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Effects of Watershed Characteristics on Stream Vulnerability to Urbanization: Implications of Future Land Use on Streams in Maine, USA

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EFFECTS OF WATERSHED CHARACTERISTICS ON STREAM VULNERABILITY TO URBANIZATION: IMPLICATIONS OF FUTURE LAND USE ON STREAMS IN MAINE, USA

By

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THESIS ACCEPTANCE STATEMENT

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EFFECTS OF WATERSHED CHARACTERISTICS ON STREAM VULNERABILITY TO DEGRADATION: IMPLICATIONS FOR THE FUTURE OF STREAMS IN MAINE, USA

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Catchment urbanization has deleterious effects on freshwater resources and aquatic communities in small stream ecosystems. In the State of Maine, many streams have been negatively affected by urbanization and are in need of management and restoration. Impervious cover (IC), i.e., any surface that impedes water infiltration into the ground, can serve as a measure of watershed urbanization. Recent studies conducted in Maine have indicated that stream biotic community structure and function begin to decline at impervious cover levels of approximately 1 to 15%. This wide range presents a challenge to regulatory agencies and watershed managers charged with protecting stream

quality to avoid costly restoration efforts. In this research, we employed three statistical analyses to identify spatially-explicit watershed characteristics associated with climate, geology, and land use/land cover that affect stream vulnerability to urbanization. First, a Kruskal-Wallis one-way analysis of variance was used to discriminate watershed characteristics associated with macroinvertebrate and algal sample data classified into high and low vulnerability categories. Next, a logistic regression analysis was applied to predict attainment of stream regulatory standards based on macroinvertebrate and algal sample data combined with watershed biophysical parameters. Finally, a Bayesian network was developed to predict stream vulnerability to urbanization using an expert-informed model structure. Results from the three approaches identified a number of watershed parameters that are associated with the vulnerability of streams to impairment from urbanization stress. The Kruskal-Wallis analysis indicated that watersheds with higher amounts of well-draining soils, deeper water tables, and fewer wetlands are less likely to become impaired at a given value of IC. The logistic regression models provided evidence that watersheds with an intact riparian buffer, a shallow aquifer, soils resistant to erosion, few wetlands, and shallower soils are more likely to attain their regulatory standards and are thus less vulnerable to urbanization. The Bayesian network shared a number of similarities with the two statistical analyses in terms of important watershed parameters. Overall, results of the three analyses indicated that stream vulnerability tends to increase with a higher percentage of agriculture and wetlands in the watershed and to decrease with a higher percentage of forested or natural buffers and percent resistant surfaces in the watershed. The ultimate goal of this research was to identify specific streams that are at risk of becoming impaired by future development. This goal was achieved by integrating the results of the three-step vulnerability analysis with earlier work that created spatially-explicit development suitability indices for two major watersheds in Maine. Areas likely to face future degradation were identified as watersheds in the top quartile of vulnerability that coincide with areas highly suitable for development are likely to face future degradation. We highlighted the locations of these "at-risk" streams and provided resource managers and policy makes with a tool that can be used to prioritize and guide the protection of vulnerable streams in the Maine landscape.

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CHAPTER ONE:

STREAM VULNERABILITY IN A CHANGING LANDSCAPE — AN INTRODUCTION

According to the Maine Department of Environmental Protection (MEDEP), the term "impaired" refers to a stream that exhibits diminished capacity to support aquatic life consistent with a specific statutory water classification of AA, A, B, or C (MEDEP 2009). Thus, if a Class A stream is designated as impaired, it no longer supports the natural community of aquatic organisms expected for that stream category. With 2,300 miles of Maine streams and rivers classified by the U.S. EPA as 303(d) impaired status, the State is obligated by the 1972 Clean Water Act to restore these degraded waterways, despite the fact that restoration will cost millions of dollars. As an example, restoration of Long Creek in Portland, Maine, is projected to cost $14 million (FB Environmental Associates, 2009), and yet this is only one of the 30 federally-registered 303(d) urban-impaired streams in the state (Maine IC TMDL 2012).

The manifestations of stream impairment most commonly seen throughout the state are high nutrients and eutrophication, elevated *E. coli* fecal coliform, and biotic assemblages indicative of degradation (EPA 2010). These symptoms are associated with agricultural runoff, industrial discharge, municipal sewage, and urban stormwater runoff (EPA 2010). While point-source pollutants such as industrial discharge and municipal sewage can be minimized through regulation, agricultural and urban runoff are widespread nonpoint source pollutant stressors whose effects are more challenging to ameliorate. With increasing urbanization across the landscape, stream quality generally decreases when impervious cover (IC) – i.e., any surface such as a road, parking lot, or roof that impedes water infiltration into the soil – approaches or exceeds 10% of the area in a watershed (Schueler et al. 2009). In fact, Maine watersheds with IC values ≥ 6% have been shown to exhibit marked declines in aquatic insect diversity that are indicative of ecological degradation (Morse et al. 2006). Unfortunately, many of the available options for reducing contamination and stress associated with urbanization are impractical for widespread use due to political and economic constraints. As a result, it is in the interest of municipalities, public agencies, policy makers, and land owners to develop a more proactive approach to sustaining aquatic resources by identifying streams that are most at-risk of becoming impaired in the future and targeting these waterways as priorities for conservation protection and/or smart growth land-use planning strategies.

We envision that the next generation of impaired streams in Maine will include those that experience future development in their watersheds in combination with watershed characteristics that are associated with low resistance or high vulnerability to degradation from land-use changes. "Resistance" can be defined as the ability of an ecosystem to maintain structure and function in response to increasing stressors. Several watershed characteristics have been shown to contribute to stream resistance. For example, the presence of wetlands has been associated with a decrease in nutrients, toxins, and sediments entering streams (Johnston et al. 1990, Jordan et al. 2011, Marton et al. 2014); calcareous bedrock in a watershed increases acid neutralizing capacity (ANC) in streams and prevents acidification (Sullivan et al. 2007, USGS 1989); and shallow slopes decrease the flashy flows associated with impervious cover by allowing better water infiltration and groundwater recharge.

Conversely, some features in a landscape may make streams more vulnerable to degradation. “Vulnerability” is defined by Turner et al. (2003b) as “the degree to which a system, subsystem, or system component is likely to experience harm due to exposure to a hazard, either a perturbation or stress/stressor.” For example, urbanization of former agricultural lands causes a smaller change in species richness (i.e., lower vulnerability) compared with urbanization of forests, because degradation has already occurred on the former farmlands (Cuffney et al. 2011). Based on these and other studies, it can be hypothesized that whereas streams are generally adversely affected by stressors associated with urbanization in a watershed, the vulnerability of streams to urbanization varies as a function of differing watershed and environmental characteristics.

In this investigation, statistical and modeling approaches were used to explore the relationships between spatially-explicit landscape characteristics and metrics of stream biotic integrity in order to predict which Maine streams are more likely to become degraded due to future development in the watershed. Previous research efforts aimed at predicting the potential vulnerability, resistance, resilience, or sensitivity of streams have included: (1) studies using expert opinion to define vulnerability based on channel characteristics (Besaw et al. 2009); (2) ranking streams according to vulnerability to future climate change based on network connectivity and habitat heterogeneity (Anderson et al. 2013, McCluney et al. 2014); (3) examining factors associated with resistance and resilience to flooding in Oregon (Pearsons et al. 1992); and (4) observing effects of natural watershed disturbance such as fire on stream resistance and resilience (e.g., Vieira et al. 2004).

Cuffney et al. (2011) conducted one of the few studies focused on examining how landscape characteristics affect stream macroinvertebrate responses to urbanization. In a comparison of nine major watersheds in the U.S., they found that the condition of biotic assemblages degraded more rapidly per unit area of urbanization as mean annual precipitation increased in the watershed, and that the response of aquatic macroinvertebrates to urbanization was more sensitive to temperature, precipitation, and agriculture than was algal response.

The objectives of this research were to: (1) develop spatially-explicit models based on environmental data, stream biotic metrics, and expert knowledge in order to predict the potential vulnerability of streams in the Maine landscape to future urbanization stress; and (2) assess the spatial distribution of at-risk or vulnerable streams in relation to alternative futures modeling projections of areas in Maine that are most likely to experience future development pressures and urbanization stress (Meyer et al. 2014). In combination, these results are expected to provide a valuable tool for land use planners and watershed managers to use in prioritizing vulnerable streams for protection, developing sustainable management strategies to prevent degradation and loss of biotic integrity, and avoiding expensive restoration costs.

LITERATURE REVIEW

Effects of Catchment Attributes on Stream Condition

There is a large body of scientific literature that focuses on the causes of stream impairment and the interactions between landscape attributes and their effects on downstream water quality. Williams et al. (2004) examined a river basin in Massachusetts and found that nitrate, chloride, sulfate, and acid neutralizing capacity (ANC) had positive, mostly exponential relationships with increasing urban and agricultural area, while dissolved organic nitrogen (DON) and dissolved organic carbon (DOC) had positive, exponential relationships with increasing amount of wetlands and open water. In a study by Allan et al. (1997), there was a negative correlation between agricultural area and habitat quality and biotic integrity in a Midwestern catchment, while forested riparian area exhibited a positive correlation with those response variables. Sediment concentrations during low flows were higher in areas of greater agriculture. Their model indicated that an increase in forested land cover would result in dramatic declines in runoff, suspended sediment, and nutrient yields.

Strayer et al. (2003) used empirical models to evaluate the effects of land cover in the Mid-Atlantic region on nitrate, species richness of fish and macroinvertebrates, cover of aquatic plants, and riparian vegetation. Land cover, dam density and point-source pollution were the most significant variables in the model. Of the land cover variables, cultivated and urban land were associated with signs of degradation – e.g., high N, low fish species richness, high proportion of exotic fish, and low macroinvertebrate species richness — while wetlands, forest, and pastoral land were associated with desirable stream quality traits such as high fish species richness, low percentage of non-native fish, and low N. In contrast to results reported by Williams et al. (2004), they found that their predictive power was lower in smaller watersheds and that wetlands exhibited a negative relationship with total nitrogen.

In a study by Jones (2001), the amount of agriculture, riparian forests, and atmospheric nitrate deposition consistently explained a high proportion of the variation in model predictions of nitrogen, phosphorous and sediment in streams of the Mid-Atlantic states. Poff et al. (2006) assessed hydrologic change in response to land use across the U.S. With increasing urban area, peak flows increased, minimum flows increased in some regions and decreased in others, duration of near-bankfull flows declined, and flow variability increased. Response to agriculture was less pronounced, although minimum flow decreased, near-bankfull flows increased and flow variability declined. The effects of dams were largely consistent across regions, with a decrease in peak flows, an increase in minimum flows, an increase in near-bankfull flow durations, and a decrease in flow variability.

Wang et al. (2001) reported that urbanization in Wisconsin watersheds consistently caused degraded streams, whereas agricultural watersheds exhibited more variable responses. Forested stream riparian area, non-agricultural vegetated land, and open water/wetland cover were good predictors of stream condition and all increased stream quality.

Vander Laan et al. (2013) examined the effects of mining, agriculture, urbanization and hydrologic modification on in-stream stressors and biological condition in streams throughout Nevada. The stressors they addressed were total dissolved solids as measured by electrical conductivity, nutrient enrichment, trace-metal contamination and flow alteration. They reported that agricultural land area, mine density, and urban area in a watershed were the best predictors of stream biological condition. Measures of precipitation, elevation, and temperature best predicted arsenic levels, while urban area, precipitation, elevation, hydrologic stability scores and mine density predicted Cu and Zn.

It is apparent that across a broad range of conditions and regions, agriculture and urban areas have potentially large effects on many aspects of stream water quality and biotic integrity. As such, the strongest predictors of stream condition are often based on variables associated with agriculture, urban area, wetlands, and forests. Dams and mines have also proven to be important predictors in cases where they have been studied. Environmental variables such as elevation and annual precipitation have not been considered in many studies, which limits our ability to draw conclusions about the influence of these variables on stream conditions. This is problematic because some of the patterns that are attributed to land cover variables may be partially explained by spatial correlation with environmental or climatic variables. For example, in the State of Maine urban area is largely located in warmer regions. As a whole, previous studies indicate that although relationships between land cover and in-stream variables are dynamic and vary from region to region, anthropogenic impacts and stressors universally affect stream condition either directly through urban and agricultural runoff or indirectly through removal of forests and wetlands.

Effects of Catchment Urbanization on Water Quality

Many studies have exclusively looked at the effect of urban areas on stream water quality. Urbanization causes changes in the hydrology, chemistry and biology of stream ecosystems, with symptoms that include flashy hydrographs, elevated nutrients and contaminants, changes in channel geomorphology, reduced biotic richness, and higher levels of pollution-tolerant species (Walsh et al. 2005, Coles et al. 2012, Paul and Meyer 2001, Chadwick et al. 2006, Roy et al. 2005). The flashiness caused by IC in a watershed causes hydraulic disturbance to biota, channel incision and bank erosion. Even summer rain events of only a few millimeters can cause overland flow that transports chemicals and heated water to streams, causing stress to biota (Walsh et al. 2005).

The impervious cover model (ICM) was proposed by Schueler (1994) to describe the amount of degradation that occurs in a stream with increasing percent impervious cover in its watershed. This model is prescribed for first- through third-order streams with no point source pollution or dams in their watershed. In a meta-analysis of 65 recent papers studying impervious cover related to water quality, Schueler et al. (2009) found that 69% of studies confirmed or reinforced the ICM. The average threshold at which degradation was initially detected was 7% IC. Some researchers reported a secondary threshold around 20%, a level of IC at which most indicators declined.

In Maine, evidence suggests that stream water and habitat quality begin to decline at a threshold value of 6% IC in a catchment, with a marked decrease in species richness and intolerant taxa of aquatic insects beyond that value (Morse et al. 2003). Interestingly, Schueler et al. (2009) concluded that IC is not the best predictor of stream quality when it exceeds 10% of the watershed. Beyond 10%, forest cover, road density, or crop cover may have better predicting power. In addition, patterns of stream macroinvertebrate abundance can be variable at low levels of IC due to inter-site differences in nutrients and organic compounds (Wright 1995). Algal communities generally respond to increasing urbanization with an initial increase, followed by a decrease at higher levels of urban IC (Coles et al. 2012). Given the variability of results among studies of stream quality at low values of watershed IC, Schueler et al. (2009) proposed a new version of the ICM that takes the shape of a cone – i.e., at low values of IC, water quality indices vary substantially while at higher values of IC, water quality is universally poor. This conceptual approach implies that at low values of IC, some streams may be more resistant to degradation than others—a finding significant for this study.

In an exhaustive study of the physical, chemical and biological response of streams to increasing urban area in nine drainages associated with major U.S. metropolitan areas, Coles et al. (2012) found varying stream responses to urbanization. Nitrogen, chloride, insecticides and polycyclic aromatic hydrocarbons (PAHs) — compounds associated with incomplete combustion of gas — increased with urban development in most study regions. The increase in nutrients and herbicides was more limited in watersheds where predevelopment land cover was agriculture, as compared to forested catchments, due to higher initial ambient concentrations in the former. The rate of decline in the number of sensitive macroinvertebrates species was steeper in watersheds where predevelopment land cover type was forest versus agriculture or even grasslands, owing to the high sensitivity of macroinvertebrate assemblages in forested catchments. Pollution-sensitive diatoms typically were present at rural sites and decreased with urban development, implying that agriculture does not especially damage diatom assemblages. The most consistent geomorphic responses of streams to increasing urban area were changes in the size, shape, and sediment composition of channels. The study also found that chloride concentrations increased with increasing urban area in all nine study areas, even in warm areas and across all seasons, indicating that multiple factors besides road salt may be involved.

As a whole, previous studies indicate that as urban area or IC increases beyond a certain threshold, stream water quality declines. However, the rate of degradation and the IC threshold are variable, suggesting that differences in watershed or environmental characteristics may influence the rate of impairment, as well as the IC value at which observable impairment begins to occur.

Effects of Wetlands on Stream Water Quality

The National Wetlands Inventory of the U.S. Fish and Wildlife Service contains records for most wetlands in the United States. In this dataset, freshwater wetlands in Maine are grouped into three types: forested/shrub, emergent, and ponds (Table 1.1). Forested wetlands are the dominant wetland type in the state (87% of total wetland area), followed by emergent (10%) and ponds (3%). Altogether, wetlands comprise approximately 10% of the land area in Maine.

Table 1.1. Major wetland types in Maine. Table lists the acreage and percent of total land cover in the state by wetland type. From the National Wetlands Inventory (USFWS, 2014).

Wetland Type	Area (acres)	Percent of Total Land Cover	Percent of Total Freshwater Wetlands
Forested/Shrub	1,770,000	8%	87%
Emergent	206,000	0.9%	10%
Pond	58,000	0.2%	3%

Results from multiple studies indicate that the effect of wetlands on downstream water quality is variable. Johnston et al. (1990) indicated that stream proximity to wetlands was related to a decrease in inorganic suspended solids, fecal coliform, specific conductivity and nutrients. Yavitt et al. (2006), however, found that water flowing out of a small, in-stream wetland was only slightly higher in Na^+, NH_4^+ and ANC and slightly lower in H^+ and dissolved inorganic carbon (DIC) than water flowing into it; in comparison, Ca^{2+}, Mg^{2+}, K^+, organic Al, Cl^-, NO_3^-, SO_4^{2-} and SiO_2 were unchanged. In a review of wetlands worldwide, mean nitrogen removal efficiency was 47% overall and 25% for latitudes above 50 degrees (Jordan et al. 2011). Because of this, it is expected that wetlands within a watershed would tend to decrease nitrogen concentration in downstream waters. Indeed, many studies support the idea that wetlands are able to retain nutrients, especially N and P, and export DOC (Jordan et al. 2011, Marton et al. 2014, Bowden 1987, Saunders and Kalff 2001, Strayer et al. 2003). Yet in contrast, Gorham et al. (1998) found that streams draining catchments in Nova Scotia with greater than 50% wetlands had significantly higher total dissolved nitrogen, higher DOC, and lower pH. Fitzhugh et al. (1999) reported that wetlands retained sulfate, especially during the growing season, which led to increased ANC in downstream waters. In general, wetlands can affect nutrient concentrations, total suspended solids, pH, and ANC in downstream waters, but the direction and magnitude of change vary from region to region.

It is likely that there are environmental factors that influence whether wetlands have more or less of an effect on streamwater. For example, Walker et al. (2012) found flow-weighted slope (FWS) to be a better predictor of water chemistry than wetland type and total watershed area. Wetlands in areas with high FWS are narrower in width and thus water residence times are shorter as water moves more quickly through the system. Wetlands in areas with low FWS have the opportunity to exert more of an influence on water chemistry as water residence times are higher in shallow slopes, thereby decreasing dissolved oxygen, increasing temperatures and dissolved organic carbon, increasing the ratio of NH_4^+ to dissolved inorganic nitrogen, and lowering the ratios of dissolved inorganic nitrogen to total nitrogen and PO_4^{3-} to total phosphorous. Flow-weighted slope is a landscape characteristic that can be derived from remotely-sensed elevation data, and therefore is a useful metric for determining potential effects of wetlands at a landscape scale.

Influence of Riparian Forest Buffers on Stream Water Quality

Riparian forests are essential in maintaining the structure and function of stream ecosystems. For example, headwater streams with intact riparian forest cover benefit from subsidies of organic material from leaf-litter (Vannote 1980); maintain a consistent temperature as a result of shading from the forest canopy and the base flow of cool groundwater (Gregory et al. 1991); and are protected by riparian vegetation that prevents bank erosion as well as riparian soil that filters out sediments and nutrients (Peterjohn and Correll 1984). Weller et al. (1998) modeled riparian areas and found that wider forest buffers are more efficient in removing nutrients, and that buffers of variable width are less efficient because stream segments without sufficiently wide buffers allow large amounts of nutrients to enter the stream.

Other studies have shown that riparian buffers may have mixed effects on stream quality parameters. Hession et al. (2003) reported that forested riparian zones in urban catchments positively affected channel geomorphology, concentrations of bioavailable nutrients, and algal biomass. However, macroinvertebrates, fishes, and diatoms were better predicted by the urban density gradient than the riparian buffer variable. Steedman (1988) found that when comparing urban, forested, and riparian forest areas, only urban and forested area were reliable predictors of an index of biotic integrity (IBI). Furthermore, at high levels of IC, riparian forests no longer offset the damaging effects of urbanization (Schueler et al. 2009). The mitigating effects of riparian forests may be compromised in many cases by channel incision from erosion, a lower water table associated with impervious cover, and pollutants entering from the uplands through piped drainage (Walsch et al. 2005).

Agricultural Effects on Downstream Water Quality

Agriculture is the largest cause of stream impairment in the U.S. (USOTA 1995). Many studies have found that increases in agricultural cover in a watershed are associated with a decline in stream water quality, especially as a result of increased nutrients which can lead to eutrophication, declines in macroinvertebrate communities, and fish kills (e.g., Carpenter et al. 1998). Hydrologic variation from agriculture, although less pronounced than that for urbanization, is associated with decreased abundance and diversity of intolerant species (Poff et al. 2006). Percent agricultural area is positively correlated with total dissolved solids and nutrients in stream water and is negatively related to biologic indicators of stream health (Vander Laan et al. 2013).

In Maine, percent agricultural area is positively correlated with nitrate, calcium, sulfate, magnesium, and chlorine, and is negatively correlated with DOC (Cronan et al. 1999). Quinn et al. (1997) compared agricultural and forested catchments and found that streams draining the former received more light, were warmer, had smaller amounts of woody debris, and had higher nutrient levels and algal biomass. Similarly, in a study by Wang et al. (1997), agricultural area was negatively correlated with biotic indices and habitat quality, while forest cover had a positive relationship with these variables. Clearly, agriculture has consistent, negative effects on stream water quality across all regions of the U.S., including the study region.

Geology and Acid Neutralizing Capacity (ANC):

Stream acidification is of particular concern in the Northeast because of the high rate of acidic deposition from the surrounding regional airshed (Driscoll et al. 2001). Bedrock and soil composition can affect acid neutralizing capacity (ANC) in streams, thereby making them less susceptible to acidification (Sullivan et al. 2007, USGS 1989). Kaplan et al. (1981) found soils to be more influential than bedrock on stream pH and alkalinity in the Northeast and Mid-Atlantic U.S. Herlihy et al. (1993) found that acidic streams and streams with low ANC in the mid-Appalachian Mountains were almost all located in upland forested catchments with base-poor bedrock. In a study by Nelson et al. (2009), the pH, conductivity, ANC, and concentrations of calcium, magnesium and ammonium in streamwater were higher in basins with mixed crystalline and sedimentary bedrock than in basins with only crystalline bedrock. As such, these studies provide evidence that both bedrock and soil composition in a watershed can affect streamwater characteristics.

Using Landscape Characteristics to Predict and Classify Stream Condition

Many investigators have created models based on interactions of landscape variables and stream water quality to predict physical, biological or chemical conditions in streams. Carlisle et al. (2009) found riparian land cover, road-stream intersections, elevation, soil content, soil permeability, depth to water table and percent agricultural land cover to be among the best spatial variables to predict biological condition of streams in the Eastern U.S. Bedoya et al. (2011) used in-stream and off-stream variables to predict the IBI (index of biotic integrity) score for sampling locations throughout Ohio.

Variables with the best predicting power were the area of hay/pasture and deciduous forest, low intensity development and open urban area within a 100-m buffer, and percent area of woody wetlands and deciduous forest within a 30-m buffer. Total stream connectedness—i.e., the proportion of connected length to the total basin network length—and the number of dams were also among the most powerful predictive variables. Sullivan et al. (2007) used a geologic classification system based on capacity to increase streamwater ANC along with other landscape variables to predict the locations of acid-sensitive and acid-impacted streams in a watershed in the Southern Appalachian Mountains. Their logistic regression model found percent siliceous bedrock, percent forested area, elevation, and watershed area to be the best predictors of stream ANC throughout their study area. Jager et al. (1990) took a different approach to predicting stream ANC in another part of the Appalachian Mountains using a technique called cokriging. This method uses the assumption of spatial autocorrelation to interpolate point measurements over a designated area. Here, evenly-spaced stream ANC measurements along with elevation predicted ANC in un-sampled streams with a mean standard error of 0.286, which reflects good accuracy.

Another modeling approach involves classifying regions based on similar landscape characteristics in order to prioritize conservation efforts or to understand interactions among land use variables and water quality. Esselman et al. (2011) built a model relating fish IBI to anthropogenic disturbance variables such as percent urban or agricultural area in the watershed, population density, road density, dams and mines, and used this model to calculate a cumulative disturbance index for each watershed throughout the United States. Merovich et al. (2013) classified segment-level watersheds (segments between confluences) based on their predicted water chemistry in a mine-impacted region in the central Appalachians. They related landscape information such as elevation, drainage area, coal geology, mining intensity, surficial geology, and land use to water chemistry and macroinvertebrate biotic integrity and used this model to predict the locations of other mine-impacted streams. Mining intensity and distance to mining and coal type were the dominant predictors. Preston (2000) developed Hydrological Response Units (HRUs) for the State of Maryland that represent regions of similar land cover, soil type, slope and geology. This type of classification allowed for more efficient and thorough sampling of water quality parameters in the state. Clearly, there are a variety of approaches and objectives that have been applied to model streamwater – watershed interactions.

Predicting Future Stream Conditions

The central question motivating this research is whether we can predict future stream conditions in response to land-use change, and do so before such development occurs in order to avoid expensive stream mitigation costs. Similar studies have addressed this issue in other ways, namely through alternative futures scenarios. Van Sickle et al. (2004) used four alternative future scenarios to predict the biological condition of streams in Oregon's Willamette River basin for the year 2050. Their models related current land cover amounts to five different biotic indices of stream condition and used this relationship to predict future stream biological condition given varying amounts of land cover predicted by their alternative future scenarios. Agriculture and development within a 120m buffer of the stream were primary driving variables in each model, while gradient, elevation, stream power, area, distance to watershed divide and longitude comprised the next grouping of best predictors. The alternative future scenario with the highest probability of high stream quality was their conservation scenario, which included steps to restore and protect ecosystems.

Santelmann et al. (2004) used similar methods to predict changes in water quality in two predominantly agricultural watersheds in Iowa using alternative futures scenarios. Their Water Quality Scenario had the largest positive impact on future water quality by calling for policy changes in water quality standards, widening riparian buffers, and strengthening best management practices (BMPs) to mitigate stormwater runoff.

Turak et al. (2011) predicted future stream biodiversity under different management scenarios in Australia. They developed a regression model to predict a stream's macroinvertebrate biotic index using anthropogenic disturbance variables such as extractive industries, point sources, infrastructure, land use and impoundments, as well as natural features such as elevation, slope and precipitation. Ten different management strategies were evaluated by refitting the model with new land cover percentages to reflect each strategy. For example, sustainable grazing replaced over-grazed areas, and the model was then used to predict biological condition of the stream under that management scenario. In this way, they were able to forecast the potential effects of management strategies and identify watersheds in which those strategies would be most effective. Much like this research, these applications of alternative futures scenarios help to predict the future of streams in order to address strategies that will be effective in avoiding or mitigating impairment.

Another component of predicting future condition of streams involves looking at climate forecasts, and considering how streams have responded to climate change in the past. Since the 1970s, the Northeast has seen an increase of 0.25°C/decade in mean annual temperatures and 0.7°C/decade in winter temperatures (Hayhoe et al. 2007). Climate projections predict that the Northeast will receive about 15% more precipitation in the winter, but this increase will be seen as more winter rain than snow (Palmer et al. 2009). These changes will decrease winter snow depth and snow cover and will reduce the length of ice cover, as well as cause earlier peak spring stream flow, earlier bloom dates, extended growing seasons, more frequent droughts, increased water temperature, and extended low-flow periods in the summer (Hayhoe et al. 2007).

Climate change is expected to have a large effect on the timing of events, which may have serious implications for aquatic biota whose life stages are dictated by changes in temperature and stream flow (Hayhoe et al. 2007). Furthermore, because each river has its own unique flow regime that harbors a unique suite of biota, climate trends that alter that regime will change the native structure of the ecosystem (Palmer et al. 2009).

When changes due to climate are coupled with changes due to human impact (e.g., development and increased IC), stream ecosystems are further threatened. Nelson et al. (2009) explored the combined potential effects of climate change and urbanization on stream hydrology, geomorphology and temperature and used this to predict future fish IBI. They found that most fish species were affected by climate change, and that adding urbanization stress increased the total percent of stressed fish species by 50 to 75%. Similarly, Castillo et al. (2014) used a scenario analysis to determine that a major estuarine watershed in Texas is likely to be more threatened by climate change than by land-use change, although localized effects of land-use change can significantly damage smaller aquatic ecosystems.

Resistance, Resilience and Sensitivity Studies

Predicting the potential resistance, resilience or sensitivity of streams is a new research area that has not yet been explored in depth. Besaw et al. (2009) used reach- and watershed-level stream parameter data and expert opinion to cluster streams into seven groups of sensitivity to geomorphic adjustment based on stream characteristics such as geology, vegetation, current stressors and geomorphic condition. They argued that if a stream is currently in adjustment, e.g., incising or aggrading, it is at greater risk of further adjustments given additional stressors.

Anderson et al. (2013) examined all stream networks in the Northeast and Mid-Atlantic for their potential resilience by considering factors that would contribute to maintaining a full spectrum of biodiversity despite changing ambient conditions. Their assumption was that connected regions with high variability in habitat and temperature allow for refuges where species can remain during times of stress, making them resistant/resilient to disturbance. Their unit of analysis was the "functionally connected stream network," defined as all the streams bounded upstream by headwaters or a dam and downstream by a dam or the ocean. They scored the networks for their resistance/resilience based on seven key metrics: network complexity (number of stream and lake size classes in a network), length of connected network, number of gradient classes in the network, number of temperature classes in the network, degree of natural cover in the floodplain, and the cumulative extent of impervious surfaces in the watershed.

McCluney et al. (2014) expressed a similar view of resistance and resilience. They argued that decreases in habitat heterogeneity would decrease ecosystem resistance because of the portfolio effect – i.e., the idea that having more species makes a system more stable. Because of this, local ecosystems may be sensitive to degradation, but whole macrosystems can be resistant and resilient if they have a high level of habitat heterogeneity. Factors that modify macrosystem dynamics, like dams and extensive urban area, will have large impacts on whole-basin resistance/vulnerability. The authors also made the point that an intermediate amount of connectivity is best for resilience as it allows species to move about and recolonize after a disturbance, but also does not let disturbances affect the entire system. Similarly, Pearsons et al. (1992) found that habitat complexity of streams is a major factor in resistance and resilience to flooding for fish assemblages in a basin in eastern Oregon. Finally, Vieira et al. (2004) found that streams draining catchments in which there has been a fire have less resistance and resilience in response to flash floods. All of the preceding studies used different methods to determine stream resistance or resilience, but no studies have used the interactions between landscape characteristics and stream biotic conditions to predict stream vulnerability to land-use change.

CHAPTER TWO:

RELATIONSHIPS BETWEEN WATERSHED BIOPHYSICAL CHARACTERISTICS AND STREAM RESPONSE TO URBANIZATION

INTRODUCTION

Maine's Water Classification Program (38 M.R.S.A Section 464 et. seq.), administered by the Department of Environmental Protection (MEDEP), is a stream water quality monitoring program that assesses the ecological condition of macroinvertebrate and algal communities for all streams in Maine, with the intent of sustaining the biotic integrity of aquatic resources. This biomonitoring program (BIOMON) uses the aquatic taxa measured in these community samples to derive approximately 30 variables or metrics that are used in a discriminant analysis statistical model to determine attainment of biological criteria described in the state's water classification regulations.

The output of the statistical model places the stream sample into one of four classes – AA, A, B, or C (Table 2.1) – that range from pristine, non-disturbed conditions (i.e., AA), to lower quality degraded status. A final class of non-attainment (NA) is used to designate a degraded biological community that does not meet a minimum standard (i.e., Class C). Each stream in Maine is assigned a statutory class of either AA/A, B or C, and is therefore held to different environmental expectations (Table 1). For example, if a stream is assigned to statutory Class A, but attains only Class B standards based on current monitoring data, it is assessed as not meeting its environmental goal and is therefore in need of restoration.

Table 2.1. Statutory classes and Maine's narrative aquatic-life and habitat standards for rivers and streams. Source: Maine Revised Statutes: Title 38, Chapter Three, Sections 464-465.

Class	Biological Standard
AA	Habitat shall be characterized as natural and free flowing. Aquatic life shall be as naturally occurs.
A	Habitat shall be characterized as natural. Aquatic life shall be as naturally occurs.
B	Habitat shall be characterized as unimpaired. Discharges shall not cause adverse impacts to aquatic life. Receiving water shall be of sufficient quality to support all aquatic species indigenous to the receiving water without detrimental changes in the resident biological community.
C	Habitat for fish and other aquatic life. Discharges may cause some changes to aquatic life, provided that the receiving waters shall be of sufficient quality to support all species of fish indigenous to the receiving water and maintain the structure and function of the resident biological community.

In a recent MEDEP study, these classifications were used to examine differential stream responses to urbanization (Danielson et al. In Press). Results indicated that the percent watershed IC at which a stream becomes vulnerable to impairment varies with each class (Figure 1.1). Most AA/A streams pass the threshold into non-attainment at between 1% and 3% IC. For streams in statutory Class B, this range is between 3% and 6 % IC, and the threshold for statutory Class C is 10% to 15% IC. Danielson et al. (In Press) noted that "each stream has different factors that make it more or less vulnerable to negative impacts from IC. Some streams may maintain healthy aquatic communities at greater % IC than the ranges shown above because of stream or watershed factors that mitigate negative impacts of development. In contrast, other streams have stream or watershed characteristics that make them more vulnerable and less resilient to development.” It is that intriguing interplay between urbanization stressors and watershed characteristics that formed the basis of the research investigation described in this chapter.

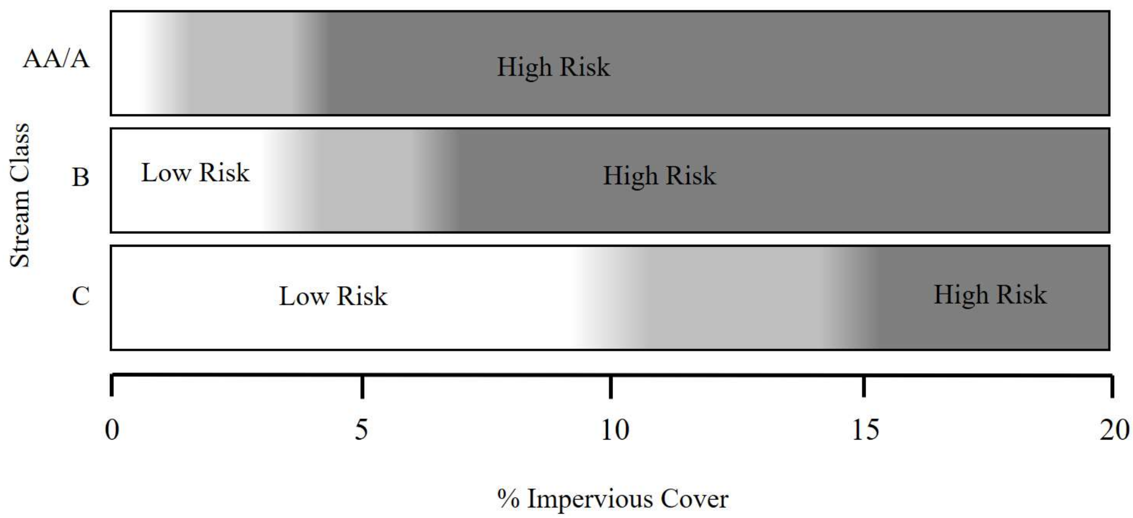


Figure 2.1. Impervious cover vulnerability ranges from Danielson et al. (In Press). These ranges represent the percent impervious cover at which attainment of statutory class is less likely.

In this study, statistical analyses were performed to examine the relationships between watershed environmental parameters and stream responses to urbanization stress in the Maine landscape. Our objective was to determine whether there are specific spatial variables related to land use/land cover, soil properties, geologic conditions, and climate/geography that can be used to identify the distribution of streams that are more or less vulnerable to urbanization stress. We define “high vulnerability” as streams that will pass the threshold into non-attainment at a percent IC value lower than the DEP impairment threshold described above and in Figure 2.1. As such, non-attaining streams with low percent IC levels are considered highly vulnerable. In contrast, we define “low vulnerability” as streams that manage to attain their statutory class at percent IC levels that exceed MEDEP’s impairment thresholds. Thus, attaining streams with high percent IC levels would be categorized as “low vulnerability” due to their ability to resist impairment.

This interplay between urbanization stressors, watershed characteristics, and stream vulnerability has important implications for communities, landowners, and regulatory agencies. Planning development with stream health in mind can save tens of millions of dollars in restoration costs, as well as maintain the structure and function of biotic communities living in these fragile aquatic ecosystems. Surface water is the main source of drinking water in Maine, and therefore it is essential to protect this resource (Mockrin et al. 2014). Watersheds that are more vulnerable to urbanization stress can be prioritized for conservation, or steps can be taken to mitigate the effects of development on the stream ecosystem through Best Management Practices (BMPs) and Low Impact Development (LID).

Stormwater BMPs are strategies that can be installed around development to effectively remove pollutants, cool the stormwater, protect the stream channel, and dampen the flood surge (MEDEP 2013). Low Impact Development is a site-based strategy to protect the hydrologic cycle usually disturbed during development (MEDEP 2013). Both strategies can be applied to new or already existing developed areas.

However, retrofitting established development is often costly, giving even more incentive to plan development in a way that minimizes impacts to stream health.

In general, our research is intended to help communities and regulatory agencies identify which watersheds are more likely to become impaired with poorly managed development and are therefore in need of LID, BMPs, or land conservation. Additionally, we will better understand which watersheds might be able to withstand higher amounts of urbanization before impairment, giving alternative options for developers.

METHODS

Stream Water Quality Data

Stream biotic community data collected during 2003 – 2013, inclusive, were acquired from MEDEP's Stream Biomonitoring (BIOMON) program, which periodically collects a suite of physical, chemical and biological data at fixed stream locations throughout the entire state. This wide range of sample dates was used to maximize the number of samples included in the analysis. The year 2003 is when MEDEP took over regulation of streams in Maine, and 2013 is the most recent year with available sample data. Stream sites are sampled from July through September on a 5-year rotation, with a primary focus on macroinvertebrate and algal taxa, and biotic community composition. Sample data are the same as those used in Danielson et al. (In Press) in order to maximize our ability to compare their results to ours.

Macroinvertebrates such as mayfly (Ephemeroptera) and stonefly (Plecoptera) larvae were collected by MEDEP using rock bags, whereas algae were collected from cobbles and small boulders (Danielson et al. 2011, 2012, Davies and Tsomides 2002). Sample data were excluded from this study if the watershed exceeded 125 km^2, if the sample data were somehow compromised during collection, or if a stressor other than urbanization (e.g., agriculture or a significant point source) was suspected to be the primary driver of stream degradation.

From an initial dataset of 388 streams, our screening process left a total of 108 sample sites with macroinvertebrate community data, and 88 sites with algal community data (Figure 2.2). Only one sample date was used for each site, and the most recent sample date was chosen. Sample sites ranged from minimally disturbed to highly urbanized, and ranged in size from 0.35 km^2 to 118 km^2. The attainment class of each stream (i.e., AA/A, B, C, or NA) was determined by MEDEP through a statistical decision model that used 30 variables describing the sampled biotic community (Davies and Tsomides 2002). These attainment classes were used in our statistical models and analyses because they represent a synthesis of all 30 community variables, and are the basis from which regulatory decisions are made as to whether or not a stream is impaired.

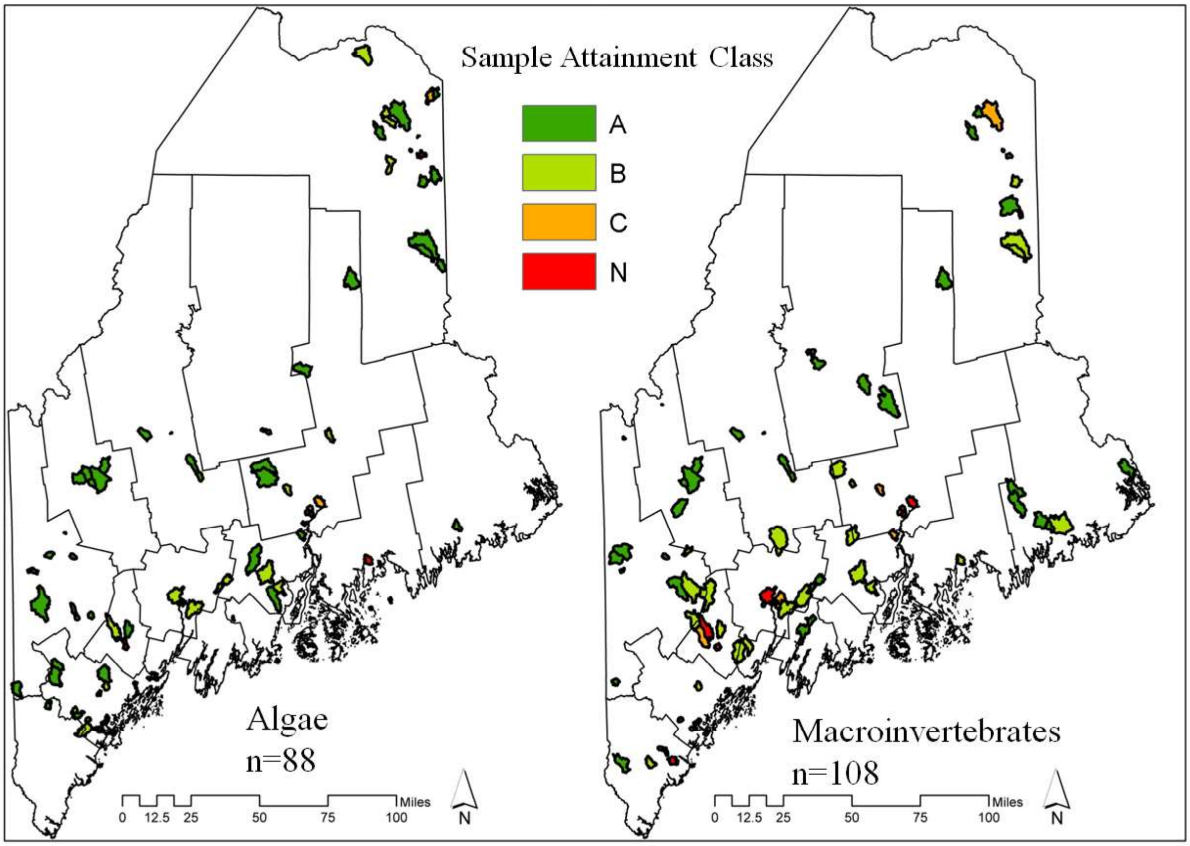


Figure 2.2. Watershed study sites and sample attainment class.

Watershed Biophysical Variables

In order to identify a suite of watershed spatial variables likely to affect a stream's vulnerability to urbanization, we consulted with a range of experts who specialize in urban watershed management, aquatic ecology, and/or aquatic disturbance indicators. More information about the process of expert elicitation is provided in Chapter Three. Once the final variables listed in Table 2 were selected, spatial GIS layers were processed in ArcMap 10.0 (ESRI 2010). All layers were projected into UTM 19N. Impervious cover as of 2007 was mapped for most of the state at a 1-m scale. For watersheds without full coverage of IC data at the 1-m scale, 5-m data based on 2004 imagery were used and linear regression was used to estimate 2007 IC at 1-m resolution (see Danielson et al. in press). Most layers were summarized at the watershed scale, the riparian scale (defined as a 100-m buffer on each side of the stream), and the point scale (defined as one km upstream of the sample site within the 100-m buffer) (Figure 2.3).

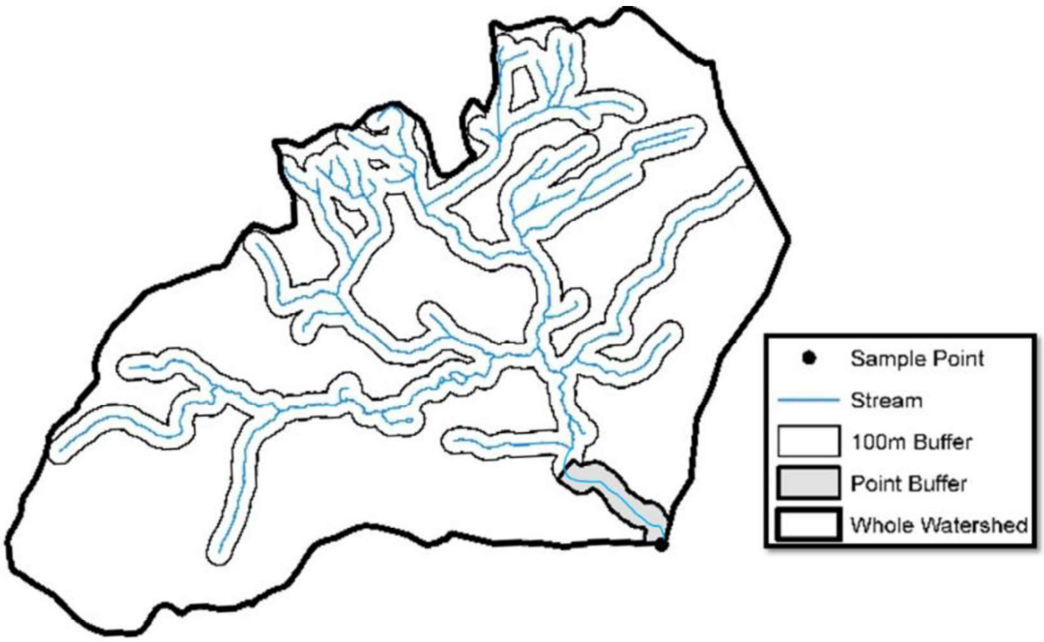


Figure 2.3. Schematic representation of the three landscape scales used in the analysis. These scales are: (1) whole watershed; (2) 100-m buffer on each side of the stream; and (3) the point buffer, which includes one km of the 100-m buffer upstream from the sample site.

Table 2.2. Variables used in the logistic regression and Kruskal-Wallis analyses. Mean values (and standard deviations) are shown for three scales as well as the variable source information.

	Mean (SD)						
	Watershed		Buffer		Point		
Variables	Macroinvertebrates	Algae	Macroinvertebrates	Algae	Macroinvertebrates	Algae	**Source**
% Impervious Cover	8.61 (12.07)	6.0 (8.9)	-	-	-	-	MEGIS
Dams (count)	-	-	0.3 (0.8)	0.35 (0.8)	-	-	MEGIS
Stream/road Intersections (density)	-	-	0.44 (0.6)	0.46 (1.0)	-	-	MEGIS, NHDPlus V2 Flowlines
% Resistant Surface	63.4 (34.4)	68.0 (30.2)	52.9 (39.9)	58.6 (35.8)	43.8 (44.5)	40.2 (43.4)	MGS
% Sand/Gravel Aquifers	8.9 (19.6)	3.9 (7.3)	10.4 (22.6)	4.6 (7.9)	15.3 (27.9)	10.3 (20.2)	MGS
Area (KM^2)	24.8 (27.6)	35.5 (33.8)	-	-	-	-	NHDPlus V2
Nearest Healthy Stream	1.09 (0.8)	1.1 (0.9)	-	-	-	-	NHDPlus V2 + MEDEP
% Agricultural Area	5.4 (11.4)	3.3 (7.4)	4.0 (8.40	2.3 (4.5)	4.6 (11.5)	3.2 (10.3)	MELCD 2004
% Nonpoint Sources	12.5 (13.5)	8.7 (12.3)	10.7 (13.2)	7.9 (12.1)	12.9 (15.8)	10.9 (16.8)	MELCD 2004
% Natural Area	66.6 (28.4)	74.3 (25.9)	70.6 (26.4)	73.9 (25.3)	65.7 (31.6)	68.7 (31.1)	MELCD 2004
% Forested Area	62.9 (27.28	70.3 (25.0)	64.7 (25.2)	67.4 (25.2)	62.2 (31.4)	64.9 (30.8)	MELCD 2004
% Lake Area	0.7 (2.2)	1.4 (4.1)	-	-	-	-	NWI
% Retained Water Area (Lakes + Wetlands)	8.6 (6.9)	9.06 (7.5)	-	-	-	-	NWI
% Acidic Wetlands	0.6 (1.9)	0.4 (1.3)	0.5 (1.6)	0.5 (1.9)	0.06 (0.7)	0.09 (0.8)	NWI
% Wetlands Area	7.9 (6.7)	7.6 (6.4)	17 (13.5)	16.5 (11.6)	13.6 (16.2)	11.2 (12.3)	NWI
Average July Maximum Air Temperature (^oC)	26 (0.8)	25.9 (1.0)	-	-	-	-	PRISM
Average Summer Precip (inches)	28.2 (2.1)	28.3 (2.3)	-	-	-	-	PRISM
Buffering Capacity	-	-	-	-	-	-	TNC NEAHCS
% A or B Soils	23.3 (20.9)	17.8 (15.8)	21.3 (22.1)	16.0 (15.3)	27.4 (29)	24.2 (25.9)	USDA NRCS
K Factor (erosion coefficient)	0.33 (0.07)	0.35 (0.06)	0.34 (0.09)	0.37 (0.07)	0.33 (.12)	0.36 (0.1)	USDA NRCS
% D Soils	34.4 (22.8)	40.2 (21.9)	39.9 (27.0)	45.8 (27.3)	32.4 (28.8)	35.3 (30.6)	USDA NRCS
Soil Depth	132.5(44.9)	122.0 (43.3)	155.5 (44.0)	146.0 (45.2)	155.5 (44.0)	146.0 (453.2)	USDA NRCS
Depth to Water Table	105.1 (34.5)	100.7 (32.4)	84.4 (39.0)	81.3 (36.6)	90.3 (48.9)	83.4 (42.5)	USDA NRCS
Slope (%)	6.3 (5.3)	7.4 (6.4)	4.9 (4.1)	5.7 (4.9)	4.9 (3.5)	5.6 94.5)	USGS DEM
Longitude	-	-	-	-	-	-	MEDEP
Latitude	-	-	-	-	-	-	MEDEP
Drains to Ocean	-	-	-	-	-	-	-

Percent Agricultural Area was defined as MELCD 2004 Cultivated Crops land cover category. Percent “natural area” included the following MELCD 2004 land cover classes: Deciduous Forest, Evergreen Forest, Mixed Forest, Grassland/Herbaceous, Scrub/Shrub, Wetland Forest, Wetlands, Recent Clearcut, Light Partial Cut, Heavy Partial Cut, Regenerating Forest, and Alpine. Percent “forested area” included MELCD 2004 cover classes Deciduous Forest, Evergreen Forest, Mixed Forest, Recent Clearcut, Light Partial Cut, Heavy Partial Cut, and Regenerating Forest. Percent Nonpoint Sources was derived from MELCD 2004 Developed Open Space and Cultivated Crops.

These MELCD 2004-derived variables were processed by reclassifying to Boolean raster layers (e.g., a value of 1 for classes of interest, value of 0 for all others). Then zonal statistics were applied to sum the number of pixels within each watershed. Percent area was derived by dividing the sum of pixels of the land cover class by the total number of pixels in the watershed, and multiplying by 100.

Percent “lake area” was created by extracting the Lake class of the National Wetland Inventory (NWI). Percent wetland area is the Wetland category of the NWI, while Percent Acidic Wetlands is the Wetland category with the qualifying class of "a," which denotes an acidic wetland. These vector layers were converted to 5-m Boolean rasters and processed in the same manner as the MELCD variables described above.

Stream/Road Intersections were created by using the Intersect tool in ArcMap to get points where the MEGIS road layer intersected with the NHDPlus V2 flowlines. Points were summarized for each watershed, and then divided by total watershed area to arrive at a density metric. Dams were acquired through MEGIS, and subsequently summed by watershed for a count metric. Slope was derived from USGS 10-m DEM. Average July Maximum Temperature and average summer precipitation were provided by the 14-km PRISM climate raster. Data for the years 2009 through 2013 were averaged, and then zonal statistics were applied to arrive at an average value for each watershed.

The dichotomous variable Buffering Capacity was created from the Northeastern Aquatic Habitat Classification System (NEAHCS) maintained by The Nature Conservancy (Olivero and Anderson 2008). This dataset assigns each stream in the NHDPlus V2 network to one of three categories: acidic, low buffered; neutral, moderately buffered; and calcareous, highly buffered. Highly buffered and moderately buffered categories were considered 'Buffered' and assigned a value of 1, while the acidic category was considered not buffered and assigned a value of 0.

The Drains-to-Ocean variable was proposed by one of the experts we consulted. The rationale is that small watersheds that drain directly into the ocean are more susceptible to impairment from urbanization (and other stressors) because they have a lower chance of being recolonized from downstream. This dichotomous variable was created by visually selecting BIOMON watersheds that drain directly into the ocean and assigning them a value of 1, and giving all other watersheds a value of 0. Nearest Healthy Stream was determined by creating watershed centroids inside the NHDPlus V2 catchments, then removing those associated with watersheds with over 7% IC (Morse et al. 2006). Watershed centroids were created using the Polygon to Point tool in ArcMap. The Nearest tool was then applied to BIOMON watersheds to determine the distance (km) to the nearest NHDPlus V2 catchment centroid.

The Percent Resistant Surfaces variable was created with the help of an expert who selected the following categories of the Maine Geological Survey (MGS) surficial geology layer as resistant to erosion: bedrock, ribbed moraine, stagnation moraine, till, and thin drift. The layer was then converted to a 5-m pixel raster and summarized in the same way as the MELCD variables. Sand/gravel aquifers were downloaded from MGS and summarized the same way as the MELCD variables to determine the percent area. Longitude and latitude of sample sites were provided by MEDEP.

A critically important factor in understanding stream resilience to urbanization is groundwater input. Because groundwater is not available as a GIS spatial layer, we instead used proxy variables. In an attempt to approximate groundwater input into the stream, we used the variable Depth-to-Water Table from the NRCS Web Soil Survey (USDA NRCS 2012). We reasoned that stream sites with shallow water tables were more likely to receive groundwater inputs. Along with three other variables that relate to groundwater input— Percent Sand/Gravel Aquifers, Percent A or B Soils, and Soil Depth—Depth-to-Water Table should help the signal of groundwater input to be observable in the analysis.

Depth-to-Water Table and the other soil variables – Percent A or B Soils, Percent D Soils, K Factor (i.e., erosion coefficient), and Soil Depth (i.e., depth-to-soil restrictive layer) – were derived from USDA NRCS web soil survey data. Layers were extracted from the Soil Data Viewer tool installed in ArcMap 10.0 for all Maine counties, and then stitched together using the Merge tool. After conversion to 5-m pixel raster layers, soil variables were processed the same way as the MELCD variables. The variables Percent A or B Soils, Percent D Soils, K Factor (i.e., erosion coefficient), and Soil Depth (i.e., depth-to-soil restrictive layer) are not commonly found in analyses of watershed-stream interactions. We included these variables because we predict that soil drainage plays a major role in stream response to urbanization. Percent A or B soils and Percent D soils refer to the hydrologic group classification assigned to the soil column by the USDA Natural Resource Conservation Service. Soils are classified into the categories A through D in order of decreasing drainage capacity. While it is logical that better draining soil would increase stream health due to dampened flood surges during precipitation events and increased effectiveness of BMPs, other theories posit that development on poorly-draining soils would not cause a large change in the stream hydrograph and therefore the aquatic system would not be as greatly affected (MEDEP 2013).

The erosion coefficient (K factor) was included in the study because it indicates the capacity for siltation into the stream and bank incision. We used the K factor averaged for the whole soil profile within a 60 m buffer of the stream. This variable should give us an idea of how prone the soil adjacent to the stream is to erosion. The K factor is defined by the USDA NRCS as "the susceptibility of a soil to sheet and rill erosion by water. Factor K is one of six factors used in the Universal Soil Loss Equation (USLE) and the Revised Universal Soil Loss Equation (RUSLE) to predict the average annual rate of soil loss by sheet and rill erosion in tons per acre per year. The estimates are based primarily on percentage of silt, sand, and organic matter and on soil structure and saturated hydraulic conductivity (Ksat). Values of K range from 0.02 to 0.69. Other factors being equal, the higher the value, the more susceptible the soil is to sheet and rill erosion by water." The K Factor is low for soils high in clay because of their resistance to erosion, but it is also low for soils high in sand and coarse materials because their infiltration capacity reduces surface flow (USDA NRCS 2012). The K factor is high for soils with high silt content due to their susceptibility to erosion. Thus, this variable represents an increased risk of erosion and siltation.

Statistical Analysis

Two statistical analyses were applied to the dataset: logistic regression and Kruskal-Wallis one-way analysis of variance. Logistic regression was used to predict stream attainment class, while Kruskal-Wallis tests helped to determine which watershed characteristics are associated with more- or less-vulnerable sites. Logistic regression models predict the probability of a dichotomous response variable attaining one of its two states, using one or more independent variables. Predictor variables can be either categorical or continuous, and do not need to be normally distributed (Hosmer and Lemeshow 2001). The Kruskal-Wallis test is a non-parametric method of testing differences in sample distributions. In this test, the null hypothesis is that the medians of the distributions are the same. All statistical analyses were conducted using version 3.1.2 of the R Statistical Computing Software (R Core Team 2014).

The Kruskal-Wallis rank test was used to determine which watershed characteristics are associated with stream sample data that were classified into either low or high vulnerability categories. High vulnerability sites are those that do not attain A, B, or C at IC values at or below the higher value of the DEP vulnerability thresholds. Low vulnerability sites are those that do attain A, B, or C at IC values greater than the lower value of the vulnerability thresholds (Figure 4). More specifically, sites with low vulnerability are those that attain A at greater than 1% IC, attain B at greater than 3% IC, or attain C at greater than 10% IC. Sites with high vulnerability are those that do not attain A at 3% IC or lower, do not attain B at 6% IC or lower, or do not attain C at 15% IC or lower. For example, sites with low vulnerability are those that attain A at greater than 1% watershed IC, attain B at greater than 3% IC, or attain C at greater than 10% IC (Figure 2.4). Sites with high vulnerability are those that fail to attain Class A at less than 3% IC, fail to attain B at less than 6% IC, or fail to attain C at less than 15% IC.

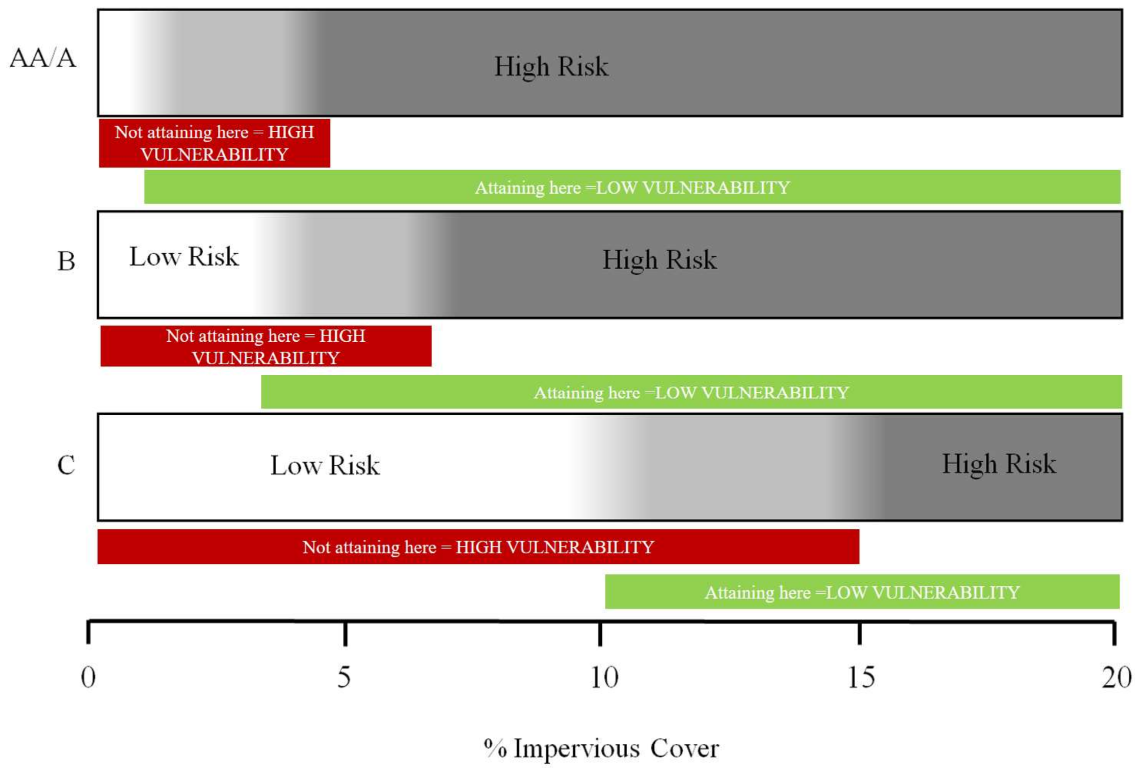


Figure 2.4. Definition of high and low vulnerability sites. High vulnerability ranges are displayed in red while low vulnerability ranges are displayed in green.

For most variables, median values of watershed characteristics were compared at three scales: the whole watershed, the riparian scale of 100-m on either side of the stream, and the point scale at the first kilometer of the 100-m buffer upstream of the sample site. Variables that were only measured at the watershed scale are Percent IC, Watershed Area, Percent Lake Area, July Maximum Temperature, Summer Precipitation, Buffering Capacity, Drains-to-Ocean, and Nearest Healthy Stream. Variables measured only at the buffer scale are Dams and Stream/Road Intersections. Longitude and Latitude were recorded only for the sample site.

Logistic regression was used to predict stream attainment class using spatial watershed characteristics at all three landscape scales. Six separate logistic models were created – three for macroinvertebrates, and three for algae. The first model for each predicts whether a stream attains Class A, the second model predicts whether a stream attains Class B, and the third model predicts whether a stream attains Class C.

Macroinvertebrates and algae were modeled separately because they are likely to respond differently to watershed characteristics. For example, we expect algae to be more sensitive to siltation and nutrients, while macroinvertebrates would be more sensitive to flood disturbances (Cuffney et al. 2011). For both macroinvertebrate and algal models, 30% of the streams were removed randomly to use as a validation set, and the models were then created using the remaining data.

Prior to model generation, we screened variables for multicollinearity and found that many were highly correlated (i.e., Pearson correlation coefficient > 0.8). To avoid multicollinearity, we removed variables from the analysis until there was no correlation greater than 0.8. Models were created using forward selection, entering each variable one at a time and keeping variables with a p-value less than 0.2 in the model. After forward selection, variables with a p-value greater than 0.05 were removed, leaving only variables significant at the 95% confidence level. Models were screened for their significance (p-value), explanation of variance (R^2), and area under the Receiver Operating Characteristic (ROC) curve. The area under the ROC curve describes the goodness-of-fit for a model with a binary outcome, where a value closer to 1 indicates better model fit. For each independent variable, the intercept coefficient, the standard error, p-value, Wald statistic, and odds ratios were reported.

RESULTS

Kruskal-Wallis Rank Tests

For macroinvertebrate samples, seven sites fell into the high vulnerability category and 27 sites fell into the low vulnerability category (Figure 2.5). Among sites with low vulnerability, variables with significantly higher median values ($p<0.05$) were Percent A or B Soils, Depth-to-Water Table, July Maximum Temperature, and Summer Precipitation (Table 2.3). All variables were only significant at the whole watershed scale, except Depth-to-Water Table which was also significant at the buffer scale. Among these sites, Percent A or B Soils and Depth-to-Water Table were correlated at 0.69, which may indicate that only one or the other is important in determining vulnerability. For sites with high vulnerability, variables with significantly higher median values were Percent Agricultural Area, Percent D Soils, Percent Wetlands, Longitude, and Latitude. Percent D Soils were significant at all three scales, and Percent Wetlands were significant at both the watershed and buffer scale. Percent Agricultural Area was only significant at the watershed scale. Longitude and Latitude were correlated at 0.66, which may signify that only one or the other is important in determining vulnerability.

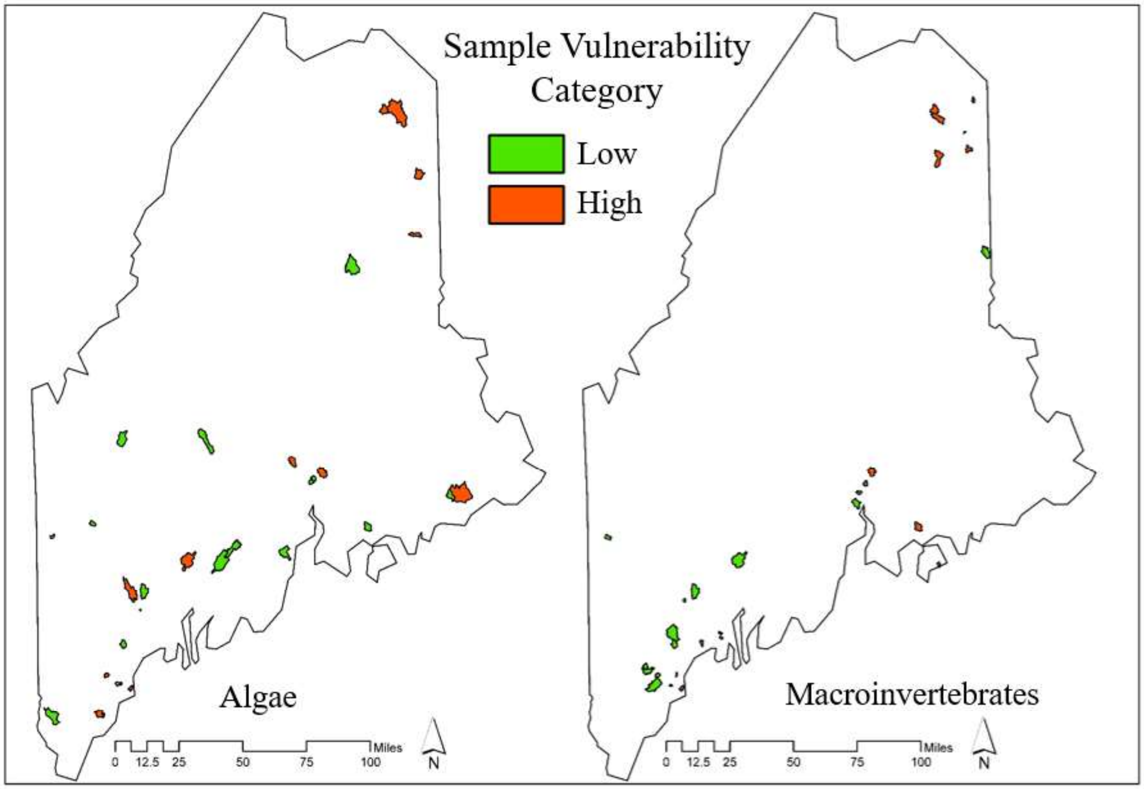


Figure 2.5. Distribution of high and low vulnerability sites for algae and macroinvertebrate sample types.

Table 2.3: Results of Kruskal-Wallis rank tests between high and low vulnerability macroinvertebrate sites. Variables with significantly different medians ($p<0.05$) are shown with the median for low vulnerability sites (Median Low Vuln Sites) and high vulnerability sites (Median High Vuln Sites), the Kruskal-Wallis statistics (KW Stat) and p-value.

Macroinvertebrate Samples					
Higher distribution among low vulnerability sites					
	Variable	A or B soils (%)	Depth to water table (cm)	July Maximum Temperture (^{o}C)	Summer Precipitation (in)
Watershed Scale	Median Low Vuln Sites	30.2	166.8	26.5	28.1
	Median High Vuln Sites	6.2	128.8	25.4	26.4
	KW Stat	5.29	5.29	8.02	5.56
	p-value	0.02	0.02	0.005	0.02
Buffer Scale	Median Low Vuln Sites	-	185.5	-	-
	Median High Vuln Sites	-	184.1	-	-
	KW Stat	-	7.09	-	-
	p-value	-	0.01	-	-
Higher distribution among high vulnerabilty sites					
	Variable	Agricultural Area (%)	D Soils (%)	Wetlands (%)	Longitude (DD)
Watershed Scale	Median Low Vuln Sites	2.4	24.1	6.1	-
	Median High Vuln Sites	4.7	67.1	13.8	-
	KW Stat	4.42	8.02	7.54	-
	p-value	0.035	0.005	0.006	-
Buffer Scale	Median Low Vuln Sites	-	29.3	13.9	-
	Median High Vuln Sites	-	74.2	33.4	-
	KW Stat	-	9.8	9.27	-
	p-value	-	0.0015	0.002	-
Point Scale	Median Low Vuln Sites	-	26.9	-	-
	Median High Vuln Sites	-	48.3	-	-
	KW Stat	-	6.21	-	6.64
	p-value	-	0.0126	-	0.01

Based on algal monitoring data, 13 sites fell into the high vulnerability category and 20 sites were placed in the low vulnerability category. Sites with algal data had fewer significant differences in median values for watershed characteristics compared with the macroinvertebrate sites (Table 2.4). Summer Precipitation had a significantly higher median value for sites with low vulnerability, whereas Percent Agricultural Area had a significantly higher median value for sites with higher vulnerability. Summer Precipitation was only measured at the watershed scale, and Percent Agricultural Area was only significant at the watershed scale.

Table 2.4: Results of Kruskal-Wallis rank tests between high and low vulnerability algae sites. Only one landscape scale is displayed because no others had significantly different variable distributions. Variables with significantly different medians (p<0.05) are shown with the median for low vulnerability sites (Median Low Vuln Sites) and high vulnerability sites (Median High Vuln Sites), the Kruskal-Wallis statistics (KW Stat) and p-value.

Algae Samples				
Higher distribution among low vulnerability sites				
	Watershed Scale			
Variable	Median Low Vuln Sites	Median High Vuln Sites	KW Stat	p-value
Summer Precipitation (in)	28.12	27	4.27	0.038
Higher distribution among high vulnerability sites				
	Watershed Scale			
Variable	Median Low Vuln Sites	Median High Vuln Sites	KW Stat	p-value
Agricultural Area (%)	1.15	2.63	5.84	0.015

Results of the Kruskal-Wallis analysis presented in Tables 2.3 and 2.4 provide a basis for determining which watersheds may be more or less vulnerable to urbanization stress. Low vulnerability watersheds are expected to have approximately 30% A/D soils, a Depth-to-Water Table of 167 cm or more, agriculture area less than 2.4%, Percent D Soils less than 24, and wetland area less than 6%. In contrast, highly vulnerable watersheds are expected to be those that have less than 6.2% A or B soils, a Depth-to-Water Table of 128 cm or less, agricultural area more than 4.7%, more than 67% D soils, and wetland area more than 13.8%.

Logistic Regression

Macroinvertebrate Analysis

The macroinvertebrate model of attaining A had an R^2 of 0.77 ($p < 0.0001$), an area under the ROC curve of 0.96, and predicted the attainment class of the 36 validation sites with a success rate of 80%. This model contained four variables besides IC that were significant: Percent Wetland Area, Percent Agricultural Area, Percent Sand/Gravel Aquifers, and Percent Resistant Surface (Table 2.5). Percent IC, Percent Wetlands, and Percent Agricultural Area were associated with a decrease in the probability of attaining Class A, whereas Percent Sand/ Gravel Aquifer Area as well as Percent Resistant Surface at the point scale were associated with an increase in probability of attainment.

Table 2.5. Logistic regression results for macroinvertebrate samples. Three models are displayed: attainment of Class A, attainment of Class B or better, and attainment of Class C or better. For each model, p-value, area under ROC curve (C), R^2, and confusion matrix of model validation are given. Significant variables are displayed with beta coefficients, standard error (S.E.), Wald Z statistic, p-value, and odds ratio. Variables with negative coefficients and odds ratios less than one indicate the variables are associated with a decrease in probability of attaining that statutory class.

Macroinvertebrate Attainment Models

Attaining A — R^2=0.77 C=0.956 p<0.0001

	Coefficient	S.E.	Wald Z	p-value	Odds ratio
Intercept	3.38	1.55	2.19	0.03	-
IC (%)	-0.98	0.36	-2.70	0.01	0.73
Wetlands (%)	-0.27	0.10	-2.66	0.01	0.92
Agriculture (%)	-0.12	0.05	-2.31	0.02	0.99
Aquifer (%)	0.10	0.04	2.82	0.00	1.03
Resistant Substrate - point scale (%)	0.03	0.01	2.39	0.02	1.02

Predicted \ Observed: Class	A	B or Below		
A	12	2	14	
B or Below	5	17	22	
totals	17	19	36	80% correct

Attaining A or B — R^2=0.78 C=0.955 p<0.0001

	Coefficient	S.E.	Wald Z	p-value	Odds ratio
Intercept	0.17	1.45	0.12	0.91	-
IC (%)	-0.33	0.14	-2.42	0.02	0.73
Natural Area - point scale (%)	0.05	0.02	2.40	0.02	1.04

Predicted \ Observed: Class	A or B	C or Below		
A or B	21	0	21	
C or Below	1	14	15	
totals	22	14	36	97% correct

Attaining A, B, or C — R^2=0.74 C=0.97 p<0.0001

	Coefficient	S.E.	Wald Z	p-value	Odds ratio
IC (%)	-0.14	0.05	-2.68	0.01	0.93
Forest - buffer scale (%)	0.08	0.03	2.33	0.02	1.06

Predicted \ Observed: Class	A, B, or C	N		
A, B, or C	24	2	26	
N	3	7	10	
totals	27	9	36	86% correct

The logistic model for predicting attainment of Class B or better contained only two significant variables: Percent IC and the Percent Natural Area at the point scale. This model had an R^2 of 0.78 ($p< 0.0001$), an area under the ROC curve of 0.95, and predicted attainment class of the 36 validation sites with a success rate of 97%. Percent IC was associated with a decrease in the probability of attaining B or better, while Percent Natural Area at the point scale increased the probability of attainment. Because these two variables were correlated (-0.63), Percent IC may be the main driver in this model.

The macroinvertebrate model predicting attainment of Class C or better exhibited an R^2 of 0.74 ($p<0.0001$), area under the ROC curve of 0.97, and predicted attainment of the validation sites with a success rate of 86%. The two variables that were significant in this model were Percent IC (-0.14, $p=0.01$) and Percent Forested Area at the buffer scale (0.08, $p=0.02$). Percent IC is associated with a decrease in the probability of attaining C or better, while Percent Forested Area at the buffer scale is associated with an increase in probability of attaining C or better.

Algal Analysis

The logistic model that used algal monitoring data to predict whether a stream site attains Class A produced an R^2 of 0.74 ($p<0.0001$), an area under the ROC curve of 0.94, and predicted attainment of Class A for the validation sites with a success rate of 97%. These metrics all indicate good model fit and prediction success (Table 2.6). Variables associated with a significant decrease in the probability of attaining Class A were Percent IC (-0.52, p=0.04), Percent Agricultural Area (-0.43, p=0.01), and the erosion coefficient, or K Factor (-0.29, p=0.01). Logistic variables associated with a significant increase in the probability of attaining Class A were Percent D Soils (0.06, p=0.03) and Percent Resistant Surface at the point scale (0.04, p=0.01).

Table 2.6. Logistic regression results for algal samples. Two models are displayed: attainment of Class A and attainment of Class B or better. For each model, p-value, area under ROC curve (C), R^2, and confusion matrix of model validation are given. Significant variables are displayed with beta coefficients, standard error (S.E.), Wald Z statistic, p-value, and odds ratio. Variables with negative coefficients and odds ratios less than one indicate the variables are associated with a decrease in probability of attaining that statutory class.

Algae Attainment Models

Attaining A — $R^2=0.74$ C=0.94 p<0.0001

	Coefficient	S.E.	Wald Z	p-value	Odds Ratio
Intercept	7.75	3.44	2.25	0.02	-
IC (%)	-0.52	0.25	-2.05	0.04	0.53
Agriculture (%)	-0.43	0.16	-2.65	0.01	0.73
K Factor	-0.29	0.11	-2.55	0.01	0.79
D Soils (%)	0.06	0.03	2.19	0.03	1.06
Resistant Substrate - point scale (%)	0.04	0.01	2.62	0.01	1.06

	Observed				
Predicted	Class	A	B or Below		
	A	8	1	9	
	B or Below	0	20	20	
	totals	8	21	29	97% correct

Attaining A or B — $R^2=0.81$ C=0.97 p<0.0001

	Coefficient	S.E.	Wald Z	p-value	Odds Ratio
Intercept	10.39	3.83	2.71	0.01	-
IC (%)	-0.48	0.20	-2.43	0.02	0.62
Soil Depth (cm)	-0.06	0.02	-2.35	0.02	0.97

	Observed				
Predicted	Class	A or B	C or Below		
	A or B	13	2	15	
	C or Below	2	12	14	
	totals	15	14	29	83% correct

The algal model for predicting attainment of Class A or B contained only two variables that were significant – Percent IC (-0.48, p=0.02) and Soil Depth (-0.06, p=0.02) – and both were associated with a decrease in the probability of attaining Class A or B. The model had an R^2 of 0.81($p<0.0001$), an area under the ROC curve of 0.97, and predicted the attainment of the validation sites with a success rate of 83%.

The final algal logistic model for predicting attainment of Class C or better could not be validated. Given that only six of the 58 sites did not attain C or better, there were insufficient data to create a reliable model. For exploratory purposes, a model was created using the entire dataset of 88 sample sites. The only significant variable in this model was Percent IC (-0.28, $p<0.0001$), which was associated with a decrease in the probability of attaining Class C or better.

DISCUSSION AND CONCLUSION

Results from both the logistic regressions and the Kruskal-Wallis paired comparisons provided some discrimination among the watershed and environmental variables that might be expected to influence stream vulnerability. Based on both macroinvertebrate and algal BIOMON data, variables associated with low vulnerability and higher probability of attaining statutory class were Percent Sand and Gravel Aquifers, Percent Resistant Surface at the point scale, Percent Natural Area at the point scale, Percent Forested Area at the buffer scale, Percent A or B Soils, Depth-to-Water Table, July Maximum Temperature, and Summer Precipitation (Table 2.7).

Variables associated with not attaining statutory class and/or high vulnerability were Percent IC, Percent Wetlands, Percent Agricultural Area, K Factor, Soil Depth, Longitude, and Latitude. Many of these variables correlate with and reflect the spatial distribution of sample sites, as indicated by the differences in Longitude and Latitude between high and low vulnerability sites. There is a clear geographic separation between sites that attain their statutory class (many of which are located in the southwestern portion of the state where summer temperatures and precipitation are higher on average), and those that do not attain (which tend to be concentrated in the northeastern portion of the state in a region associated with relatively high Percent Agricultural Area) (Figure 2.5).

Table 2.7. Summary of significant watershed variables. Variables (and units) that are correlated with macroinvertebrate and algal indicators of stream health and integrity are listed based on their influence on attainment of statutory classes and/ or their effect on vulnerability.

Macroinvertebrates	
Variables associated with attainment and/or low vulnerability	
Logistic Regression	Kruskal-Wallis
Aquifer (%) Resistant Surface - point scale (%) Natural Area - point scale (%) Forest - buffer scale (%)	A/B Soils (%) Depth-to-Water Table (cm) July Maximum Temperature (ºC) Summer Precipitation (in)
Variables associated with not attaining, and/or high vulnerability	
Logistic Regression	Kruskal-Wallis
Wetlands (%) Agriculture (%)	Wetlands (%) Agriculture (%) D Soils (%) Longitude (DD) Latitude (DD)
Algae	
Variables associated with attainment and/or low vulnerability	
Logistic Regression	Kruskal-Wallis
D Soils (%) Resistant Surface - point scale (%)	Summer Precipitation (in)
Variables associated with not attaining, and/or high vulnerability	
Logistic Regression	Kruskal-Wallis
K Factor Soil Depth (cm) Agriculture (%)	Agriculture (%)

A number of variables associated with Soil Depth and drainage properties varied independently of the geographic gradients described above. Soil variables associated with a decrease in vulnerability included: Percent Resistant Surface, Percent A or B Soils, Depth-to-Water Table, and Percent Sand/Gravel Aquifers. Sand/gravel aquifers at the watershed scale decrease stream vulnerability because these hydrogeologic features serve as a reliable source of groundwater. A higher Percent A or B Soils allows increased soil infiltration, which leads to cooling and filtering of drainage water before it enters the stream (Poff et al. 2006). In addition, the presence of well-draining soils allows IC remediation efforts such as infiltration ponds to be more effective (MEDEP 2013). A higher percentage of surfaces resistant to erosion, especially at the point scale, indicates that the stream bed is less likely to be affected by flood episodes.

Percent Natural Area at the point scale and Percent Forested Area at the buffer scale are highly correlated with IC (-0.85 and -0.89, respectively), and they tend to have the opposite effect on attainment and vulnerability compared to IC. Prior research has demonstrated the important role that intact riparian areas serve in maintaining aquatic community structure and function (e.g., Jones 2001, Wang et al. 2001, Vannote 1980, Gregory et al. 1991). As a result, we would expect an inverse relationship between the percent riparian forested buffer and stream vulnerability. Several significant variables in the models were more difficult to interpret. In the macroinvertebrate logistic regression of attaining Class A, Percent Wetland Area is associated with a decrease in the probability of attainment. Additionally, in the Kruskal-Wallis tests, Percent Wetland Area was significantly higher among macroinvertebrate high-vulnerability sites.

Wetlands can serve as a stabilizing hydrologic and chemical buffer, as well as a modifier of stream habitat conditions. The potential influence of wetlands depends in part on their scale, type, and location.

There are several ways in which wetlands may contribute to stream vulnerability. In Chapter One, a review of literature regarding wetland effects on downstream water quality indicated that wetlands may have a positive effect on water quality by decreasing inorganic suspended solids, fecal coliform, specific conductivity and nutrients (Johnston et al. 1990), and by retaining nutrients and increasing DOC (Jordan et al. 2011, Marton et al. 2014, Bowden 1987, Saunders and Kalff 2001, Strayer et al. 2003). However, other researchers found very little change in nutrients and ANC between water flowing into and out of wetlands (Yavitt et al. 2006). Finally, some studies concluded that wetlands increased dissolved nitrogen and DOC, and decreased pH (Gorham et al. 1998).

In light of these previous studies, it is plausible that wetlands in our study watersheds exerted a negative effect on attainment of stream Class A. Where they are present, riparian wetlands may correspond with altered inputs of detritus, more solar input and algal NPP, or oxygen depletion of drainage inflows to the stream, any of which could affect aquatic insect assemblages. Where acidic fens drain into streams, the dystrophic acidic conditions may alter the biotic community so that it differs from the reference forested baseline community composition. Moreover, the anoxic soils and sediments of wetlands and beaver impoundments may be a source of sulfide derived from microbial sulfate reduction, and this may act as a stressor for aquatic biota.

Soil-related variables that are associated with an increase in vulnerability are K Factor and Soil Depth. We expect K Factor to increase stream vulnerability because it increases with soils that are more prone to erosion and subsequent siltation of downstream waters (USDA NRCS 2012). It is counterintuitive that increasing Soil Depth would negatively affect the algal community, but this variable is positively correlated with IC (0.60), as well as negatively correlated with percent natural and forested area (-0.76 and -0.75, respectively); therefore, Soil Depth could be confounded by the urban-to-natural gradient of the sample sites. Deeper soils may also correspond with increased sediment loading to streams from channel incision of deep soil deposits, and possible temporal delays in the delivery of winter road salt stress to streams (i.e., most salt leaching occurs in spring when biota are more vulnerable, rather than in late winter). In addition, if deeper soils correlate with agricultural land use, it may be the farm activities on deep soils that degrade streams. A final possibility is that deeper soils may be composed of a thick marine deposit of silt and clay (i.e., low permeability) overlaying porous glacial till, so that the two-layer soil acts more like a thin soil that delivers hydrologic quickflow to streams. Furthermore, this variable is weak in the model (odds ratio 0.97), and therefore is not highly influential.

The variable Depth-to-Water Table was included in the analysis to serve as a proxy for groundwater input. In our results, a shallower water table at both the watershed and buffer scale was associated with high vulnerability sites based on the Kruskal-Wallis tests. This is counterintuitive in one sense, because a higher water table would indicate more groundwater input into the stream. However, this variable may be behaving similarly to Soil Depth, creating quick flow along shallow flow paths during precipitation events, which can generate more hydrologic disturbance in the stream channel.

Another variable, Percent D Soils, had a differential enigmatic relationship to macroinvertebrates and algae. Based on macroinvertebrate data, there was a large difference in median Percent D Soils between low and high vulnerability sites at all three scales (6.1 vs. 13.8 at the watershed scale, 13.9 vs. 33.4 at the buffer scale, and 26.9 vs. 48.3 at the point scale, respectively), indicating that an increase in the area of D soils is associated with higher vulnerability and non-attainment. On the other hand, Percent D Soils was significant in the algal model of attaining Class A and had a positive coefficient (0.06) and an odds ratio above 1 (1.06). This indicates that Percent D Soils increased the probability of attainment of Class A in the algal model. Why might poorly drained D soils be correlated with attainment and low vulnerability in some cases, but correlate with high vulnerability in other cases?

Cuffney et al. (2011) reported that algae are sensitive to siltation and nutrients, while macroinvertebrates are susceptible to flood disturbances. As a result, differences in habitat requirements between the two communities may play a role in explaining the differential responses of these two biotic indices. In general, landscape analyses examining the effects of watershed characteristics on stream water quality focus primarily on anthropogenic variables, with additional consideration of simple natural variables such as riparian area, elevation, or precipitation (e.g., Esselman et al. 2011, Jones 2001, Poff et al. 2006, Wang et al. 2001). Because of this, there is very little research investigating the effects of poorly draining soils on downstream water quality.

We might expect streams surrounded by D soils to be flashier in terms of hydrology and perhaps warmer in summer because of increased shallow, rapid flow contributions to overall stream discharge. These conditions create an in-stream stress regime that may negatively affect macroinvertebrate communities. On the other hand, D soils are characterized by having a high percentage of clay and therefore are more resistant to erosion and subsequent sedimentation of downstream waters. This can create more stable banks, as well as decrease siltation of the water column, allowing for better health of algal communities. Finally, because D soils cause more overland flow and a flashier hydrograph following precipitation events, the stream channel may be more accustomed to this flow regime and thus less affected by the addition of impervious surfaces as compared to streams in well-draining watersheds. Taken together, uncertainty remains regarding the effect of D soils on stream response to urbanization, and more research is needed to determine the effect of poorly draining soils on stream vulnerability.

In general, it appears that sites with lower vulnerability are able to remain at higher attainment classes despite high IC levels if they have well-draining soils, low erosion capacity, high groundwater input, resistant stream bed substrate, and intact riparian buffers. Streams with higher vulnerability to IC stress tend to be associated with watersheds containing wetlands, more shallow poorly-draining soils, more erodible soils, and a higher percentage of agricultural area.

We would be remiss if we neglected to mention the error associated with multiple comparisons. The Kruskal-Wallis rank test was used to compare distributions of 27 variables, most of which are measured at three spatial scales, resulting in approximately 80 tests. As the number of tests increases, the likelihood of type I error increases. This is because random errors accumulate with repetitive testing and it then becomes more likely that the two groups being compared will appear to differ in terms of at least one variable. While we did not correct for the error associated with multiple comparisons, we are confident in the results of the Kruskal-Wallis rank tests because they are largely consistent with the logistic regression results, and they make logical sense based on the literature.

Results of this study provide a conceptual basis for an initial assessment of stream vulnerability to ongoing and future development activities in Maine. In combination with results presented in the next chapter, this research can help municipalities, landowners, regulators and land-use planners to guide land use practices in such a way as to minimize negative stream impacts and to avoid the need for costly stream restoration.

CHAPTER THREE:

PREDICTING STREAM VULNERABILITY TO URBANIZATION STRESSORS USING A BAYESIAN NETWORK MODEL PARAMETERIZED WITH EXPERT KNOWLEDGE

INTRODUCTION

When a drop of rain hits the ground, it follows a path through a watershed and eventually makes its way to a stream or river. Throughout the journey, the drop of water interacts with different components of the watershed. For example, it can pass across an agricultural field and pick up soil and fertilizer, or wash over a parking lot and collect oil residues. Once it reaches a stream, the drop of water that is now contaminated from human land use in the watershed can affect the biological community living in the stream.

Almost universally, anthropogenic changes in a watershed have the potential to exert negative effects on a stream's biotic community. However, all streams are not created equal; some have the capacity to withstand higher amounts of human-induced land use change than others. This is because watersheds can have natural built-in buffering capacity or resistance/resilience factors such as an intact forest on either side of the stream or wetlands which help buffer flows and filter out sediments and toxins. In this chapter, a network modeling approach was used to explore the influence of watershed resistance and resilience factors on the vulnerability of streams to anthropogenic stressors associated with urbanization.

Differing Responses of Watersheds to Increases in Urban Area

The term 'urban stream syndrome' was coined to describe the complex interconnected suite of stressors and responses that accompany urban development in a watershed. In an effort to provide a conceptual framework for understanding this phenomenon, Schueler (1994, 2009) proposed the impervious cover model (ICM) to describe the amount of degradation that occurs in a stream with increasing urbanization in the surrounding watershed. Impervious cover (IC) is any surface that impedes movement of precipitation into subsurface flow; thus, IC includes roads, roofs, and parking lots. In Maine, evidence suggests that beyond a threshold value of ~ 6% impervious cover in a catchment, stream water and habitat quality begin to decline, with an associated decrease in aquatic species richness and intolerant taxa in the macroinvertebrate community (Morse et al. 2003). IC, however, is not always the best predictor of stream quality, especially when there is less than 10% IC in the watershed. At these low IC levels, forest cover, road density or crop cover may have better predictive power (Schueler et al. 2009). Furthermore, Wright (1995) reported that patterns of aquatic insect abundance can vary at low levels of IC due to site-specific factors related to nutrients and organic compounds.

Given the observed variability of stream quality at low values of watershed IC, Schueler et al. (2009) proposed a new version of the ICM that resembles the shape of a cone (Figure 3.1). In that model, water quality varies substantially at low values of IC, whereas stream quality is more consistently degraded at higher values of IC. As such, the ICM reflects our understanding that some streams may be more sensitive or resistant to degradation than others, especially at low values of IC.

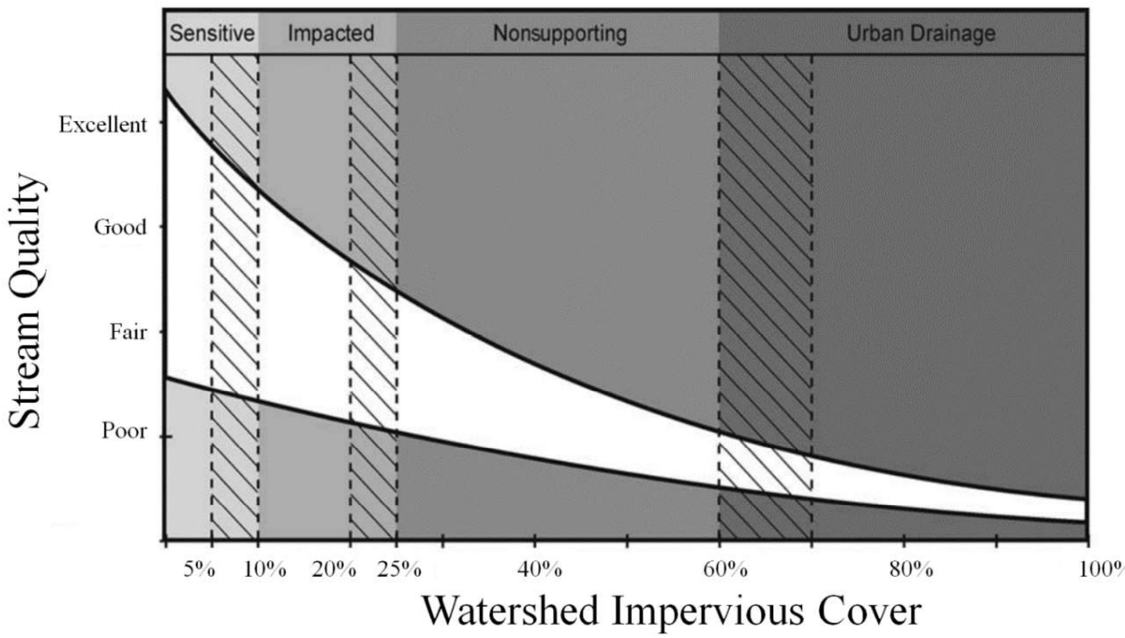


Figure 3.1. Response of stream quality with increasing percent watershed impervious cover. From Schueler et al. (2009).

Because the thresholds of IC at which streams exhibit symptoms of impairment differ among watersheds, we hypothesize that there are watershed characteristics that either ameliorate or enhance the effects of urbanization on water quality. For example, the presence of wetlands has been associated with a decrease in exports of nutrients, toxins, and sediments to streams (Johnston et al. 1990, Jordan et al. 2011, Marton et al. 2014). Calcareous bedrock in a watershed increases acid neutralizing capacity (ANC) in streams and helps to prevent acidification and biotic stress (Sullivan et al. 2007, USGS 1989). Shallow slopes decrease the flashy flows associated with impervious cover and allow water to infiltrate into the ground. Alternatively, some aspects of a landscape may make streams more vulnerable to degradation. If we can begin to identify and to understand the primary watershed characteristics associated with stream resistance to degradation, it may be possible to predict which streams are more vulnerable to future land-use changes and to avert future impairment.

Bayesian Networks in Ecological Applications

Traditional statistical methods struggle to tease apart which aspects of urbanization negatively affect stream biota and water quality. In this research, a Bayesian network (BN) was used to explore the causal web of interacting factors that account for stream vulnerability to the urban stress syndrome. Bayesian networks, also known as probability networks or Bayes nets, are statistical tools that represent systems based on interactions among variables leading from primary causes to a specific outcome (Chen and Pollino 2012). BNs are increasingly being applied to ecological research problems, where they are advantageous because of their ability to: (1) model systems despite uncertainty and missing data; (2) be updated with additional knowledge as it becomes available; (3) incorporate sub-models into the larger model framework; and (4) incorporate different types of data, including qualitative, quantitative and expert-derived data (Chen and Pollino 2012, Marcot et al. 2001, Uusitalo 2007).

Bayesian networks have been used to assess population viability of at-risk fish and wildlife (Marcot et al. 2001), for land suitability analyses (Meyer et al. 2014, Chow and Sadler 2010), for adaptive management decisions (Nyberg et al. 2006), and for water quality predictions (Reckhow 1999). McCloskey et al. (2011) used BNs in combination with GIS data layers, empirical data, and expert knowledge in order to identify areas of potential conflict between land-uses in Maine’s Lower Penobscot River Watershed.

Kashuba et al. (2012) used expert-derived BNs to examine the relationships linking urban development to physical, chemical, and biological conditions in a stream.

Because BNs can be effective in helping to visualize complex ecological processes, the modeling process itself can be very informative, highlighting areas in which understanding is not complete and identifying areas that need more research (Gaddis and Voinov 2008, Marcot et al. 2001). By explicitly acknowledging the inclusion of subjective analysis, BNs provide a practical and transparent way to quantify the uncertainty associated with the inevitable subjectivity in ecological modeling (Krueger et al. 2012).

In situations in which the system is too complex or there is insufficient data to create a BN, the use of expert- or stakeholder-derived knowledge is common and is referred to as "participatory modeling." Beyond using expert or stakeholder knowledge to fill in data gaps, participatory modeling has several advantages. First, it creates buy-in from stakeholders who help to generate the model and consequently have more trust in the final product (Gaddis and Voinov 2008). Additionally, the process of participatory modeling creates a network of individuals who share similar concerns, creating a stronger platform from which to initiate change in a system (Krueger et al. 2012). Finally, a diverse group of experts can provide data that were not previously known or available. Moreover, some experts know the feasibility of management strategies the model proposes while others can provide anecdotal evidence that may be the only data available for some specific factors or processes (Gaddis and Voinov 2008).

Study Objectives

The objective of this research was to create an expert-derived Bayesian Network that uses spatially-explicit watershed characteristics as causal variables to predict the probability that a stream will become degraded in response to land-use change and urbanization. The investigation focused on the following related question: Can we predict the hypothetical future condition of streams in response to land-use change, but before the land-use change occurs? Other related studies have addressed this issue using alternative futures scenarios in Oregon (Van Sickle et al. 2004) and Iowa (Santelmann et al. 2004), and exploring the influence of different management scenarios on streams in Australia (Turak et al. 2011). This research is intended to provide a tool for ranking watersheds throughout the State of Maine based on their vulnerability to urbanization, so that prospective development can be diverted from susceptible watersheds to other watersheds that are less likely to become degraded by land-use change. In this way, local governments will be able to allow urban expansion while protecting stream health and minimizing municipal tax burdens associated with stream restoration.

METHODS

Study Area

As the most northeastern state in the U.S., Maine is characterized by cold winters, mild summers, and is dominated by forested land cover (80%), wetlands (10%), agriculture (5%), and human development (5%). Maine has an east-to-west and south-to-north gradient of human development, with most development focused on the coast and in the warmer southern region of the state, but tapering off towards the north and west.

Most agriculture is concentrated in the northeastern part of the state, while the western mountains and the northwestern portion of the state are primarily working forests or protected forest land. Although currently Maine has a relatively sparse population, development has been increasing substantially and is predicted to continue increasing. The US Forest Service Forests on the Edge (FOTE) research indicated that four major watersheds in Maine are ranked at the top of the list for watersheds expected to experience substantial development growth on private forests (Stein et al. 2006, Stein et al. 2009, Mockrin et al. 2014). Preliminary data from the most recent study indicated that housing density is expected to increase within major watersheds in Maine by up to 48.6% on private, non-industrial land, with development concentrated in the more southern and coastal regions of the State (Figure 3.2).

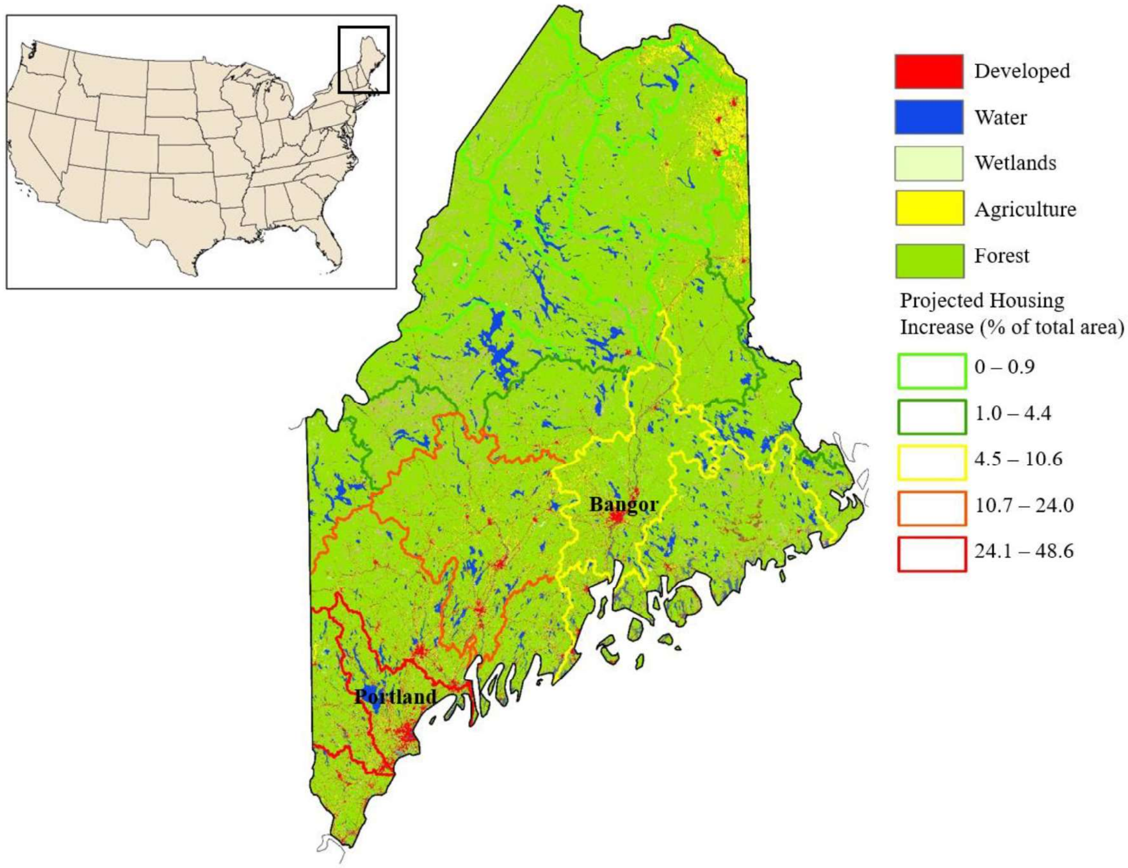


Figure 3.2: Maine primary land use/land cover, with major watersheds outlined to indicate projected housing increase on private forest land. Housing data based on Mockrin et al. (2014) and land cover from MELCD 2004.

Expert Elicitation, Data Processing, and Model Creation

Expert Recruitment

The BN was created with the guidance and participation of nine experts who were recruited from a list of Maine professionals in the fields of watershed management, stream ecosystem monitoring, environmental engineering and stormwater management, or stream ecosystem research. It was our goal to recruit participants with a wide range of expertise and views in order to develop a holistic understanding of the processes driving stream impairment in the state (Krueger et al. 2012). For the purposes of BN model development, experts are individuals who have detailed or specialized knowledge gained through experience, education, or training regarding the system in question (Kuhnert et al. 2010). A person who researches streams or works with streams frequently would be one example of an "expert" in this research. Beyond these requirements, our recruitment was not biased by any factor such as age or gender. Eight of the nine experts on our research team have devoted most of their careers to the study and management of streams in Maine, and all experts possess extensive knowledge of stream ecology. Recruitment was done using an initial email and follow-up phone calls (Appendix A).

Initial Expert Elicitation, Variable Identification and Model Structure

A large body of research describes techniques to elicit expert judgments effectively and with minimal bias. Expert elicitation can be done directly, by asking experts about values or criteria to use in the model, or indirectly, by compiling information from broad survey questions answered by experts (Martin et al. 2011). There are several different complications that can arise in expert elicitation, including motivational bias, overconfidence, dominance of one or more members of the group, polarization within the group, and group think (agreeing on an answer in the interest of finishing the task or not wanting to raise a contrary view; Martin et al. 2011, Low Choy et al. 2009). To avoid some of these issues, experts can be made aware of the potential for bias (Low Choy et al. 2009) and experts can work together but report their answers individually (Martin et al. 2011). Throughout the BN development, it is important that the process and goals are clear to the experts, so the elicitation can be as accurate as possible (Low Choy et al. 2009). When necessary, experts can be asked to explain their answers when they voice counter-intuitive views or outlying opinions (Low Choy et al. 2009).

In this study, expert elicitation began with a four-hour long focus group during which participants learned the goal of our research, the motivation for creating an expert-derived BN (Low Choy et al. 2009), our definition of stream vulnerability, and the basic principles of the Bayesian modeling process. We then asked participants to list all of the factors that they believe influence or govern stream vulnerability to urbanization in the State of Maine. Equipped with that list, spatial data layers were acquired that either directly represented the factor, or served as a proxy variable when no direct data were available. This then set the stage for construction of an alpha level model based on Marcot (2006).

The first step in BN model development was to create an influence diagram representing the "causal web" of interacting watershed environmental variables and the probabilities of different combinations of those variables that lead to the probability of a final ecological response outcome (Marcot et al. 2006). BNs consist of nodes describing categorical or discretized continuous variables, and links that connect the interacting variables. Nodes with incoming links (child nodes) have conditional probability tables (CPTs) that describe the probability of different outcomes occurring given all the possible combinations of the various input nodes (parent nodes). Parent nodes have prior distributions based on data or expert opinion; in our case, the distributions were based on spatial GIS data. Given that model parsimony is an important consideration in creating a

BN, Marcot et al. (2006) suggested limiting the number of parent nodes linked to any child node to three or fewer, and the number of levels of the model to four or fewer.

Processing Catchment Data

The National Hydrography Dataset (NHD) Version 2 (USGS 2012) was used as the watershed layer in this analysis. This dataset represents watersheds and sub watersheds at the reach scale, starting at headwater streams and spanning the whole stream length by reach-scale subcatchments. Because the watersheds are nested and overlap each other down the stream network, preprocessing of the catchments was necessary. Catchments were separated into three groups: headwater catchments, reach-scale catchments, and adjoint catchments that span the entire upstream area of the reach-scale catchment (Figure 3.3).

Adjoint catchments were created using ArcHydro Tools in ArcMap 10.0 (ESRI, Redlands, CA). Spatial variables were transformed to 30m pixels and were then summarized for each group of catchments using the Raster package in R. Summarized data for each adjoint catchment were then combined with summarized data for the reach-scale catchment, and headwater catchments and reach-scale catchments were recombined for analysis. An upper size limit of 125 km^2 was chosen because catchments larger than this were assumed to be inherently less vulnerable to urbanization stress due to their dilution capacity. This decreased the number of catchments from approximately 67,000 to 23,554. Collection of each spatial variable included in the model is described in greater detail later in this chapter.

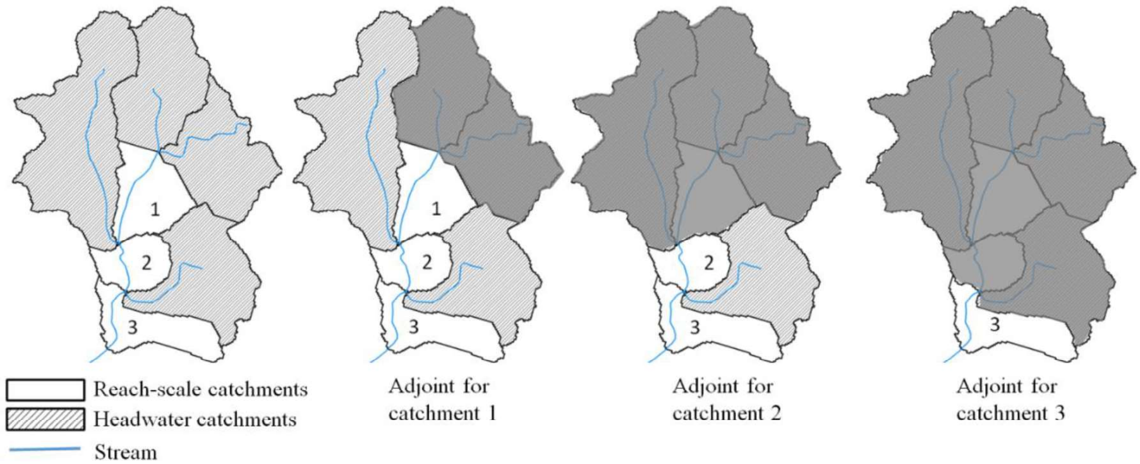


Figure 3.3. Diagram of the process of summarizing watershed information for reach-scale watersheds using adjoint catchments.

Discretization and Conditional Probability Tables

BNs are limited in their ability to use continuous data; therefore, all continuous data must be separated into two or more different classes through a process called "discretization" (Chen and Pollino 2012). Discretization of continuous variables can cause a number of complications in the BN development process. Choosing the number of states and the discretization values is challenging, and differences in these values can lead to large differences in the model output, so it is best to base the discretization on the numerical distribution of the input data in order to minimize error (Uusitalo 2007). In discretizing our continuous variables, the summaries for each spatial variable across all watersheds were presented to the experts with suggestions for cutoff values (Appendix B). Through iterative emails and phone calls, all experts registered their opinions for optimal cutoff values, and variables were ultimately classified into no more than three states as per Marcot et al. (2006).

Surveys containing the BN influence diagram and all conditional probability tables were given to the experts to complete (Appendix C). CPT surveys were administered in small group meetings or one-on-one with the principal investigator (PI). During the meetings, the PI explained the model objectives again and helped to guide the experts through the process of completing the complex CPTs. The CPTs depicted each possible unique combination of the input variables and provided a 1 – 5 scale for ranking the unique combinations based on their potential contribution to stream vulnerability from urbanization stressors (Table 3.1).

Below each CPT, a comment section was provided where each expert was asked "What assumptions are you making about the interactions of these variables in affecting vulnerability to this stressor? Do you have other thoughts or comments?" This information helped the PI to determine whether the CPTs were filled out correctly, where experts had differing opinions, and where experts had comments about variables or variable interactions.

Table 3.1. Example of a CPT survey table. Here the distinct states of the variables well-draining soils and drainage area are given a value between 1 and 5, with 1 being least vulnerable to salt stress and 5 being most vulnerable to salt stress.

Well-draining Soils	Drainage Area (km^2)	Probability of Vulnerability to Salt Stress: Less Vulnerable				More Vulnerable
> 30%	> 5	1	2	3	4	5
	0 - 5	1	2	3	4	5
10 - 30 %	> 5	1	2	3	4	5
	0 - 5	1	2	3	4	5
< 10%	> 5	1	2	3	4	5
	0 - 5	1	2	3	4	5

To help in visualizing the meaning of the values between one and five, Figure 3.4 was shown to the experts. It was assumed that a value corresponding to 3 on the regression curve between stream water quality and impervious cover represented the average response of a stream to watershed urbanization. Values of 1 and 2 represented streams that are less disturbed in response to impervious cover, and are therefore below the curve. Values of 4 and 5 represented streams that become degraded with less impervious cover in their watersheds, and thus are more vulnerable to urbanization.

Throughout the survey, care was taken to keep this spectrum of "good" to "bad" ranging from 1 to 5 in order to minimize confusion. Within the small groups, discussion was encouraged but experts were asked to write their answers separately in order to minimize group bias (Martin et al. 2012, Low Choy et al. 2009). In most cases, surveys were not finished in the time allotted and were returned after several weeks.

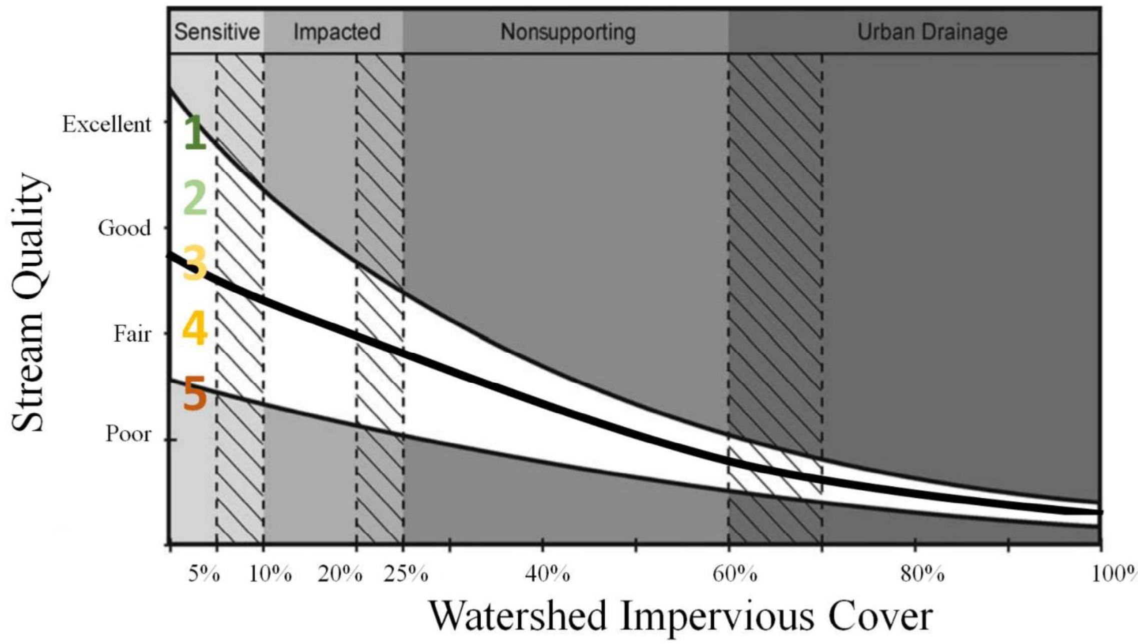


Figure 3.4. Conceptual image of Likert ranking of stream vulnerability adapted from Schueler et al. (2009).

In order to convert the 1 to 5 Likert scale into probability distributions, methods from Meyer et al. (2014) were followed. Likert scores were converted to probability values by first taking the median of all expert responses. The median was chosen to minimize the influence of outlying expert responses. Then these summarized Likert values were converted to a probability range using the scale shown in Table 3.2. In order to account for some of the variation in expert responses, the coefficient of variation (CV) was used for Likert values between 2.8 and 3.2 for three-state nodes. If the median of expert responses fell in this range and the CV was low, then there is high confidence that the probability of the node being in the "Medium" state is 100. Alternatively, if the experts did not agree, which results in a high CV, then there is low confidence that the resulting child node will be in the "Medium" state and therefore the probability is spread across all three states.

Table 3.2. Conversion of median values of expert responses on the Likert scale to state probabilities for two- and three-state nodes.

	Stakeholder Likert		Score	State Probabilities		
	Min.	Max.	CV	Low	Medium	High
Three-State Nodes	1	1.3		100	0	0
	1.3	1.6		75	25	0
	1.6	2.2		50	50	0
	2.2	2.8		25	75	0
	2.8	3.2	< 0.15	0	100	0
	2.8	3.2	0.15 - 0.3	25	50	25
	2.8	3.2	> 0.3	33	34	33
	3.2	3.8		0	75	25
	3.8	4.4		0	50	50
	4.4	4.7		0	25	75
	4.7	5		0	0	100
Two-State Nodes	1	1.8		100		0
	1.8	2.6		75		25
	2.6	3.3		50		50
	3.3	4.2		25		75
	4.2	5		0		100

The model structure and conditional probability values were entered into the modeling software Netica (version 5.12, 2013, Norsys Software Corporation, Vancouver, British Columbia). Netica allows each watershed to be processed individually, and predicts a final probability of vulnerability. This final BN takes spatial data compiled for Maine watersheds, discretized at the values agreed upon by the experts, and runs through the CPTs that are based on expert judgment to give a value for probability of vulnerability to urbanization for each watershed.

Sensitivity Analysis and Model Validation

A sensitivity analysis was performed on the BN model in an effort to rank the variables based on their predictive power in the model (Gaddis and Voinov 2008) and to determine the direction of influence for each variable. Sensitivity analysis is a function built into Netica that assigns a value of variation reduction to each variable and node in the model, ranking them from most important variable or node to least important. This gives us insight into the main drivers of stream vulnerability, and can help determine the agreement between the model and the input of the experts.

An important part of making any model is validation. Bayesian networks, however, are often difficult to validate and in many cases are not validated at all. Validation techniques include using actual data (Allan et al. 2011), consulting with an expert panel (Meyer et al. 2014), or simply using the sensitivity analysis (Aguilera et al. 2011). In many cases, BN model validation is skipped entirely (Aguilera et al. 2011). In this research, model validation was done using two techniques. First, the samples in the high and low vulnerability categories used for the Kruskal-Wallis rank test in Chapter Two were run through the model to get vulnerability scores. We assumed that, if our model is representing vulnerability to urbanization correctly, samples in the high vulnerability category would be in either quartile 3 or 4—the quartiles of highest probability of vulnerability to urbanization. Samples in the low vulnerability category would fall into either quartile 1 or 2, indicating that they have a low probability of vulnerability.

Another approach was taken to ascertain model agreement with attainment of statutory class expectations. Every stream in Maine is expected to attain a statutory class of AA/A, B, or C, in order of decreasing habitat quality and aquatic community composition (38 M.R.S.A Section 464 et. seq.). We expected that samples with lower than the MEDEP impervious cover vulnerability thresholds (Figure 2.1; Danielson et al. in press) that are not attaining will be in either quartile 3 or 4 of the BN vulnerability range. Similarly, samples that still attain their statutory class at higher than the vulnerability threshold will be in the lowest two vulnerability quartiles, indicating low vulnerability. In combination, the two validation approaches provided a way to test the model accuracy in a robust way.

RESULTS

Variable Selection

With assistance and feedback from the nine members of the focus group, 26 watershed variables were chosen for use in the model (Table 3.3). Unlike the variables used in the analysis described in Chapter Two, spatial variables used for this analysis were all rasters of 30m pixels. Instead of MELCD 2004 land cover data, 2011 National Land Cover Dataset (NLCD) 30m pixel information was used for land use/land cover information. Each variable was measured at only one scale—most variables were measured at the whole watershed scale, although some were measured at a 30 m or 60 m riparian buffer scale. One variable, Percent Resistant Surfaces, was measured in a 30 m riparian buffer at the reach-scale of each catchment.

Percent Agricultural Area was defined as the NLCD 2011 Cultivated Crops land cover category. Percent Natural Area is NLCD 2011 Deciduous Forest, Evergreen Forest, Mixed Forest, Grassland/Herbaceous, Sedge/Herbaceous, Woody Wetlands and Emergent Herbaceous Wetlands land cover classes. Percent Forested Area is NLCD 2011 Deciduous Forest, Evergreen Forest, and Mixed Forest classes. Percent Nonpoint Sources is NLCD 2011 Developed Open Space and Cultivated Crops. These NLCD 2011-derived variables were processed by reclassifying to Boolean raster layers, using a value of 1 for classes of interest, value of 0 for all others. Then zonal statistics in R was applied to sum the number of pixels in each watershed. Percent area was derived by dividing the sum of pixels of the land cover class by the total number of pixels in the watershed and multiplying by 100.

Percent Lake Area was created by extracting the Lake class of the National Wetland Inventory (NWI). Percent Wetland Area is the Wetland category of the NWI, while the variable Percent Acidic Wetlands is the Wetland category designated with the qualifying class of "a", which denotes an acidic wetland. These vector layers were converted to 5m Boolean rasters and were processed in the same manner as the NLCD variables described above.

Table 3.3. Final list of variables used in the Bayesian network. Also displayed is the scale at which they were measured; minimum, median, mean, and maximum values for all 23,554 catchments; and the source of the original data.

Variables	Scale	Min	Median	Mean	Max	Source
Dams (count)	Watershed	0	0	0.14	15	MEGIS
Stream/road Intersections (density)	Watershed	0	0.08	0.27	12.4	MEGIS roads + NHDPlus V2 Flowlines
Percent Resistant Substrate	30m stream buffer at the reach scale	0	82.46	60.3	100	MGS
Presence of Sand/Gravel Aquifers	60m stream buffer	-	-	-	-	MGS
Area (KM^2)	Watershed	0.5	6.2	16	125	NHDPlus V2
Drains to Ocean	Watershed	-	-	-	-	NHDPlus V2
Nearest Healthy Stream	Watershed	0	1.2	1.3	7	NHDPlus V2
Percent Agricultural Area	Watershed	0	0	2	88	NLCD 2011
Percent Non-point Sources	Watershed	0	1.3	4.2	88	NLCD 2011
Upstream Riparian Buffer Area	60m stream buffer	0	0.6	1.9	70	NLCD 2011
Percent Natural Area	60m stream buffer	0	94	84	100	NLCD 2011
Percent Forested Area	60m stream buffer	0	80.2	74	100	NLCD 2011
Percent Lake Area	Watershed	0	0	2.4	100	NWI
Percent Retained Water Area (Lakes + Wetlands)	Watershed	0	9.5	11.5	100	NWI
Percent Acidic Wetlands	Watershed	0	0	0.8	95	NWI
Percent Wetlands Area	Watershed	0	6.9	9.1	100	NWI
Average July Maximum Air Temperature (^{o}C)	Watershed	11.9	25.7	25.5	28.25	PRISM
Average Summer Precip (inches)	Watershed	14	28.2	28.4	43	PRISM
Buffering Capacity	Stream reach	-	-	-	-	TNC NEAHCS
Percent A or B Soils	Watershed	0	5.6	14.3	100	USDA NRCS
K Factor	30m stream buffer	0.7	5.2	5.7	13.3	USDA NRCS
Percent D Soils	Watershed	0	43	45	100	USDA NRCS
Soil Depth	Watershed	0	87.6	98.7	*	USDA NRCS
Percent A, B, A/D, or B/D soils	Watershed	0	6	15	100	USDA NRCS
Slope (percent)	Watershed	0	6	7.2	53.2	USGS DEM
Stream Gradient	30m stream buffer	0	3.9	4.7	64.9	USGS DEM

Stream/Road Intersections were created by using the Intersect tool to get points where the MEGIS road layer intersected with the NHDPlus V2 flowlines. Points were summed for each watershed, and were then divided by total watershed area to obtain a density metric. Dam locations were acquired through MEGIS, and were then summed by watershed for a count metric. Slope was derived from a USGS 10 m DEM. Average July Maximum Temperature and Average Summer Precipitation were obtained from the 14km PRISM climate raster. Data for the years 2009-2013 were averaged and then zonal statistics was applied to get an average value for the watershed.

The dichotomous variable Buffering Capacity was created from the Northeastern Aquatic Habitat Classification System (NEAHCS) produced by The Nature Conservancy (Olivero and Anderson 2008). This dataset assigns each stream in the NHDPlus V2 network to one of three categories: acidic, low buffered; neutral, moderately buffered; and calcareous, highly buffered. Highly buffered and moderately buffered categories were considered "buffered" and were assigned a value of 1, while the acidic category was considered not buffered and was assigned a value of 0.

The variable Drains to Ocean was proposed by an expert we consulted who has observed that small watersheds that drain directly into the ocean have a lower chance of being recolonized from downstream, and therefore are more susceptible to impairment due to urbanization. This dichotomous variable was created by visually selecting catchments that drain directly into the ocean, assigning them a value of 1, and giving all other watersheds a value of 0. Nearest Healthy Stream was determined by creating the centroids of the NHDPlus V2 catchments, and then removing those associated with watersheds with over 7% IC (Morse et al. 2006). The Nearest tool was then applied to all headwater catchments to obtain the distance in kilometers to the nearest catchment centroid. This was calculated for headwater streams only because we assume stream reaches lower in the network will be recolonized with downstream drift. Percent Resistant Surfaces was created with the help of an expert who selected the following categories of the MGS surficial geology layer as resistant to erosion: bedrock, ribbed moraine, stagnation moraine, till, and thin drift. The layer was then converted to a 30m pixel raster and was summarized in the same way as the NLCD variables. Percent Sand/Gravel Aquifers were downloaded from MGS and were summarized the same way as the NLCD variables to obtain the percent area.

Model Structure

Spatial variables in the model were organized on the basis of their direct or indirect effect on stream vulnerability in relation to nine stress categories, including: flashiness, low base flow, sedimentation, heat, DO, nutrients, salt (chloride), acid, and toxins. Because it is important to keep CPTs simple, some individual stressors were separated into two intermediate nodes that organized spatial variables into either *contributors* or *mitigators* of that particular stressor. For example, because heat stress has five spatial variables that potentially contribute to vulnerability, this would create a CPT too large to be easily interpreted by the experts. Two variables were considered mitigators—groundwater input and percent forested riparian area—while the other three variables—air temperature, small drainage area, and retained water—were considered contributors. The nine stress categories were aggregated into one of two major stress regimes based on whether their contribution to vulnerability was likely to be exerted through chemical or physical stress (Figure 3.5). A third section of the influence diagram was added to represent the variables that influence *resilience*, which is the capacity of a watershed to recover from stress or a stress event. Spatial variables included in this category are those that contribute to potential recolonization of the stream after a disturbance event. The output of these three collective nodes—vulnerability to physical stress, vulnerability to chemical stress, and resilience—were combined in the final node that predicts the overall probability of vulnerability to urbanization stress.

In some cases, not all experts agreed on including certain stressors. In these cases, the stressor remained in the model and experts were informed that they could chose to weigh that stressor less than the others in the respective conditional probability table. For example, all experts considered precipitation to be an important variable, but the range of precipitation summarized for all watersheds across the state was small enough that many experts decided not to consider this variable as important when filling in the Contributors to Flashiness Stress node.

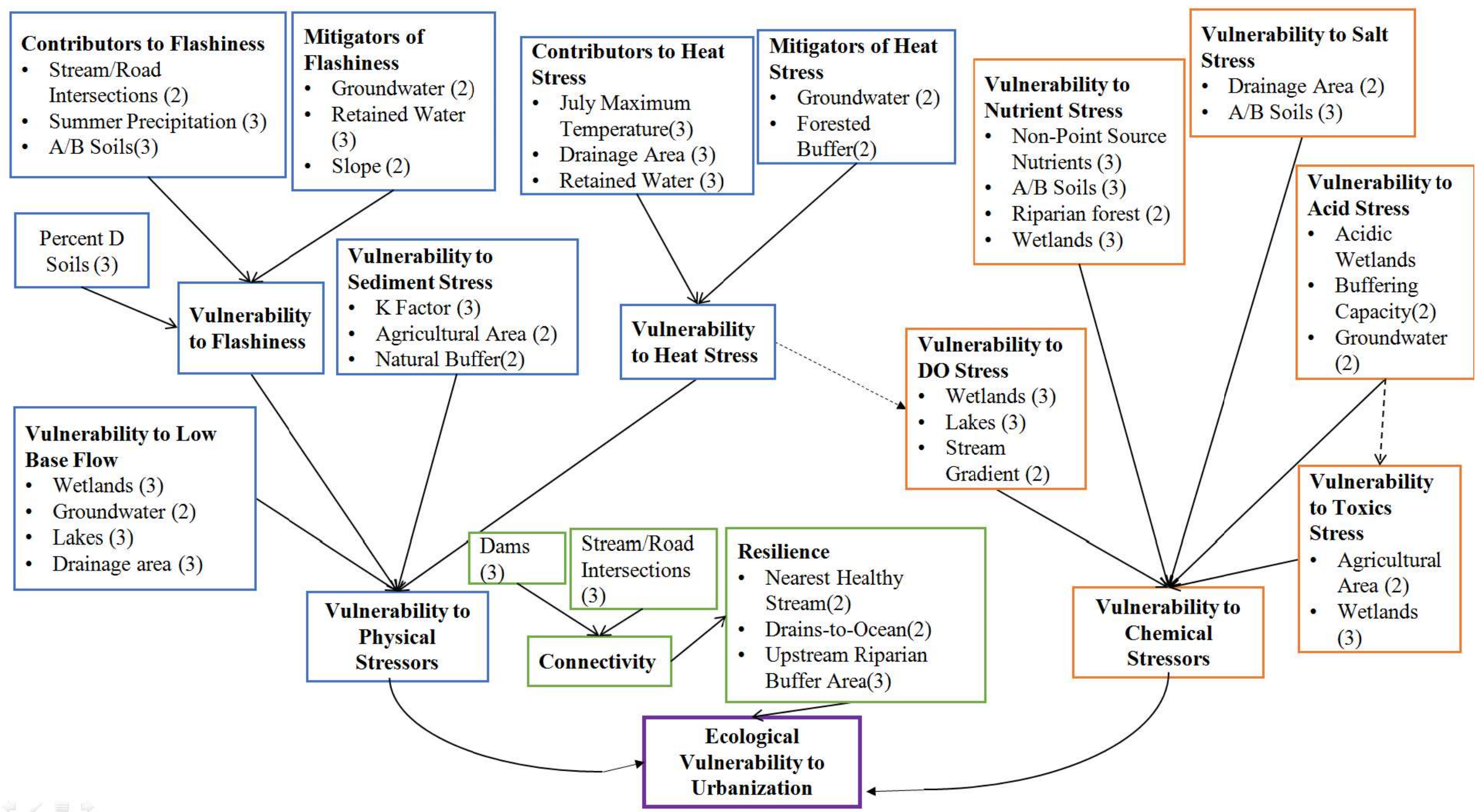


Figure 3.5. Final influence diagram. Box headings describe the child node which combines the bulleted input variables. Numbers in parentheses describe the number of discrete states.

The definition of the groundwater variable was a source of difficulty. Despite its role as one of the most important variables affecting stream ecosystem health, there is no reliable spatial layer that represents groundwater inputs across the State of Maine. To circumvent this obstacle, experts were consulted about proxy variables that could be used to estimate groundwater input into streams. As a result, three variables were chosen: Percent Sand/Gravel Aquifer at the riparian scale, Soil Depth, and the combined Percent A, B, A/D, and B/D Soils. This last variable is moderately different than the variable Percent A or B soils and was compiled through the NRCS Web Soil Survey the same way as the other soil variables, described above. Besides the area of soils classified in hydrologic groups A and B, we added the classes A/D and B/D which describe well-draining soils with water tables higher than 50 cm (USDA NRCS 2012). We assume well-draining soils with high water tables are likely to add groundwater into streams. To combine the three variables, a CPT was created and was completed by all the experts. In every part of the influence diagram where groundwater was a parent node, the CPT combining the three variables was used.

Model Results—Vulnerability to Urbanization Stress

Vulnerability scores are the output of the final node in the Bayesian network. The output is the probability of vulnerability; therefore, it represents the likelihood that the stream is highly vulnerable. Low probability of vulnerability indicates that based on our model the stream has low vulnerability. High probability of vulnerability indicates that the stream is highly vulnerable. These probability values are therefore a vulnerability “score” for the stream. The spatial distribution of watersheds grouped into the four different vulnerability quartiles is displayed in Figure 3.6.

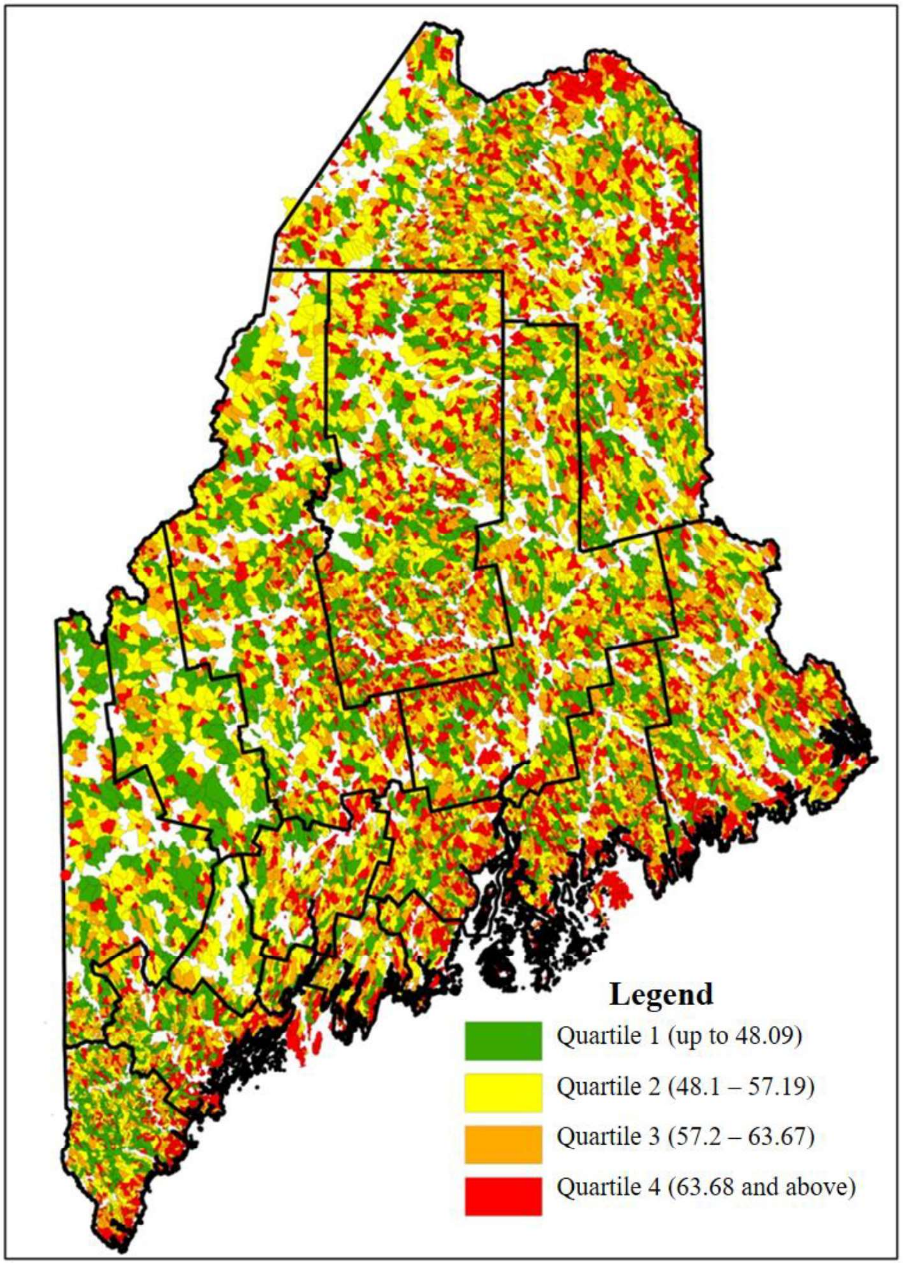
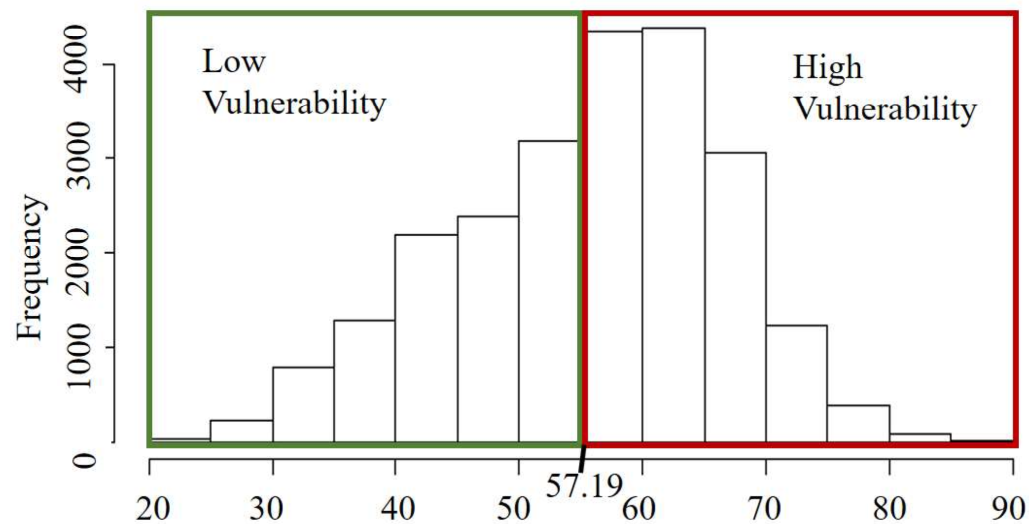


Figure 3.6. Vulnerability scores for 23,554 reach-scale catchments displayed by quartile (from lowest =1 to highest = 4) for the State of Maine. County boundaries are shown in black.

The distribution of vulnerability scores is semi-normal with an average vulnerability score of 55.61, indicating that there are more watersheds with high vulnerability than low vulnerability (Figure 3.7). The range of vulnerability is broken into “high” and “low” categories based on quartiles. Low vulnerability is a vulnerability score in quartiles one and two, or less than the median (57.19). High vulnerability are those watersheds with a vulnerability score greater than the median, which are in quartiles three and four.



Vulnerability Score					
Min	1st Q	Med	Mean	3rd Q	Max
20.15	48.09	57.19	55.61	63.67	87.46

Figure 3.7. Range of vulnerability scores as well as values for minimum, median, mean, maximum, and quartiles. The red box is the range of values considered high vulnerability and the green box is the range of values considered low vulnerability.

Sensitivity Analysis

Sensitivity analysis shows the order of importance of variables in determining the final probability of high vulnerability (Marcot 2006). In Netica, the variance reduction tool gives a value for each input variable and node that indicates its influence on the final model output (Figure 3.8). In order to determine the direction of influence of each variable and node, each node was set to its highest state while all others remained unchanged, and the direction of change in the probability of high vulnerability was recorded. If the probability of being highly vulnerable decreased when the variable was set to its highest state, that variable was considered to increase stream resistance to degradation. In this analysis, model variables that increased the probability of vulnerability were termed "negative" variables, while variables that decreased the probability of vulnerability were termed "positive" variables.

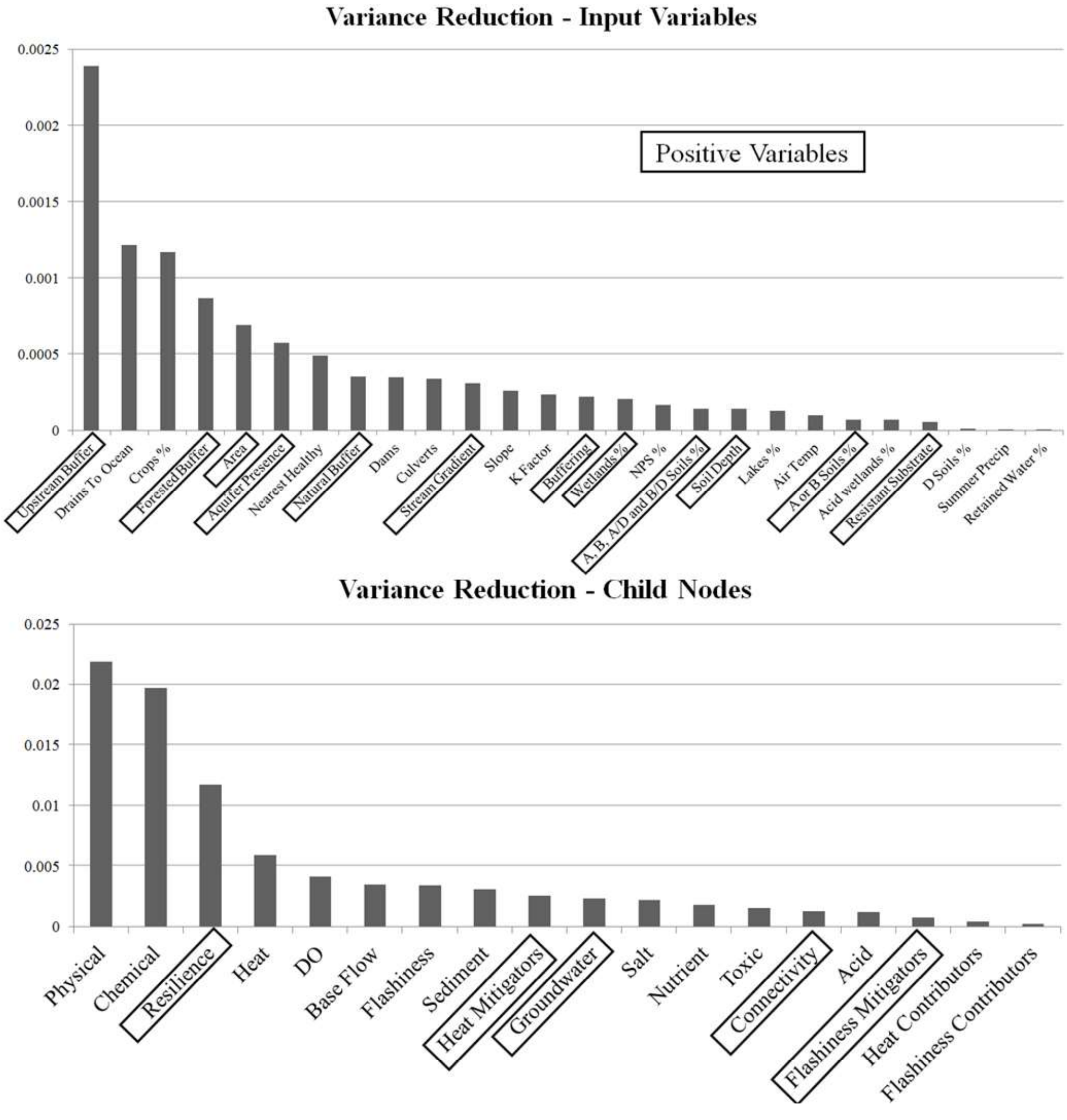


Figure 3.8. Variance reduction and direction of influence of input variables and child nodes. Positive variables and nodes—those that decrease the probability of vulnerability—are shown in boxes. All other variables and nodes increase the probability of vulnerability.

Based on the variance reduction sensitivity analysis, the most influential variables in the model were Upstream Buffer, Drains-to-Ocean, Percent Crops, Forested Buffer, Watershed Area, and Presence of a Sand/Gravel Aquifer. Least important variables were Percent Retained Water, Summer Precipitation, Percent D Soils, and Resistant Substrate.

Upstream Buffer, Riparian Forest, Watershed Area, and Presence of Sand/Gravel Aquifers decreased the probability of vulnerability (positive variables), while Drains-to-Ocean and Percent Agricultural Area caused an increase in probability of vulnerability (negative influence). Upstream Buffer combines two factors that can influence biotic communities: the degree to which a riparian zone is intact, and the length of upstream network from which organisms can drift downstream to re-colonize a stream reach after a disturbance event.

Forested buffers have been shown in myriad studies to be an effective mitigator of stream stress (e.g., Peterjohn and Correll 1984, Weller et al. 1998). Decreasing stream vulnerability with increasing watershed size is an underlying assumption of this study, and this variable is the third most important of the positive variables in the model. The variable Presence of Sand/Gravel Aquifers in the 60m stream buffer was added to the model because of its potentially large influence on groundwater input. To paraphrase one expert's opinion of this variable, although the aquifers do not exist in the majority of the watersheds, where they do intersect a stream they can make all the difference in resistance to urbanization stress. The fact that these variables emerged as having the greatest positive effect on stream resistance to degradation in our model indicates another noteworthy agreement with the expert opinion.

The variable Drains-to-Ocean was proposed by one expert because in his personal experience monitoring streams in Maine, small streams that discharge directly into the ocean are incapable of handling much urbanization in their catchments. He ascribed this to the fact that organisms cannot migrate upstream from larger stream reaches that are less vulnerable, because they are absent when a stream drains into the nearby ocean. Although the inclusion of this variable was not proposed by more than one expert, it emerged as the most influential negative variable in the model. This is both because it is located close to the final output node in the model so its influence is not diluted by multiple conditional probability nodes, but also because experts agreed that it can have a large effect on recolonization potential.

Agricultural area is a well-documented stressor (e.g., Allan et al. 1997), and therefore it makes sense as one of the most influential negative variables. In some cases, however, the variable was not interpreted by the experts as negative due to the increased stress it may cause to downstream ecosystems. In the experience of many of the experts, agricultural area is often among the first areas to be developed. Therefore, the variable Percent Agricultural Area was scored in the CPT as negative because it represented area suitable for, and likely to be, developed.

The most influential child nodes were Vulnerability to Physical Stress, Vulnerability to Chemical Stress, and Resilience, because they are directly linked to the Overall Vulnerability node. After these nodes, Vulnerability to Heat Stress, Vulnerability to DO Stress, Vulnerability to Base Flow Stress, and Vulnerability to Flashiness Stress were most influential in affecting Overall Vulnerability. This corresponds to the sentiment of the experts, who generally agree that these stressors are the most important in affecting stream biotic communities.

Model Validation

Model validation was performed through two different techniques in order to gain a robust understanding of how our results compare with real-world stream condition and response to urbanization. The first technique compared model results with the high and low vulnerability sample categories used for the Kruskal-Wallis rank test presented in Chapter Two. The second technique investigated how well our model predicts attainment of a stream's expected statutory class using 108 macroinvertebrate samples collected by MEDEP that were used in the logistic regression presented in Chapter Two.

Validation using High and Low Vulnerability Categories

Algal and macroinvertebrate sample data were categorized into "Low" and "High" vulnerability categories based on the impervious cover vulnerability thresholds from Danielson et al. (In Press) as well as their attainment class based on the MEDEP discriminant analysis of 30 biotic community variables. Sites with low vulnerability are those that attain A at greater than 3% IC, attain B at greater than 6% IC, or attain C at greater than 15% IC. Sites with high vulnerability are those that do not attain A at less than 1% IC, do not attain B at less than or equal to 3% IC, or do not attain C at less than 10% IC (Figure 3.9).

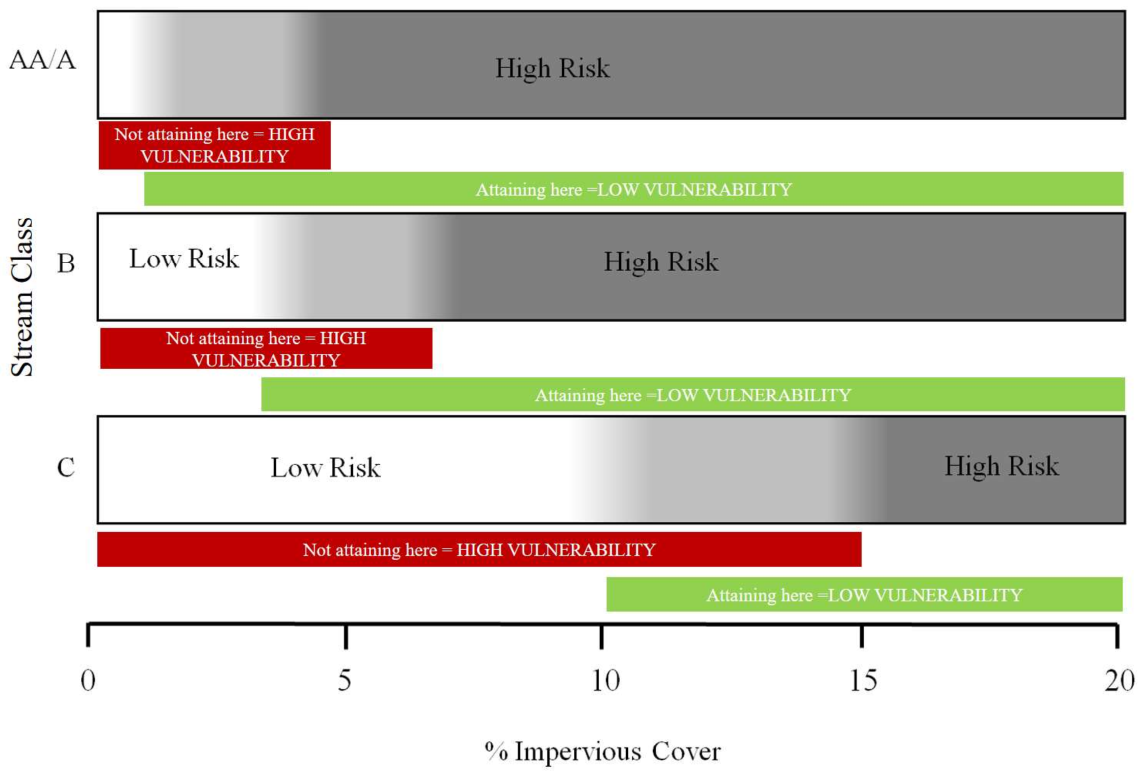


Figure 3.9. Definition of high and low vulnerability sites. The range of high vulnerability sites is shown in red and the range of low vulnerability sites is shown in green.

Thirteen algal samples fell into the high vulnerability category and 20 fell into the low vulnerability category. Seven macroinvertebrate samples fell into the high vulnerability category and 27 fell into the low vulnerability category. To validate the model, these High and Low vulnerability sample sites were run through the BN to get their vulnerability scores. Vulnerability scores are broken into four quartiles, as described in Figure 3.6. We hypothesized that high vulnerability sites should fall into quartiles 3 or 4, while low vulnerability sites should fall into quartiles 1 or 2 (Table 3.4).

Table 3.4. BN model validation based on high and low vulnerability categories. Data is from algal and macroinvertebrate samples used in Kruskal-Wallis analysis.

	Macroinvertebrates		Algae	
	High	**Low**	**High**	**Low**
Number in category	7	27	13	20
Number Correct	4	14	2	11
Percent Correct	57.1	51.9	15.4	55.0

Based on this validation technique, the model performs poorly. For macroinvertebrates, high and low vulnerability categories fall into the appropriate quartile about 50% of the time. For algal samples, the low vulnerability sites fell into the lower two vulnerability quartiles 55% of the time, while only 15% of the high vulnerability sites fell into the two highest vulnerability quartiles.

Model Validation with Statutory Classes

The second validation technique places 108 MEDEP macroinvertebrate samples into categories based on the DEP vulnerability ranges and the statutory class they are expected to attain (Table 3.5). We expected that samples should not attain their statutory class at IC values greater than the vulnerability threshold, or they should be in one of the two lowest vulnerability quartiles. This is because we define low vulnerability as the ability of a stream to withstand development pressure past the IC impairment threshold. Similarly, we expect that samples should attain their statutory class at IC values lower than the DEP impairment threshold, or should be in one of the two highest vulnerability quartiles. This is consistent with our definition of high vulnerability being the impairment of a stream with low development pressure, specifically percent watershed IC less than the DEP impairment threshold.

Table 3.5. Model validation table of IC impairment thresholds by statutory class vs. quartile of vulnerability. Statutory classes A, B and C are shown broken into their respective vulnerability thresholds based on Danielson et al. (in press), as well as each quartile of vulnerability.

	StatClass A			StatClass B			StatClass C			
	<1	1-3	>3	<3	3-6	>6	<10	10-15	>15	TOTAL
number not attaining	**0**	**1**	**1**	**3**	**0**	**21**	**0**	**1**	**5**	**32**
number in Q1	0	1	0	2	0	0	0	0	0	**3**
number in Q2	0	0	0	0	0	2	0	0	0	**2**
number in Q3	0	0	0	1	0	3	0	0	0	**4**
number in Q4	0	0	1	0	0	16	0	1	5	**23**
number attaining	**12**	**9**	**2**	**30**	**14**	**5**	**2**	**0**	**2**	**76**
number in Q1	6	3	1	18	6	2	0	0	0	**36**
number in Q2	2	3	1	8	6	1	1	0	0	**22**
number in Q3	1	3	0	4	1	1	0	0	0	**10**
number in Q4	3	0	0	0	1	1	1	0	2	**8**
										108

The only difference in this validation approach is that it considers the statutory class the stream is expected to attain, whereas the first approach looks simply at the attainment class of the sample taken at the stream and does not consider statutory class. Other than that, the validation is similar in the definition of low and high vulnerability as well as the cutoff values of IC (Figure 3.9). A sample is accurately classified if it is not attaining its statutory class at an IC value less than the higher DEP threshold and it falls in quartile 3 or 4 of vulnerability. A sample is also accurately classified if it is attaining its statutory class at an IC value greater than the lower DEP threshold and it falls in quartile 1 or 2 of vulnerability. If the sample is not attaining at high values of IC or still attaining at low values of IC, it is responding exactly how we would expect and therefore is medium vulnerability. Here we are only testing the high and low vulnerability, so we ignore those sites.

This validation technique can tell us multiple things about our model. There are 32 streams that are not attaining their statutory class, compared with 76 streams that are attaining their statutory class. Only three streams are not attaining their statutory class at an IC value lower than the threshold, and the model classified one of these into the correct quartiles of vulnerability – i.e., quartile three or four (Table 3.6). Nine streams were attaining at higher than the IC threshold value, and the model classified five of them into the correct quartiles of vulnerability i.e., quartile one or two. Overall, the results of this second validation test were generally similar to results from the first validation test described earlier.

Table 3.6. Results of second validation technique incorporating statutory classes

	Is attaining, high IC (should be in Q1 or Q2)	Not attaining, low IC (should be in Q3 or Q4)
Total Number	9	3
Number in correct quartile	5	1
Percent in correct quartile	56	33

It is interesting to note that Table 3.5 also provides another perspective on the validity of the model, if we focus on the 27 out of 32 non-attaining streams that are above the IC threshold for their statutory class. Twenty-five of these high IC streams are in the 3rd or 4th quartile of vulnerability, which means that vulnerability and IC are convergent rather than divergent for these streams. As such, one or both factors may contribute to the lack of attainment. Although it may seem obvious that the streams are not attaining because they are in watersheds above the IC threshold, this may or may not be the complete explanation. It is possible that some or all of the streams are only non-attaining at that IC level because they are also in the highest vulnerable category. We cannot conclude that the DEP model for IC is sufficient to explain the pattern and we cannot discount the possible influence of vulnerability. Thus, we have 25 out of 32 streams where both metrics are consistent in that: (1) the IC is high enough to be a stress; and (2) the watershed is in the most vulnerable category for responding adversely to the IC stress.

DISCUSSION AND CONCLUSION

A major advantage of expert modeling is the ability to gain a better understanding of the state of knowledge surrounding the model topic (Chen and Pollino 2012, Marcot et al. 2001, Uusitalo 2007). Throughout our modeling process, we encouraged discussion among experts about all the variables and our model structure. In some cases, experts had opposing views about the effect of a variable on stream vulnerability to urbanization, and our modeling process helped to clarify and oftentimes resolve these debates.

A focus of discussion throughout the modeling process was the effect of well-draining soils (i.e., Percent A or B Soils vs. Percent D Soils) on vulnerability to urbanization. Some experts argued that well-draining soils allow infiltration of water surrounding urban IC, which tends to increase stream health. Others thought that a watershed with poorly draining soils supports a stream that is naturally exposed to flashy flows, so the difference in hydrologic disturbance due to urbanization is not as large as a watershed with well-draining soils. This debate caused CPT surveys to be filled out differently depending on which opinion the expert held, and it is clear from the summary in Figure 3.10 that some CPTs were more controversial than others.

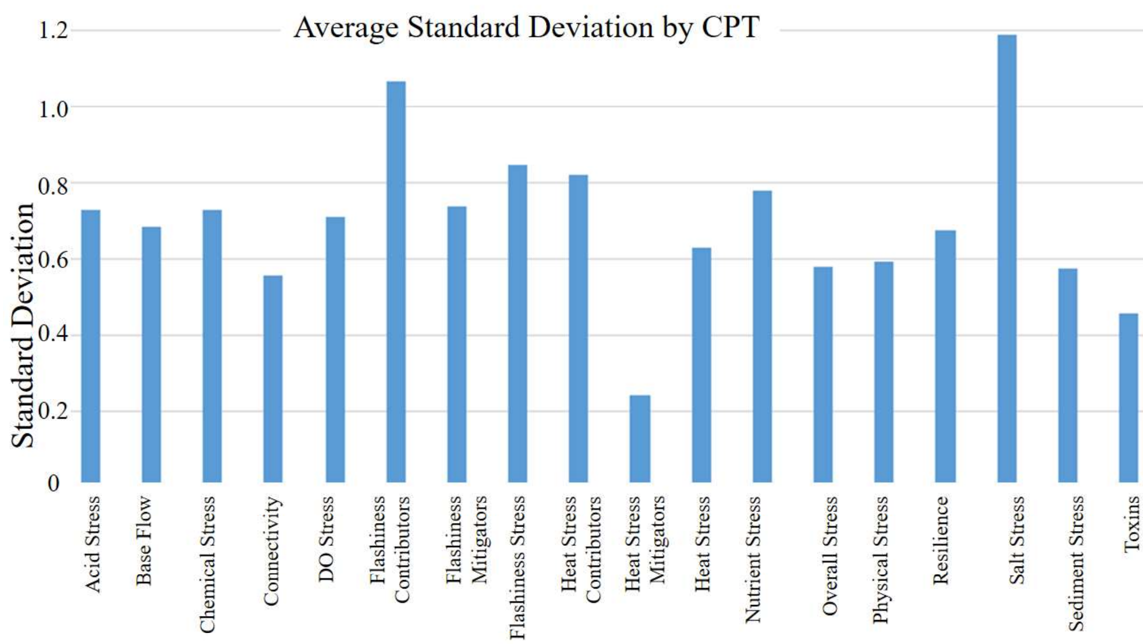


Figure 3.10. Average standard deviation of responses to CPTs for all child nodes in the BN. Greater standard deviation of responses indicates less agreement among experts.

It is clear that this BN network model contains a large amount of uncertainty that reflects the state of knowledge and the range of perspectives among our focus group panel of experts. While this leads to results that are less conclusive, it is enlightening nonetheless to discuss the sources of uncertainty. Child nodes with large standard deviations of CPT survey responses are areas in which experts are uncertain about the effect of the input variables on the vulnerability related to that node. For example, the table with the highest average standard deviation is Vulnerability to Salt Stress (sd = 1.2), indicating there was little agreement among the experts about how the input variables affect stream vulnerability to chloride contamination. Figure 3.5 lists the input variables to each child node and Table 3.1 shows the CPT for the Vulnerability to Salt Stress node. Vulnerability to Salt Stress has two input variables: Percent A or B Soils and Watershed Area. All experts agreed that increased drainage area would decrease vulnerability to chloride stress due to larger dilution capacity. Experts disagreed on the effect of well-draining surfaces. Five experts argued that increased amounts of well-draining soils would increase vulnerability, because chloride contaminated snow melt can seep into groundwater and be released into streams during summer months. The other four experts argued that well-draining soils would decrease stream vulnerability. No consensus could be reached. This shows us an area of research that should be more thoroughly explored.

The model validation process indicated that the BN predicts stream vulnerability at a success rate of about 50%. Many complications arose during the modeling process that could have affected the accuracy of the final model. Firstly, our definition of vulnerability was hard to grasp for many experts. This led to groups of experts understanding the model differently than others, causing confusion and inconsistency. Another problem that arose was domination of one voice over others. While we attempted to account for this by initiating discussion among experts and then having each person write his or her own separate response, some expert opinions still dominated. Furthermore, ease of use was a priority in designing the CPT survey, but some experts still were confused. We mitigated this problem by working in small groups to fill out the CPTs and by reviewing the responses and communicating with experts when responses seemed unintended or counterintuitive. Additionally, because the CPTs covered 27 pages and required 419 Likert-scale responses, expert exhaustion became a problem. It could be the case that experts filled out CPTs later in the survey with more haste and less care.

The model structure itself lacks a robust quantification of uncertainty among expert responses. While the coefficient of variation is used to break probability distributions among Likert scores around 3 (Table 3.2), a better way of converting Likert scales to probability distributions would quantify uncertainty around all values, 1 through 5. Other options are available to convert expert opinion to CPT responses that may be more appropriate than employing the Likert scale (Gaddis and Voinov 2008). Finally, Bayesian networks, while appropriate in many cases, are not universally applicable. They are strong in their capacity to synthesize many variables and include expert opinion, but there are many drawbacks to this modeling technique. Discretizing continuous variables is largely guess work, and in general it would be preferable to use the continuous variable instead of distinct states.

Bayesian networks are advantageous in their ability to facilitate learning (Marcot 2006), and we can ask in what ways the model can be changed in order to increase prediction success. As illustrated in Figure 3.7, there are several nodes characterized by high uncertainty among expert responses. These nodes require further research to fully understand how the variables interact to affect vulnerability to urbanization.

On the whole, this modeling process was informative and enlightening, but was not as successful as we had hoped in predicting stream vulnerability to urbanization especially when compared to the statistical results presented in Chapter Two. Despite this, the modeling process was productive in identifying gaps in our understanding of watershed vulnerability to urbanization stressors, and helped to create a discussion among nine experts and university researchers who would not otherwise be communicating and jointly exploring this topic in such depth.

CHAPTER FOUR:

INTEGRATING MODELS OF STREAM VULNERABILITY AND URBAN DEVELOPMENT SUITABILITY TO PREDICT THE LOCATIONS OF AT-RISK STREAMS IN MAINE

INTRODUCTION

The goal of this research was to identify the next generation of impaired streams by creating a modeling framework that relates spatial watershed variables to metrics of stream degradation in order to describe the potential vulnerability of Maine streams to impairment in response to future development. The premise of this study is that streams at risk of future impairment are those that will experience new development in their watersheds and which have attributes associated with high vulnerability to degradation from urbanization. This final chapter presents an integration of three key aspects of this investigation: (1) a summary and synthesis of the results of the stream vulnerability statistical analysis and BN model; (2) an introduction and overview of the alternative futures land use suitability model developed by Meyer et al. (2014); and (3) a synthesis that identifies the intersection of high-vulnerability watersheds with watersheds having the highest suitability for future development. Using those integrated components, it was possible to create a map that predicts the locations of watersheds with streams that are at risk of impairment based on their probability of vulnerability and suitability for future development. It is our hope that the results of this research will provide valuable guidance for land use planners and conservation organizations in their efforts to protect vulnerable streams and to direct future development to watersheds that are less sensitive to degradation associated with urbanization.

SYNTHESIS OF WATERSHED VULNERABILITY MODELS

Previous chapters used various statistical methods to determine watershed characteristics that affect stream vulnerability to urbanization stress. Kruskal-Wallis one-way analysis of variance, logistic regression, and an expert-derived Bayesian network identified a host of variables that increase or decrease stream vulnerability, as well as some variables that did not affect vulnerability despite our expectations to the contrary. A synthesis of these techniques is presented here in an effort to understand general trends across the different methodologies. In addition, we compare the empirical vs. expert-derived results to better understand the capacity of BNs to predict stream vulnerability in the absence of stream sample data (Table 4.1).

Table 4.1. Comparison of key variables that influence stream vulnerability. For each statistical analysis—Kruskal-Wallis rank tests, logistic regression, and the BN—plus (+) marks indicate that the variable decreases vulnerability; minus (-) marks indicate the variable increases vulnerability. The variables Latitude and Longitude were not included in the Bayesian network, and the variable Upstream Buffer was only included in the Bayesian network. These are indicated with "NA".

Important Variables	**Important in Kruskal-Wallis Analysis**	**Important in Logistic Regression**	**Important in BN**
Drains to Ocean			-
Agricultural Area (%)	-	-	-
Forested Buffer (%)		+	+
Watershed Area (km^2)			+
Presence of a Sand/Gravel Aquifer		+	
Nearest Healthy Stream (km)			-
Natural Buffer (%)		+	+
Dams (count)			-
Stream/Road Intersections (density)			-
Stream Gradient/Slope (%)			
Resistant Surfaces (%)		+	+
A or B Soils (%)	+		
Depth-to-Water Table (cm)	+		
Temperature (°C)	+		
Precipitation (in)	+		
Wetlands (%)	-	-	
D Soils (%)	-	+	
K Factor		-	-
Soil Depth (cm)		-	
Longitude (DD)	-		NA
Latitude (DD)	-		NA
Upstream Buffer (km^2)	NA	NA	+

As shown in Table 4.1, there were six variables that were found to be significant as positive or negative influences on vulnerability by either two out of three or three out of three of the statistical and modeling approaches. All three methods identified agriculture as a key factor associated with increases in vulnerability. The logistic regression and BN network models both agreed that forested buffers, natural buffers, and resistant surfaces were associated with decreases in vulnerability. Finally, both the Kruskal-Wallace and logistic regression approaches identified wetlands as an important factor associated with increased vulnerability, whereas the BN network and logistic regression both targeted the erosion index (K factor) as a parameter associated with increased vulnerability.

Variables that were important in the Bayesian network only but were not significant in the statistical analysis were Drains-to-Ocean, Watershed Area, Nearest Healthy Stream, Dams, Culverts, and Stream Gradient/Slope (Table 4.1).

During the BN modeling process, our panel of experts debated the effect of well-draining vs. poorly-draining soils on stream vulnerability. According to the statistical analysis in Chapter Two, well-draining soils decreased stream vulnerability. Due to the uncertainty among our experts, however, this variable was not significant in the Bayesian network. Further research is needed to determine the effect of soil drainage, but evidence in Chapter Two suggests that this variable is indeed important and well-draining soils are likely to decrease stream vulnerability.

Many studies suggest that land cover such as agriculture, wetlands, urban area and forests are the best predictors of stream condition (e.g., Wang et al. 2001, Vander Laan et al. 2013, Bedoya et al. 2011). Dams and mines were also important predictors in those studies that included them (e.g., Poff et al. 2006, Esselman et al. 2011). Environmental variables such as elevation and precipitation are not considered in some of the studies, which makes it difficult to draw conclusions about the influence of these variables across studies and regions. This is problematic because some variations that are attributed to land cover may be partially explained by spatial correlation with environmental or climatic variables (Allan 2004, King et al. 2005). Collectively, these studies suggest that although the relationship between land cover and in-stream variables is dynamic and varies from region-to-region, anthropogenic impacts universally affect stream condition either directly through urban runoff or indirectly through removal of forests and wetlands. Our results from both analyses align with these previous findings.

Other studies have sought to use landscape characteristics to predict empirical measurements of stream water quality such as nutrient loading or biotic community attributes. Instead, our analyses sought to predict the more abstract idea of stream vulnerability, which combines both the current state of the stream and its surrounding watershed, as well as likely future responses to urbanization. While the approach is important in determining the locations of at-risk streams and what variables contribute to watershed response to urbanization, it made the analysis difficult for several reasons.

First, a challenge for many landscape ecology studies is the common presence of spatial autocorrelation between many geographic variables (King et al. 2005). In our analyses, many variables were correlated. This creates problems with interpretation, and identifying causal variables that directly vs. indirectly affect stream vulnerability to urbanization. In addition, explaining the concept of vulnerability to our expert panel was challenging. Some experts interpreted vulnerability to urbanization as predicting which watersheds were more likely to be developed, causing them to overemphasize the percent agricultural area variable as important. The logic is that watersheds with high amounts of agriculture are more likely to be developed, based on the professional experience of the experts who have witnessed this phenomenon.

Furthermore, many experts were unhappy that the model output of the Bayesian network was a range of vulnerability scores – an output that is oftentimes difficult to interpret. Many experts suggested that we use a more empirical definition, such as the probability that a stream will drop below its attainment class given some increase in impervious cover. While our output node does not give this level of detail – instead it gives the probability of vulnerability to urbanization on a scale of 0 to 100 – our model validation process and comparison with development suitability does. We incorporate four analyses to better understand the whole story: (1) IC vulnerability ranges from Danielson et al. (In Press); (2) our vulnerability scores based on expert guidance; (3) BIOMON stream attainment classes based on stream biotic community data; and (4) development suitability maps from Meyer et al. (2014). Altogether, this creates a robust understanding of landscape characteristics that contribute to stream vulnerability, while identifying streams across Maine that are at-risk for future impairment.

PREDICTING FUTURE DEVELOPMENT

Meyer et al. (2014) used Bayesian networks to incorporate stakeholder knowledge and over 100 geospatial data layers in order to predict the probability of suitability for four different land uses across two major watersheds in Maine – the 1-million-hectare Lower Penobscot River Watershed (LPRW), and the 640,000-hectare Casco Bay and

Lower Androscoggin Watershed (CBLA). Land use suitability for development, conservation, agriculture, and forestry was determined at 30m x 30m pixel resolution. using a BN co-created by stakeholders and experts from all four user groups.

Results of the modeling process are available through the Maine Futures Community Mapper (MFCM) (www.MaineLandUseFutures.org). MFCM is an online mapping tool that not only makes it easy for various stakeholders to perform an initial assessment to identify land suitable for particular needs, but also allows lands to be identified that are suitable for more than one land-use type – e.g., lands that have the potential to cause conflicts in the future. For example, conservationists can identify land that is highly suitable for both development and conservation, and work to conserve these lands before development pressures mount. Conversely, land that is suitable for conservation but is not suitable for development may warrant less-urgent protection efforts given the limited likelihood of development. In addition, areas of compatibility can be identified where coalitions of supporters might find common ground. An example might be lands that are highly suitable for conservation, forestry and agriculture. In such areas, development can be viewed as a common threat, and a variety of non-development interests could conceivably work together to provide options for maintaining land for forestry, agriculture and/or conservation.

One of our final objectives was to compare our stream vulnerability scores with Meyer et al.'s (2014) development suitability maps for the LPRW and CBLA watersheds. Both watersheds exhibit a strong forest-to-urban land use spectrum, and contain lands identified as being among the most likely to experience major development pressures in future years (Mockrin et al. 2014). Within both watersheds, substantial areas were found by Meyer et al. (2014) to be suitable for development (Figure 4.1). For the purpose of this analysis, we used the top quartile of development suitability to identify watersheds containing streams at risk of future impairment due to development. For example, of the 836,015 hectares of land in the LPRW that are classified as being available for development (i.e., land that is not already developed or conserved), 41,768 hectares or 4% are highly suitable for development. Of the 648,973 hectares of land available for development in the CBLA watershed, 244,616 hectares or 38% are highly suitable.

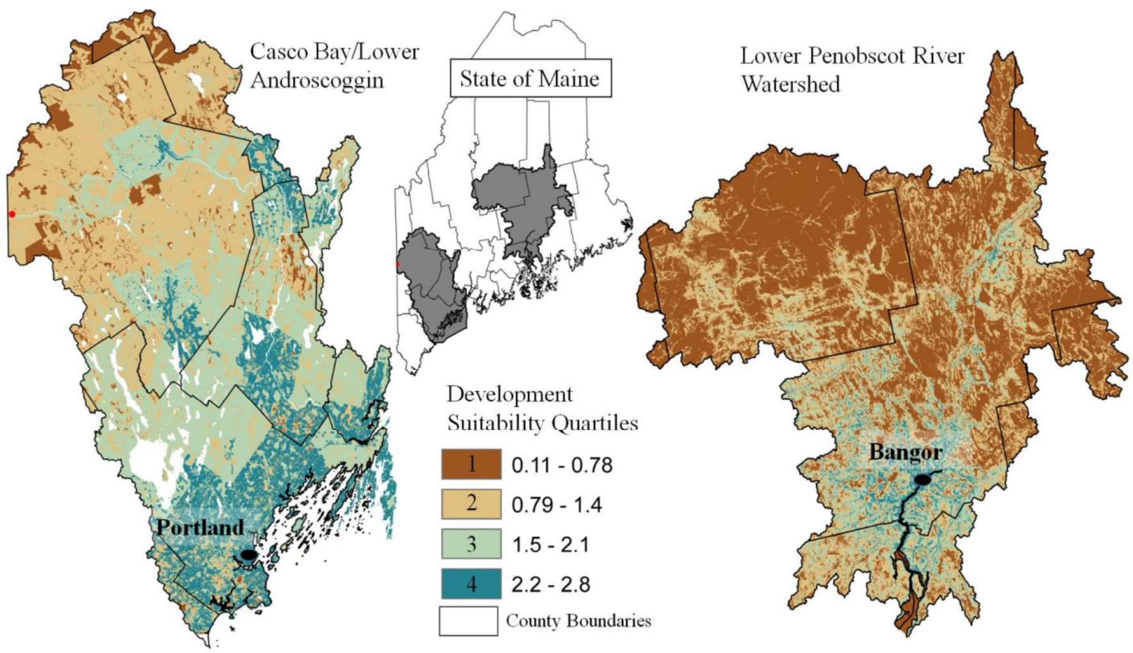


Figure 4.1. Casco Bay/Lower Androscoggin (CBLA) and Lower Penobscot River Watershed (LPRW) study areas. Development suitability is displayed by quartile, with quartile 4 representing areas with the highest probability of suitability for development. Areas in white are unavailable for development (e.g., conserved land).

IDENTIFYING AT-RISK STREAMS

In forecasting the future of streams, it is important to consider not only the current human impacts that are affecting the stream but also future anthropogenic changes that the stream is likely to face. In this final step of our investigation, our vulnerability predictions were combined with the development suitability projections reported by Meyer et al. (2014) for the LPRW and CBLA watersheds. In this research, we asked the question, "If all lands within a watershed that are highly suitable for development are developed, how will this threaten local stream ecosystems and the future of Maine's water resources?" We overlaid the development suitability maps on our stream vulnerability map output to find watersheds with large amounts of land suitable for development and high probabilities of vulnerability to urbanization stress.

Intersection of Development Suitability and Stream Vulnerability

Results from the Bayesian network vulnerability analysis in Chapter Three yielded a probability of vulnerability to urbanization for 23,554 watersheds across the State of Maine. In order to compare these results to development suitability by Meyer et al. (2014), watersheds were extracted that fell in the CBLA and LPRW study areas. From this subset of catchments, those with vulnerability scores in the highest quartile (>62.9, n = 1394) were selected for analysis. For these catchments, percent area suitable for development was calculated from the results of Meyer et al. (2014), using the same methods as described in Chapter Three (Figure 4.2).

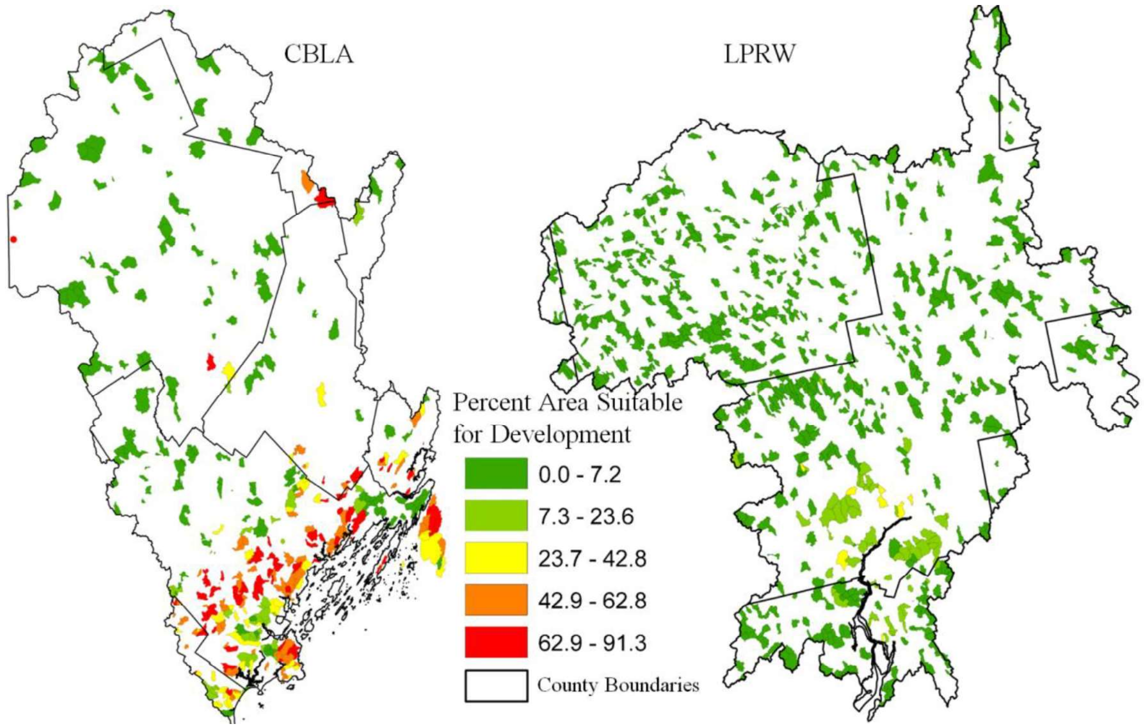


Figure 4.2. Study areas with catchments in the top quartile of vulnerability. Colors reflect percent area suitable for development.

Baseline of Current Impaired Streams

Before proceeding with predictions of streams facing future impairment, we first examined current baseline conditions of impaired or at-risk streams in Maine. Impervious cover was estimated for the catchments using 2004 5m pixel impervious cover data (MELCD 2004). The regression equation from Danielson et al. (In Press) was applied, estimating the percent of impervious cover from the 2007 1m measurements. Using the 2007 1m percent IC estimates, highly vulnerable watersheds (top quartile) with greater than 6% watershed IC were identified. These selection criteria follow from the results of Morse et al. (2006), who found that at this level of percent IC most indicators begin to decline, and also correspond with the more recent MEDEP IC threshold associated with streams that no longer attain A or B statutory classes (Danielson et al. In Press). Overall, there were 166 catchments that met our criteria of high vulnerability and percent IC > 6%, and these were predicted to be currently impaired and were defined as the baseline conditions of impaired streams (Figure 4.3).

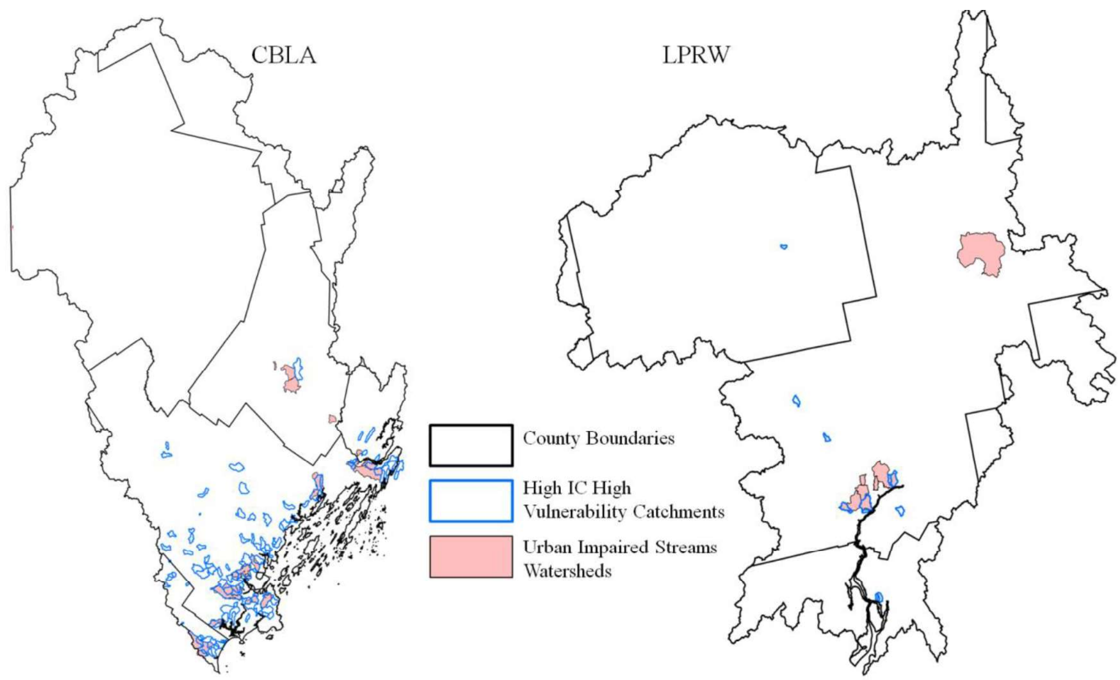


Figure 4.3. Catchments in the top quartile of vulnerability that currently have greater than 6% IC (n=166). Also shown are current urban impaired streams watersheds from the Maine IC TMDL (2012).

Currently, Maine has 30 streams listed as 303 (d) urban-impaired streams (Maine IC TMDL 2012), and 29 of these are located in the LPRW and CBLA study areas. We used the GIS layer associated with these watersheds and compared it to our watersheds that are in the top quartile of vulnerability and that also have over 6% IC. Although one urban-impaired watershed is outside our study area, our map identified 23 of the 29 remaining impaired streams – a success rate of 79%.

At-Risk Streams

In order predict which streams are at risk of future impairment, we used 6% IC as our threshold for impairment. However, the algorithms for converting development to IC generally indicate that only 25-80% of developed land can be classified as IC (Danielson 2015). In order to account for this, we took the current IC and then added percent area suitable for development divided by two (assuming about half will be actual IC), to arrive at an estimate for future IC levels. Those watersheds with future IC levels greater than 6% and high vulnerability (quartile 4) were classified as at-risk streams (n=415; Figure 4.4).

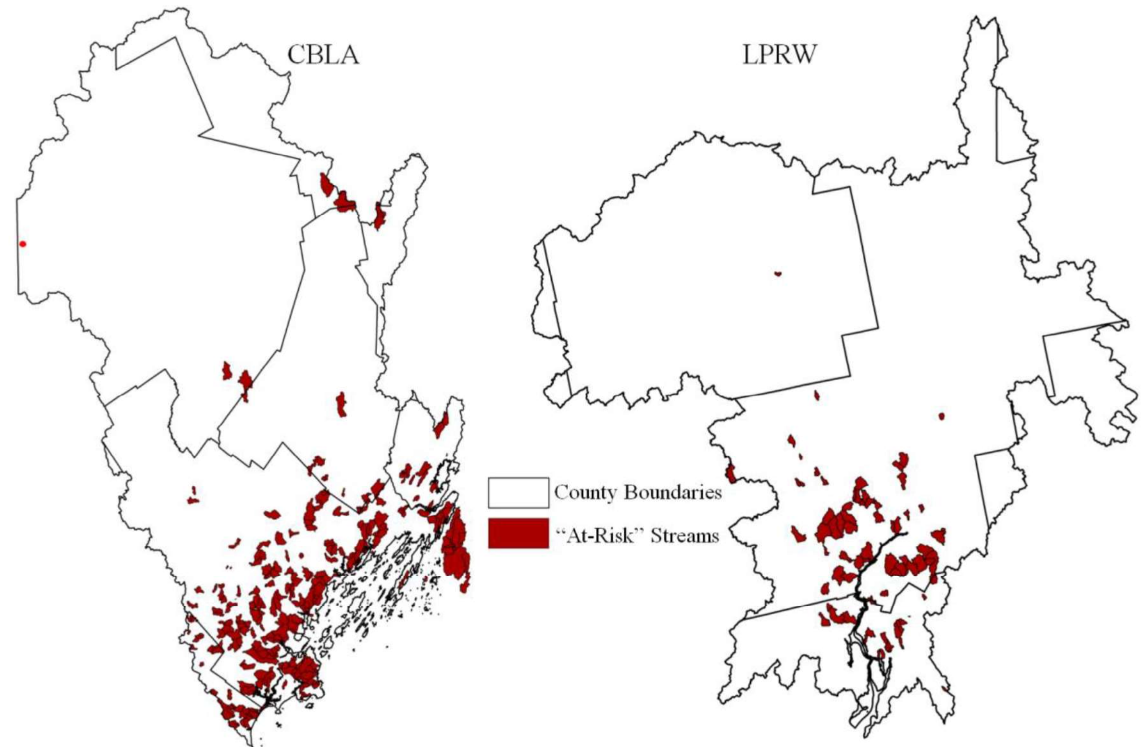


Figure 4.4. "At risk" watersheds. These watersheds exhibit both high vulnerability (quartile 4) and a high potential future IC, where percent area suitable for development divided by two plus current IC is greater than 6% (n = 415).

The streams in Figure 4.4 are those likely to face future urbanization levels that exceed the 6% IC threshold used by the State of Maine to indicate the onset of impairment of aquatic life (Danielson et al. In Press, Morse et al. 2006). These areas are also likely to be highly vulnerable to urbanization based on the results of the vulnerability analysis presented in Chapter Three. These watersheds are prime candidates for conservation, implementation of Best Management Practices, or special zoning restrictions that can mitigate deleterious effects on aquatic life in the stream (MEDEP 2013).

DISCUSSION

Our comparison of watershed vulnerability with development suitability revealed several watersheds that will likely be impaired in the future in the absence of steps taken to mitigate development impacts. This analysis can be used not only to guide development away from vulnerable watersheds, but can also be used to identify watersheds that are less likely to be negatively affected by development – i.e., areas more suitable for future growth. This allows developers, municipalities and other decision-makers to plan proactively for development that will likely avoid the expensive costs of stream restoration. Moreover, the combined results of Chapters 2 and 3 indicate which watershed characteristics are likely to increase or to decrease the probability of vulnerability, and highlight those watershed characteristics that require further research to fully understand their effects on stream vulnerability to urbanization.

This area of research faces many inherent challenges. Factors such as covariation of anthropogenic and natural gradients in the landscape; the existence of multiple, scale-dependent mechanisms; nonlinear responses; and the difficulties of separating present-day from historical influences all complicate the ability to relate landscape characteristics to water quality (Allan 2004, King et al. 2005). The nature of watershed land cover is such that variables are non-independent, so that as one land cover type increases in area, another decreases. Walsch et al. (2005) note that because urban areas and riparian degradation tend to co-vary, their effects are obscured.

To demonstrate the problem of collinearity, King et al. (2005) removed the overwhelming effect of cropland on nitrate-N and revealed underlying correlations of nitrate-N with wetlands and development. Further, they found that the strong correlation between cropland and macroinvertebrate composition was reduced when development and wetland variables were removed, indicating that the lack of development and wetlands had more of an effect than the presence of cropland. In addition, Vander Laan et al. (2013) pointed out that natural variability will cause different water chemistries and biotic conditions among reference sites across a landscape.

The finite availability of spatial data further limits our analytical capabilities. Many landscape characteristics that affect stream water quality are not available as spatial data, or are not available for the entire geographic region or at a sufficient scale to be useful. For example, groundwater connectivity to streams is important in regulating stream temperature, a necessary aspect of resistance and resilience, but this is not available as spatial data throughout the State of Maine. Proxy variables were used to account for this, but it is unclear whether they sufficiently represented groundwater input into streams.

Another unanswered question about watershed analysis is at what distance, if any, a landscape variable stops being influential in stream water quality. Some evidence suggests that the strongest effect is seen when landscape variables are measured within a buffer of the stream or in small watersheds versus large (Strayer et al. 2003, King et al. 2005), which suggests that proximity to the stream gives a stronger effect. For example, Wang et al. (2001) found that impervious cover had a much stronger correlation with biotic indicators than other land cover variables within a 1.6 and 3.2 km radius. The slope of the relationship was steeper in the 1.6 km buffer, indicating that the proximity of urban area to the stream plays a role in the amount of degradation that occurs. Beyond a 3.2km radius the relationship with imperviousness was weaker and the amounts of agriculture, woodland and water-wetland were more influential.

Steedman (1988) found land-use immediately upstream of the sample location to be more influential than land use measured at the watershed scale. On the other hand, some studies have concluded that landscape variables measured for the whole watershed have better predictive capacity than measurements from a stream buffer. Hunsaker and Levine (1995) discovered that using land cover within a 400m buffer around streams in an Illinois watershed had a weaker relationship between land use and water quality than at the watershed scale. Similarly, Bedoya et al. (2011) measured land cover variables within the whole watershed, within 30- and 100m buffers, and within a 3.2 km length upstream of the sample location, and predictive power was best at the whole watershed scale. Williams et al. (2004) also reported that land cover in the entire basin was a better predictor than using various sizes of buffers.

Strayer et al. (2003) measured variables at three spatial extents—the whole watershed, within a buffer, and within a radius from the sample site—and there were significant predictors in each one, indicating the need to look at multiple spatial scales. King et al. (2005) noted that developed land had more of an effect closer to the stream where threshold values were lower (18-23%) than threshold values for the entire watershed (21-32%). They found that sites with high IBI scores that had moderate percentages of developed land in their watersheds had little to none of it within the 250m buffer. However, many low-quality sites had substantial development in their catchments but only low amounts in the 250m buffer, which would lead to inaccuracies in model prediction if only the 250m buffer was used. These results elucidate the importance of incorporating several spatial scales in landscape watershed analysis. We did our best to account for this by including three spatial scales in the logistic regression and Kruskal-Wallis analyses, as well as consulting with experts on the preferred scale at which to measure variables for the Bayesian network.

Land cover classification and threshold values introduce difficulty into the analysis as well. The most robust spatial land cover dataset for the country is the National Land Cover Dataset (USDA 2011), which provides 27 land cover classes. As this level of detail is too high for large-scale analysis, we must group the classes into larger land cover groups. Different studies choose to do this in different ways, which may influence the results. Williams et al. (2004) used landcover subclasses such as high vs. low intensity development, but found that this did not have better predicting power than using an overall development class. In a study by King et al. (2005), cultivated land had a large impact on stream N while pasture had none, indicating the need to separate these two agricultural variables. Clearly, care must be taken in choosing how to group land cover classes in a meaningful manner.

Determining threshold values—the point at which a large change in an ecosystem occurs due to a small change in a specific driver—can be difficult as well. Dodds et al. (2010) highlight the risk associated with defining threshold values in a system. In some cases, nonlinearity can be confused with the existence of a threshold value. For example, a system that alternates between two steady states in a sine-wave fashion may be diagnosed as having a threshold value when only one part of the wave is detected. The challenge of identifying thresholds is further confounded by the fact that climate and anthropogenic stressors are causing continuous change, so a threshold may be identified for a system using recent data but that threshold will likely change in the future. Furthermore, the response of an ecosystem component to exceeding a threshold could have a lag over time, meaning that we cannot detect that the threshold has already been passed.

Finally, many studies have found that there is a threshold around 6-10% IC where stream degradation begins to occur. However, Coles et al. (2012) argue there is no "safe zone" for development in a watershed as many assemblages are already degraded due to legacy effects of past land use or the presence of highly sensitive species, and that defining a threshold value is risky due to natural variability among watersheds. Also, because new construction causes spikes in sediment and nutrients, a system on the verge of exceeding the threshold may see substantial reduction in species richness or abundance due to a large disturbance pulse (Dodds et al. 2010).

CONCLUSION

In 2001, Kates et al. defined sustainability science as "meeting fundamental human needs while preserving the life-support systems of planet Earth." At that time, sustainability science was barely beginning to take form. Now, sustainability is a term that has become so ubiquitous it has almost begun to lose meaning. Despite this, the urgency to implement sustainability has increased as burgeoning human populations threaten natural systems and exploit increasingly more resources from the Earth. In this research, a landscape approach to sustainability was emphasized, looking at a broad scale to determine what can be done to keep our waterways healthy and capable of providing ecosystem services for generations to come (Wu 2013). Wu (2013) noted that “landscapes are the scale at which people and nature mesh and interact most acutely, and thus the composition and configuration of a landscape both profoundly affect, and are affected by, human activities.” A major component of landscape sustainability science is vulnerability analysis, as sustainability often coincides with low vulnerability and high resilience (Wu 2013, Kates et al. 2001).

Turner et al. (2003) argue that vulnerability analyses must take a place-based approach, and incorporate the multiple interacting stressors and the sensitivity of the system to those stressors. They further propose that these analyses should identify the complexities of the system, incorporate both quantitative and qualitative information, and develop metrics and models that can measure vulnerability (Turner et al. 2003).

In our research we attempted to accomplish all of these goals through the implementation of a Bayesian belief network coupled with our analysis of empirical data. In addition, multiple spatial scales were considered, incorporating the importance of hierarchical ecological structure. Equipped with the results of our study, land-use planners and managers throughout the State of Maine can more effectively choose landscape designs that divert or modify land-use change from watersheds with vulnerable streams.

Further, policy makers can implement regulations in watersheds with vulnerable streams, obligating developers to use BMPs and other mitigating strategies in order to avoid the high cost of restoration in the future. Sustainability science seeks to find harmony between human needs and ecosystem health, and emphasizes that viewing the world as a coupled human and natural system allows us to understand how our actions affect the natural world which we all depend upon for our livelihoods (Wu 2013). We live in a time when streams are becoming impaired, but by understanding how watersheds modulate stream response to stressors, we can design proactive management plans that balance our need for development while keeping our precious water resources safe for generations to come.

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APPENDIX A:

INITIAL EXPERT RECRUITMENT EMAIL

Dear <Insert Name Here>

I am a master's student working under the advisement of Drs. Chris Cronan and Rob Lilieholm at the University of Maine and I am writing to request your assistance with research being conducted in conjunction with the Sustainability Solutions Initiative (SSI). Our current research is investigating relationships between land use and stream impairment in Maine. We are planning to hold a focus group in April where we work with experts like yourself to create a model relating land cover variables with stream response to land-use change.

Attached to this email is an information sheet describing our research and the details of the **4-hour focus group** we are planning to hold in **April**. The goal of the focus group is to create a model that describes the response of streams in Maine to land-use change.

Given your expertise related to streams in Maine, we would greatly appreciate your input in creating the model. The commitment we are asking you to make involves:

1. One 4-hour focus group from **9 am to 1 pm** (we will be providing lunch) in which we will work together to:

a) Identify landscape characteristics affecting stream susceptibility to degradation from development;

b) Arrange these factors in a hierarchical model; and

c) Determine thresholds at which to break-up continuous variables incorporated into the conceptual model (e.g. 'steep slope' = slopes > 6%).

2. After the focus group, you will be asked to respond to a brief emailed survey that will further aid us in developing our model.

We may also make intermittent contact with you after the focus group to gather further information for calibrating the model via email, phone, or letter.

I hope you will consider participating in our study. We expect it will be a fun, informative experience for all participants. We will announce the meeting location when we determine one that is most convenient for all those attending. If you are able to attend, please follow this link to enter the dates in April that you are available:

http://whenisgood.net/BBNfocusgroupUMaine

Please read over the attached **Information Sheet** and **Informed Consent Form**, and I look forward to your reply.

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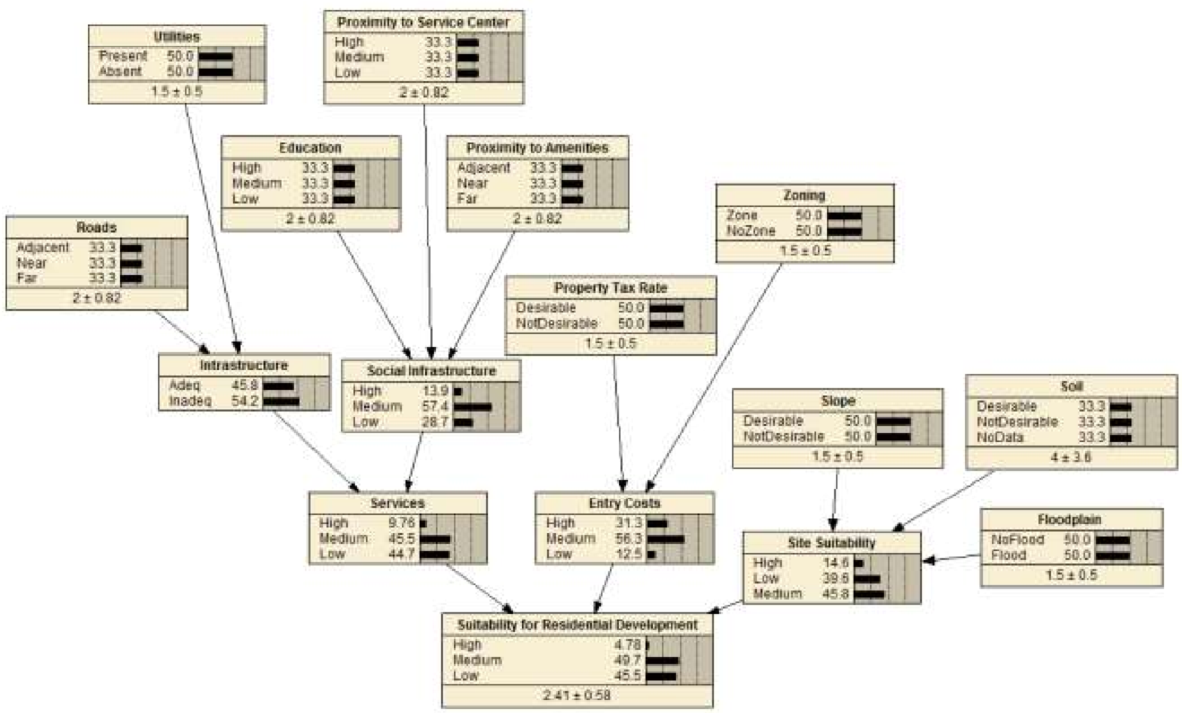
Stream Sensitivity Focus Group Information Sheet

Millions of dollars have been spent on restoring streams that have become degraded by pollution from runoff of urban or agricultural areas. In this research, we hope to identify streams that are at risk of becoming degraded in the future so that steps can be taken to avoid impairment in the first place, thus avoiding the high costs of remediation and restoration. The first step towards tackling this issue is to determine which streams in Maine are more susceptible to degradation in response to land-use change in their watersheds. We will do this by creating a Bayesian Belief Network (BBN) based on expert opinion. Bayesian Belief Networks are models that represent systems based on the interactions between variables leading from primary causes to a specific outcome[1]. An example of a BBN is provided below:



FigureA.1 Example Bayesian Belief Network to determine suitability of residential development

The BBN we seek to create with your help will relate spatial variables (e.g. land use/land cover, soil properties, etc.) to the probability of a stream becoming degraded in response to land-use change. This approach is based on evidence that some aspects of a stream's watershed may make it more or less resistant to degradation. For example, calcareous bedrock in a watershed contributes to higher alkalinity which makes the stream more resistant to acidification[2, 3]. The BBN we create

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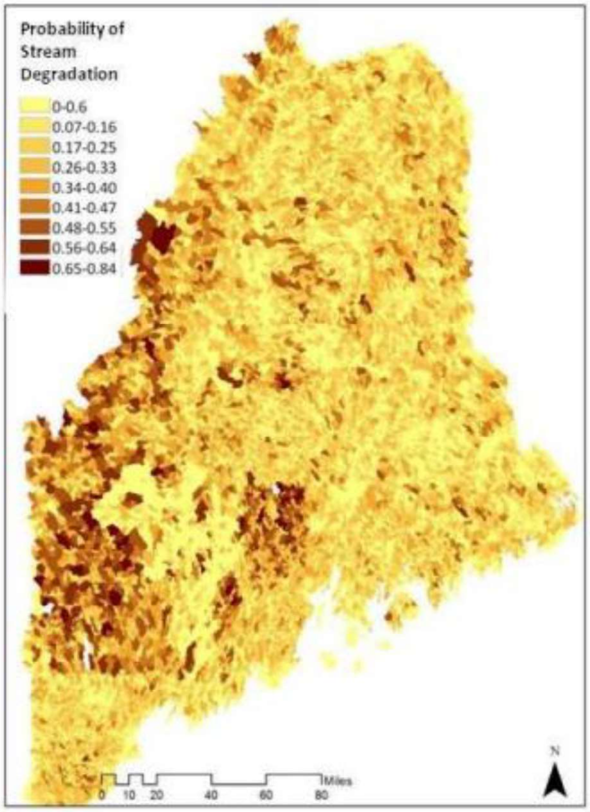
Maine Stream Sensitivity



*Figure*A.2 *Example of what the final map will look like*

will describe how watershed characteristics such as these work together to influence how a stream will respond to land-use change in its catchment. The final output will be a vulnerability map that depicts watersheds throughout the State of Maine based on their predicted probability of becoming degraded in response to land-use change (figure 2).

This map will lead to the second step of this project – identifying streams that are at risk of impairment from future residential and commercial development. To do this, we will compare our vulnerability map output with suitability maps from the Maine Futures Community Mapper (MFCM) created by our Alternative Futures Team of the University of Maine's Sustainability Solutions Initiative. The MFCM is an online mapping tool that shows land throughout the Lower Penobscot and Lower Androscoggin/Casco Bay watersheds that is suitable for development, agriculture, conservation or forestry. This work is the result of a BBN co-created by stakeholders and experts from all four user groups. We will overlay the MFCM suitability maps on our stream vulnerability map output to find watersheds that have both large amounts of land suitable for agricultural or human development and also streams predicted to be susceptible to degradation. This will identify which streams in these watersheds are at risk of future impairment, and will form the basis for identifying targets for proactive planning and conservation aimed at sustaining our water resources.

1. Chen S. G. and C. A. Pollino. 2012. Good practice in Bayesian network modelling. *Environmental Modelling and Software*. 37:134-145.
2. Sullivan et al. 2007. Spatial distribution of acid-sensitive and acid-impacted streams in relation to watershed features in the Southern Appalachian Mountains. *Water Air Soil Pollution*. 182:57-71.
3. United States Geological Survey. Acidic deposition to streams: a geology-based method to predict their sensitivity. *Environmental Science and Technology*. 23:379-385.

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Informed Consent Form

You are invited to participate in a research project being conducted by Kristen Weil, a graduate student in the Department of Ecology and Environmental Sciences at the University of Maine. This research is conducted as part of the Alternative Futures/Urban Stream Team of the University of Maine's Sustainability Solutions Initiative (SSI). The goal of this focus group is to create a model that incorporates expert opinion which will be used to predict stream response to land-use change in watersheds throughout the State of Maine.

What will you be asked to do?
We invite you to join us in a 4-hour focus group with between 8 and 12 participants and then respond to an emailed survey following the focus group. The overall time commitment, including the focus group, will be around 7 hours.

At the focus group, we will ask you and the other participants to work together to identify watershed characteristics that affect stream response to land-use change, and arrange these factors into a model framework. We will then break-up continuous variables into discrete values (e.g. "steep" = slope > 6%).

Following the focus group, you will be emailed a survey to fill out that will further aid in calibrating the model. Additional communication via email, telephone or mail may occur as well.

Risks
Except for your time and inconvenience, there are little risks to you from participating in this study.

Benefits

a) We believe the benefits of our research will be substantial for our communities and watershed ecosystems as the output of our model will help avoid future stream impairment.
b) We also feel that participating in the study would be beneficial to you through discussion and networking with peers interested in the same subject.

Compensation
You will receive no compensation for participating in this study. Snacks, beverages and lunch will be provided at the focus group.

Confidentiality
Beyond discussions and interactions in the focus group, your views and comments will be confidential and names will not be associated with our data. There will be no audio, video, or film recordings, and only the research team will have access to the notes collected at these gatherings. Research records from the focus group (e.g., notes) as well as survey results will be kept in a locked office for seven years and then destroyed; only researchers will have access to the records. Also, we will ask all focus group participants to keep our deliberations confidential, although we cannot

guarantee that everyone will honor this request. There will be no records linking you to the data.

Voluntary
Your participation in this study is voluntary. If you choose to participate, you may stop at any time or skip any questions or discussion items that you do not wish to answer.

Contact Information
If you have any questions, please contact Kristen Weil at 505-400-9274 or kristen.weil@maine.edu. If you have questions about your rights as a research participant, please direct them to Gayle Jones, Assistant to the Protection of Human Subjects Review Board, at 207-581-1498 or gayle.jones@umit.maine.edu.

APPENDIX B:

VARIABLE DESCRIPTIONS AND CUTOFF VALUES

Vulnerability to Physical Stressors: This submodel determines the vulnerability of a watershed to the physical stress of urban development. The number of states is shown in parentheses after the variable name.

1. **Vulnerability to Sediment Stress**-

- Soil erodibility: K factor averaged for the whole soil profile within a 60 m buffer of the stream. This variable should give us an idea of how prone the soil adjacent to the stream is to erosion. The K factor is defined by the USDA NRCS as “the susceptibility of a soil to sheet and rill erosion by water. Factor K is one of six factors used in the Universal Soil Loss Equation (USLE) and the Revised Universal Soil Loss Equation (RUSLE) to predict the average annual rate of soil loss by sheet and rill erosion in tons per acre per year. The estimates are based primarily on percentage of silt, sand, and organic matter and on soil structure and saturated hydraulic conductivity (Ksat). Values of K range from 0.02 to 0.69. Other factors being equal, the higher the value, the more susceptible the soil is to sheet and rill erosion by water.” We assigned the cutoff values for this variable by breaking the range (not the distribution) of our data up into three equal parts.

  - 0.01 – 0.05
  - 0.06 – 0.09
  - 0.1 – 0.14

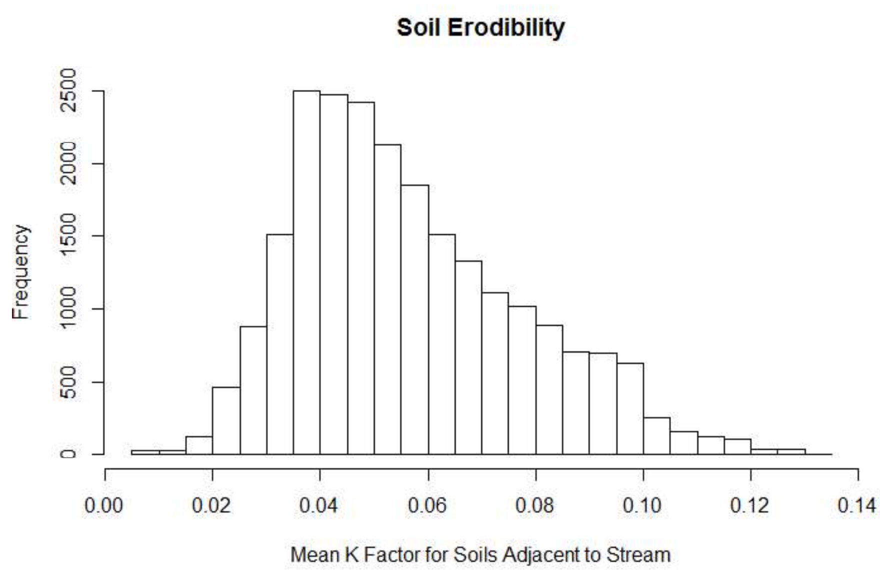

Figure B.1. Histogram of Soil Erodibility.

Table B.1. Distribution of Soil Erodibility.

Soil Erodibility					
Min	1st Q	Med	Mean	3rd Q	Max
0.7	4	5.2	5.7	7	13.3

- Intact/Natural Riparian zone: the percent of the riparian zone (60 m on either side of the stream) with National Land Cover Dataset (NLCD) 2011 land use classification as forest, shrubland, herbaceous, or wetlands.
  - 0 – 50%
  - 50 – 80%
  - >80%

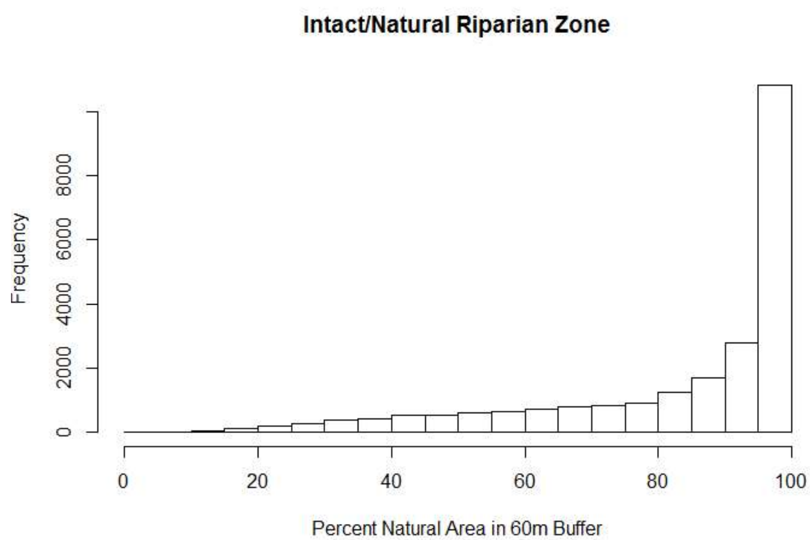

Figure B.2. Histogram of Percent Natural Area.

Table B.2. Distribution of Percent Natural Area.

Intact/Natural Riparian Zone					
Min	1st Q	Med	Mean	3rd Q	Max
0	74	94	84	99	100

- Cultivated land: the percent of the entire watershed area classified by the NLCD 2011 as "Cultivated Crops".
  - 0 – 5%
  - > 5%

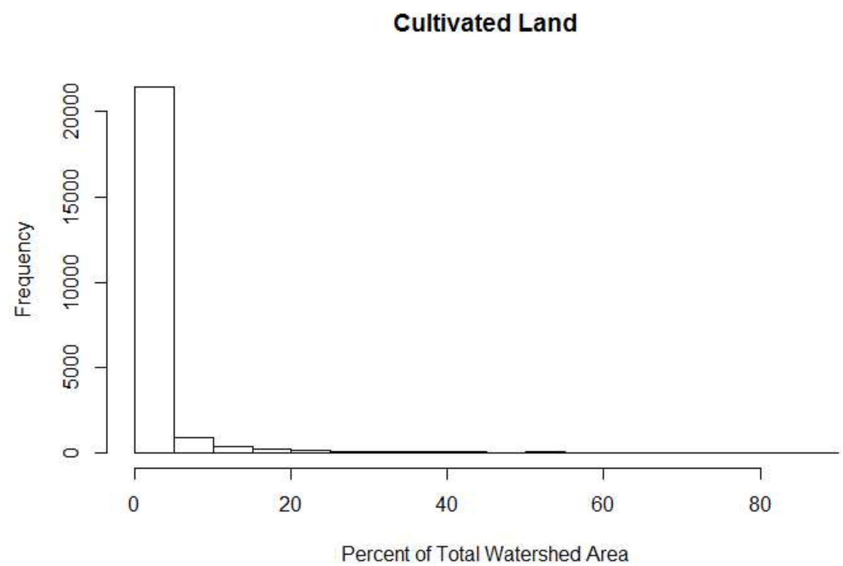

Figure B.3. Histogram of Percent Agricultural Area.

Table B.3. Distribution of Percent Agricultural Area.

Cultivated Land					
Min	1st Q	Med	Mean	3rd Q	Max
0	0	0	2	1	88

2. **Vulnerability to Heat Stress**: the vulnerability of a stream to heat stress associated with watershed urbanization.

a. **Contributors**

- Air Temperature: maximum July air temperature in degrees Fahrenheit averaged over five years, 2009 to 2013. We assigned the first state to be the 1st quartile, the second state to be the 2nd and 3rd quartiles, and the third to be the 4th quartile.
  - < 76
  - 76 – 80
  - > 80

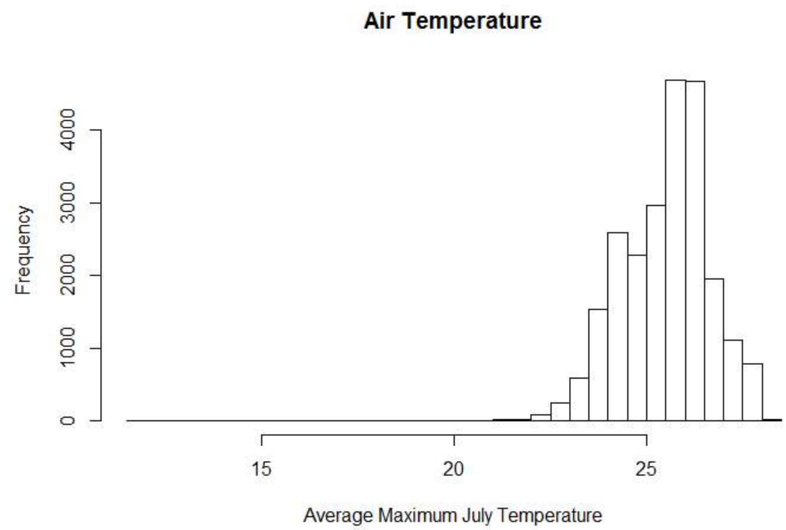

Figure B.4. Histogram of Maximum July Air Temperature.

Table B.4. Distribution of Maximum July Air Temperature.

Air Temp					
Min	1st Q	Med	Mean	3rd Q	Max
11.9	24.7	25.7	25.5	26.3	28.25

- Drainage Area: measured in square kilometers. We assigned the 1st category to be watersheds that are likely to dry up during summer low flows. The upper limit for drainage area was set to 125 square kilometers.

  - < 1
  - 1 – 10
  - > 10

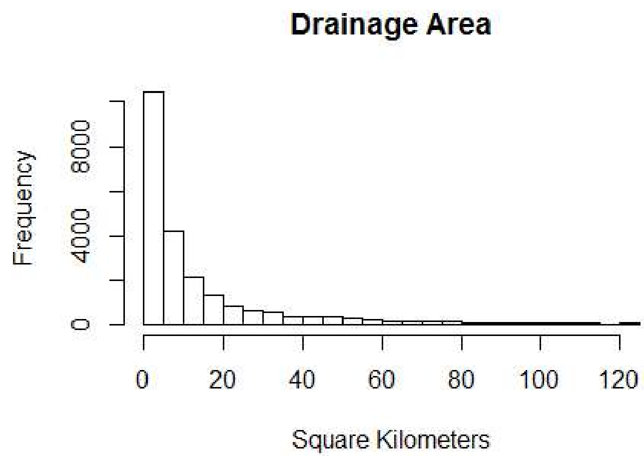

Figure B.5. Histogram of Watershed Area.

Table B.5. Distribution of Watershed Area.

Drainage Area					
Min	1st Q	Med	Mean	3rd Q	Max
0.5	2.5	6.2	16	18	125

- Retained water: Percent watershed area with National Wetland Inventory waterbodies labeled as "Lakes", "Freshwater Emergent Wetlands", or "Freshwater Forested/Shrub Wetlands." This variable is broken up by assigning one third of the data into each state.

  - 0 – 6% (33.33% of all watersheds)
  - 6 – 14% (33.33% of all watersheds)
  - > 14% (33.33% of all watersheds)

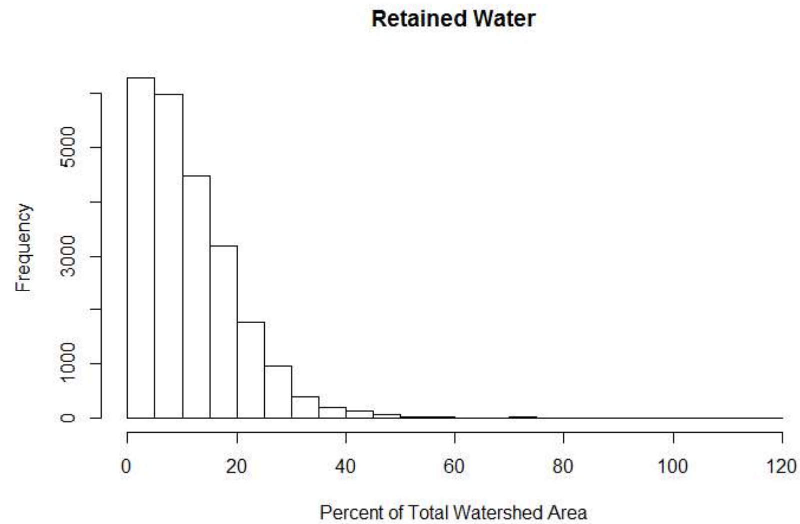

Figure B.6. Histogram of Retained Water.

Table B.6. Distribution of Retained Water.

Retained Water					
Min	1st Q	Med	Mean	3rd Q	Max
0	4.7	9.5	11.5	16.2	100

b. **Mitigators**

- Groundwater: Unfortunately, there is no reliable spatial data for shallow groundwater in the State of Maine. In order to get some sense of groundwater input into streams, we are working on a linear regression to predict summer stream temperature data for 114 watersheds using soil characteristics that might indicate a groundwater signal. Variables included in the model are percent of total watershed area with soils in hydrologic group A, percent of total watershed area with soils in hydrologic group D, average percent sand, percent of total watershed area with sand and gravel aquifers, percent of total watershed area with surficial texture that is sand and gravel, and percent of total watershed area with surficial texture that is mostly till, boulders and gravel. With this linear model we will make two states,
  - More
  - Less

- Riparian Forest: the percent of the riparian zone (60 m on either side of the stream) with NLCD 2011 land use classification as forest, shrubland, herbaceous, or wetlands.
    - 0 – 40%
    - 40 – 75%
    - > 75%

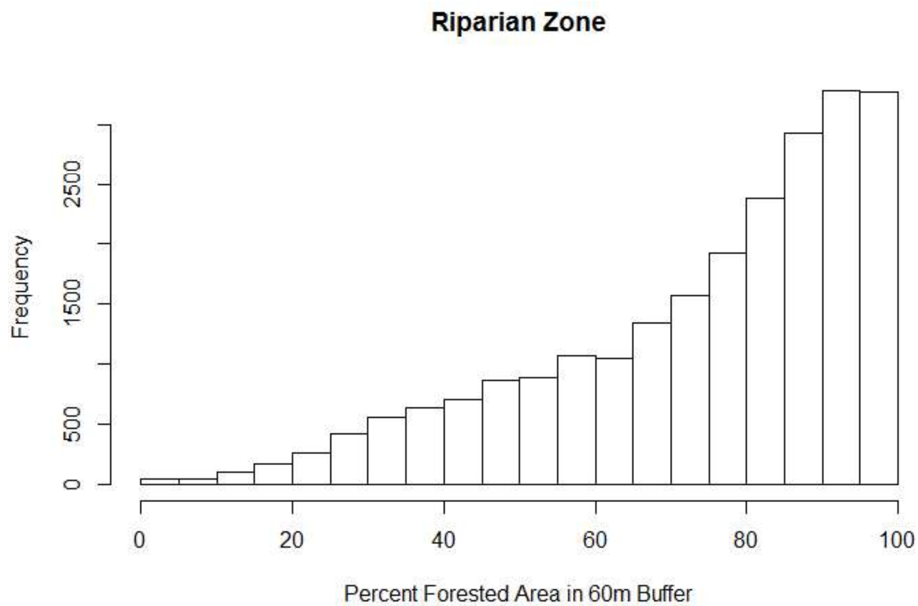

Figure B.7. Histogram of Percent Forested Riparian Zone.

Table B.7. Distribution of Percent Forested Riparian Zone.

Riparian Forest					
Min	1st Q	Med	Mean	3rd Q	Max
0	60.6	80.2	74	91	100

3. **Hydrologic factors, vulnerability to flashiness**

a. **Contributors**:

- Stream/road intersections: Number of stream/road intersections per square kilometer. The cutoff value of 0.3 was chosen because it is the mean of the distribution.
  - 0 – 0.5
  - > 0.5

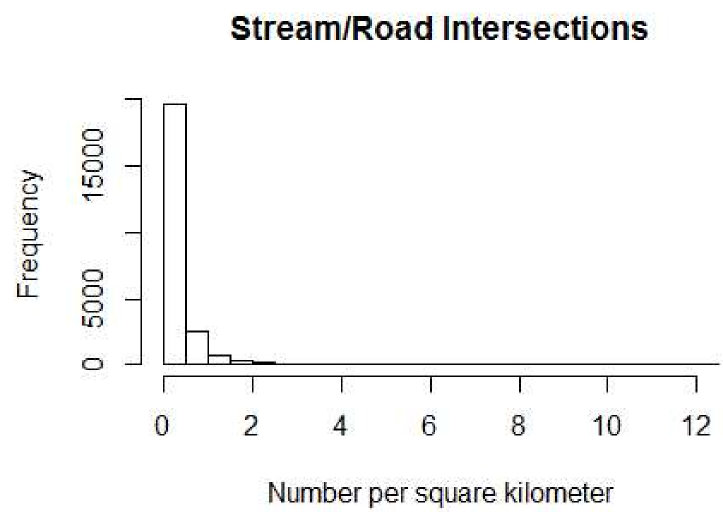

Figure B.8. Histogram of Stream/Road Intersection Density.

Table B.8. Distribution of Stream/Road Intersection Density.

Stream/road Intersections					
Min	1st Q	Med	Mean	3rd Q	Max
0	0	0.08	0.27	0.34	12.4

- Precipitation: The sum of May through October precipitation averaged over five years, 2009 to 2013. We assigned the first state to be the 1st quartile, the second state to be the 2nd and 3rd quartiles, and the third to be the 4th quartile.
    - < 27
    - 27 – 29
    - > 29

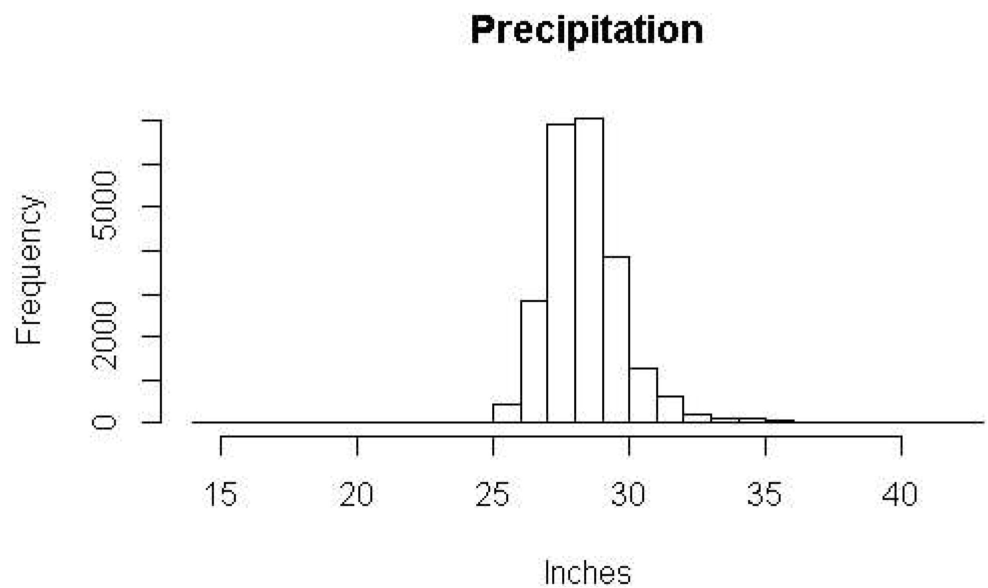

Figure B.9. Histogram of Average Summer Precipitation.

Table B.9. Distribution of Average Summer Precipitation.

Precipitation					
Min	1st Q	Med	Mean	3rd Q	Max
14	27.5	28.2	28.4	29	43

b. **Mitigators:**

- Groundwater: same as "Heat Stress" above.
- Retained Water: same as "Heat Stress" above.
- Slope: average slope of the whole watershed, in percent rise.
  - < 1%
  - 1 – 4.5%
  - 4.5 – 20%
  - > 20%

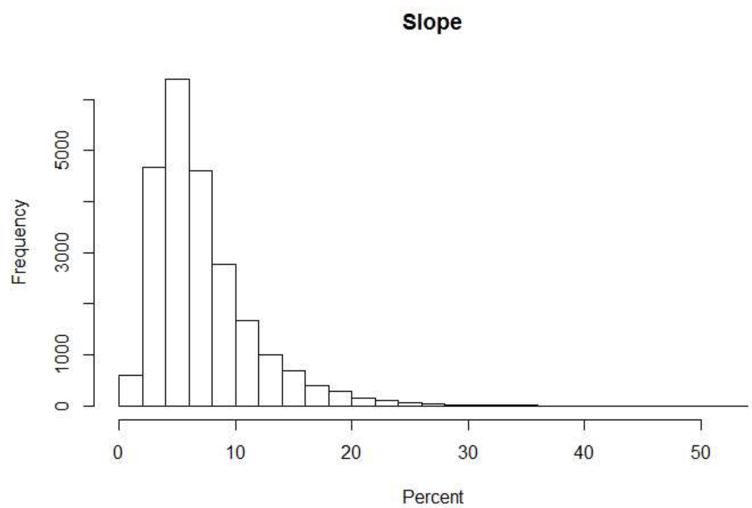

Figure B.10. Histogram of Area-Weighted Slope.

Table B.10. Distribution of Area-Weighted Slope.

Slope					
Min	1st Q	Med	Mean	3rd Q	Max
0	4.2	6	7.2	8.9	53.2

- Substrate:
  - Erodible
  - Resistant
- Poorly Draining Soils: Percent of total watershed area with soils classified in Hydrologic Group D. These soils are defined by the USDA NRCS:
  "Hydrologic soil groups are based on estimates of runoff potential. Soils are assigned to one of four groups according to the rate of water infiltration when the soils are not protected by vegetation, are thoroughly wet, and receive precipitation from long-duration storms. The soils in the United States are assigned to four groups (A, B, C, and D). The groups are defined as follows:

Group A. Soils having a high infiltration rate (low runoff potential) when thoroughly wet. These consist mainly of deep, well drained to excessively drained sands or gravelly sands. These soils have a high rate of water transmission.

Group B. Soils having a moderate infiltration rate when thoroughly wet. These consist chiefly of moderately deep or deep, moderately well drained or well drained soils that have moderately fine texture to moderately coarse texture. These soils have a moderate rate of water transmission.

Group C. Soils having a slow infiltration rate when thoroughly wet. These consist chiefly of soils having a layer that impedes the downward movement of water or soils of moderately fine texture or fine texture. These soils have a slow rate of water transmission.

Group D. Soils having a very slow infiltration rate (high runoff potential) when thoroughly wet. These consist chiefly of clays that have a high shrink-swell potential, soils that have a high water table, soils that have a claypan or clay layer at or near the surface, and soils that are shallow over nearly impervious material. These soils have a very slow rate of water transmission."

- 0 – 25% (1st Quartile)
- 25 – 50%
- > 50%

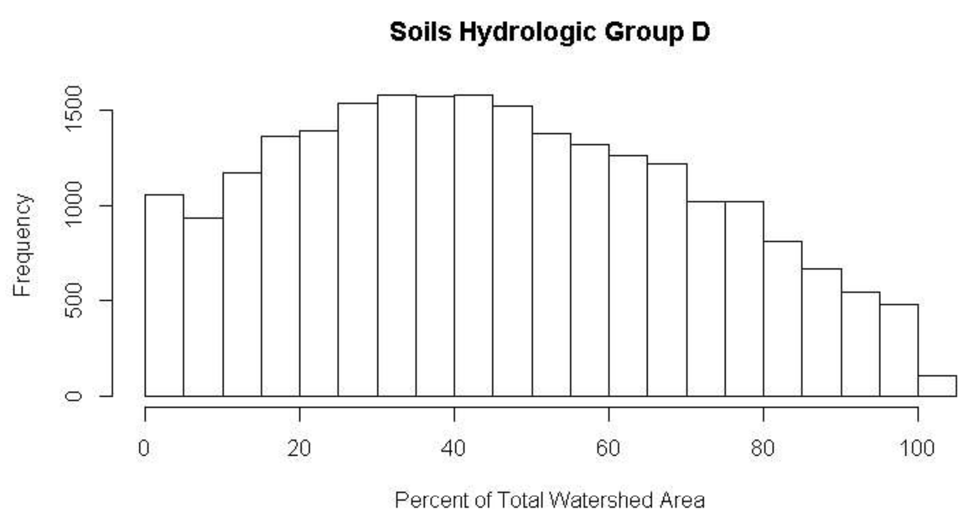

Figure B.11. Histogram of Percent D Soils.

Table B.11. Distribution of Percent D Soils.

Poorly Draining Soils					
Min	1st Q	Med	Mean	3rd Q	Max
0	25	43	45	65	100

4. **Hydrologic factors- vulnerability to low base flow**

- Wetlands: Percent of total watershed area with National Wetland Inventory waterbodies labeled as “Freshwater Emergent Wetlands” or “Freshwater Forested/Shrub Wetlands.”
  - 0 – 10%
  - 10 – 20%
  - > 20%

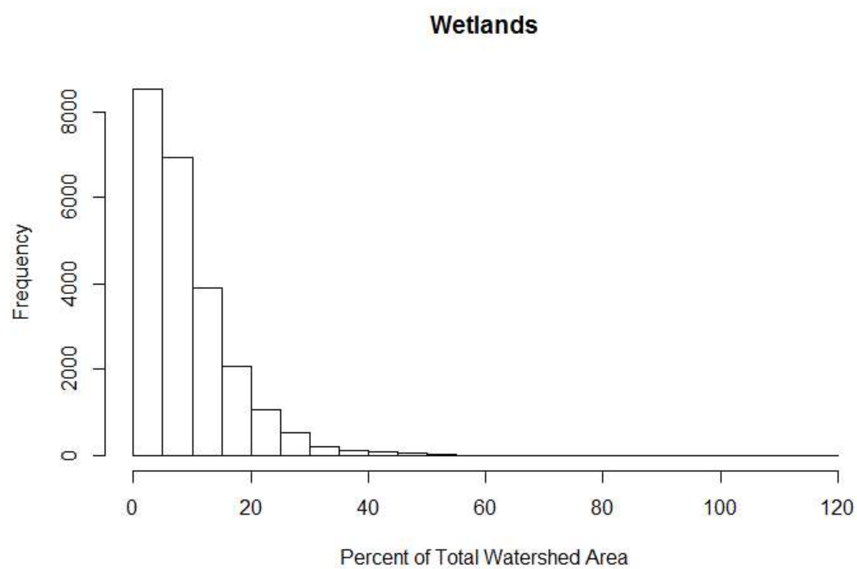

Figure B.12. Histogram of Percent Wetlands.

Table B.12. Distribution of Percent Wetlands.

Wetlands					
Min	1st Q	Med	Mean	3rd Q	Max
0	3.5	6.9	9.1	12.5	100

- Groundwater: same as “Heat Stress” above.
- Drainage Area: same as “Heat Stress” above.

- Lakes: Percent of total watershed area with National Wetland Inventory waterbodies labeled as “Lakes”.
  - 0% (median)
  - 0.01 – 10%
  - > 10 %

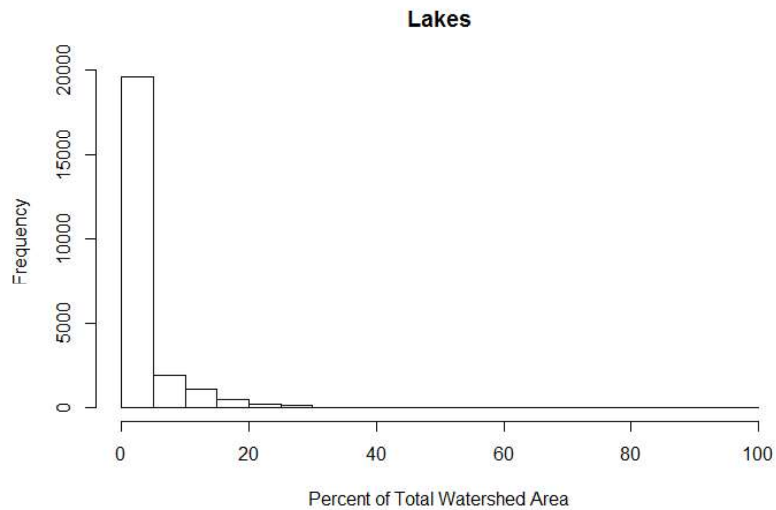

Figure B.13. Histogram of Percent Lake Area.

Table B.13. Distribution of Percent Lake Area.

Lakes					
Min	1st Q	Med	Mean	3rd Q	Max
0	0	0	2.4	2.1	100

<u>Vulnerability to Chemical Stressors:</u> This submodel determines the vulnerability of a watershed to the chemical stress of urban development. The number of states is shown in parentheses after the variable name.

1. **<u>Vulnerability to Salt Stress:</u>**

- <u>Drainage area:</u> measured in square kilometers.
  - 0 – 5
  - > 5
- <u>Good soil drainage/deep soils:</u> Percent of total watershed area with soils classified in Hydrologic Group A or B. These soils are defined by the USDA NRCS: "Hydrologic soil groups are based on estimates of runoff potential. Soils are assigned to one of four groups according to the rate of water infiltration when the soils are not protected by vegetation, are thoroughly wet, and receive precipitation from long-duration storms. The soils in the United States are assigned to four groups (A, B, C, and D). The groups are defined as follows:

  Group A. Soils having a high infiltration rate (low runoff potential) when thoroughly wet. These consist mainly of deep, well drained to excessively drained sands or gravelly sands. These soils have a high rate of water transmission.

  Group B. Soils having a moderate infiltration rate when thoroughly wet. These consist chiefly of moderately deep or deep, moderately well drained or well drained soils that have moderately fine texture to moderately coarse texture. These soils have a moderate rate of water transmission.

  Group C. Soils having a slow infiltration rate when thoroughly wet. These consist chiefly of soils having a layer that impedes the downward movement of water or soils of moderately fine texture or fine texture. These soils have a slow rate of water transmission.

  Group D. Soils having a very slow infiltration rate (high runoff potential) when thoroughly wet. These consist chiefly of clays that have a high shrink-swell potential, soils that have a high water table, soils that have a claypan or clay layer at or near the surface, and soils that are shallow over nearly impervious material. These soils have a very slow rate of water transmission."

  - 0 – 10%
  - 10 – 30%
  - >30%

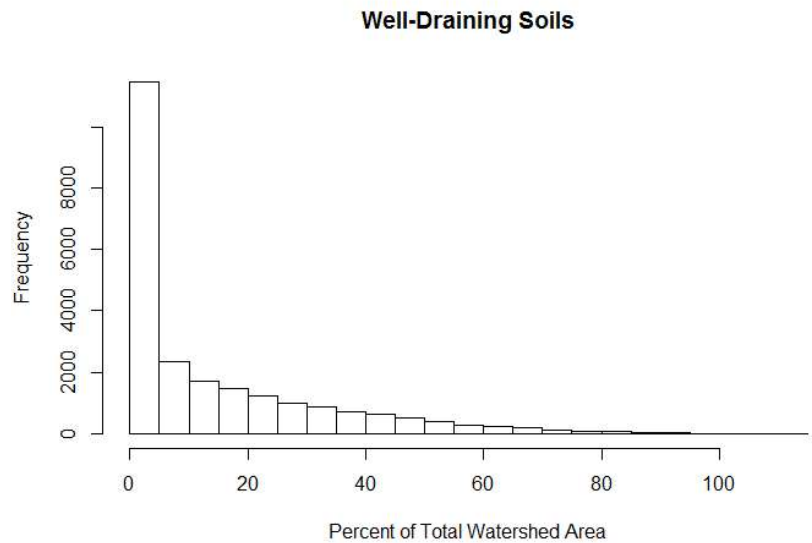

Figure B.14. Histogram of Percent A or B Soils.

Table B.14. Distribution of Percent A or B Soils.

Well-Draining Soils					
Min	1st Q	Med	Mean	3rd Q	Max
0	0	5.6	14.3	22.6	100

2. **Acid Stress:** current amount of acid stress the stream is experiencing.

- Acid Wetlands: Percent of total watershed area with wetlands in the National Wetlands Inventory with the classifier "a" which means acidic.
  - 0 %(median)
  - > 0.1%

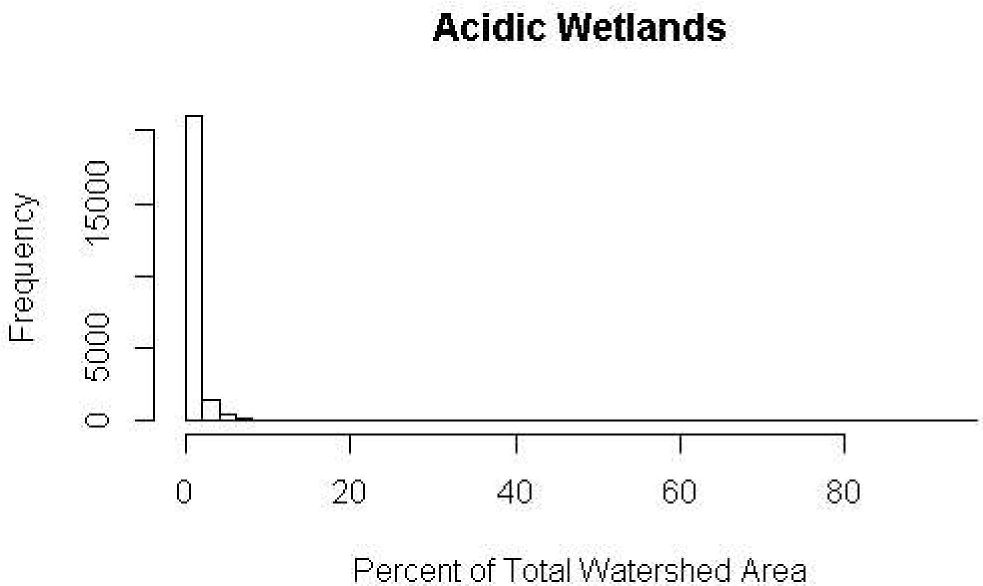

Figure B.15. Histogram of Percent Acidic Wetlands.

Table B.15. Distribution of Percent Acidic Wetlands.

Acidic Wetlands					
Min	1st Q	Med	Mean	3rd Q	Max
0	0	0	0.8	0.5	95

- Stream Buffering Capacity: based on The Nature Conservancy Northeastern Aquatic Habitat Classifications.
  - Buffering: Assigned to the classification "High Buffering, Calcareous" or "Moderately Buffering, Neutral"
  - Not Buffering: Assigned to the classification "Low Buffering, Acidic"
- Groundwater: same as "Heat Stress" above.

3. **Vulnerability to Toxic Stress:** The tolerance of the watershed to increased toxic load associated with urbanization

- Cultivated land: same as "Sediment Stress" above.
- Wetlands: same as "Hydrologic Factors" above.

4. **Vulnerability to DO Stress:**

- Wetlands: same as "Hydrologic Factors" above.
- Lakes: same as "Hydrologic Factors" above.
- Stream Gradient: average slope, in percent rise, of the 60m stream buffer.
  - > 5%
  - 3 - 5%
  - < 3%

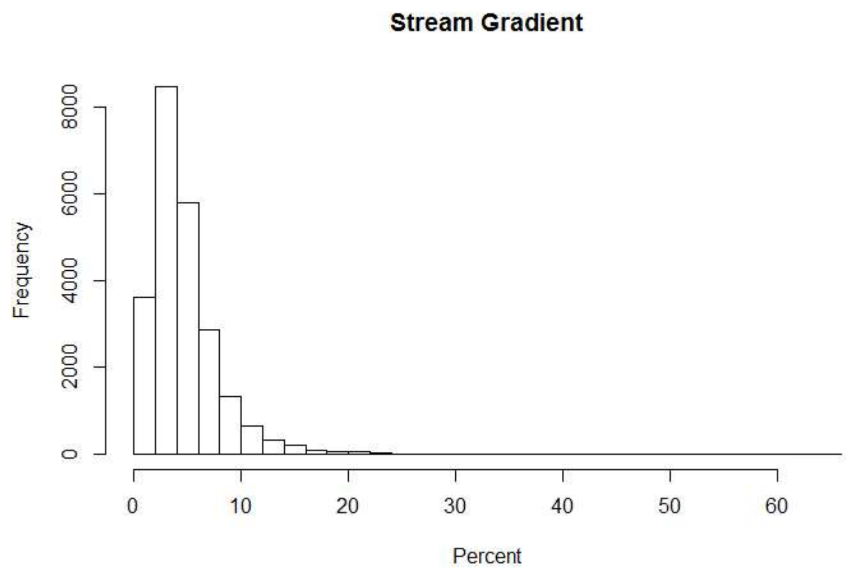

Figure B.16. Histogram of Stream Gradient.

Table B.16. Distribution of Stream Gradient.

Stream Gradient					
Min	1st Q	Med	Mean	3rd Q	Max
0	2.3	3.9	4.7	5.9	64.9

- Heat Stress: The output of the Heat Stress node described above.
  - Low
  - High

5. **Vulnerability to Nutrient Stress:** The degree to which a watershed can withstand the increase in nutrients associated with urbanization.

- Nonpoint nutrient sources: NLCD 2011 land use classified as "Cultivated Crops" or "Developed Open Space". Developed open space is used to capture private lawns that could contribute fertilizer nutrients to streams.
  - 0 – 5% (3rd Quartile)
  - > 5%

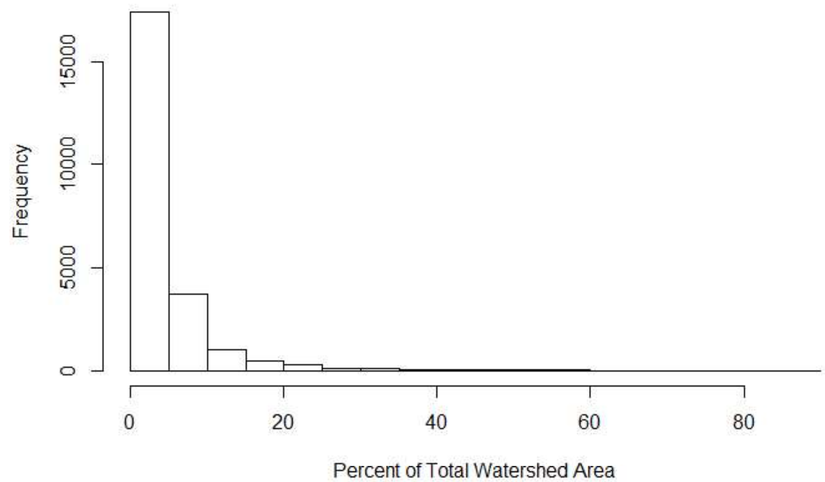

Figure B.17. Histogram of Nonpoint Nutrient Sources.

Table B.17. Distribution of Percent Nonpoint Nutrient Sources.

Nonpoint Nutrient Sources					
Min	1st Q	Med	Mean	3rd Q	Max
0	0	1.3	4.2	5.2	88

- Good soil drainage/deep soils: same as "Salt Stress" above.
- Riparian Forest: the percent of the riparian zone (60 m on either side of the stream) with NLCD 2011 land use classification as forest, shrubland, herbaceous, or wetlands.
  - 0 – 80%
  - > 80%
- Wetlands: same as "Hydrologic Factors" above.

Ecological Vulnerability to Urbanization- This final node represents the output of the entire model. The value given by this node will be the vulnerability score for the watershed in question. We expect that a watershed that is given a high score for vulnerability and that currently has urban area should be degraded.

1. **Resilience**

- Aquatic connectivity:
  - Culverts: number of stream/road intersections per square kilometer.
    - 0 – 0.1
    - 0.1 – 1
    - > 1

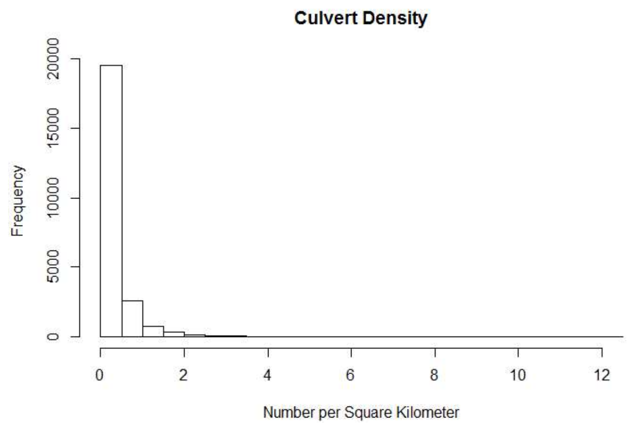

Figure B.18. Histogram of Culvert Density.

Table B.18. Distribution of Culvert Density.

Culverts					
Min	1st Q	Med	Mean	3rd Q	Max
0	0	0.08	0.27	0.34	12.4

  - Dams: number in the watershed. The “Low” category is the median of the distribution.
    - 0
    - 1
    - > 1

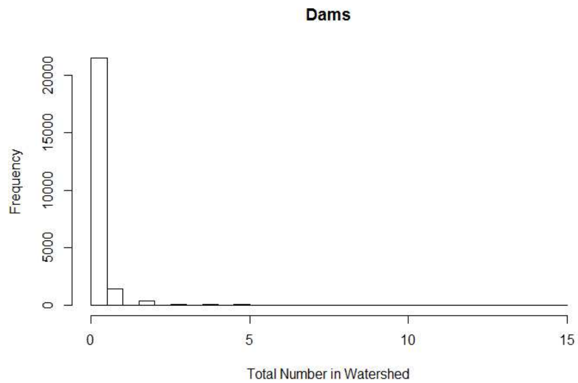

Figure B.19. Histogram of Dam Count.

Table B.19. Distribution of Dam Count.

Dams					
Min	1st Q	Med	Mean	3rd Q	Max
0	0	0	0.14	0	15

- Proximity to nearest stream: this variable is measured for headwater streams only. It is the distance from the centroid of the headwater stream watershed to the nearest centroid of any other watershed. This represents the potential for recolonization across catchments. The cutoff of 1.5km is approximately the mean of the distribution.
  - 0 – 1.5 km
  - > 1.5km

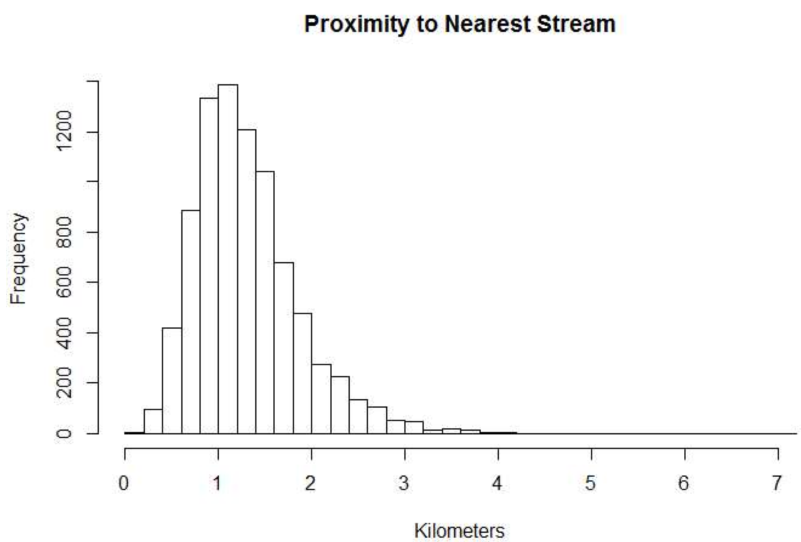

Figure B.20. Histogram of Nearest Healthy Stream.

- Drains directly into ocean: binary variable indicating whether the small catchment (< 50 km^2) drains directly into the ocean.
  - Yes
  - No

- <u>Area of upstream forested buffer</u>: the area of the upstream riparian zone (60 m on either side of the stream) with National Land Cover Dataset (NLCD) 2011 land use classification as forest, shrubland, herbaceous, or wetlands. We used this in order to merge the variables “Upstream watershed area” and “Intact/Natural Riparian Zone,” which were identified in earlier steps of the modelling process as important to resilience. This composite variable represents the potential for downstream drift of organisms from healthy areas upstream. For larger catchments this value will be higher. This value will also be high for medium-sized watersheds with fully intact riparian buffers.
  - 0 – 0.5 (median)
  - 0.5 – 2 (3rd quartile)
  - > 2

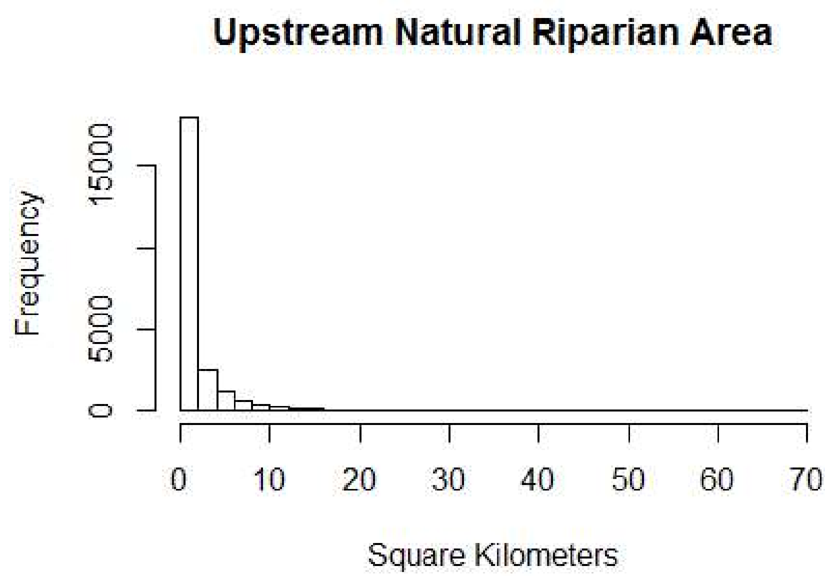

Figure B.21. Histogram of Upstream Forested Buffer.

Table B.20. Distribution of Upstream Forested Buffer.

Upstream Forested Area					
Min	1st Q	Med	Mean	3rd Q	Max
0	0.3	0.6	1.9	0.9	70

Ecology and Environmental Sciences

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APPENDIX C:

CONDITIONAL PROBABILITY TABLES SURVEY

The next step of the Bayesian network modelling process is to rank the unique combinations of input variables based on their likelihood of contributing to the state defined by the node. We do this using conditional probability tables (CPTs). For example, the Vulnerability to Salt Stress CPT is given below. A score of 1 through 5 is given based on the probability that a watershed with those unique characteristics will be vulnerable to the salt stress associated with urbanization. A score of 1 indicates a low likelihood of vulnerability and a score of 5 indicates a high likelihood of vulnerability. For each CPT, please use your expert judgment to rank the combinations of the input variables. We also provide space under each CPT to write comments; we would especially like to hear the assumptions you are making about how the variables interact to affect vulnerability.

Table C.1. Vulnerability to Salt Stress CPT.

		Probability of Vulnerability to Salt Stress				
Well-draining Soils	Drainage Area (km^2)	Less Vulnerable				More Vulnerable
> 30%	> 5	1	2	3	4	5
	0 - 5	1	2	3	4	5
10 - 30 %	> 5	1	2	3	4	5
	0 - 5	1	2	3	4	5
< 10%	> 5	1	2	3	4	5
	0 - 5	1	2	3	4	5

What assumptions are you making about the interactions of these variables to affect vulnerability to salt stress? Do you have any other thoughts or comments?

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How confident are you about your answers on this table?

1	2	3	4	5

Less More

Thanks for sharing your time and expertise with us!

<u>Vulnerability to Physical Stressors-</u> This submodel determines the vulnerability of a watershed to the physical stress of urban development. The number of states is shown in parentheses after the variable name.

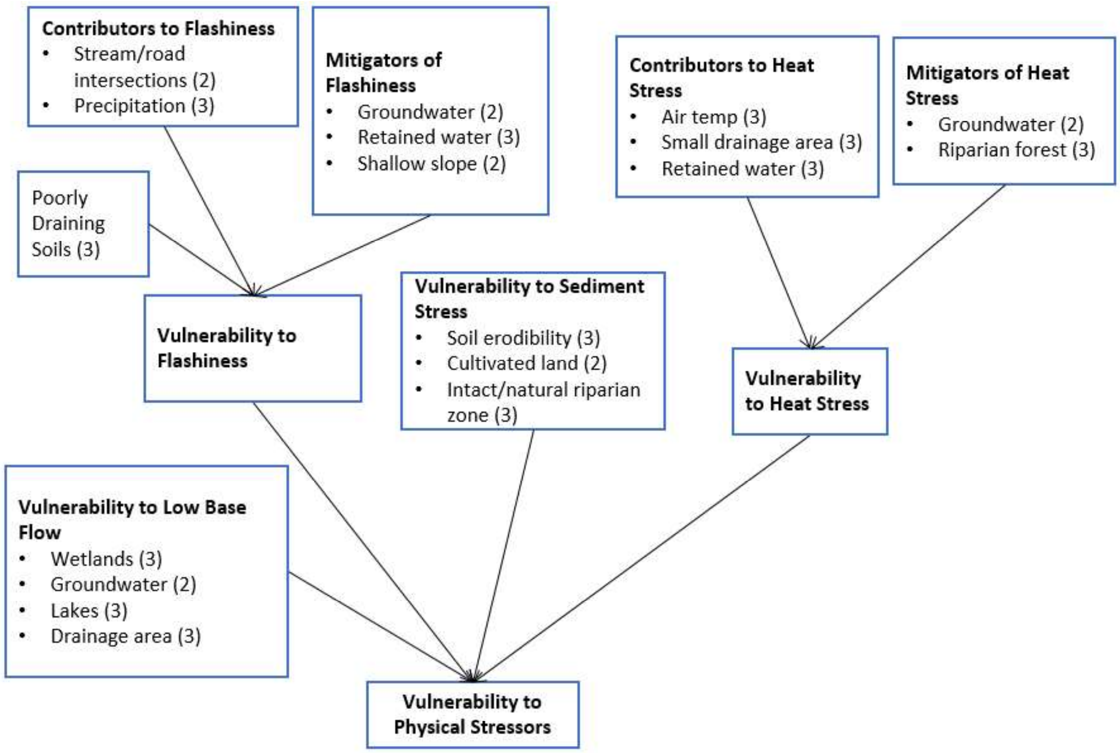

Figure C.1. BN influence diagram for vulnerability to physical stressors.

1. **Vulnerability to Sediment Stress.** The vulnerability of a stream to sediment stress associated with watershed urbanization.

Table C.2. Vulnerability to Sediment Stress CPT.

			Probability of Vulnerability to Sediment Stress				
Cultivated Land	Soil Erodibility (mean K factor)	Intact/Natural Riparian Buffer	Less Vulnerable				More Vulnerable
Percent of total area > 5	0.1 - 0.14	> 80 % of 60 m buffer is natural	1	2	3	4	5
		50 - 80 %	1	2	3	4	5
		0 - 50 %	1	2	3	4	5
	0.06 - 0.09	> 80 % of 60 m buffer is natural	1	2	3	4	5
		50 - 80 %	1	2	3	4	5
		0 - 50 %	1	2	3	4	5
	0.01 - 0.05	> 80 % of 60 m buffer is natural	1	2	3	4	5
		50 - 80 %	1	2	3	4	5
		0 - 50 %	1	2	3	4	5
0 - 5 %	0.1 - 0.14	> 80 % of 60 m buffer is natural	1	2	3	4	5
		50 - 80 %	1	2	3	4	5
		0 - 50 %	1	2	3	4	5
	0.06 - 0.09	> 80 % of 60 m buffer is natural	1	2	3	4	5
		50 - 80 %	1	2	3	4	5
		0 - 50 %	1	2	3	4	5
	0.01 - 0.05	> 80 % of 60 m buffer is natural	1	2	3	4	5
		50 - 80 %	1	2	3	4	5
		0 - 50 %	1	2	3	4	5

What assumptions are you making about the interactions of these variables to affect vulnerability to sediment stress? Do you have any other thoughts or comments?

How confident are you about your answers on this table?

1	2	3	4	5

Less More

1. **Vulnerability to Heat Stress**- the vulnerability of a stream to heat stress associated with watershed urbanization.

a. **Contributors**- factors that might contribute to stream heat stress from watershed urbanization.

Table C.3. Contributors to Heat Stress CPT.

			Probability of Vulnerability to Heat Stress				
Air Temp (degrees Fahrenheit)	Drainage Area (sq km)	Retained Water	Less Vulnerable				More Vulnerable
> 80	> 10	Percent total area > 14	1	2	3	4	5
		6 - 14 %	1	2	3	4	5
		< 6 %	1	2	3	4	5
	1 - 10	Percent total area > 14	1	2	3	4	5
		6 - 14 %	1	2	3	4	5
		< 6 %	1	2	3	4	5
	< 1	Percent total area > 14	1	2	3	4	5
		6 - 14 %	1	2	3	4	5
		< 6 %	1	2	3	4	5
76 - 80	> 10	Percent total area > 14	1	2	3	4	5
		6 - 14 %	1	2	3	4	5
		< 6 %	1	2	3	4	5
	1 - 10	Percent total area > 14	1	2	3	4	5
		6 - 14 %	1	2	3	4	5
		< 6 %	1	2	3	4	5
	< 1	Percent total area > 14	1	2	3	4	5
		6 - 14 %	1	2	3	4	5
		< 6 %	1	2	3	4	5
< 76	> 10	Percent total area > 14	1	2	3	4	5
		6 - 14 %	1	2	3	4	5
		< 6 %	1	2	3	4	5
	1 - 10	Percent total area > 14	1	2	3	4	5
		6 - 14 %	1	2	3	4	5
		< 6 %	1	2	3	4	5
	< 1	Percent total area > 14	1	2	3	4	5
		6 - 14 %	1	2	3	4	5
		< 6 %	1	2	3	4	5

What assumptions are you making about the interactions of these variables to affect vulnerability to heat stress? Do you have any other thoughts or comments?

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How confident are you about your answers on this table?

1	2	3	4	5

Less More

b. **Mitigators-** factors that might mitigate stream heat stress from watershed urbanization.

Table C.4. Mitigators to Heat Stress CPT.

		Probability of Mitigating Heat Stress				
Riparian Forest	Groundwater	Less Vulnerable				More Vulnerable
> 70 % of 60 m buffer is forested	More	1	2	3	4	5
	Less	1	2	3	4	5
40 -70 %	More	1	2	3	4	5
	Less	1	2	3	4	5
< 40 %	More	1	2	3	4	5
	Less	1	2	3	4	5

What assumptions are you making about the interactions of these variables to affect vulnerability to heat stress? Do you have any other thoughts or comments?

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How confident are you about your answers on this table?

1	2	3	4	5

Less More

c. **<u>Combining Mitigators and Contributors for Heat Stress</u>**: In the CPT below, we combine the output of the heat contributors and the heat mitigators node to get one value for vulnerability to heat stress.

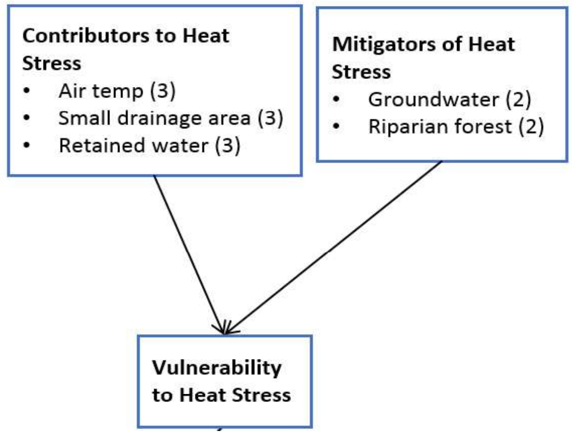

Figure C.2. Combining mitigators and contributors for heat stress.

Table C.5. Vulnerability to Heat Stress CPT.

		Probability of Vulnerability to Heat Stress				
Mitigators	Contributors	Less Vulnerabl e				More Vulnerabl e
High	High	1	2	3	4	5
	Medium	1	2	3	4	5
	Low	1	2	3	4	5
Med	High	1	2	3	4	5
	Medium	1	2	3	4	5
	Low	1	2	3	4	5
Low	High	1	2	3	4	5
	Medium	1	2	3	4	5
	Low	1	2	3	4	5

What assumptions are you making about the interactions of these input nodes to affect vulnerability to heat stress? Do you have any other thoughts or comments?

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___________________________ How confident are you about your answers on this table?

1	2	3	4	5

Less More

2. **Vulnerability to Flashiness Stress-** the vulnerability of a stream to changes in timing and amplitude of peak flow during a precipitation event associated with watershed urbanization.
a. **Contributors:** factors that might contribute to stream flashiness stress from watershed urbanization.

Table C.6. Contributors to Flashiness Stress CPT.

		Probability of Contributing to Flashiness Vulnerability				
Stream/Road Intersections	Precipitation (inches per year)	Less Vulnerabl e				More Vulnerabl e
> 0.5 per km^2	> 29	1	2	3	4	5
	27 - 29	1	2	3	4	5
	< 27	1	2	3	4	5
0 – 0.5 per km^2	> 29	1	2	3	4	5
	27 - 29	1	2	3	4	5
	< 27	1	2	3	4	5

What assumptions are you making about the interactions of these variables to affect vulnerability to flashiness stress? Do you have any other thoughts or comments?

How confident are you about your answers on this table?

1	2	3	4	5

Less More

b. **<u>Mitigators</u>**- factors that might mitigate stream flashiness stress from watershed urbanization.

Table C.7. Mitigators to Flashiness Stress CPT.

				Probability of Mitigating Vulnerability to Flashiness				
Substrate	Slope	Groundwater	Retained Water	Less Vulnerable				More Vulnerable
Erodible	>20%	any	any	1	2	3	4	5
	4.5 - 20%	High	Percent total area > 14	1	2	3	4	5
			6 - 14 %	1	2	3	4	5
			< 6 %	1	2	3	4	5
		Low	Percent total area > 14	1	2	3	4	5
			6 - 14 %	1	2	3	4	5
			< 6 %	1	2	3	4	5
	1 - 4.5%	High	Percent total area > 14	1	2	3	4	5
			6 - 14 %	1	2	3	4	5
			< 6 %	1	2	3	4	5
		Low	Percent total area > 14	1	2	3	4	5
			6 - 14 %	1	2	3	4	5
			< 6 %	1	2	3	4	5
	<1%	any	any	1	2	3	4	5
Resistant	>20%	any	any	1	2	3	4	5
	4.5 - 20%	High	Percent total area > 14	1	2	3	4	5
			6 - 14 %	1	2	3	4	5
			< 6 %	1	2	3	4	5
		Low	Percent total area > 14	1	2	3	4	5
			6 - 14 %	1	2	3	4	5
			< 6 %	1	2	3	4	5
	1 - 4.5%	High	Percent total area > 14	1	2	3	4	5
			6 - 14 %	1	2	3	4	5
			< 6 %	1	2	3	4	5
		Low	Percent total area > 14	1	2	3	4	5
			6 - 14 %	1	2	3	4	5
			< 6 %	1	2	3	4	5
	<1%	any	any	1	2	3	4	5

Combining Mitigators and Contributors: In the CPT below, we combine the output of the flashiness contributors and the flashiness mitigators nodes to get one value for vulnerability to flashiness. We added poorly draining surfaces to this table because opinions of the experts differ on whether it should be included as a mitigator or a contributor.

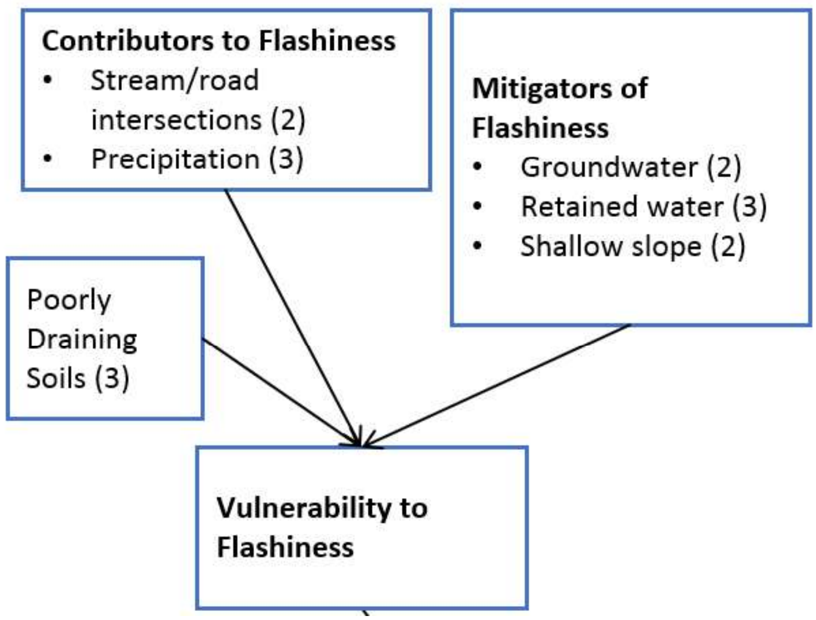

Figure C.3. Combining mitigators and contributors for vulnerability to flashiness.

Table C.8. Vulnerability to Flashiness Stress CPT.

Poorly Draining Surfaces	Mitigators	Contributors	Probability of Vulnerability to Flashiness: Less Vulnerable				More Vulnerable
>50 %	High	High	1	2	3	4	5
		Medium	1	2	3	4	5
		Low	1	2	3	4	5
	Med	High	1	2	3	4	5
		Medium	1	2	3	4	5
		Low	1	2	3	4	5
	Low	High	1	2	3	4	5
		Medium	1	2	3	4	5
		Low	1	2	3	4	5
25 - 50 %	High	High	1	2	3	4	5
		Medium	1	2	3	4	5
		Low	1	2	3	4	5
	Med	High	1	2	3	4	5
		Medium	1	2	3	4	5
		Low	1	2	3	4	5
	Low	High	1	2	3	4	5
		Medium	1	2	3	4	5
		Low	1	2	3	4	5
< 25 %	High	High	1	2	3	4	5
		Medium	1	2	3	4	5
		Low	1	2	3	4	5
	Med	High	1	2	3	4	5
		Medium	1	2	3	4	5
		Low	1	2	3	4	5
	Low	High	1	2	3	4	5
		Medium	1	2	3	4	5
		Low	1	2	3	4	5

What assumptions are you making about the interactions of these input nodes to affect vulnerability to flashiness stress? Do you have any other thoughts or comments?

How confident are you about your answers on this table?

1	2	3	4	5

Less More

3. **Vulnerability to Low Base Flow:** the vulnerability of a stream to a decrease in base flow associated with watershed urbanization. (See Next Page)

What assumptions are you making about the interactions of these variables to affect vulnerability to low base flow? Do you have any other thoughts or comments?

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How confident are you about your answers on this table?

1	2	3	4	5

Less More

Table C.9. Vulnerability to Low Base Flow. Continued on next page.

				Probability of vulnerability to low base flow				
Groundwater	Lakes	Wetlands	Drainage area (sq km)	Less Vulnerable				More Vulnerable
More	Percent of total area > 10	Percent of total area >20	> 10	1	2	3	4	5
			1 - 10	1	2	3	4	5
			< 1	1	2	3	4	5
		10 - 20 %	> 10	1	2	3	4	5
			1 - 10	1	2	3	4	5
			< 1	1	2	3	4	5
		< 10%	> 10	1	2	3	4	5
			1 - 10	1	2	3	4	5
			< 1	1	2	3	4	5
	0 - 10 %	Percent of total area >20	> 10	1	2	3	4	5
			1 - 10	1	2	3	4	5
			< 1	1	2	3	4	5
		10 - 20 %	> 10	1	2	3	4	5
			1 - 10	1	2	3	4	5
			< 1	1	2	3	4	5
		< 10%	> 10	1	2	3	4	5
			1 - 10	1	2	3	4	5
			< 1	1	2	3	4	5
	0	Percent of total area >20	> 10	1	2	3	4	5
			1 - 10	1	2	3	4	5
			< 1	1	2	3	4	5
		10 - 20 %	> 10	1	2	3	4	5
			1 - 10	1	2	3	4	5
			< 1	1	2	3	4	5
		< 10%	> 10	1	2	3	4	5
			1 - 10	1	2	3	4	5
			< 1	1	2	3	4	5

				Probability of vulnerability to low base flow				
Groundwater	Lakes	Wetlands	Drainage area (sq km)	Less Vulnerable			More Vulnerable	
Less	Percent of total area > 10	Percent of total area >20	> 10	1	2	3	4	5
			1 - 10	1	2	3	4	5
			< 1	1	2	3	4	5
		10 - 20 %	> 10	1	2	3	4	5
			1 - 10	1	2	3	4	5
			< 1	1	2	3	4	5
		< 10%	> 10	1	2	3	4	5
			1 - 10	1	2	3	4	5
			< 1	1	2	3	4	5
	0 - 10 %	Percent of total area >20	> 10	1	2	3	4	5
			1 - 10	1	2	3	4	5
			< 1	1	2	3	4	5
		10 - 20 %	> 10	1	2	3	4	5
			1 - 10	1	2	3	4	5
			< 1	1	2	3	4	5
		< 10%	> 10	1	2	3	4	5
			1 - 10	1	2	3	4	5
			< 1	1	2	3	4	5
	0	Percent of total area >20	> 10	1	2	3	4	5
			1 - 10	1	2	3	4	5
			< 1	1	2	3	4	5
		10 - 20 %	> 10	1	2	3	4	5
			1 - 10	1	2	3	4	5
			< 1	1	2	3	4	5
		< 10%	> 10	1	2	3	4	5
			1 - 10	1	2	3	4	5
			< 1	1	2	3	4	5

4. **<u>Overall Physical Vulnerability</u>**: The vulnerability of a stream to physical stressors associated with watershed urbanization.

Table C.10. Vulnerability to Physical Stress CPT.

Flashiness Vulnerability	Sediment Stress Vulnerability	Heat Stress Vulnerability	Low Base Flow Vulnerability	Probability of Vulnerability to Physical Stress				
				Less Vulnerable				More Vulnerable
High	High	High	High	1	2	3	4	5
			Low	1	2	3	4	5
		Low	High	1	2	3	4	5
			Low	1	2	3	4	5
	Low	High	High	1	2	3	4	5
			Low	1	2	3	4	5
		Low	High	1	2	3	4	5
			Low	1	2	3	4	5
Low	High	High	High	1	2	3	4	5
			Low	1	2	3	4	5
		Low	High	1	2	3	4	5
			Low	1	2	3	4	5
	Low	High	High	1	2	3	4	5
			Low	1	2	3	4	5
		Low	High	1	2	3	4	5
			Low	1	2	3	4	5

What assumptions are you making about the interactions of these variables to affect overall stream vulnerability to physical stressors? Do you have any other thoughts or comments?

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How confident are you about your answers on this table?

1	2	3	4	5

Less More

Vulnerability to Chemical Stressors- This submodel determines the vulnerability of a watershed to the chemical stress of urban development. The number of states is shown in parentheses after the variable name.

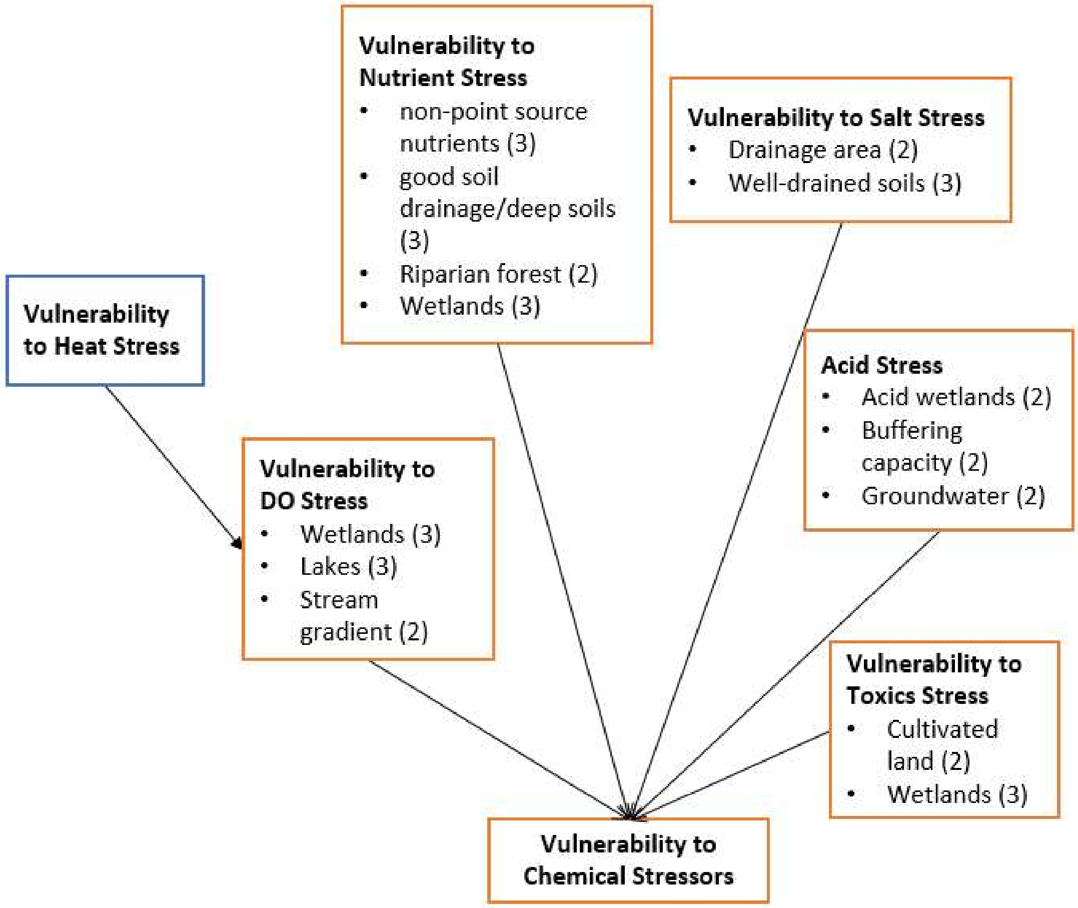

Figure C.4. BN influence diagram for vulnerability to chemical stressors.

1. **Vulnerability to Salt Stress-** We already did this one!

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2. **Acid Stress-** current amount of acid stress the stream is experiencing.

Table C.11. Vulnerability to Acid Stress CPT.

Acid Wetlands	Buffering Capacity	Groundwater	Probability of Acid Stress: Less Acidic				More Acidic
> 0.1%	Buffering	High	1	2	3	4	5
		Low	1	2	3	4	5
	Not Buffering	High	1	2	3	4	5
		Low	1	2	3	4	5
0%	Buffering	High	1	2	3	4	5
		Low	1	2	3	4	5
	Not Buffering	High	1	2	3	4	5
		Low	1	2	3	4	5

What assumptions are you making about the interactions of these variables to affect acid stress? Do you have any other thoughts or comments?

How confident are you about your answers on this table?

1	2	3	4	5

Less More

3. **Vulnerability to Toxic Stress-** The vulnerability of a stream to increased toxic load associated with watershed urbanization. Both salt stress and acid stress can affect vulnerability to toxics, but this will be considered in the overall chemical vulnerability CPT.

Table C.12. Vulnerability to Toxic Stress CPT.

		Probability of Vulnerability to Toxics Stress				
Cultivated Land	Wetlands	Less Vulnerable				More Vulnerable
Percent total area > 5	Percent of total area > 20	1	2	3	4	5
	10 - 20 %	1	2	3	4	5
	< 10 %	1	2	3	4	5
0 - 5 %	Percent of total area > 20	1	2	3	4	5
	10 - 20 %	1	2	3	4	5
	< 10 %	1	2	3	4	5

What assumptions are you making about the interactions of these variables to affect vulnerability to toxics stress? Do you have any other thoughts or comments?

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How confident are you about your answers on this table?

1	2	3	4	5

Less More

4. **<u>Vulnerability to DO Stress-</u>** The vulnerability of a stream to decreased concentrations of dissolved oxygen associated with watershed urbanization (see next page).

What assumptions are you making about the interactions of these variables to affect vulnerability to DO stress? Do you have any other thoughts or comments?

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How confident are you about your answers on this table?

1	2	3	4	5

Less More

Table C.13. Vulnerability to DO Stress CPT. Continued on next page.

				Probability of Vulnerability to DO Stress				
Vulnerability to Heat Stress	Lakes	Wetlands	Stream Gradient	Less Vulnerable			More Vulnerable	
High	Percent of total area > 10	Percent of total area > 20	> 5%	1	2	3	4	5
			3 - 5%	1	2	3	4	5
			< 3%	1	2	3	4	5
		10 - 20 %	> 5%	1	2	3	4	5
			3 - 5%	1	2	3	4	5
			< 3%	1	2	3	4	5
		< 10 %	> 5%	1	2	3	4	5
			3 - 5%	1	2	3	4	5
			< 3%	1	2	3	4	5
	0 - 10 %	Percent of total area > 20	> 5%	1	2	3	4	5
			3 - 5%	1	2	3	4	5
			< 3%	1	2	3	4	5
		10 - 20 %	> 5%	1	2	3	4	5
			3 - 5%	1	2	3	4	5
			< 3%	1	2	3	4	5
		< 10 %	> 5%	1	2	3	4	5
			3 - 5%	1	2	3	4	5
			< 3%	1	2	3	4	5
	0%	Percent of total area > 20	> 5%	1	2	3	4	5
			3 - 5%	1	2	3	4	5
			< 3%	1	2	3	4	5
		10 - 20 %	> 5%	1	2	3	4	5
			3 - 5%	1	2	3	4	5
			< 3%	1	2	3	4	5
		< 10 %	> 5%	1	2	3	4	5
			3 - 5%	1	2	3	4	5
			< 3%	1	2	3	4	5

				Probability of Vulnerability to DO Stress				
Vulnerability to Heat Stress	Lakes	Wetlands	Stream Gradient	Less Vulnerable			More Vulnerable	
Low	Percent of total area > 10	Percent of total area > 20	> 5%	1	2	3	4	5
			3 - 5%	1	2	3	4	5
			< 3%	1	2	3	4	5
		10 - 20 %	> 5%	1	2	3	4	5
			3 - 5%	1	2	3	4	5
			< 3%	1	2	3	4	5
		< 10 %	> 5%	1	2	3	4	5
			3 - 5%	1	2	3	4	5
			< 3%	1	2	3	4	5
	0 - 10 %	Percent of total area > 20	> 5%	1	2	3	4	5
			3 - 5%	1	2	3	4	5
			< 3%	1	2	3	4	5
		10 - 20 %	> 5%	1	2	3	4	5
			3 - 5%	1	2	3	4	5
			< 3%	1	2	3	4	5
		< 10 %	> 5%	1	2	3	4	5
			3 - 5%	1	2	3	4	5
			< 3%	1	2	3	4	5
	0%	Percent of total area > 20	> 5%	1	2	3	4	5
			3 - 5%	1	2	3	4	5
			< 3%	1	2	3	4	5
		10 - 20 %	> 5%	1	2	3	4	5
			3 - 5%	1	2	3	4	5
			< 3%	1	2	3	4	5
		< 10 %	> 5%	1	2	3	4	5
			3 - 5%	1	2	3	4	5
			< 3%	1	2	3	4	5

5. **<u>Vulnerability to Nutrient Stress-</u>** The vulnerability of a stream to increased concentrations of

Table C.14. Vulnerability to Nutrient Stress CPT.

				Probability of Vulnerability to Nutrient Stress				
Riparian Forest	Well-draining Soils	Non-point sources	Wetlands	Less Vulnerable				More Vulnerable
> 80 % of 60 m buffer is forested	> 65%	> 5 %	Percent of total area > 20	1	2	3	4	5
			10 -20 %	1	2	3	4	5
			< 10 %	1	2	3	4	5
		0 - 5%	Percent of total area > 20	1	2	3	4	5
			10 -20 %	1	2	3	4	5
			< 10 %	1	2	3	4	5
	30 - 65%	> 5 %	Percent of total area > 20	1	2	3	4	5
			10 -20 %	1	2	3	4	5
			< 10 %	1	2	3	4	5
		0 - 5%	Percent of total area > 20	1	2	3	4	5
			10 -20 %	1	2	3	4	5
			< 10 %	1	2	3	4	5
	< 30%	> 5 %	Percent of total area > 20	1	2	3	4	5
			10 -20 %	1	2	3	4	5
			< 10 %	1	2	3	4	5
		0 - 5%	Percent of total area > 20	1	2	3	4	5
			10 -20 %	1	2	3	4	5
			< 10 %	1	2	3	4	5
0 - 80 % of 60 m buffer is forested	> 65%	> 5 %	Percent of total area > 20	1	2	3	4	5
			10 -20 %	1	2	3	4	5
			< 10 %	1	2	3	4	5
		0 - 5%	Percent of total area > 20	1	2	3	4	5
			10 -20 %	1	2	3	4	5
			< 10 %	1	2	3	4	5
	30 - 65%	> 5 %	Percent of total area > 20	1	2	3	4	5
			10 -20 %	1	2	3	4	5
			< 10 %	1	2	3	4	5
		0 - 5%	Percent of total area > 20	1	2	3	4	5
			10 -20 %	1	2	3	4	5
			< 10 %	1	2	3	4	5
	< 30%	> 5 %	Percent of total area > 20	1	2	3	4	5
			10 -20 %	1	2	3	4	5
			< 10 %	1	2	3	4	5
		0 - 5%	Percent of total area > 20	1	2	3	4	5
			10 -20 %	1	2	3	4	5
			< 10 %	1	2	3	4	5

What assumptions are you making about the interactions of these variables to affect vulnerability to nutrient stress? Do you have any other thoughts or comments?

How confident are you about your answers on this table?

1	2	3	4	5

Less More

6. **Overall Vulnerability to Chemical Stress:** The vulnerability of a stream to chemical stressors

Table C.15. Vulnerability to Chemical Stress CPT.

					Probability of Vulnerability to Chemical Stress				
Nutrient Vulnerability	Low DO Vulnerability	Acid Stress	Toxic Vulnerability	Salt Vulnerability	Less Vulnerable				More Vulnerable
High	High	High	High	High	1	2	3	4	5
				Low	1	2	3	4	5
			Low	High	1	2	3	4	5
				Low	1	2	3	4	5
		Low	High	High	1	2	3	4	5
				Low	1	2	3	4	5
			Low	High	1	2	3	4	5
				Low	1	2	3	4	5
	Low	High	High	High	1	2	3	4	5
				Low	1	2	3	4	5
			Low	High	1	2	3	4	5
				Low	1	2	3	4	5
		Low	High	High	1	2	3	4	5
				Low	1	2	3	4	5
			Low	High	1	2	3	4	5
				Low	1	2	3	4	5
Low	High	High	High	High	1	2	3	4	5
				Low	1	2	3	4	5
			Low	High	1	2	3	4	5
				Low	1	2	3	4	5
		Low	High	High	1	2	3	4	5
				Low	1	2	3	4	5
			Low	High	1	2	3	4	5
				Low	1	2	3	4	5
	Low	High	High	High	1	2	3	4	5
				Low	1	2	3	4	5
			Low	High	1	2	3	4	5
				Low	1	2	3	4	5
		Low	High	High	1	2	3	4	5
				Low	1	2	3	4	5
			Low	High	1	2	3	4	5
				Low	1	2	3	4	5

What assumptions are you making about the interactions of these input nodes to affect vulnerability to chemical stress? Do you have any other thoughts or comments?

How confident are you about your answers on this table?

1	2	3	4	5

Less More

<u>Ecological Vulnerability to Urbanization</u>- This final node represents the output of the entire model. The value given by this node will be the vulnerability score for the watershed in question. We expect that a watershed that is given a high score for vulnerability and that currently has urban area should be degraded.

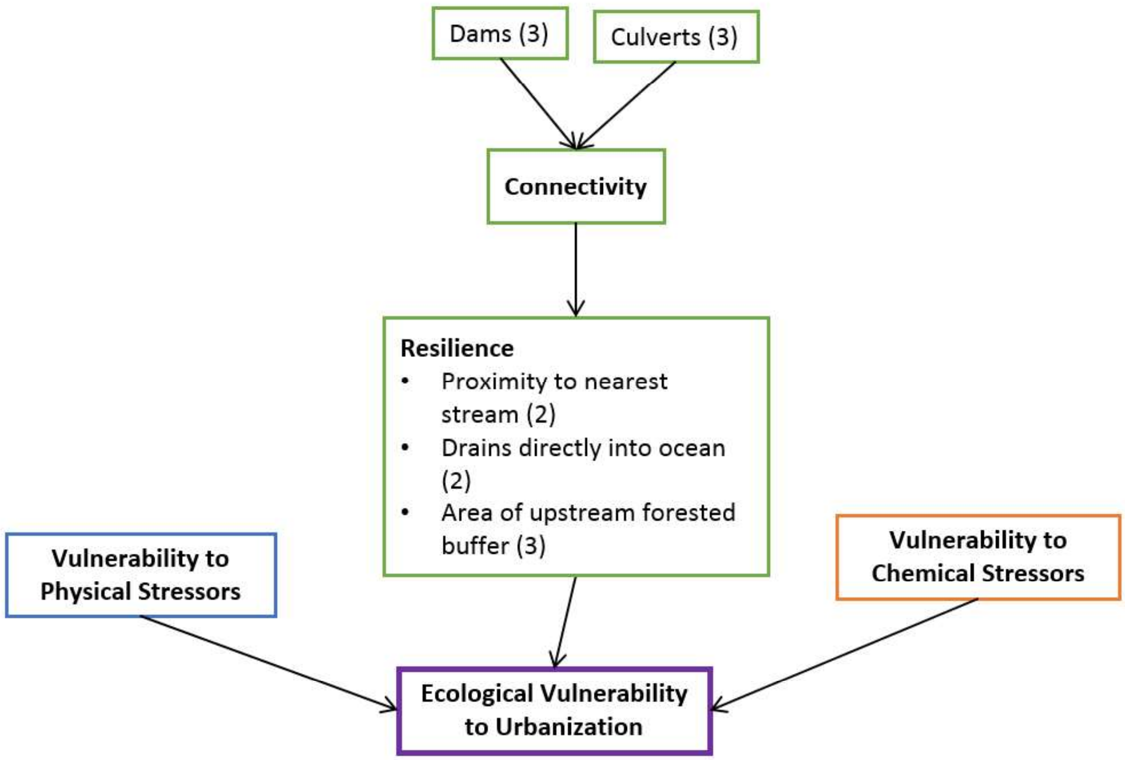

Figure C.5. Combining submodels to obtain overall vulnerability to urbanization.

1. **Connectivity**: Stream connectivity in regards to recolonization potential.

Table C.16. Connectivity CPT.

		Connectivity				
Culverts	Dams	More Connected				Less Connected
> 1 Per square kilometer	> 1	1	2	3	4	5
	1	1	2	3	4	5
	0	1	2	3	4	5
0.1 - 1	> 1	1	2	3	4	5
	1	1	2	3	4	5
	0	1	2	3	4	5
< 0.1	> 1	1	2	3	4	5
	1	1	2	3	4	5
	0	1	2	3	4	5

What assumptions are you making about the interactions of these variables to affect connectivity? Do you have any other thoughts or comments?

How confident are you about your answers on this table?

1	2	3	4	5

Less More

2. **Recolonization potential/resilience**: The likelihood of a stream to recover after a disturbance

Table C.17. Recolonization CPT.

				Probability of Recolonization Potential/Resilience				
Drains Directly to Ocean	Proximity to Nearest Stream	Area of Upstream Forested Buffer	Connectivity	More Resilient				Less Resilient
Yes	> 1.5 km	2 - 70 km²	High	1	2	3	4	5
			Med	1	2	3	4	5
			Low	1	2	3	4	5
		0.5 - 2	High	1	2	3	4	5
			Med	1	2	3	4	5
			Low	1	2	3	4	5
		0 - 0.5	High	1	2	3	4	5
			Med	1	2	3	4	5
			Low	1	2	3	4	5
	0 - 1.5 km	2 - 70 km²	High	1	2	3	4	5
			Med	1	2	3	4	5
			Low	1	2	3	4	5
		0.5 - 2	High	1	2	3	4	5
			Med	1	2	3	4	5
			Low	1	2	3	4	5
		0 - 0.5	High	1	2	3	4	5
			Med	1	2	3	4	5
			Low	1	2	3	4	5
No	> 1.5 km	2 - 70 km²	High	1	2	3	4	5
			Med	1	2	3	4	5
			Low	1	2	3	4	5
		0.5 - 2	High	1	2	3	4	5
			Med	1	2	3	4	5
			Low	1	2	3	4	5
		0 - 0.5	High	1	2	3	4	5
			Med	1	2	3	4	5
			Low	1	2	3	4	5
	0 - 1.5 km	2 - 70 km²	High	1	2	3	4	5
			Med	1	2	3	4	5
			Low	1	2	3	4	5
		0.5 - 2	High	1	2	3	4	5
			Med	1	2	3	4	5
			Low	1	2	3	4	5
		0 - 0.5	High	1	2	3	4	5
			Med	1	2	3	4	5
			Low	1	2	3	4	5

What assumptions are you making about the interactions of these variables to affect recolonization potential/resilience? Do you have any other thoughts or comments?

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How confident are you about your answers on this table?

1	2	3	4	5

Less More

3. **<u>Overall Ecological Vulnerability to Urbanization Stress:</u>** Way to go, you made it to the last CPT! This table compiles all the previous variables and nodes to give the overall vulnerability of a stream to watershed urbanization stress.

Table C.18. Overall vulnerability CPT.

Physical Vulnerability	Chemical Vulnerability	Resilience	Probability of Vulnerability to Urbanization Stress: Less Vulnerable				More Vulnerable
High	High	High	1	2	3	4	5
		Medium	1	2	3	4	5
		Low	1	2	3	4	5
	Medium	High	1	2	3	4	5
		Medium	1	2	3	4	5
		Low	1	2	3	4	5
	Low	High	1	2	3	4	5
		Medium	1	2	3	4	5
		Low	1	2	3	4	5
Medium	High	High	1	2	3	4	5
		Medium	1	2	3	4	5
		Low	1	2	3	4	5
	Medium	High	1	2	3	4	5
		Medium	1	2	3	4	5
		Low	1	2	3	4	5
	Low	High	1	2	3	4	5
		Medium	1	2	3	4	5
		Low	1	2	3	4	5
Low	High	High	1	2	3	4	5
		Medium	1	2	3	4	5
		Low	1	2	3	4	5
	Medium	High	1	2	3	4	5
		Medium	1	2	3	4	5
		Low	1	2	3	4	5
	Low	High	1	2	3	4	5
		Medium	1	2	3	4	5
		Low	1	2	3	4	5

What assumptions are you making about the interactions of these variables to affect overall stream vulnerability to urbanization? Do you have any other thoughts or comments?

How confident are you about your answers on this table?

1	2	3	4	5

Less More

Thank you! You totally rock.

APPENDIX D:

IRB REVIEW BOARD ACCEPTANCE LETTER

APPLICATION FOR APPROVAL OF RESEARCH WITH HUMAN SUBJECTS
Protection of Human Subjects Review Board
114 Alumni Hall, 581-1498

PRINCIPAL INVESTIGATOR: Kristen K. Weil
EMAIL: kristen.weil@maine.edu TELEPHONE: 505-400-9274
CO-INVESTIGATOR(S): Christopher Cronan, Robert Lilieholm, Michelle Johnson, Spencer Meyer
FACULTY SPONSOR (Required if PI is a student): Christopher S. Cronan
TITLE OF PROJECT: Developing a Stakeholder-derived Bayesian Network to Predict Stream Response to Future Land-use Change in Maine, U.S.A.

START DATE: 3/20/14 ~~3/1/14~~ PI DEPARTMENT: Ecology and Environmental Science
MAILING ADDRESS: 5722 Deering Hall
FUNDING AGENCY (if any): USDA MAFES
STATUS OF PI:
FACULTY/STAFF/GRADUATE/UNDERGRADUATE Graduate

1. If PI is a student, is this research to be performed:

- ☐ for an honors thesis/senior thesis/capstone?
- ☒ for a master's thesis?
- ☐ for a doctoral dissertation?
- ☐ for a course project?
- ☐ other (specify)

2. Does this application modify a previously approved project? No (Y/N).

3. Is an expedited review requested? Yes (Y/N).

SIGNATURES: All procedures performed under the project will be conducted by individuals qualified and legally entitled to do so. No deviation from the approved protocol will be undertaken without prior approval of the IRB.

Faculty Sponsors are responsible for oversight of research conducted by their students. By signing this application page, the Faculty Sponsor ensures that the conduct of such research will be in accordance with the University of Maine's Policies and Procedures for the Protection of Human Subjects of Research.

______ Date ______ Principal Investigator ______ Faculty Sponsor

______ Co-Investigator ______ Co-Investigator

****

FOR IRB USE ONLY Application # 2014-03-02 Date received 3/10/14 Review (F/E): E
Expedited Category: ______

ACTION TAKEN:

X Judged Exempt; category 2. Modifications required? Y (Y/N) Accepted (date) 3/20/14
____ Approved as submitted. Date of next review: by ______. Degree of Risk: ______
____ Approved pending modifications. Date of next review: by ______. Degree of Risk: ______
Modifications accepted (date): ______.
____ Not approved. (See attached statement.)
____ Judged not research with human subjects

Date: 3/18/14 Chair's Signature: Cynthia A. Erdley 10/09

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BIOGRAPHY OF THE AUTHOR

Kristen Weil grew up in the North Valley of Albuquerque, New Mexico. She spent her childhood playing outdoors in the Rio Grande riparian forest and the nearby Sandia Mountains. At a young age, Kristen learned the value of travelling and experiencing different cultures. She spent three months living with family in Puerto Rico when she was a kid. Throughout her youth her family took trips across the country, and often spent vacations camping in the beautiful forests of New Mexico. At Valley High School, she sold candy from her backpack at school to fund a trip to Europe. After that, she was hooked. She spent the summer after high school touring six countries in a return trip to Europe. Another summer, she did an internship to learn Spanish in Spain, and intermittently she returned to Puerto Rico to visit family. After graduating from the University of New Mexico in 2011 with a Bachelor's degree in Environmental Science and a Double Major in Spanish, Kristen decided to travel to South America. She travelled across six countries over the course of a year, volunteering on organic farms learning about permaculture, teaching English to kids and adults, and practicing Spanish. Throughout all these experiences in different parts of the world, Kristen gained an understanding of the universality of environmental degradation. She was inspired to attend graduate school to further her education in order to be able to advocate for the environment as a career. In the fall of 2013, Kristen began graduate studies at the University of Maine. She worked with her advisor, Christopher Cronan, to get a landscape view of stream degradation due to urbanization across the State of Maine. Upon completion of this Master's program, Kristen plans to work in her home town to help research and solve water issues which afflict the State of New Mexico more and more each year. She is a candidate for the Master of Science degree in Ecology and Environmental Science from the University of Maine in May 2016.