Sub-Watershed	Identify how sparse and dispersed urban vegetation contributes to regional carbon storage.	Relate local water quality indices to specific features which are associated with water quality impairment within the sub-watershed unit.	Relate localized trends in plant association groups to land use raster values. Encourage land use planning that minimizes impact on sensitive habitats.	General livability of an area depends on the quality of localized ecosystem services. The sub watershed is the scale at which individuals experience the impact of degraded ecosystem service quality.

Table 1: Social-Ecological System Table for Snohomish Basin

The purpose of this project is to locate areas within the Snohomish Basin where multiple ecosystem services display high values in a representative metric, as well as areas which are spatially devoid of significant amounts of ecosystem services as exhibited by low scores. We refer to the distribution of values quantifying ecosystem services as intensity. Areas of significance are identified by their placement above or below the regional average ecosystem service value range. The methodology of determining areas of significance is detailed in Section 3 - Methods. Locating areas that have significantly high intensities of ecosystem service occurrence may assist planners in protecting critical resources from known threats and urban encroachment. Areas of significantly low intensities of ecosystem services would serve as indicators of locations that may become desirable targets for ecological rehabilitation projects.

3. Methods

3.1 Project Design

This project uses a design inspired by that of Blumstein and Thompson (2015), but with significant differences related primarily to: 1) adapting the inputs to our particular project framework; and 2) conducting the analysis using ESRI's ArcGIS suite instead of the R statistical environment. Due to constraints applied by the project timeline, we made the decision to include in our analysis a smaller number of variables, representing only regulating and provisioning ecosystem services. Cultural services were left out because these are considered to be "tightly bound to human values and behavior, as well as to human institutions and patterns of social, economic, and political organization" (MEA 2003), thus requiring the incorporation of valuation, which was determined to be outside the scope of the current project. Supporting services were also disregarded because their impacts, which can be either direct or indirect, tend to occur over very long periods of time, so we reasoned these impacts would not be of use given our study's restricted temporal scale. In addition, we chose to include representations of biodiversity in the form of terrestrial habitat quality metrics. Biodiversity is not generally considered to be a type of ecosystem service, but rather a measure of the variety of organisms present in ecosystems that enable the production of many of the services. Since organisms need habitat to fulfill their functions, measurements of 'quality' can serve as proxies for biodiversity in that the loss of habitat leads to loss of species, thus decreasing diversity and the ability of ecosystems to continue producing services.

Following Blumstein and Thompson's lead, we selected the storage of carbon in the terrestrial environment as the regulating ecosystem service of choice. Using the Carbon Storage and Sequestration model in the Natural Capital Project's InVEST suite (Sharp 2015), we generated a metric quantifying the amount of carbon stored in the landscape of our study area. For the provisioning ecosystem service, we selected water purification and, again following the example set by Blumstein and Thompson, employed the InVEST Nutrient Retention model to generate metrics for the retention and export of nitrogen and phosphorus respectively, which are two key nutrients for which runoff into streams results in degradation of water quality and higher filtration costs for the landscape. Finally, we applied the InVEST Habitat Quality model to obtain two metrics for biodiversity, one being a measure of the amount of degradation experienced by land cover types designated as habitat from user-specified threats, and the other being a measure of the fragmentation of habitat land cover from the same threats. In contrast to Blumstein and Thompson, we decided to use both these metrics, whereas they carried only degradation into the analysis. Preparation of inputs and processing of outputs using the three aforementioned InVEST models are discussed in detail in subsection 3.2-3.4 below.

For a step-by-step visual representation of the workflow of our project, please refer to the workflow diagram included as Appendix A.

<u>3.2 Carbon Storage Model</u>

Carbon storage and sequestration is a regulating ecosystem service that affects biodiversity on a global scale. While the ecological effects of climate change on the study area are not directly linked to the carbon stored within the study area, the global cumulative storage of carbon is a critical threshold that must be assessed and managed at a regional scale. Carbon storage refers to the capacity of an ecosystem to retain into pools based on the form in which the carbon exists. For this analysis two carbon pools were considered, above ground live and dead biomass or surface carbon, and the carbon stored in the top 1-meter of soil. Carbon pools that were not considered in this analysis include below ground biomass and harvested wood products.

The InVEST Carbon Storage and Sequestration model used for this analysis aggregates the capacity to store and sequester carbon by land cover type (Sharp 2015). For the purpose of this analysis we used the minimum required input for the Carbon model. The model has various applications involving timber harvest and forest land management. This analysis involved combining the current land use/land cover raster with a table articulating carbon pool values by land cover type. Input values to the carbon pools table are in units of Mega grams per hectare.

An estimation of aboveground carbon stocks for the Puget Sound urban region was performed by Hutyra et al.(2011). This resource provided a majority of the surface carbon input data required to run the Carbon model. The Hutyra study involved intensive field data collection along transects radiating from the urban center. Data was collected from a fixed range of elevations using fixed radius plots along three transect lines. Sample plots were divided into three sections based on distance from the city center and it was attempted to locate equal numbers of plots on each land cover type within each section. This produced a gradient of carbon stored in each land cover type across a range of urban densities.

Soil carbon values by land cover were taken from the USDA Rapid Assessment of U.S. Soil Carbon (RaCA). The RaCA is a lower resolution study than that of the Hutyra study. Soil carbon values are aggregated to eighteen regions across the conterminous United States. Region one is curtailed to soil types and land use specifications of Washington and northern Oregon. For each region the RaCA analysis determines stored carbon densities in the top 1 meter of soil for a variety of general land cover categories (USDA 2013). From the six categories of land cover type described in the RaCA, the soil carbon values for all of the non-urban landscapes used in our analysis were determined. It was more difficult to locate soil data for urban land cover types. We extrapolated values by comparing from a study performed in the Jilin province of China (Zhu 2011). We compared ratios of soil carbon measurements between

urban areas and land cover types for which we had accurate localized soil carbon data from the RaCA, e.g. grassland. We used this ratio to estimate soil carbon concentrations for urban land cover types within the Snohomish Basin study area.

The model combined soil and surface carbon values and interpolated values of stored carbon for each input raster cell by land cover type. The output from the Carbon storage and sequestration model is a single raster dataset which represents the amount of carbon stored in Mega grams per pixel, and is shown in Figure 2 below. The raster was carried into the analysis as variable #1.
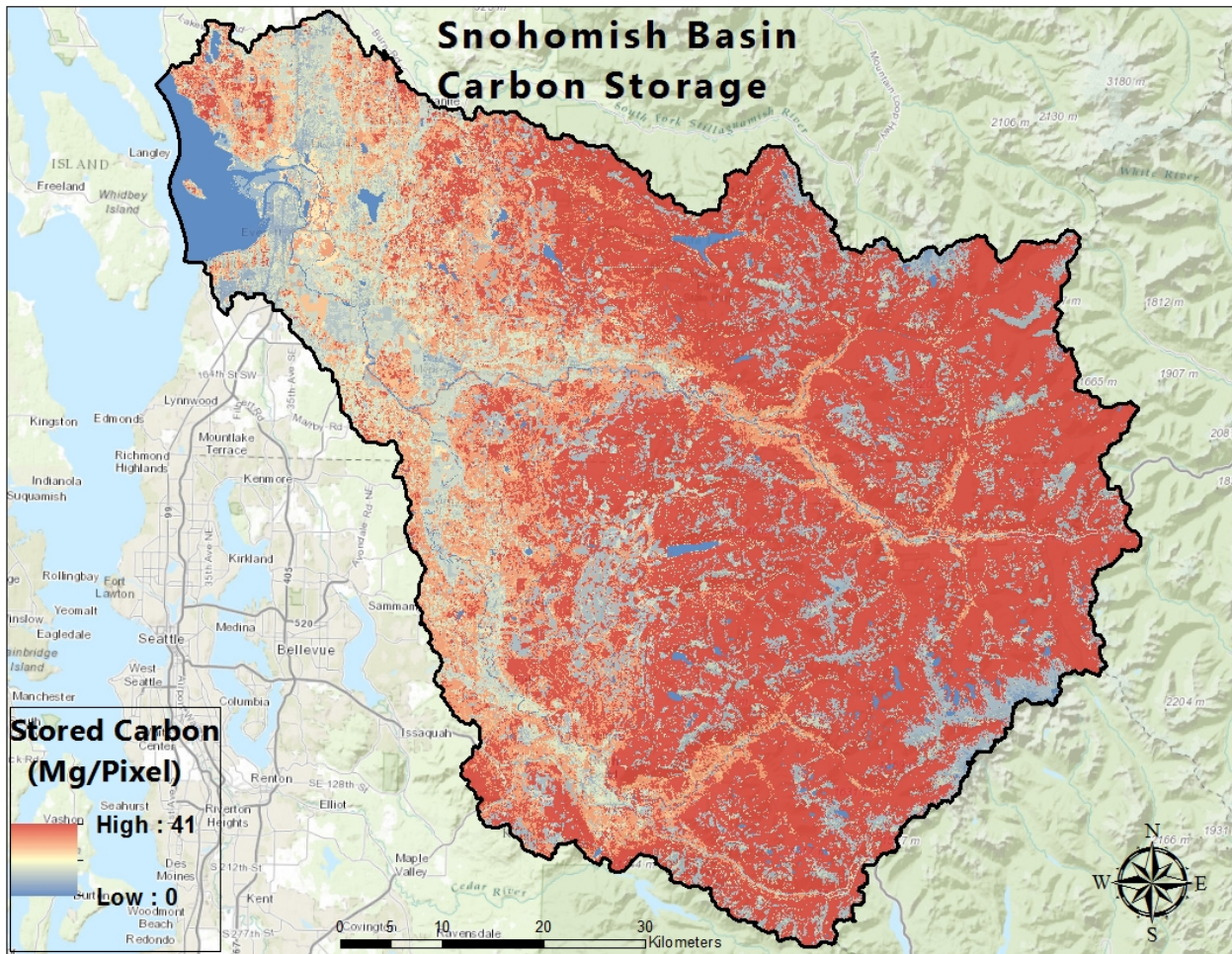
Figure 2: Regulating Ecosystem Services Represented by Carbon Storage

3.3 Nutrient Retention Model

The InVEST Nutrient Retention model estimates contribution of vegetation and soils to purifying water through the removal of nutrient pollutants from runoff (Sharp 2015). This is an essential provisioning service fundamental to most ecosystems. The model has two components: 1) the biophysical tool, which is actually the model's main tool, uses data from water yield, land use and land cover, nutrient loading and filtration rates and water quality standards to determine the nutrient retention capacity for current land use scenarios; while 2) the economic tool uses data on water treatment costs and a discount rate to determine the value contributed by the ecosystem to water purification. Since we had decided valuation analysis was outside the scope of our project, the second component of the model was ignored by not providing any of its necessary inputs (note: this did not affect execution of the biophysical tool).

Specifically, the model calculates the amount of nutrient retained on every pixel in a raster, the amount of nutrient exported on every pixel, and sums retention and export amounts per watershed (Sharp 2015). As a reminder, a raster is a data model for defining space in terms of an array of equally sized cells arranged in a grid pattern. Each cell contains an attribute value and has a spatial reference, and is also referred to as a pixel because it defines the raster resolution. For this study, we were interested only in the raster outputs of the model, therefore the results showing the distribution of nutrient retention and export per watershed, presented in vector format, were ignored. While water quality may be impacted by a large number of nutrients depending on the degree of urbanization and the amount of land converted to human use (such as agriculture), for the sake of simplicity the InVEST model calculates only the effects of nitrogen (N) and phosphorus (P) loadings in the area of interest. In order to execute the model and obtain the necessary metrics, a significant number of data inputs needed to be prepared. These inputs, along with their format and sources of acquisition, are summarized in Table 2 below. The full details on the sources are presented in the Bibliography section.

Data Requirement	Format	Source	Status
DEM (digital elevation model)	Raster	National Elevation Dataset (from The National Map)	Acquired & processed
LULC (land use land cover)	Raster	NLCD 2011	Acquired & processed
PRECIP (precipitation)	Raster	WorldClim	Acquired & processed
EVT (evapotranspiration)	Raster	CGIAR-CSI	Acquired & processed
RRLD (root-restricting layer depth)	Raster	Penn State SIEMEM	Acquired & processed
PAWC (plant available water content)	Raster	Penn State SIEMEM	Acquired & processed
Watersheds	Shapefile	Watershed Boundary Dataset	Acquired
Biophysical Table	CSV file	Liu (2010), InVEST Model	Generated
Threshold Flow Accumulation Value	Numeric	InVEST Model	Used Default Value
Water Purification Threshold Table	CSV file	InVEST Model	Generated
Seasonality Constant	Numeric	InVEST Model	Used Default Value

Table 2: Summary of required inputs for the InVEST Nutrient Retention model

A discussion of each of the required inputs is necessary in order to provide an understanding of the challenges presented by this particular InVEST model.

Digital Elevation Model (DEM)

A DEM refers to a raster dataset that contains an elevation value for each cell or pixel, in meters above sea level. The DEM is a critical input of the Nutrient Retention model, because it is used to calculate water flow and direction, as well as pollutant runoff (Sharp 2015). Therefore, the DEM needs to be acquired at the highest quality possible for the study area and it must accurately represent the hydrologic network for the area. For our project, we sourced our data from the National Elevation Dataset (NED), which represents the standard for the entire United States (USGS 2015-1). Data were acquired at 1/3 arc-second (approximately 10 meters) resolution. As it happened, the Snohomish Basin spans four separate NED grids, so additional processing steps included application of the 'Mosaic to Raster' tool in ArcGIS to assemble a single raster containing all the grids, followed by clipping this raster to the extent of the study area. Finally, the DEM needed to be corrected by filling in sinks, which refer to individual cells or sets of spatially connected cells whose flow direction cannot be assigned one of eight valid values in a flow direction raster (ESRI ArcGIS Help 2015). We used the 'Fill Sinks' tool in ArcGIS to complete this task.

Land Use/Land Cover (LULC)

The LULC is the other critical input of the model, as the calculation of nutrient retention and export is determined by the biophysical processes occurring over different types of land cover. Since we had already prepared a current land cover raster using data sourced from National Land Cover Database (NLCD), we used this dataset as our LULC input to the model. As a reminder, the NLCD product was generated using 2011 Landsat satellite surveys (updated in 2014) and has a 16-class land cover classification scheme applied consistently across the conterminous United States at a resolution of 30 meters (MRLC 2015).

Precipitation (PRECIP)

The InVEST model requires a raster quantifying the average annual precipitation values, in millimeters, for each pixel (Sharp 2015). These data were obtained from the Global Climate Data at WorldClim.org online database, generated and maintained by the Museum of Vertebrate Zoology at the University of California - Berkeley (Hijmans 2005). The data were clipped to the study area extent.

Evapotranspiration (EVT)

EVT measures the potential loss of water from soil through the processes of evaporation from the soil and transpiration by plants, provided sufficient water is available (Sharp 2015). For the InVEST model, evapotranspiration rates must be presented in millimeters per pixel in raster format. We obtained the data from the Global Soil Water Balance Geospatial Database, maintained by the CGIAR Consortium for Spatial Information (Trabuco 2010). The data were clipped to the study area extent.

Root-Restricting Layer Depth (RRLD)

RRLD refers to the soil depth at which plant root penetration is strongly inhibited because of the soil's physical or chemical characteristics (Sharp 2015). Depth values must be presented in millimeters per pixel in raster format. The data were obtained from the Soil Information for Environmental Modeling and Ecosystem Management (SIEMEM) database, maintained by the Earth System Science Center at the Pennsylvania State University (Miller 1998). Because the original files were sourced in an older ArcInfo interchange format, conversion to ESRI GRID raster dataset was implemented using the 'Import from E00' tool in ArcGIS.

Plant Available Water Content (PAWC)

PAWC is the fraction of water that can be stored in the soil profile and can be made available for plant use (Sharp 2015). These data were also obtained from the Penn State SIEMEM database, and the same conversion was needed to get them into the GRID raster dataset format. Since the input values needed to be represented in percent fractions, the 'Raster Calculator' ArcGIS tool was used to divide the original values by 100.

Watersheds

A vector layer of watersheds, to be input as a polygon shapefile, is required by the InVEST model in order to create points of interest where water quality is analyzed (Sharp 2015). The hydrology of watersheds and that of the DEM must correspond in order for results to be accurate. The watershed shapefile was extracted from the Watershed Boundary Dataset adapted by the Washington Department of Ecology for the entire state (DOE 2015). The national Watershed Boundary Dataset product "defines the areal extent of surface water drainage to a point, accounting for all land and surface areas," where hierarchical hydrologic units establish a baseline drainage boundary framework. (USGS 2015-2). Each unit in the watershed layer needed to be assigned a unique value in the *ws_id* field, which we did by applying the Field Calculator function. There were a total of 84 units in the layer, so the range of values was 1-84.

Biophysical Table

Presented as a .csv file, this table contained information on water quality coefficients used by the biophysical tool in the model (Sharp 2015). The table is based on the LULC classifications, which in our case was 16 classes. For each LULC class, we defined values for the following attributes: 1) *lucode* (matched to the codes in the LULC raster); 2) *lulc_desc* (description of LULC class, matched to descriptions in the LULC raster); 3) *root_depth* (defined only for vegetated classes); 4) *Kc* (plant evapotranspiration coefficient - based on Liu (2010)); 5) *load* (nutrient loading coefficients for both N and P - used default values from the model documentation for lack of time to thoroughly research each LULC class); 6) *eff* (removal efficiency coefficients defined by the vegetation type for both N and P - used default values from model documentation).

Threshold Flow Accumulation Value

This is a user-defined integer value necessary to generate a stream layer from the DEM. The value defines the number of upstream cells that must flow into an individual cell before it is considered to be part of the stream (Sharp 2015). We used the default of 1000 because there was no time to research the input in the context of the hydrologic network for the study area, as recommended in the model documentation.

Water Purification Threshold Table

Also in the .csv file format, this table contained threshold information for the annual nutrient load at each of the points of interest (Sharp 2015). Because the points of interest are defined by the watersheds, the table must contain a column identical to *ws_id* field in the watershed layer, so that the model can join the two inputs during execution. Threshold values for both N and P were generated for all 84 watersheds.

Seasonality Constant

Ranging from 1-20, this value corresponds to the seasonal distribution of precipitation across the study area (Sharp 2015). We used the model default of 5 due to insufficient time to research regional precipitation in more detail.

Once all eleven required data inputs were available, the inputs were calibrated in a few preliminary runs of the model. Errors related to the rasters not being in pre-defined and corresponding projections, as well as errors related to the raster value type (floating point instead of integer), were addressed following the calibration runs. Finally, the model completed successfully following a full execution with a total duration of 2 hours and 40 minutes.

There were five final outputs from the InVEST Nutrient Retention model. For both N and P, the model generated rasters in geoTIFF format for retention and export values respectively, in units of kilogram per pixel. The model also created a shapefile which aggregated the results per

watershed. As mentioned in the beginning of this section, these results, even though they represented some interesting information such as a runoff index and retention, export and annual allowed load amounts for each nutrient, were ultimately not of use to us as the data were available at the watershed level and not at the pixel level.

The four output rasters needed to be combined so as to create two measurements, one for N and one for P, which would then be carried into the analysis as variables #2 and #3. Following the setup used by Blumstein and Thompson, we used the 'Raster Calculator' tool in ArcGIS to divide retention values by export values, which created a new metric that we referred to as 'purification,' for lack of a better term. Blumstein and Thompson called their result "annual average loading," but we assumed the goal is to determine what washes off into streams (export) in relation to what is absorbed by the landscape (retention), and thus quantify the net amount of nutrient captured by the landscape of the study area. With this in mind, we think the term purification more accurately explains the results of the InVEST model.

However, the calculation of the purification metric created values with very high orders of magnitude for both nutrients. We speculated that this was due to the fact that retention and export are in effect opposite processes, which creates an inverse relationship between their measurements. Therefore, a pixel that has a high retention value would have a low export value, and vice versa. When we calculated purification by taking the ratio of the InVEST model outputs, high retention values were most likely divided by really small export values, resulting in huge numbers. For the purposes of being able to use reasonable values in the analysis, we addressed this issue by removing the orders of magnitude via division to 1×10^{35} using the 'Raster Calculator' tool. The rasters for Nitrogen Purification (variable #2) and Phosphorus Purification (variable #3) that entered the analysis are shown in Figure 3 below.
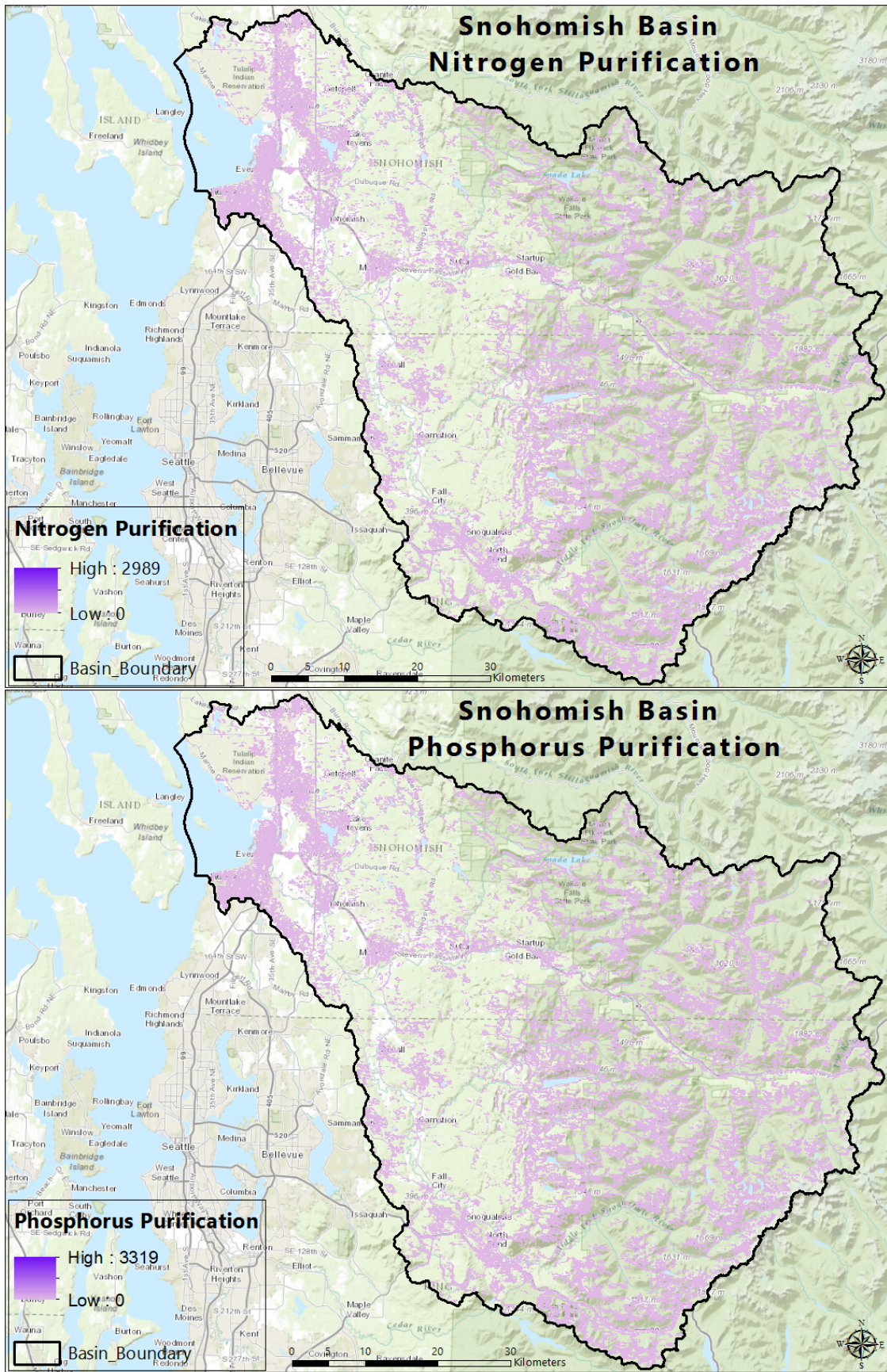
Figure 3: Provisioning Ecosystem Services Represented by Nitrogen and Phosphorus Purification

3.4 Habitat Quality Model

The InVEST Habitat Quality model contributed variables #4 and #5 to our analysis. The primary outputs from this model include a habitat degradation raster and a habitat quality raster, both of which were carried into the analysis. An optional output metric associated with multiple timeframes referred to as habitat rarity was omitted because we decided to use a single temporal scale in our project. The InVEST model requires the following inputs: a current land cover raster, a table listing present threats to habitat along with their range and intensity of impact, a table describing the sensitivity of each land cover type to each threat, and a constant value, referred to as the half-saturation constant, which determines the "spread and central tendency of habitat quality scores" (Sharp 2015). We incorporated an optional vector format input of areas with long-term legal and institutional protection of existing habitat. For this 'Accessibility to Threats' shapefile, we considered the protections provided to designated forest lands, wilderness areas, and wetlands.

For the current land cover dataset we used the NLCD 2011 raster which provides 30-meter pixel resolution. The metrics used to represent habitat quality and degradation were based on the threats listed in the 'Threats' input table. The pixel values in the rasters were calculated using three attributes from the 'Threats' table: 1) maximum impact distance; 2) relative weight of each threat; and 3) threat decay rate, combined with the relative sensitivity of each habitat, by land cover type, to each of the threats.

Designation of habitat and non-habitat of each land cover type, as well as each habitat's sensitivity to individual threats were listed the 'Sensitivity' input table. We simplified assumptions so that all habitats had equal suitability, meaning that sensitivities were based on habitats rather than be dynamically weighted to represent sensitivities of individual species with the habitats. Land use types considered habitat were given a score of 1, with all other land use types, such as developed urban areas and areas of barren rock and perennial snow/ice receiving a score of 0. Evaluating the relative sensitivity of habitat types to threats began by identifying the component hazards to habitat associated with each threat raster. We then grouped habitat types into subgroups based on their ecological similarities e.g., developed, light fuels, forest and wetland. We developed a generalized sensitivity matrix comparing the relative impacts of the component hazards of each threat to the habitat subgroups. Individual habitat sensitivities were then specified by varying the rankings of the subgroups slightly to reflect sensitivities of habitat types to degradation by specific hazards associated with each threat. The model default sensitivity values were used as a basis for establishing the general distribution of sensitivity values across the various habitat land covers.

Our processing included the use of polygon data representing areas in which habitats are less accessible to threats than the rest of the study area due to legal or institutional

protection. The features in each habitat protection layer were dissolved into a single feature polygon for that layer; the single-feature polygons were then merged into one feature class. Each protection type was than assigned a threat access weight between 0 and 1, based on the level of protection provided to the given resource designation. For example, an area that intersected an access polygon with an access weight of 0.5 would be assigned a degradation value half that of a comparable cell outside of the access polygon.

For our model we considered widespread threats that are commonly associated with major habitat quality degradation within the region. The four hazards used as in the input were urban growth areas, agricultural areas, roads, and current forest practices applications. Each threat was assigned a distance at which pixels are impacted by the given threat, a constant factor between 0 and 1 that determines the relative amount of influence that each threat has on each pixel with respect to other threats, and the rate at which the influence decays over distance, either linearly or exponentially (Sharp 2015).

Urban growth areas (UGAs) are regions of land that are intended for or undergoing land use conversion from low intensity use, e.g., residential, agricultural, or forest land, to more urban uses. Urbanization is associated with a host of attributes that contribute to habitat fragmentation, resource quality degradation, and overall loss of biodiversity (WDFW 2015). Urban growth areas were assigned a relatively large range of influence, 8 kilometers, with a low impact weight, 0.5, and a linear impact decay rate. The justification for these inputs was that UGAs are a vague, geo-institutional threat. The actual sources of habitat degradation and fragmentation may exist anywhere within an UGA. The resolution of this threat data was far more course than the overall analysis so the diminished threat weight reflects that we did not want to assume any given cell would suffer great impacts from this threat, as details pertaining to specific urbanization activities within the threat data layer were unavailable. Urban growth areas are generally associated with expansion of development in and around urban areas, so it was assumed that some amount of habitat disturbance will occur sporadically for a significant distance around these areas.

Agricultural areas were also assumed to have a linearly decaying threat rate over their range of impact. Agricultural operations are one of the most commonly recognized factors in deteriorated water quality. Surface flows are diminished and temperatures are increased by irrigation diversion, and agricultural operations are associated with the release of a host of nonpoint source pollutants including nutrients, sediments and pathogens (EPA 2014). Agricultural activities result in relatively severe and widespread impacts on water quality and associated habitats. This threat was assigned a maximum influence distance of 10 kilometers, largest of all threats being considered, with an impact weight of 0.7.

Roadways are a pervasive source of habitat degradation in most developed areas. Roads are often directly responsible for the fragmentation of habitats and migration routes. Fragmentation leads to the fragmentation of species populations and loss of genetic diversity. The potential for roadkill makes areas around roadways inherently poor habitat for most animals. The accessibility of roadways makes the surrounding area far more susceptible to anthropogenic damage. Finally, impervious road surfaces collect pollution that is discharged into the surface water during precipitation events (Findlay 2000). The degradation and fragmentation effects of roadways are mostly localized nearby to the road as all the threats except for runoff are associated with the physical location of the road. The maximum distance we determined roads to impact habitat was 5 kilometers with an impact weight of 0.6. The localized impact was modeled by giving roadways an exponential rate of impact decay.

The final hazard that was modeled in this analysis was current forest practice applications (FPAs). FPAs are applications to the state government for permits to alter forest land. These applications often involve timber harvest, road construction, forest conversion, and chemical application. Similar to roadways, FPAs are responsible for fragmenting habitat and displacing populations. While not being as widespread of a threat to habitat as roads, FPAs often involve far more traumatic disturbance to the area being permitted and the adjacent habitat. For our model, FPAs were assigned a 5-kilometer range of impact with the highest weight of 1. The threat potential of forest practice applications decayed exponentially.

The degradation raster was the primary output. It quantified the amount of cumulative degradation experienced by each pixel from all threats. Using the model defaults, land cover categories that were designated as non-habitat would receive a score of 0 for both degradation and quality. To more accurately model habitat degradation, areas that were labeled as non-habitat due to high levels of development were reclassified to equate the maximum degradation value calculated for the entire study area. In doing so, we removed the areas of negligible degradation from the urban cores that are inconsistent with the surrounding area, creating a smoother gradient of degradation from maximum at the urban centers to zero in areas where habitat value is naturally close to 0, such as perennial snow/ice and barren rock. The last step involved the application of a formula to invert the range of values using the 'Raster Calculator' tool in ArcGIS. By doing so, low values represented low habitat quality values and vice versa, making this measurement consistent with the other ecosystem service metrics.

The secondary output from the Habitat Quality model is the habitat quality raster. This raster was an extrapolation from the degradation raster. The raster was calculated as the inverse of the degradation scores with the inclusion of a half-concentration constant, which determines the rate at which quality increases or decreases in relation to degradation. The processed rasters

are displayed in Figure 4 below and were carried into the analysis as variables #4 for Inverse Degradation and #5 for Habitat Quality.

The difference between the degradation raster and the quality raster, besides being inversed coming out of the model, is that the quality raster represents areas of low degradation as having increasing quality scores with respect to degradation. The result of the above equation is that areas of significantly low degradation are represented by exceptionally high habitat quality values. We interpreted this output as a proxy for habitat connectivity on a small scale. Contiguous areas of low degradation values provide patches of quality habitat that are less impacted by fragmentation and edge effects.

The biodiversity metrics obtained from this model were limited to the current time period due to our time and modeling constraints. Future expansion upon this analysis should include predictive modeling of future habitat quality and degradation potential. Using the InVEST Habitat Quality model to generate future scenarios requires a baseline land cover layer and a future land cover data layer. It also involves modeling future threats by making assumptions about what those threats would be or where they would operate. Producing future threat data may be a more in-depth and substantive process involving localized land use plans and institutional agendas, and unfortunately this was determined to fall outside of the scope of our project.
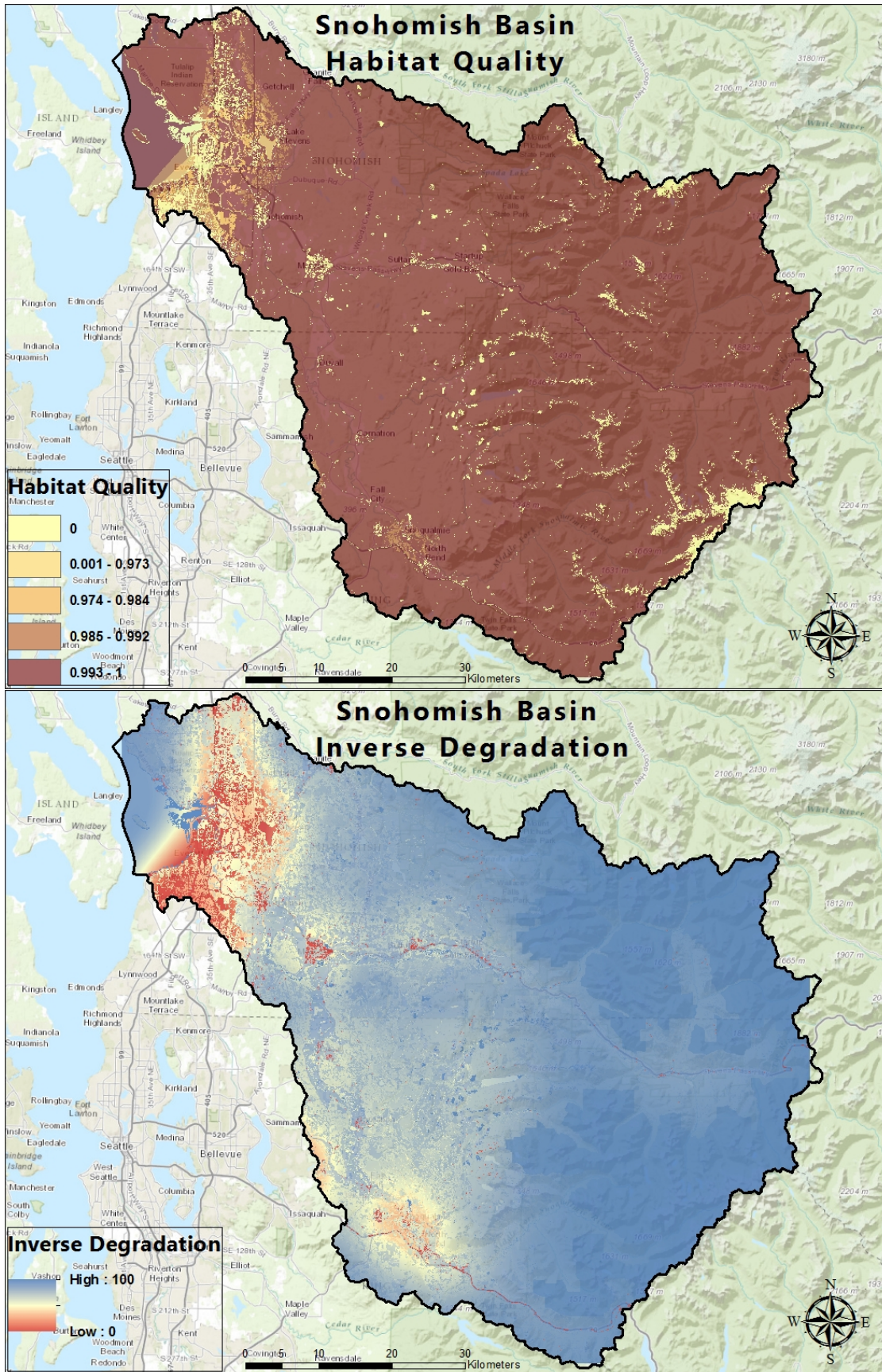
Figure 4: Biodiversity Represented by Habitat Quality and Inverse Degradation

In their analysis section, Blumstein and Thompson (2015) employed scripts in the R statistical environment to generate results in two steps. In Step 1, they calculated pairwise Spearman's correlation coefficients between all their eight variables in order to uncover and address any effects of spatial autocorrelation. To clarify, in the context of both Blumstein and Thompson's study and our own, "variables" refer to the raster values per pixel for each of the metrics calculated to quantify a particular ecosystem service. Because Blumstein and Thompson used a total of eight variables, testing for spatial autocorrelation is a sound way to ensure that each variable contributes unique information to the overall analysis. Unfortunately, due to our project timeline as well as our choice of tools (ArcGIS vs. R), we could not devote the time to replicate their cross-correlation matrix as applicable to our five variables. In addition, ArcGIS does not offer the necessary spatial statistics tools to be able to apply advanced techniques like pairwise Spearman's correlations for multiple rasters. In order to attempt a Spearman's correlation calculation, it would have been necessary to export raster values to tabular format, then import those data into the statistical program SPSS and conduct the analysis there. Since some of the rasters had millions of values, the tabular data would have resulted in enormous file sizes that could have created major operating issues in SPSS in addition to storage and transfer issues. Therefore, we decided to skip testing for autocorrelation in this project, but we would like to stress the importance of doing this in future studies where many variables are included.

For their Step 2, Blumstein and Thompson identified the values that fell in the top 20th percentile of all values for each of their eight variables. Since every value is the attribute of a specific pixel, the pixels for which the values are in the top 20th percentile were rated as high value pixels. For each metric raster, these high value pixels were coded to 1 while all other pixels were coded to 0. Finally, Blumstein and Thompson summed the reclassified pixels across all eight rasters, and identified sites as "hot spots," "warm spots" and "cold spots" depending on the range of the summed pixels. For example, a range of 5-8 would indicate a hot spot as at least five ecosystem services would be found to cluster at these particular sites. Our methods for calculating the high value pixels differed from those of Blumstein and Thompson, but once we had identified those pixels, we used the same idea of summing the recoded values across all rasters and using defined ranges of aggregated values to identify areas where ecosystem service intensity is high, medium or low rather than to know exactly where clustering of services occurs.

As a reminder, the five variables entering our analysis were: 1) Stored Carbon; 2) Nitrogen Purification; 3) Phosphorus Purification; 4) Inverse Degradation; and 5) Habitat Quality. The first step in the analysis was to standardize each variable by converting its values to z-scores. Z-scores are dimensionless quantities obtained by subtracting the mean of the distribution from each individual value and then dividing the difference by the distribution's standard deviation. In general, z-scores are considered to be useful statistics because they enable the comparison of two or more scores that are from different distributions.

Unfortunately, interpretation of z-scores is predicated upon the assumption that the original values are normally distributed, which was not the case with any of our five variables. The distributions for the variables, particularly for Nitrogen Purification and Phosphorus Purification, had very small means and very large maxima - several orders of magnitude greater than the means. As a result, the distribution of the z-scores also turned out highly skewed, with some extremely large positive values.

The purpose for standardizing a variable to z-scores is to determine the probability that an individual score occurs within the normal distribution. Probabilities are determined by the distances from the mean in terms of standard deviations. Since our z-scores were not normally distributed, we realized that interpretation of the scores in terms of probabilities would not provide any useful results. We therefore decided to establish cutoff points for what would become ecosystem service intensity categories at the quartiles of the z-score distributions. Thus, for each variable, the z-scores would be distributed either in the 25th, 50th or 75th percentile for the entire dataset. Note that this is completely different from Blumstein and Thompson's approach, which essentially took only the top 20% percent of their values and disregarded the remaining 80%. We further decided to assign specific codes for each ecosystem service intensity categories, as follows: 0 for low intensity, 1 for medium intensity and 2 for high intensity.

The project workflow diagram in Appendix A provides a good visual representation of the execution of our analysis. The 'Raster Calculator' tool in ArcGIS was used to calculate the z-scores for each of the five variables. Following the aforementioned decisions regarding interpretation of the z-scores, the 'Reclassify' tool in ArcGIS was run to recode all z-scores in each variable to just three possible values: Scores falling between the minimum and the first quartile (25th percentile) were assigned a value of 0; scores falling in the interquartile range (between the 25th and 75th percentiles) were assigned a value of 1; while scores falling in the third quartile (between the 75th percentile and the maximum) were assigned a value of 2. We settled on this reclassification scheme under the assumption that scores in the interquartile range are more likely to represent just the 'average' performance of the respective ecosystem service metric, while scores in the first or third quartiles are the results which would really allow for meaningful interpretation of the intensity of ecosystem services across our study area.

At the completion of these actions, we were left with five rasters, in which each pixel had a possible value of only 0, 1 or 2. The last step in the analysis was to execute the 'Raster Calculator' tool again and sum the reclassified pixels across all five rasters. Doing so produced one raster with a possible range of 0-6 for its values. To establish correspondence with our reclassification scheme, the following groupings were established to represent the ecosystem service intensity categories: Values from 0-1 indicate low intensity; values from 2-4 indicate medium intensity; and values from 5-6 indicate high intensity. This raster is the final product of our analysis, and is referenced extensively in the following sections, Results and Discussion.

4. Results

Figure 5 below shows the final raster produced by our analysis within the boundary of Snohomish Basin, produced at 30-meter resolution. We will refer to this as the ecosystem services intensity raster. Pixels with values representing high, medium and low service intensity were determined by using the quartile classification method described above in the Analysis subsection. Summing these pixels across all five variables resulted in a range of values from 0-6. Figure 5 displays the spatial distribution of summed values in Snohomish Basin. We note that low intensity pixels are colored red, medium intensity pixels are colored blue and high intensity pixels are colored green. The ranges of values corresponding to the colors are 0-1 for red, 2-4 for blue and 5-6 for green.
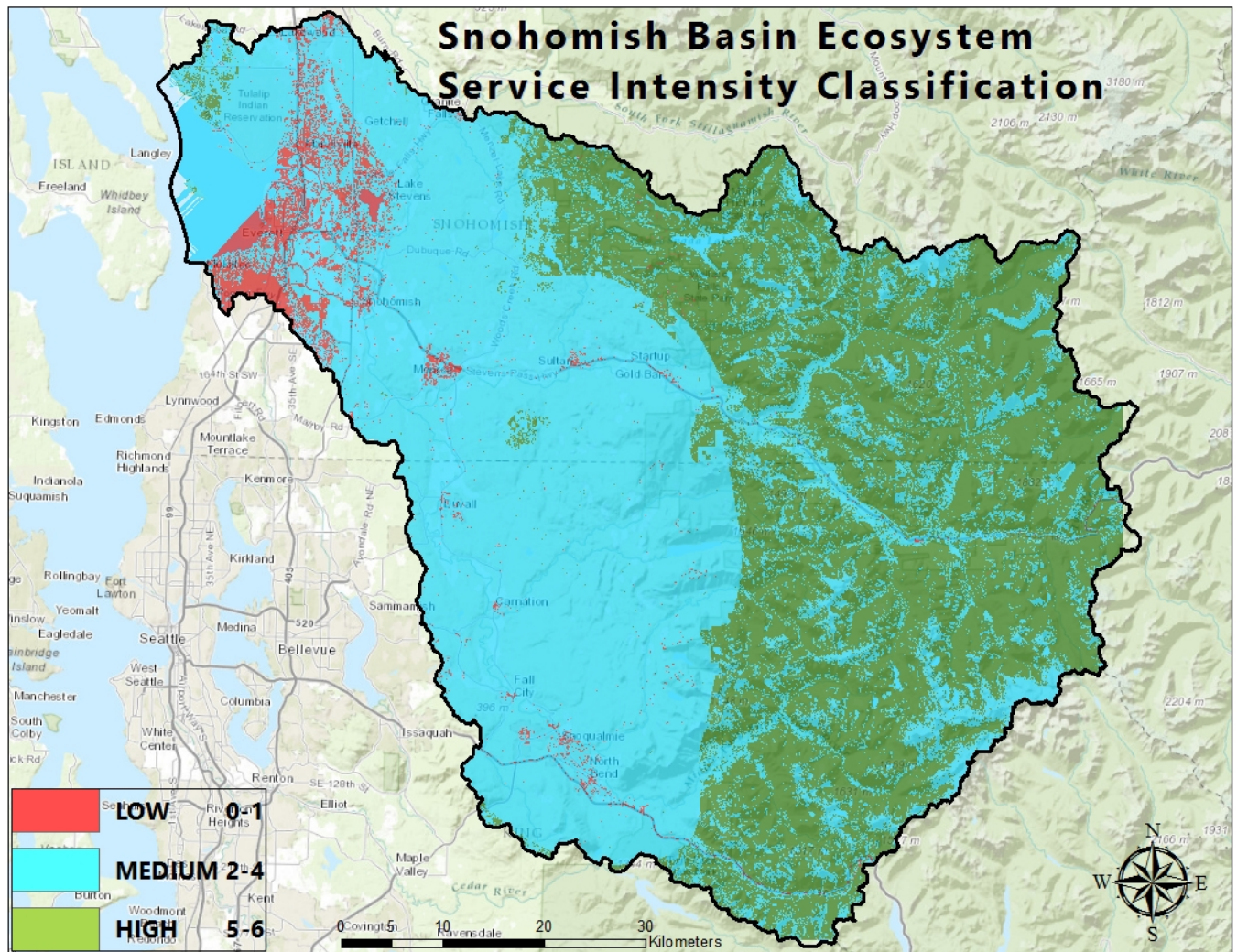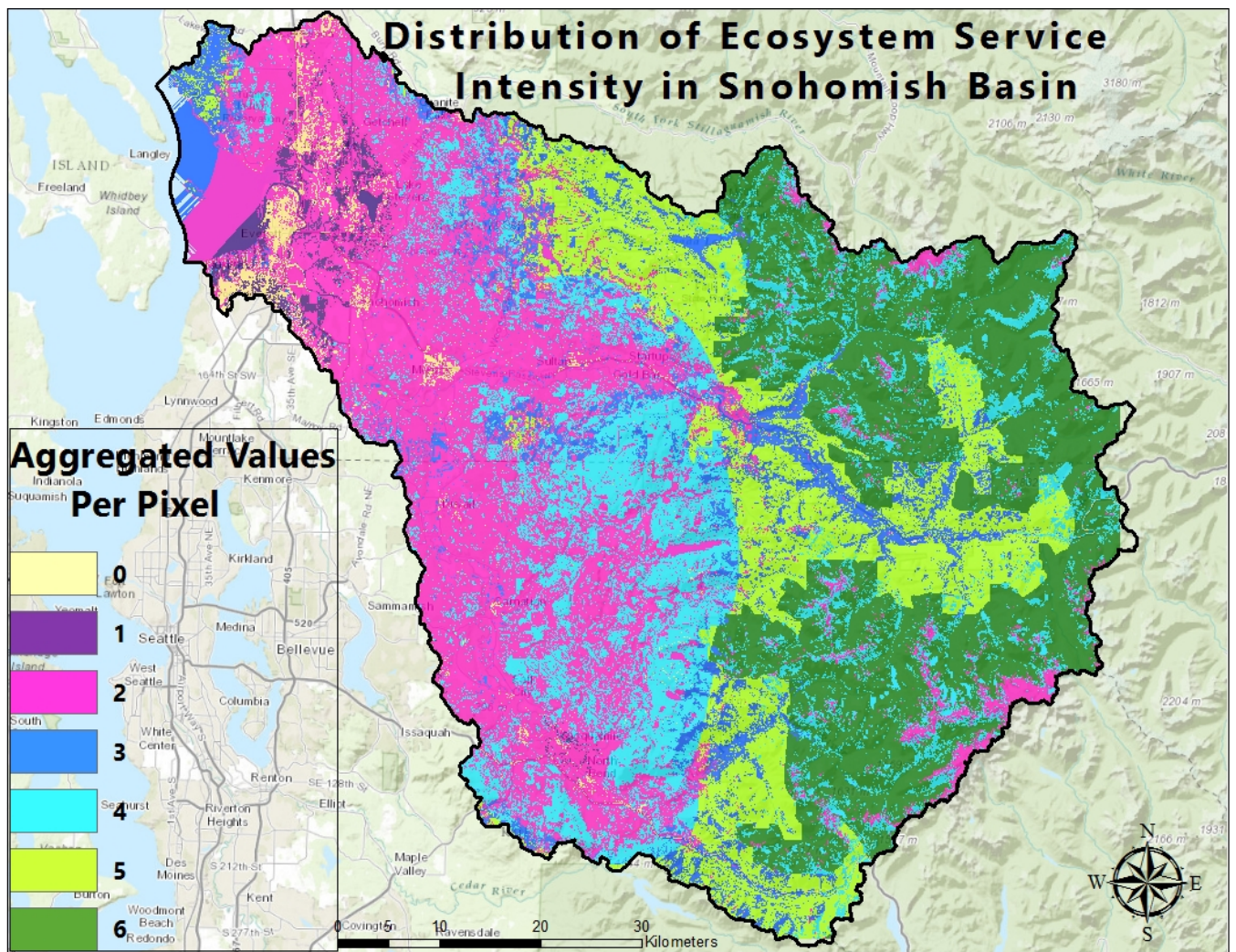

Figure 5: Ecosystem Services Intensity Raster for Snohomish Basin

It must be mentioned that the reclassification scheme discussed in the analysis should have produced a range of sums from 0-10. This means that if a pixel was coded to a value of 2 in each variable, its maximum score across all five rasters would have had to be 10. However, the results of our analysis indicate that the maximum summed value is 6, thus forcing us to admit

that we were unable to identify any pixels displaying high intensity for <u>every</u> ecosystem service metric under consideration. Upon investigation of the distribution of values for each raster, we can conclude with reasonable certainty that the two variables not contributing enough high intensity pixels are Nitrogen Purification and Phosphorus Purification respectively. The distributions of these variables revealed very few values (only about 100 for each nutrient) that recoded to 2; in addition, it is possible that the pixels with '2' values for Nitrogen and Phosphorus did not have the same code for all the other variables. We presume this is the main reason as to why we failed to obtain any summed values higher than 6.

In light of this issue, we needed to adapt the intensity category ranking to the actual range of summed values produced by the analysis. Our decision was to assume that values of 0-1 represent low intensity, 2-4 represent medium intensity and 5-6 represent high intensity. The ecosystem services intensity raster can be displayed in a slightly different way. In Figure 6 below, we show the spatial distribution of the pixels assigned one of the possible summed values between 0 and 6. Each value was given a different color to emphasize contrast with other values. The map reveals a prevalence of '2' values in the western side of Snohomish Basin and of '6' values in the eastern side, with the most of the '3', '4' and '5' values in the middle. Values of '0' and '1' are predominantly in the top northwestern corner, which is where most of the urbanization in the study areas is located.

Figure 6: Spatial Distribution of Ecosystem Service Intensities across Snohomish Basin

5. Discussion

Referring back to Figure 6, we note once again that most of the pixels in the ecosystem services intensity rasters have values of either '2' or '6', with each value dominating the western and eastern sides respectively of Snohomish Basin. '2' pixels are concentrated along the lower part of the Snohomish River watershed, and extend all the way into the urbanized areas near Puget Sound where the river meets the ocean. Interestingly enough, these values are also found along the extreme eastern and northern edges of the study area, interspersed with '6' pixels. In terms of overall numbers, '5' pixels are most numerous after the values mentioned so far, followed by the '4' and '3' pixels. '0' and '1' pixels are found mostly in the northwest corner of Snohomish Basin, especially where extensive development has occurred - like within the area occupied by the city of Everett. Overall, it appears that there is a gradient from west to east, with lower values per pixel (and consequently less intense ecosystem service occurrence) in urban areas near Puget Sound, while higher values (corresponding to more intense ecosystem service occurrence) in undeveloped and protected areas higher in elevation toward the Cascade Mountains.

It is consistent with our expectations that there exists a strong correlation between certain land use classification values and the resulting trends in ecosystem service intensity values. Each of the models used to create final input for the study included the 2011 NLCD dataset. A great variety of data was included in the process of producing our results. The land cover classification values were the key which tied all of the input data to our modeling and data processing operations. Figure 7 below shows the land use and land cover classifications for the Snohomish Basin.
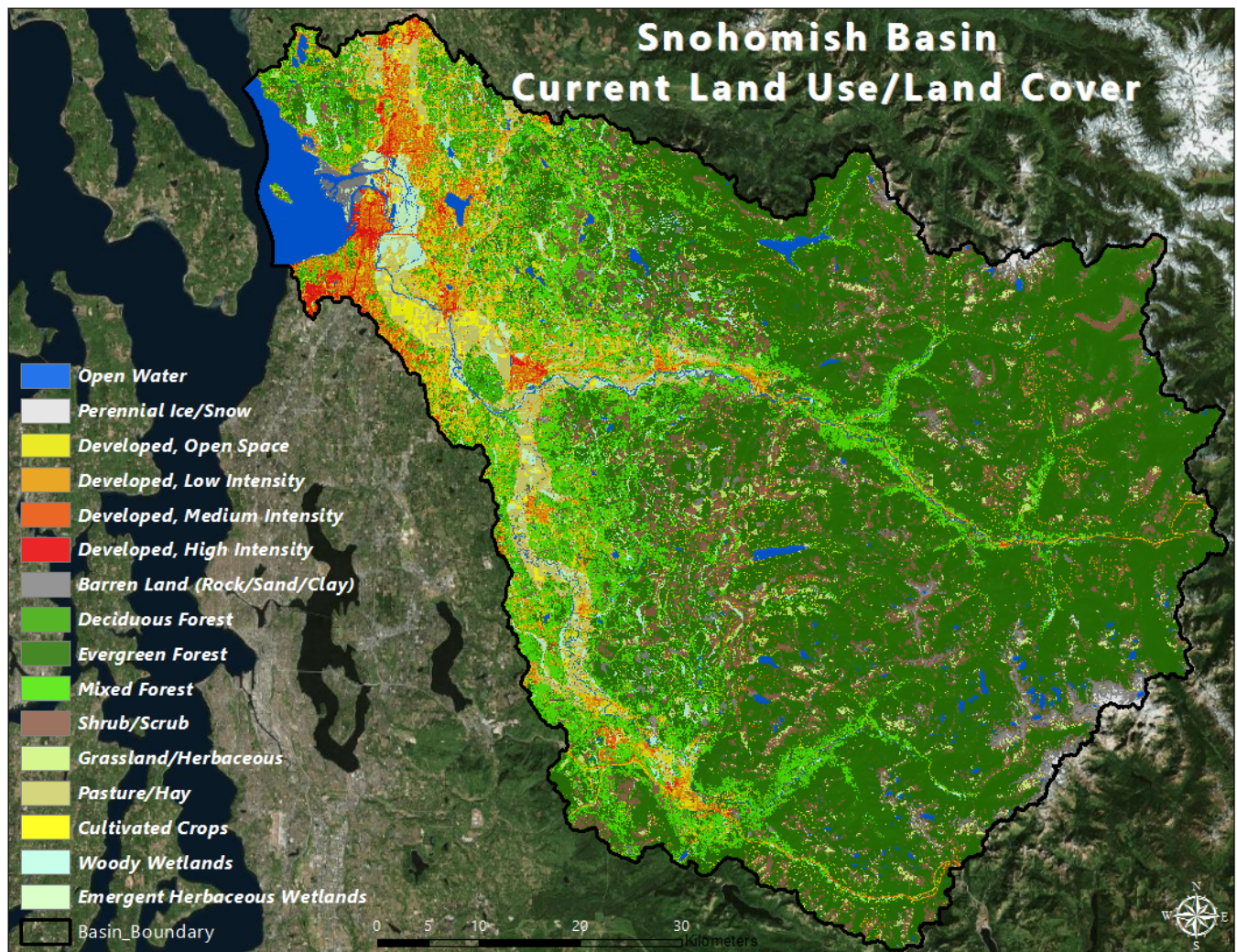
Figure 7: Current Land Use/Land Cover in Snohomish Basin (Source: 2011 NLCD)

Prior to aggregating the project output into the final three intensity classifications, low, medium and high, clear trends were visible between urban land use and ecosystem service intensity. Development related land use coverage and urban related hazards, specifically roads, are ubiquitously related to areas of medium to low ecosystem service intensity. Roadway corridors involving the overlap of 'roads' threats and developed open space that are surrounded by areas of high ecosystem service values generally associate with an ecosystem service intensity value of '3'. Areas classified as having forested land cover were ranked as having a value '5' to '6' for ecosystem service intensity depending if the forested area falls within an institutionally protected area such as wilderness or designated forest land.

The areas associated with the lowest value of ecosystem service intensity are strictly related to heavy urban land cover. The aforementioned, heavily urbanized, northwest quarter of the study area is the only region that contained ecosystem service values of '0' and '1'. The heavily urbanized areas are closely associated with multiple threats and few institutional protection mechanisms. Within this urbanized landscape there are a number of areas that stand

out as having greater ecosystem service value than their surroundings. These areas are consistently related with patches of evergreen forest within the urbanized areas of Snohomish watershed and are represented as having an ecosystem service value of 1-2 rankings higher than the surrounding pixels which are non-forested.

Similarly, areas of unusually low ecosystem service value exist in the heavily forested southeastern half of Snohomish Basin. Areas of shrub and scrub land use type are associated with ecosystem service values between '2' and '4'. These values are significantly lower than their immediate surrounding of evergreen land cover, which are generally ranked with the highest classification of service value, '6'. Another outlier of ecosystem service value in this area are rock and ice land cover type. These areas are associated with ecosystem service values of '2' which are still higher than heavily urbanized land cover but are naturally drastically lower than that of the surrounding forest land cover.
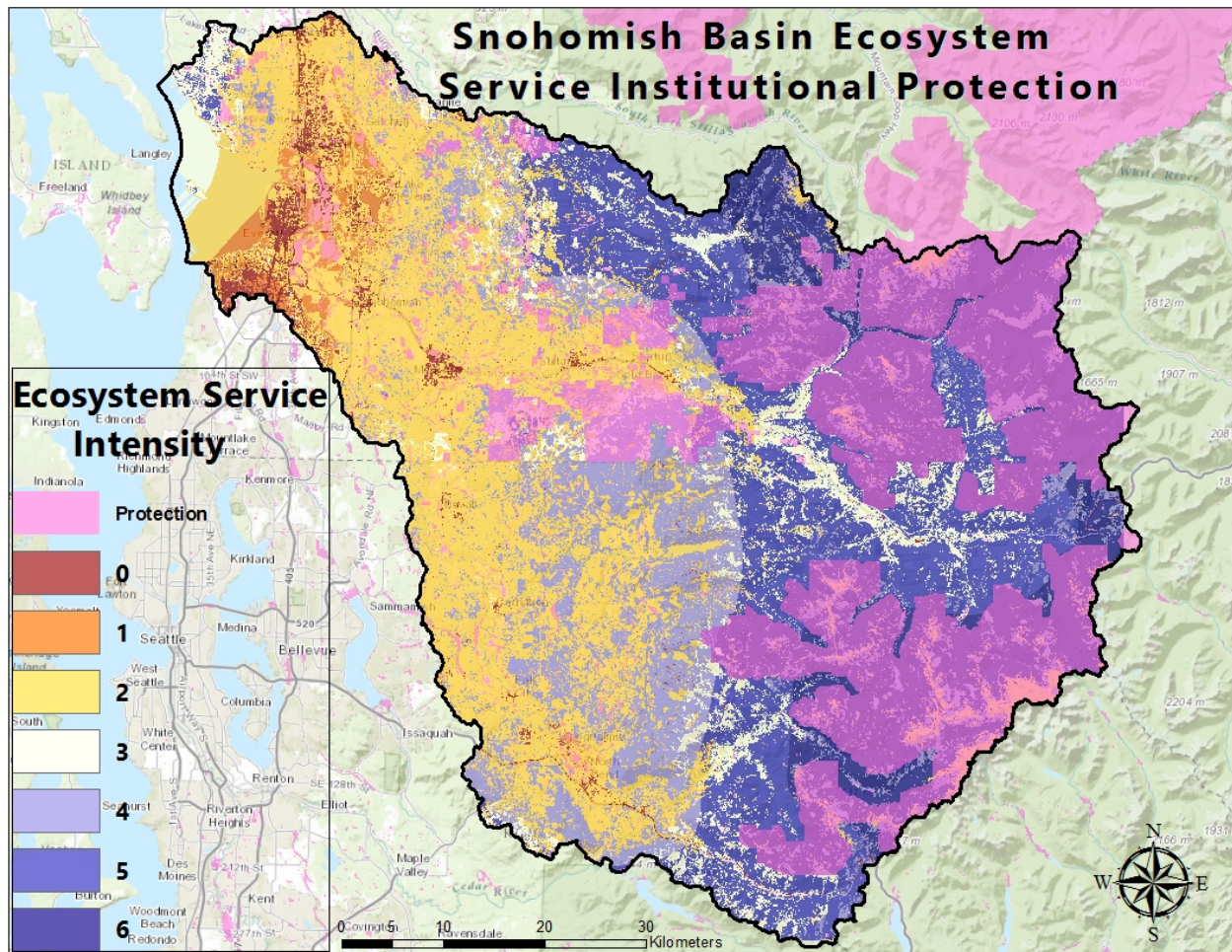
Figure 8: Ecosystem Service Intensities and Protected Lands in Snohomish Basin

Further aggregate interpretation of our results was done at lower scales using analysis units and sub watersheds. The general trend in ecosystem service distribution at the pixel scale is strongly correlated to land cover type. 42% of all pixels designated as one of the three urban

land cover types are clustered within three sub watersheds at the northwest edge of WRIA 7 along the Puget Sound. Two of these three sub watersheds are designated by this analysis as having very sparse ecosystem services. They are the only terrestrial sub watersheds which scored the lowest rank of 0 in the analysis, at the sub watershed resolution. Similarly, the three sub watersheds that scored highest in terms of ecosystem service intensity had relatively low amounts of urban land cover. The sub watersheds with the highest ecosystem service intensity had only slightly less than average urban coverage, between 0.16 and 0.30 standard deviations below the mean, but contained only 1.6% of the total urban land cover across all three sub watersheds. The maps showing the correlation between ecosystem service intensity and land cover are presented in Figure 9 below.
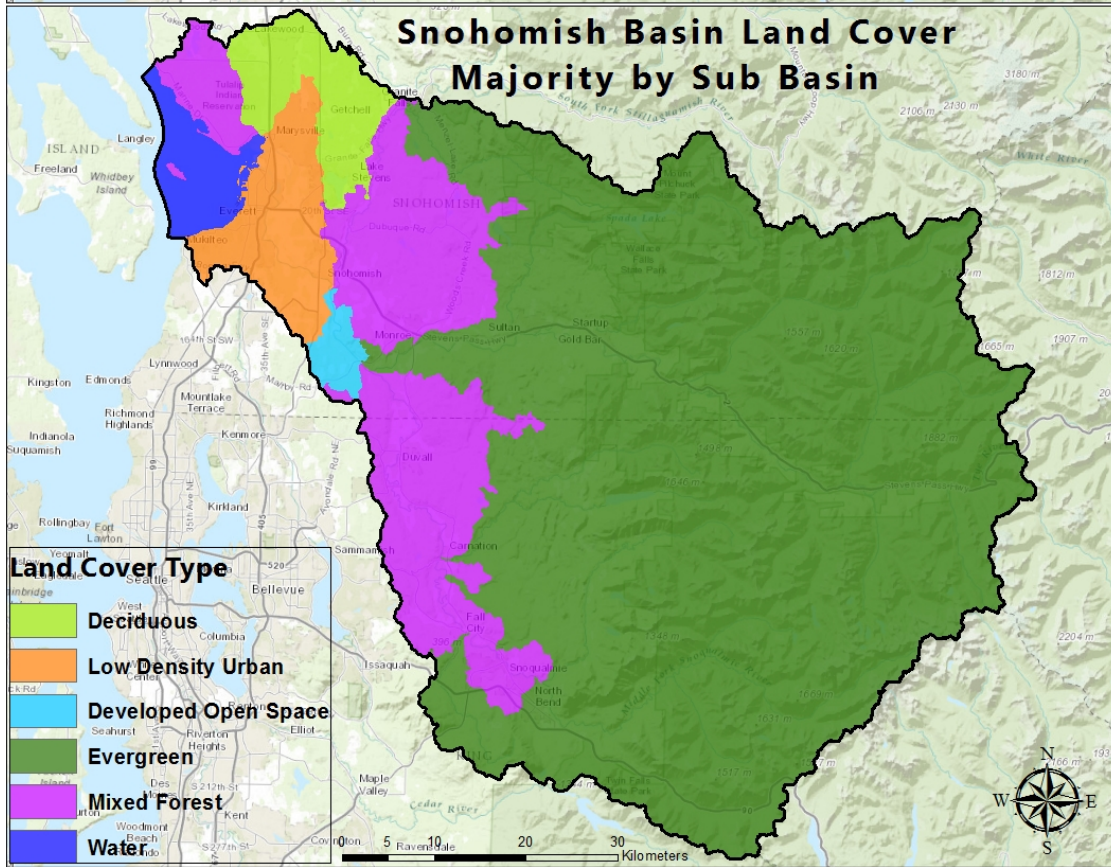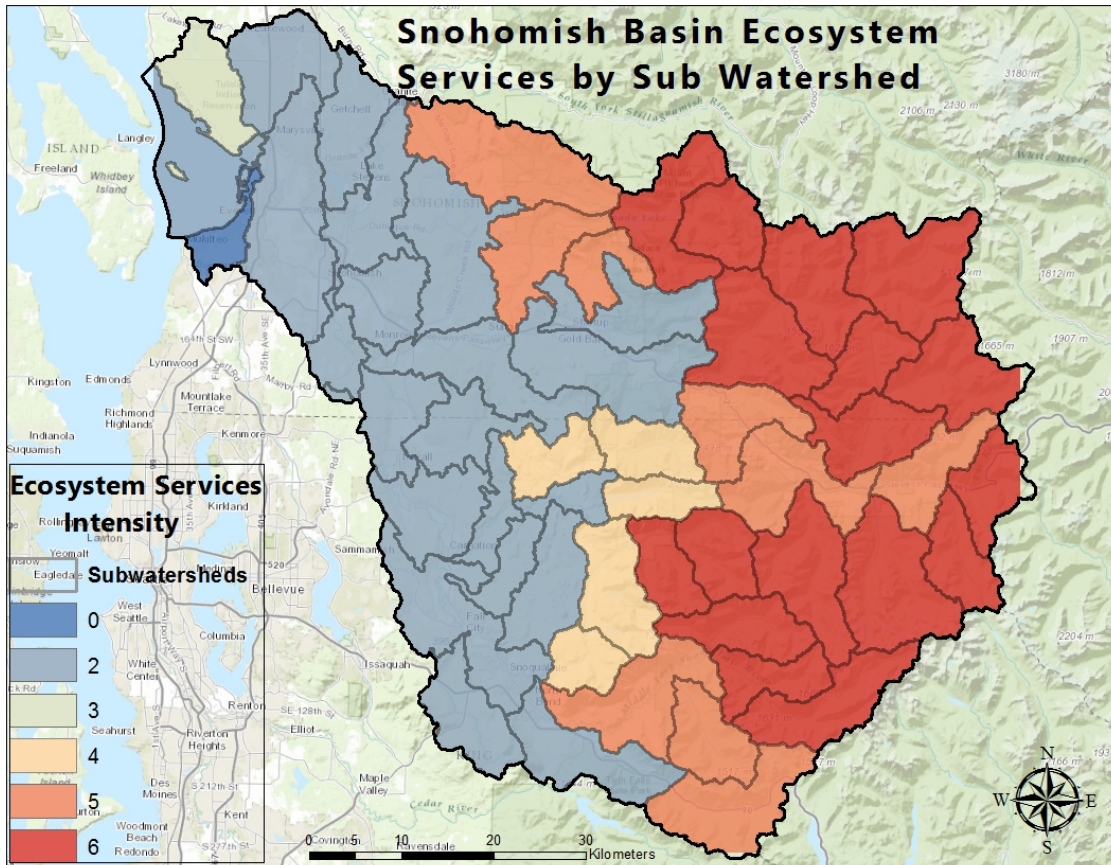
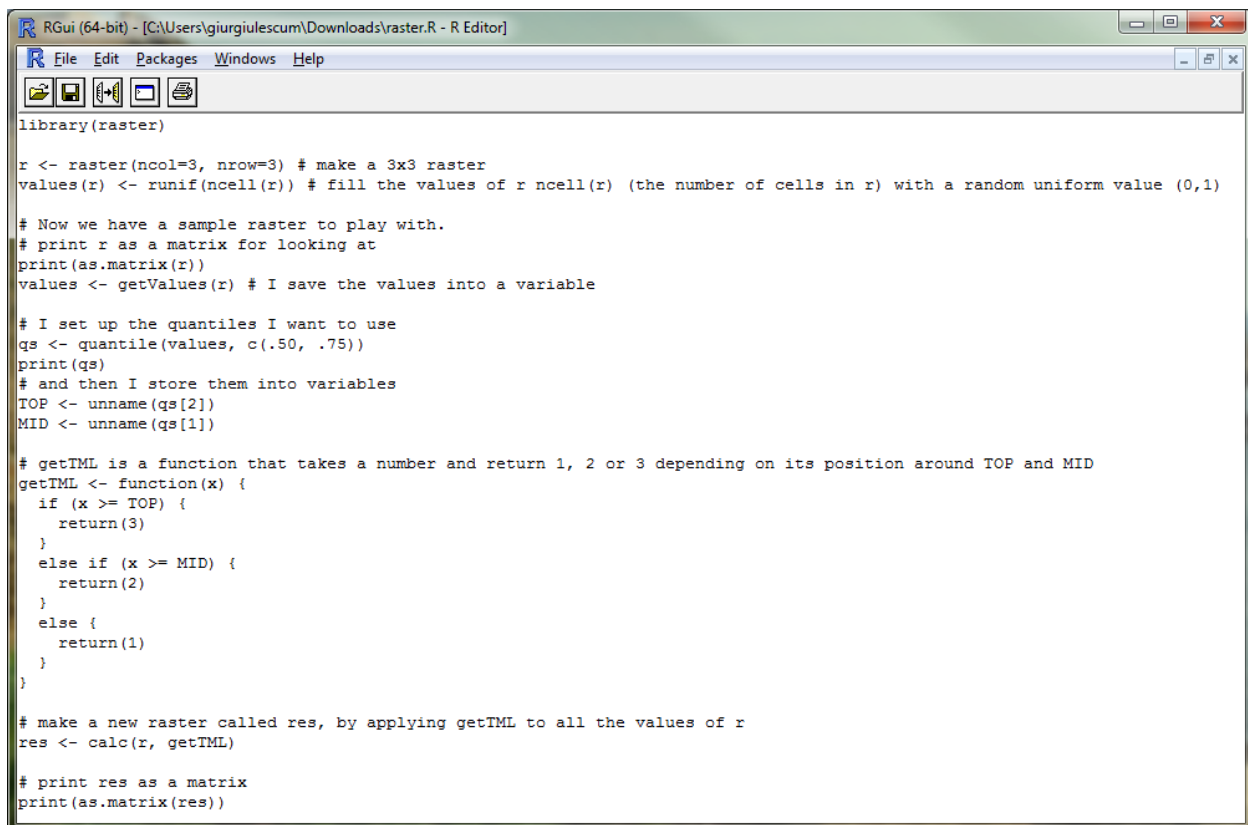**Figure 9**: Ecosystem Service Intensity and Land Cover Correlation at the Sub-Watershed Scale

6. Implementation

As much as we hoped for practical application in an organizational context, we understand that at this point our project's utility is for proof-of-concept only. Because it lacks rigorous implementation of statistical methods to validate key steps in the analysis, the framework we employed should be considered just a prototype that can serve as the foundation for a significantly more involved future research effort into quantifying and mapping the overlap of ecosystem services. This is not to say our work here was entirely useless. We strongly believe that the methods proposed by Blumstein and Thompson in their study of the configuration of ecosystem services in the state of Massachusetts can be adapted to fit study areas ranging from regional to local scales, and we attempted to show how such an adaptation would be undertaken at the watershed level in rapidly urbanizing environments like the Puget Sound region. We specifically recommend the ideas of:

- Putting metrics for regulating, provisioning and cultural services in raster format, in which pixel values represent individual measurements for each metric;
- Devising a statistical strategy for classifying the pixels in each raster into groups according to their position in the overall distribution of values - for example, a classification scheme with cutoff points at specific percentiles for the raw scores or at specific standard deviation distances from the mean for z-scores if the original distribution is standardized;
- Coding all the classified pixels into a small number of new values (e.g., 0-1-2) according to the group to which they were assigned; and
- Summing the recoded pixels across all the rasters to generate a single final raster in which the location and intensity of ecosystem services is interpreted in terms of the range of summed values, with higher values showing the effects of large ecosystem service co-occurrences.

We also recognize that the analysis could benefit greatly from automation of the tasks to be performed using a scripting language such as the R statistical environment. Indeed, Blumstein and Thompson used a collection of R scripts that allowed them to incorporate three spatial scales and three temporal scales in their study. While we would have liked to do the same, our ability to apply programming was restricted by the learning curve (neither group member had previous R experience) and by the project's timeframe. In the limited time we could to devote to getting familiar with R, we were able to write basic code creating, calculating and reclassifying values in a very simple raster. Figure 10 below shows the script. Based on this exercise, we can foresee the potential of R to take rasters with very large values, such as the millions of values in our input rasters, store these values into a user-defined variable, define the classification method (i.e., quantiles), take the values from the user-defined variable and save them into new variables according to the classification method, then employ a function to assign new codes to the variables defined by the quantiles. Essentially, this amounts to taking apart the raster, performing calculations on its original values, and reassembling it using the new

values. The only matter warranting attention is making sure each value maintains association with its corresponding pixel. R supposedly does this by storing the lower left corner coordinates of each cell when loading its value, however we have not had an opportunity to test the assumption on an actual raster. The appeal of R or other scripting languages like Python is that they can significantly reduce processing time for very large datasets (such as rasters with millions of values) by not having to burden the computer's memory with unnecessary information.

```
library(raster)

r <- raster(ncol=3, nrow=3) # make a 3x3 raster
values(r) <- runif(ncell(r)) # fill the values of r ncell(r) (the number of cells in r) with a random uniform value (0,1)

# Now we have a sample raster to play with.
# print r as a matrix for looking at
print(as.matrix(r))
values <- getValues(r) # I save the values into a variable

# I set up the quantiles I want to use
qs <- quantile(values, c(.50, .75))
print(qs)
# and then I store them into variables
TOP <- unname(qs[2])
MID <- unname(qs[1])

# getTML is a function that takes a number and return 1, 2 or 3 depending on its position around TOP and MID
getTML <- function(x) {
  if (x >= TOP) {
    return(3)
  }
  else if (x >= MID) {
    return(2)
  }
  else {
    return(1)
  }
}

# make a new raster called res, by applying getTML to all the values of r
res <- calc(r, getTML)

# print res as a matrix
print(as.matrix(res))
```

Figure 10: R Code for Creating, Calculating and Reclassifying Values in a Very Simple Raster

Results like the ones generated by this project could have limited application in initiatives such as the Watershed Open Space Strategies (WOSS) supported by ROSS. The goal of WOSS is to coordinate on-going work by agencies at the local, state and federal levels in order to provide science-based justification for attracting resources necessary to sustain open space conservation efforts (ROSS 2015). As the name implies, WOSS operate at a watershed scale, which rarely conforms to institutional or administrative boundaries, thus making cross-jurisdictional cooperation critical to success. On-going or completed WOSS projects in the Puyallup-White and the Green-Duwamish watersheds addressed issues of habitat restoration, resource allocation, pollution reduction, economic development and community involvement, among many others (ROSS 2015). While advisory work on the Snohomish WOSS, the area

considered in our project, is slated to begin in the winter of 2015, other watersheds like the Stillaguamish, Nisqually and Kitsap are still in planning stage while funding is being identified.

We believe that an analysis such as the one completed in this project may contribute to the WOSS efforts by generating a fast and inexpensive assessment of the occurrence of ecosystem services in a particular watershed. When presented in an easy to understand format like a map of intensity levels (with higher values corresponding to sites where multiple services are more intense), results of the assessment could aid fundraising, particularly in the private and non-profit sectors, by supporting a "quick pitch," so to speak, for the need to continue protecting areas of high values, as well as investing in restoration or conservation of areas of medium value that have the potential to become high value based on their positioning close to existing high value areas. Our project was completed in a timeframe of just four weeks with data freely available from a variety of sources; while we did have to generate the inputs for our analysis using specialized tools like the Natural Capital Project's InVEST models, these inputs can be obtained in other ways and not necessarily for the same metrics. The Puget Sound region has been extensively studied in terms of ecosystem services, and data are available to adapt the framework of this project to virtually any other watershed (or other sub-division) in the region. Ultimately, our goal has been to contribute to the greater ROSS vision of balancing community development and resource use with conservation of critical services and benefits provided by natural systems, such that the sustainability of these services is ensured for generations to come.

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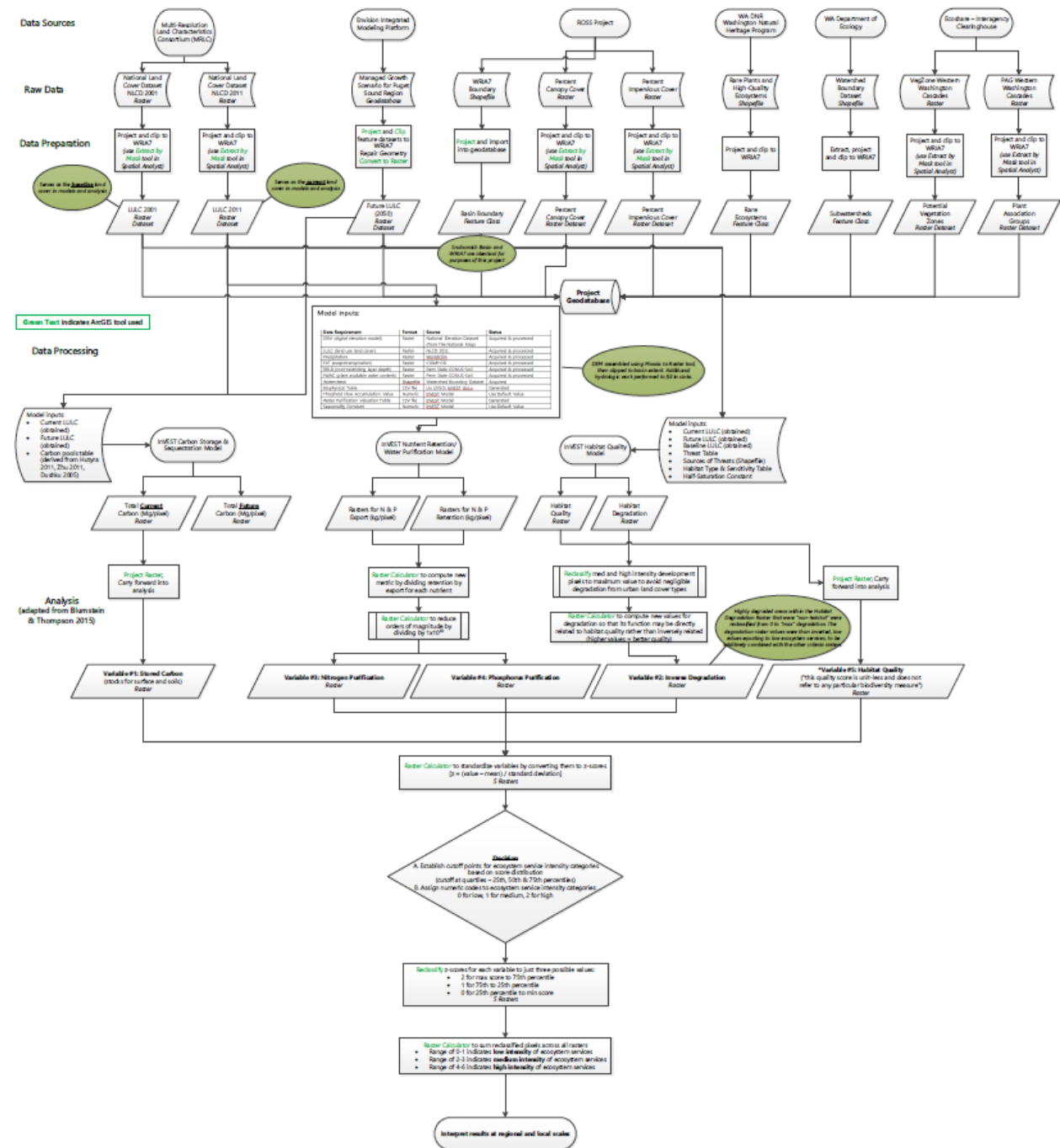
Appendix B – Land Use Classifications

Class Name	NLCD Value	Reclass Value
Open Water	11	13
Perennial Ice/Snow	12	14
Developed, Open Space	21	7
Developed, Low Intensity	22	6
Developed, Medium Intensity	23	5
Developed, High Intensity	24	4
Barren Land (Rock/Sand/Clay)	31	1
Deciduous Forest	41	3
Evergreen Forest	42	9
Mixed Forest	43	12
Shrub/Scrub	52	15
Grassland/Herbaceous	71	11
Pasture/Hay	81	10
Cultivated Crops	82	2
Woody Wetlands	90	16
Emergent Herbaceous Wetland	95	8