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Research Paper

Predicting stream vulnerability to urbanization stress with Bayesian network models

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ABSTRACT

As human development and urbanization expand across the landscape, increasing numbers of streams are threatened with impairment from disturbance and stresses associated with land use changes. In this investigation, a Bayesian Network (BN) with an expert-informed model structure was developed to predict stream vulnerability to urbanization across a range of biophysical conditions. Primary factors affecting vulnerability were stream buffers, colonization connectivity, agriculture, watershed area, and sand/gravel aquifers. On a scale from 0 to 100 (lowest to highest probability), BN model vulnerability scores ranged from a minimum of 20 to a maximum of 87.5 across the 23,554 stream catchments in our statewide study area. Catchment vulnerability scores were linked with predictions of land development suitability from a second BN model in order to map the locations of streams at risk of impairment from projected future urbanization in two large watersheds in Maine, USA. Our BN synthesis identified 5% of the streams that are at risk based on two assessment criteria: (1) their catchments have projected future impervious cover (IC) levels greater than 6% and (2) the stream catchments have predicted vulnerability scores in the highest quartile of the BN model probability distribution. These at-risk streams represent priority targets for proactive monitoring, management, and conservation efforts to avoid future degradation and expensive restoration costs. This study laid the conceptual groundwork for using BN spatial models to identify streams that are not only vulnerable to urbanization, but are also located in catchments classified with a high probability of development suitability and future urbanization.

1. Introduction

An undeveloped forested watershed can tolerate only a limited amount of urbanization and human development activity before symptoms of stress and degradation begin to appear in downstream aquatic ecosystems. However, the response of streams to anthropogenic land use changes can vary as a function of watershed biophysical conditions that influence resistance or resilience properties of the coupled catchment and stream system (Alberti and Marzluff 2004; McCluney et al., 2014; Utz et al., 2016). In general, one would expect the streams at highest risk of impairment from development to be those with watershed characteristics that confer low resistance or high vulnerability to changing land use conditions or urbanization. Here, *resistance* refers to the ability of an ecosystem to resist change and to maintain structure and function despite increased exposure to stressors (Pearsons and Li 1992; Vieira, Clements, Guevara, & Jacobs, 2004). Conversely, *vulnerability* describes the sensitivity of a system to a stress and the degree to which the system will experience harm due to exposure to a stressor or perturbation (Besaw et al., 2009; Turner et al., 2003). *Resilience* describes the ability of a system to recover from disturbance or stress.

Under authority of the federal Clean Water Act (CWA) and state water quality standards, the U.S. Environmental Protection Agency (US EPA) and state regulatory agencies endeavor to sustain healthy aquatic resources and to restore the chemical, physical, and biological integrity of waters that have been impaired by urbanization, non-point pollution, or other stressors. In Maine, the Department of Environmental Protection (Maine DEP) monitors the health of streams and determines

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if they attain water quality standards and criteria associated with four state-defined statutory classes (Courtemanch, Davies, & Laverty, 1989; Danielson et al., 2012; Davies, Drummond, Courtemanch, Tsomides, & Danielson, 2016). If a stream does not attain water quality standards or criteria associated with its designated class, then it may be listed as impaired in the CWA 303(d) inventory of impaired waters (Maine DEP, 2012a). Unfortunately, the economic cost of restoring impaired streams can be substantial − as one example, ongoing restoration of the impaired Long Creek ecosystem in Portland, Maine is projected to cost $14 million (FB Environmental Associates 2009). With 2300 miles of streams and rivers currently classified in 303(d) impaired status by US EPA, Maine faces a daunting and expensive mitigation and restoration challenge. Given this set of circumstances, we argue that a proactive policy focused on avoiding stream impairment is a more cost-effective and sustainable approach to resource management than a reactive strategy that necessitates large expenditures to restore streams and rivers after they become degraded. The question then becomes: how can we identify streams that are at risk of future impairment, so that they can be protected by appropriate smart growth strategies or watershed conservation actions?

Any answer to that question will necessarily involve a focus on impervious cover. As urbanization expands in the landscape, stream quality generally decreases when impervious cover (IC) – 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, Fraley-McNeal, & Cappiella, 2009). In fact, Maine watersheds with IC values above 6% have been shown to exhibit marked declines in aquatic insect diversity that are indicative of ecological degradation (Morse, Huryn, & Cronan, 2003). More recently, Danielson et al. (2016) reported that there is a rapid loss of sensitive species between 1 and 3% IC and the risk of not attaining Class AA and A biological criteria is high after 3% IC. There is an additional loss of sensitive species between 3 and 6% IC and the risk of not attaining Class B biological criteria is high after 6%. Although it is widely accepted that stream integrity declines when urban area or IC increases beyond a certain threshold, the rate of degradation and the IC threshold can be variable. This implies that differences in watershed or environmental characteristics may mitigate or exacerbate patterns of stream vulnerability to urbanization.

Unfortunately, few studies have examined explicit ways in which watershed biophysical factors influence stream sensitivity to development and land use changes. There is, however, an extensive literature focused on landscape attributes that contribute to stream impairment and the degradation of downstream water quality. Investigators in several studies have demonstrated that agricultural cover in a watershed contributes to declines in stream water quality and a loss of biotic integrity (Allan, Erickson, & Fay, 1997; Carpenter et al., 1998). In Wisconsin watersheds, urbanization consistently contributed to degraded streams, whereas the influence of agriculture on streams was more variable (Wang, Lyons, & Kanehl., 2001). Strayer et al. (2003) found that cultivated and urban lands in the Mid-Atlantic region were associated with symptoms of stream degradation (e.g., high N, low fish species richness, high proportion of exotic fish, and low macroinvertebrate species richness), but wetlands, forests, and pastures were correlated with desirable stream quality traits. A number of models have been created using landscape variables to predict physical, biological, or chemical conditions in streams. In one example, investigators used a geologic classification system based on acid neutralizing capacity (ANC) and other landscape variables to predict the locations of acid-sensitive and acid-impacted streams in the southern Appalachian Mountains (Sullivan, Webb, Snyder, Herlihy, & Cosby, 2007). A model developed by Carlisle et al. (2009) used riparian land cover, road-stream intersections, elevation, soil permeability, depth-to-water table, and percent agricultural land cover to predict biological condition in streams in the Eastern U.S. Esselman et al. (2011) calculated a cumulative disturbance index for each U.S. watershed using a model relating fish IBI (index of biotic integrity) to anthropogenic disturbance variables such as percent urban or agricultural area in the watershed, population density, road density, dams, and mines. In a similar study, Bedoya et al. (2011) developed a model to predict IBI scores for streams in Ohio, and identified hay/pasture lands, deciduous forest, low intensity development, open urban land, woody wetlands, and deciduous forest within a stream buffer zone as key model variables. Taken as a whole, previous studies have indicated that impacts from anthropogenic stressors are widely manifested either directly through urban and agricultural runoff or indirectly through the removal of forests and wetlands.

Despite the growing number of analyses of correlations between landscape features and water quality, there has been only a limited effort to predict the relationships between modeled future land use conditions and stream water quality. The few studies that have examined future conditions have tended to use buildout analyses (Conway and Lathrop, 2005), which consider the implications of full construction in accordance with current zoning. In one novel exception to the buildout approach, Van Sickle et al. (2004) applied four alternative land use futures scenarios to predict the biological condition of streams in the Willamette River Basin, Oregon for the year 2050. They reported that agricultural lands and development within a 120 m stream buffer were two primary determinants of stream condition. Although alternative futures models have not yet been widely applied to stream quality issues, such models provide a way to develop and to target preventive water quality protection strategies that are likely to be less expensive and disruptive than reactive strategies initiated after water quality impairment sets in.

In this research, we built on these previous efforts by integrating a model of landscape-water quality interactions with a second model of future land use development. We used a Bayesian Network (BN) to explore the causal web of interacting factors that account for stream vulnerability to urbanization stressors. Bayesian Networks (BNs) provide a novel model framework for addressing ecological research problems (Chen and Pollino, 2012; Marcot, Holthausen, Raphael, Rowland, & Wisdom, 2001; Uusitalo, 2007), and have been used in recent years to assess population viability for at-risk fish and wildlife (Marcot et al., 2001), for land suitability analyses (Chow and Sadler 2010; Meyer, Johnson, Lilieholm, & Cronan, 2014), for adaptive management decision-making (Nyberg, Marcot, & Sulyma, 2006), for water quality predictions (Reckhow 1999), and for examining relationships linking urban development to physical, chemical, and biological conditions in a stream (Kashuba et al., 2012). These prior studies have identified several potential advantages of Bayesian modeling, including the ability to incorporate expert knowledge into a deductive framework for making predictions. For our purposes, the BN modeling approach provided a tool for combining expert knowledge and GIS spatial information to predict the statewide distribution of streams that have an elevated risk of degradation from watershed urbanization.

This investigation focused on identifying resistance and resilience factors that influence the vulnerability of streams and watersheds to urbanization, and integrating that knowledge into a predictive BN modeling framework for application to the sustainable management of aquatic resources. The major objectives of this study were to: (1) develop a spatially-explicit Bayesian Network (BN) model based on environmental data, stream biotic metrics, and expert knowledge in order to identify landscape characteristics that contribute to an increase or decrease in stream vulnerability to urbanization; (2) predict the potential vulnerability of individual streams in the Maine landscape to future urbanization stress; and (3) assess the spatial distribution of at-risk or vulnerable streams in relation to areas that are most likely to experience future development and urbanization based on alternative futures modeling projections. Our results demonstrate how BN models can provide a conceptual framework and a valuable predictive tool for resource managers and planners to use in (1) envisioning alternative future scenarios of watershed development; (2) prioritizing specific vulnerable streams for conservation protection, (3) developing proactive sustainable management strategies to prevent stream degradation, and (4) avoiding costly watershed restoration efforts.

2. Study sites

This investigation focused at two scales in Maine, USA: (1) a statewide analysis of small watersheds with areas < 125 km^2 and (2) a more detailed analysis of two large drainage systems − the Casco Bay and Lower Androscoggin River Watershed (CBLA) and the Lower Penobscot River Watershed (LPRW). Although Maine has a relatively low current population size of 1.33 million persons, development has been increasing and is predicted to continue expanding. In fact, LPRW and CBLA are two of the four watersheds in Maine that were identified by the US Forest Service *Forests on the Edge* study as locations where substantial development growth on private forest lands is expected in the coming decades (Mockrin, Lilja, Weidner, Stein, & Carr, 2014 ; Stein et al., 2006, 2009).

Maine is characterized by cold winters, mild summers, moderate annual precipitation (100 cm ±), and is dominated by forested land cover (80%), wetlands (10%), agriculture (5%), and human development (5%). The state encompasses roughly 8.6 million ha, most of which is privately owned (> 90%), and 19.4% of the land area is permanently protected from development (Meyer, Cronan, Lilieholm, Johnson, & Foster, 2014). There is an east-to-west and south-to-north human population gradient, with a large proportion of development focused along the coast and in the warmer southern region of the state. Most agricultural activity is concentrated in the northeastern part of the state, while private working forests dominate the western mountains and northwestern Maine.

3. Methods

The overall process of model development and implementation involved the following general steps: identify the major parameters affecting stream vulnerability; construct an influence diagram for the BN model; assemble state-wide GIS spatial layers and determine the range of variability for each factor in the BN model; develop conditional probability tables (CPT's) based on discretized spatial data and expert opinion; run the BN model to assign vulnerability scores for each watershed in the state; test the model against Maine DEP stream attainment results for a subset of Maine streams; and determine which streams in the CBLA and LPRW are located in catchments with both high vulnerability scores and a high probability of future development. Further methodological details and approaches are described below.

3.1. Development of the Bayesian Network Model

3.1.1. Expert recruitment

The Bayesian Network (BN) model was created with the guidance and participation of nine Maine professionals with technical expertise in watershed management, stream ecosystem monitoring, environmental engineering, and aquatic ecology. A primary goal was to recruit participants with a wide range of experience and perspectives in order to develop a holistic understanding of the processes driving stream impairment (Krueger, Page, Hubacek, Smith, & Hiscock, 2012). In BN model development, experts are defined as individuals who have detailed or specialized knowledge gained through experience, education, or training regarding the system in question (Kuhnert, Martin, & Griffiths, 2010). Beyond these requirements, our recruitment was not influenced by any factor such as age or gender. Recruitment of our experts from the private and public sectors was accomplished using an initial email and follow-up phone calls.

3.1.2. Initial expert elicitation, variable identification, and model structure

There is a large body of research describing techniques for eliciting expert judgments effectively and with minimal bias. Expert elicitation can be done directly, by asking experts about values or criteria to use in a model, or indirectly, by compiling information from broad survey questions answered by experts (Martin et al., 2011). A variety of complications can arise in expert elicitation (Low Choy, O'Leary, & Mengersen, 2009; Martin et al., 2011), including motivational bias, overconfidence, dominance by one or more members of the group, polarization within the group, and group think (i.e., agreeing on an answer in the interest of finishing the task or not wanting to raise a contrary view). To avoid these pitfalls, experts can be made aware of the potential for bias (Low Choy et al., 2009) and can work together, but report their answers individually (Martin et al., 2011). Throughout the course of 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 focus group during which participants learned our research goals, the motivation for creating an expert-derived BN, our definition of stream vulnerability, and basic principles regarding the BN modeling process. Participants then worked as a group to list their choices of the important factors that influence or govern stream vulnerability to urbanization. Based on 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 (Appendix A in Supplementary file). This set the stage for construction of an alpha level BN model (Marcot, Steventon, Sutherland, & McCann, 2006).

The next step in BN model development was the creation of an influence diagram representing the "causal web" of interacting watershed environmental variables and 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 connecting the interacting variables. Nodes with incoming links (child nodes) have conditional probability tables (CPTs) that describe the probability of different outcomes occurring given all possible combinations of the various input nodes (parent nodes). Parent nodes have prior distributions based on data or expert opinion; in our case, distributions were based on GIS spatial data. In an effort to achieve model parsimony, we limited the number of parent nodes linked to any child node to 3 or less, and the number of levels in the model to 4 or less (Marcot et al., 2006; Marcot, 2012).

3.1.3. Processing catchment data for the BN model

The National Hydrography Dataset (NHD) Version 2 (USGS, 2012) was used as the state-wide watershed layer in the BN analysis. This 1:100,000 scale dataset represents watersheds and sub-watersheds, beginning with headwater streams and spanning the whole stream length by reach-scale sub-catchments. The catchments are generally smaller than 12-digit hydrological units (HUC-12). Because the NHD watersheds are nested and overlap each other down the stream network, preprocessing of the catchments was a necessary step. ArcHydro Tools in ESRI ArcMap 10.0 was used to perform an incremental mapping process for combining headwater and reach-scale catchments into linked downstream drainage units using adjoint catchments that span the entire upstream area of the reach-scale catchment (Fig. 1). GIS raster layers representing each variable in the model (Appendix A in Supplementary file) were projected into UTM 19N using ArcMap 10.0 and were transformed to 30 m pixels. Using the Zonal Statistics tool in the Raster Package version 3.1.2 of the R Statistical Computing Software (R Core Team 2013), all raster layers were summarized for the reach-scale catchments, the headwater catchments, and the adjoint catchments. Post-processing combined the area-weighted values for the reach-scale catchments and their corresponding adjoint catchment to get the final value of each spatial parameter for the reach-scale

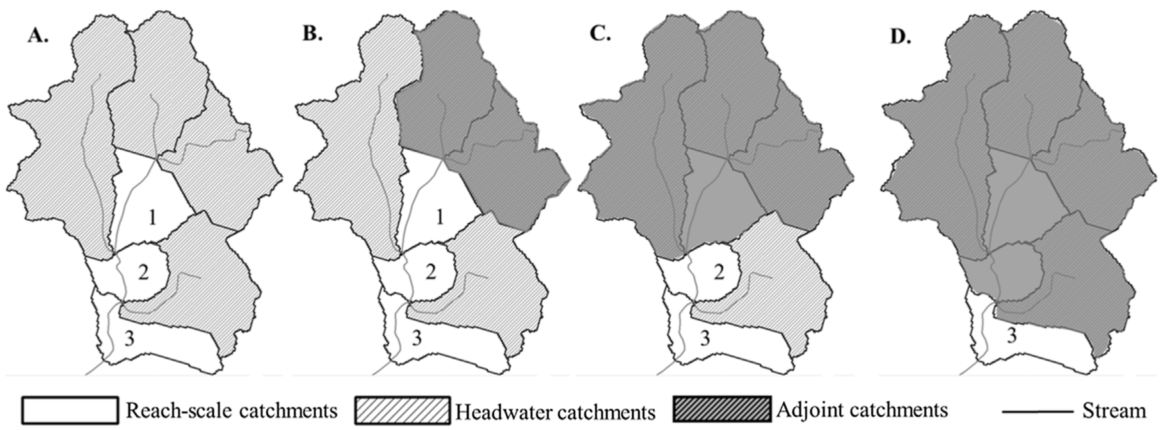


Fig. 1. The incremental mapping process for combining reach-scale watersheds into linked downstream drainage units using adjoint catchments. This iterative process is continued down the network until the size of the reach-scale catchment plus the adjoint catchment reaches 125 km^2. (A) Headwater catchments and reach-scale catchments, with no adjoint catchments. (B) The adjoint catchment (dark gray area) for the reach-scale catchment 1; the adjoint catchment represents the upstream area contributing runoff to catchment 1. (C) The adjoint catchment (dark gray area) for reach-scale catchment 2. This adjoint catchment includes reach-scale catchment 1, as well as all of the headwater catchments contributing runoff to catchment 2. (D) The shaded portion represents areas contributing to catchment 3.

catchments. It was necessary to use 30 m pixels in this work, because 5 m pixels required an inordinate amount of computing power and time for this type of large-scale spatial model.

3.1.4. Discretization and conditional probability tables

All continuous data in the BN were separated into two or more classes through the process of "discretization" (Chen and Pollino 2012). Choosing the number of states and the discretization values for a CPT is challenging, and differences in these values can affect model outputs. Thus, it is preferable to base discretization on the numerical distribution of input data in order to minimize errors (Uusitalo 2007). In discretizing our continuous variables, summaries for each spatial variable across all watersheds were presented to the panel of experts, along with suggestions for cutoff values. Through iterative emails and phone calls, 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. The CPT surveys (Appendix B in Supplementary file) were administered in small group meetings or one-on-one with the principal investigator (PI). During meetings, the PI reiterated the model objectives and helped to guide the experts through the process of completing the complex surveys. The CPTs depicted each possible unique combination of input variables and provided a 1–5 point Likert-type scale for ranking separate combinations based on their potential contribution to stream vulnerability to urbanization stressors. Within the small groups, discussion was encouraged, but experts were asked to write their answers separately in order to minimize group bias (Low Choy et al., 2009; Martin et al., 2011). Methods described by Meyer, Johnson et al. (2014) were followed in order to convert the 1–5 point scales into probability distributions (Appendix B in Supplementary file). Below each CPT, a comment section was provided to allow experts to indicate the assumptions they made regarding interactions among the BN variables in affecting vulnerability to the stressor.

Model structure and conditional probability values were entered into the modeling software Netica version 5.12 (Norsys Software Corporation 2013), which allowed each watershed to be processed individually. The BN model computed a value for the probability of vulnerability to urbanization for each watershed based on biophysical spatial data compiled for Maine watersheds, expert-derived CPTs, and the discretized data distributions.

3.2. Model evaluation

3.2.1. Sensitivity analysis

In their discussion of recommended practices in Bayesian network modeling, Chen and Pollino (2012) noted that model evaluation in its various forms helps to confirm that interactions and model outcomes are feasible and defensible. Evaluation techniques can include a sensitivity analysis (Chen and Pollino 2012), testing a model with independent empirical data (Allan et al., 2011), consulting with an expert panel (Meyer, Johnson et al., 2014), or testing the ability of the model to perform under a range of conditions or scenarios (Chen and Pollino 2012).

We performed a sensitivity analysis based on the variance reduction method in an effort to rank the variables from most to least influential in the final model output; the process also indicated the direction of influence for each variable. For this procedure, each node was set to its highest state while all others remained unchanged; then, the direction of change in probability was recorded. If the probability of being vulnerable decreased when a variable was set to its highest state, that factor was considered to decrease vulnerability to degradation and was termed a "positive" variable. Model variables that increased the probability of vulnerability were termed "negative" variables.

3.2.2. Stream monitoring data and attainment criteria used in model validation

Maine has four statutory classes of streams with different aquatic life criteria (a.k.a., biological standards) (Table 1). Biological, physical, and chemical measurements are routinely collected by Maine DEP's Stream Biomonitoring (BIOMON) program at fixed stream locations throughout the state in order to track the status of these aquatic resources (Danielson, Tsomides, Suitor, DiFranco, & Connors, 2016). Stream sites are normally sampled between July and September on a 5-year rotation, with a primary focus on macroinvertebrate and algal community composition (Danielson 2006; Danielson, Loftin, Tsomides, DiFranco, & Connors, 2011; Davies and Tsomides 2002). Maine DEP evaluates the macroinvertebrate and algal metrics to determine if streams attain aquatic life criteria consistent with the State's water quality standards. Streams that fail to attain the aquatic life criteria assigned to them by the State Legislature are identified as impaired. Streams that fail even to attain Class C aquatic life criteria are categorized as non-attainment (NA) streams. The attainment class of each stream (i.e., AA/A, B, C, or NA) is determined by Maine DEP using linear discriminant models based on variables describing macroinvertebrate and algal communities (Danielson et al., 2012; Davies and

Table 1
Statutory classes and corresponding aquatic-life and habitat standards for rivers and streams in Maine.
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.

Tsomides 2002; Davies et al., 2016). We used these Maine DEP statutory class attainment data for our validation test of the BN model.

Stream sites were excluded from this investigation if (1) the watershed area exceeded 125 km^2; (2) evidence suggested that sample data were compromised during collection; or (3) a stressor other than urbanization (e.g., agriculture or a significant point source) was suspected to be the primary driver of stream degradation. The upper size limit of 125 km^2 was intended to restrict the analysis to first through third order streams, which are generally more vulnerable due to their small dilution capacity. From an initial dataset containing 388 streams, our screening process yielded a total of 108 sample sites with macroinvertebrate community data and 88 sites with algal community data. Only one sample date was used for each site, and the selected date was always the most recent. Sample sites were located in catchments ranging from minimally disturbed to highly urbanized, and varied in size from 0.35 km^2 to 118 km^2.

3.2.3. Model validation

Although validation is an important part of model evaluation, BNs are often difficult to validate in a thorough or rigorous way (Marcot 2012). In fact, Aguilera et al. (2011) reported that model validations were absent from over a third of the BN models they reviewed. For this study, model validation was based on comparing the correspondence between BN model vulnerability predictions, stream attainment of statutory class, and impervious cover risk thresholds. Although every stream in Maine is expected to attain a statutory class of either AA/A, B, or C (38 M.R.S.A Section 464), many streams do not attain the standard assigned to them. We tested the prediction that non-attaining streams draining catchments with% IC values below Maine DEP impervious cover risk thresholds (Fig. 2) are intrinsically more sensitive to urbanization and exhibit BN model scores in the two highest quartiles of the BN vulnerability range. These high vulnerability sites are those that do not attain Class AA/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. Similarly, we expected that streams which attain their statutory class at % IC values above the Maine DEP risk thresholds (Fig. 2) would be relatively more resilient, with BN vulnerability scores in the lower quartiles 1 and 2. As such, the sites with low vulnerability are those that attain Class AA/A at greater than 1% IC, attain at least B at greater than 3% IC, or attain at least C at an IC value greater than 10%.

3.3. Integrating predictions of stream vulnerability with future development scenarios

For the final stage of our investigation, we performed a digital overlay analysis to examine which streams with high BN vulnerability scores are more likely to experience increased future land development activity that may contribute to impairment of sensitive streams. In a previous study, we used a BN model to incorporate stakeholder knowledge and over 100 geospatial data layers in order to predict the probability of suitability for four land use categories across two major watersheds in Maine − the 1 million hectare Lower Penobscot River Watershed and the 0.8 million hectare Casco Bay and Lower Androscoggin Watershed (Meyer, Johnson et al., 2014). We determined land use suitability for development, conservation, agriculture, and forestry in each watershed at 30 m pixel resolution using expert knowledge and CPT inputs from stakeholders and experts in all four land use categories. Estimates for development suitability from that model were used in this investigation to determine which streams with high BN vulnerability scores are located in catchments with a high probability of suitability for future development and urbanization.

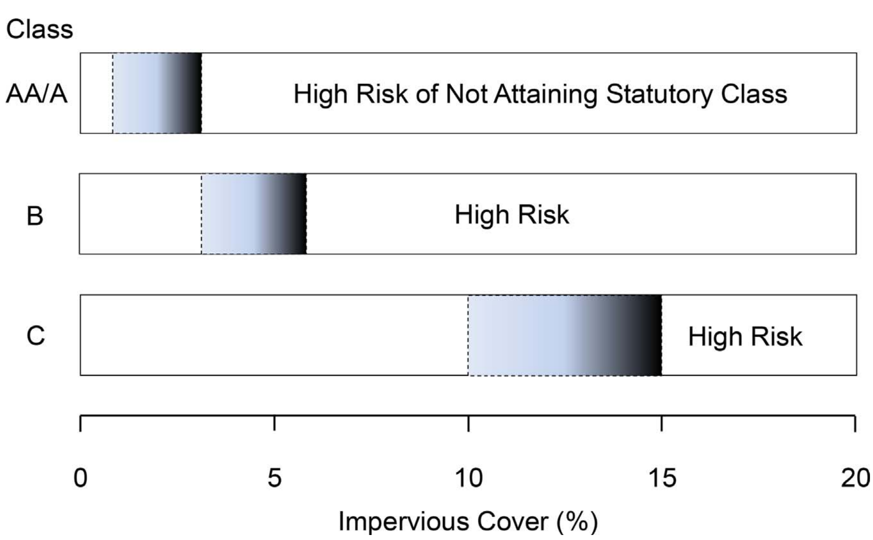


Fig. 2. Threshold levels of watershed impervious cover (dark shading) at which a stream is at risk of not attaining biological criteria associated with Classes AA/A, B, or C. The thresholds correspond to 1–3% IC for Class AA/A, 3–6% for Class B, and 10–15% for Class C.

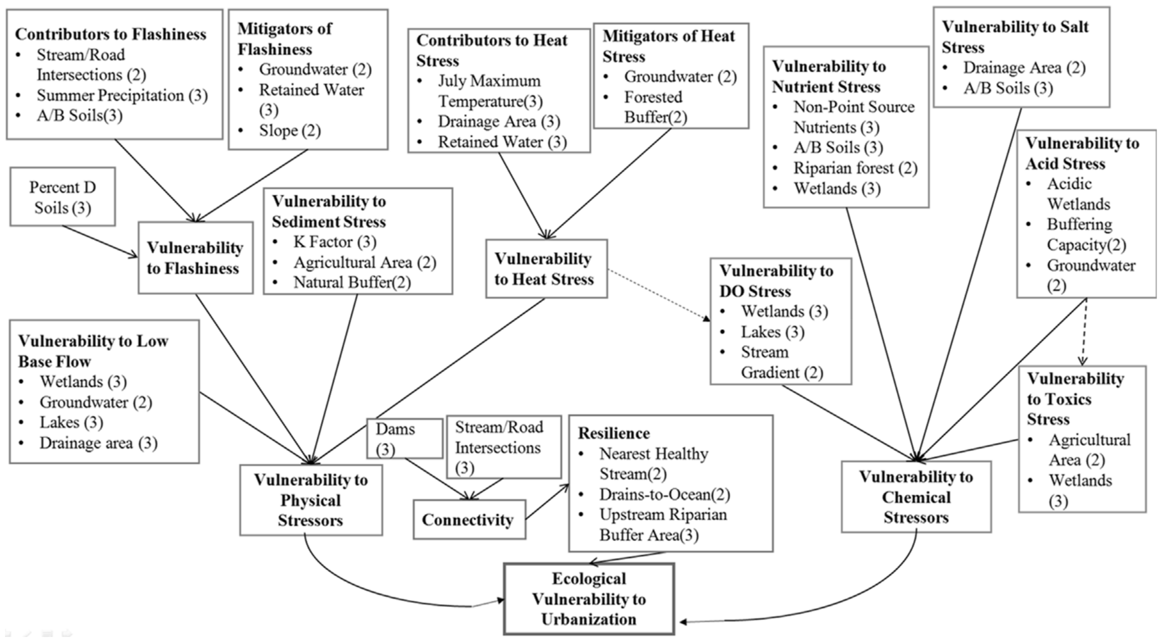


Fig. 3. Influence diagram for a Bayesian network model that predicts the probability of stream vulnerability to urbanization stress as a function of physical, chemical, and resilience factors. The numbers in parenthesis indicate the number of discrete states for a given variable.

4. Results

4.1. Using a Bayesian network and expert knowledge to predict stream vulnerability

4.1.1. Model structure

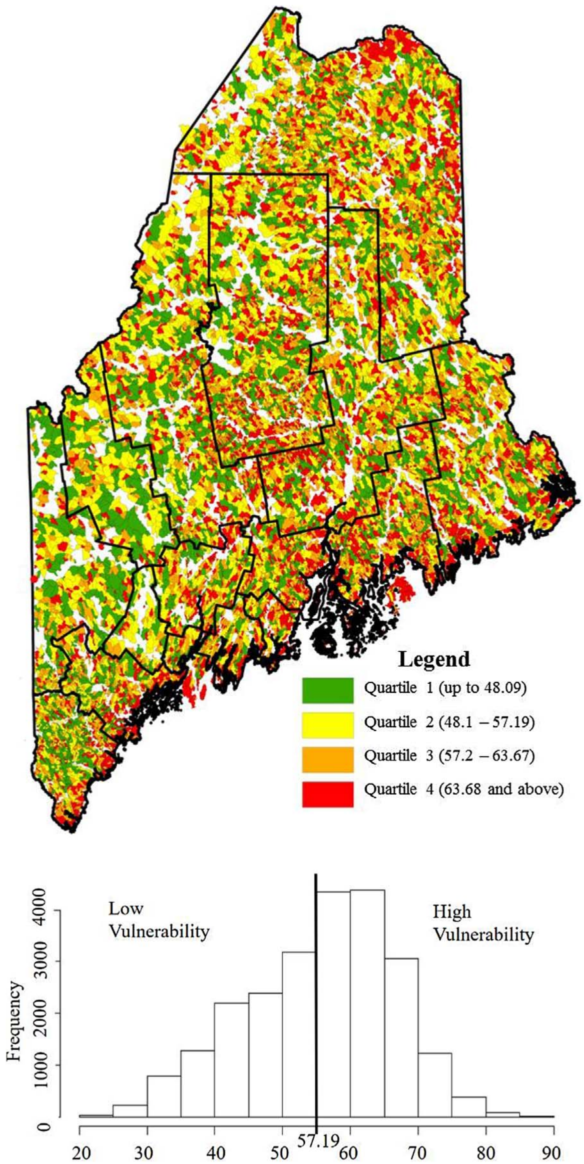
The structure of our BN model was organized around an influence diagram (Fig. 3) that incorporated the biophysical spatial variables listed in Table 2 and contained nine stress categories that exert direct or indirect effects on stream vulnerability. The categories included flashiness, low base flow, sedimentation, heat, DO, nutrients, salt (chloride), acidity, and toxics. Within the influence diagram, some of the more complex individual stressors were separated into two intermediate nodes containing spatial variables that either act as contributors or mitigators of a particular stressor. For example, the five variables associated with heat stress were divided into two mitigators (groundwater input and percent forested riparian area) and three contributors (air temperature, small drainage area, and retained water).

The nine stress categories were aggregated into one of two major stress regimes based on whether their contribution to vulnerability was

Table 2
Variables used in the Bayesian network model, including the minimum, median, mean, and maximum values for all 23,554 catchments. Soil depth has no maximum value, because if the soil is deeper than 201 cm, the depth is unknown. See Appendix A for variable descriptions.

Variable	Scale	Min	Median	Mean	Max
Dams (count)	Watershed	0	0	0.14	15
Stream/road intersections (density)	Watershed	0	0.08	0.27	12.4
Percent resistant substrate	30 m stream buffer − reach scale	0	82.46	60.3	100
Sand/gravel aquifers (presence/absence)	60 m stream buffer	[a]	[a]	[a]	[a]
Area (km^2)	Watershed	0.5	6.2	16	125
Drains to ocean (yes/no)	Watershed	[a]	*	[a]	[a]
Nearest healthy stream (km)	Watershed	0	1.2	1.3	7
Percent agricultural area	Watershed	0	0	2	88
Percent non-point sources	Watershed	0	1.3	4.2	88
Upstream riparian buffer area (km^2)	60 m stream buffer	0	0.6	1.9	70
Percent natural area	60 m stream buffer	0	94	84	100
Percent forested area	60 m stream buffer	0	80.2	74	100
Percent lake area	Watershed	0	0	2.4	100
Percent retained water area (lakes + wetlands)	Watershed	0	9.5	11.5	100
Percent acidic wetlands	Watershed	0	0	0.8	95
Percent wetlands area	Watershed	0	6.9	9.1	100
Average July maximum air temperature (°C)	Watershed	11.9	25.7	25.5	28.25
Average summer precipitation (inches)	Watershed	14	28.2	28.4	43
Buffering capacity (buffered/not buffered)	Stream reach	[a]	[a]	[a]	[a]
Percent soil drainage class A or B	Watershed	0	5.6	14.3	100
K factor	30 m stream buffer	0.7	5.2	5.7	13.3
Percent soil drainage class D	Watershed	0	43	45	100
Soil depth (cm)	Watershed	0	87.6	98.7	> 201
Percent soil drainage class A, B, A/D, or B/D	Watershed	0	6	15	100
Slope (percent)	Watershed	0	6	7.2	53.2
Stream gradient	30 m stream buffer	0	3.9	4.7	64.9

[a] Data do not fit into these categories.



Vulnerability Score					
Min	1st Q	Med	Mean	3rd Q	Max
20.2	48.1	57.2	55.6	63.7	87.5

Fig. 4. Vulnerability scores for 23,554 reach-scale catchments in Maine displayed by quartile (from lowest = 1 to highest = 4), with county boundaries shown in black (upper figure). For reference, the easternmost point on the map, Eastport, ME, is at 44.90° N, 66.99° W. The lower graph illustrates the distribution of vulnerability scores, including values for minimum, median, mean, maximum, and quartile boundaries.

likely to be exerted through chemical or physical stress (Fig. 3). A third section of the influence diagram represented the variables that influence resilience, which is the capacity of a watershed to recover from stress or a stress event. Variables assigned to this category included those that contribute to potential recolonization of a 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 a final node predicting the overall probability of vulnerability to urbanization stress.

4.1.2. Model outputs – vulnerability scores

The BN model was used to generate probabilities of vulnerability for each of the 23,554 stream catchments with areas less than 125 km^2 in our statewide study area. On a scale of 0–100 (lowest to highest probability), the distribution of BN vulnerability scores ranged from a minimum of 20.2 to a maximum of 87.5, with a median value of 57.2 (Fig. 4). The highest quartile of vulnerability included watersheds with vulnerability scores ranging from 63.7 to 87.5. Catchments representing the four quartiles of the BN vulnerability distribution were present in all 16 state counties, but the two upper quartiles of higher vulnerability were relatively more abundant along the coastal plain from Portland to Calais, in the central portion of the state south of Mt. Katahdin, and in the northeastern portion of the state (Fig. 4).

4.1.3. Sensitivity analysis

A sensitivity analysis was performed to examine the order of importance of variables in determining the final probability of high vulnerability (Marcot 2012). Based on results shown in Fig. 5, the most influential variables in the model were upstream buffer, the drains-to-ocean parameter (which affects colonization from downstream reaches), percent crops, forested buffer, watershed area, and presence of a sand/gravel aquifer. Least important variables were percent retained water, summer precipitation, percent of soils in drainage class D, and resistant substrate.

Upstream buffer, forested buffer, watershed area, and presence of sand/gravel aquifers acted as positive variables to decrease the probability of vulnerability, 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.

4.1.4. Validation of the Bayesian Network model

In evaluating the BN model, we applied a validation step that was based on determining the correspondence between stream attainment of its statutory class, watershed urbanization based on % IC, and the predicted BN model vulnerability score for that stream. Our data set included 32 non-attaining streams and 76 streams that attain their statutory class (Table 3a). Because most non-attaining streams have watershed % IC values above the Maine DEP impairment threshold, this severely limited the streams available for validation of the BN model. Out of three streams that do not attain their statutory class at an IC value below the impairment threshold, one of these was classified by the BN model into the correct quartile of elevated vulnerability – i.e., quartile 3 or 4 (Table 3b). For the 9 streams that attain their statutory class at an IC value above the impairment threshold, 5 of them were classified by the BN model into the correct quartiles of lower vulnerability – i.e., quartile 1 or 2.

It is important to note that the data in Table 3 provide another valuable perspective on model validation, if we look more closely at 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 BN model vulnerability scores, which means that high vulnerability and high IC are convergent rather than divergent for these streams. One or both factors may contribute to the lack of attainment, given that (1) the IC is high enough to be a stress; and (2) the stream is in the most vulnerable category for responding adversely to the IC stress.

4.2. Predicting streams at risk of future impairment based on BN models

Our third objective was to integrate stream BN vulnerability scores with independent predictions of watershed-level development suitability in order to map the distribution of streams at risk of impairment from projected future urbanization. This analysis focused on the Lower Penobscot River Watershed (LPRW) and Casco Bay and Lower Androscoggin River Watershed (CBLA), where development suitability was previously assessed by Meyer, Johnson et al. (2014) using a coupled BN-GIS spatial model of land use suitability (Fig. 6).

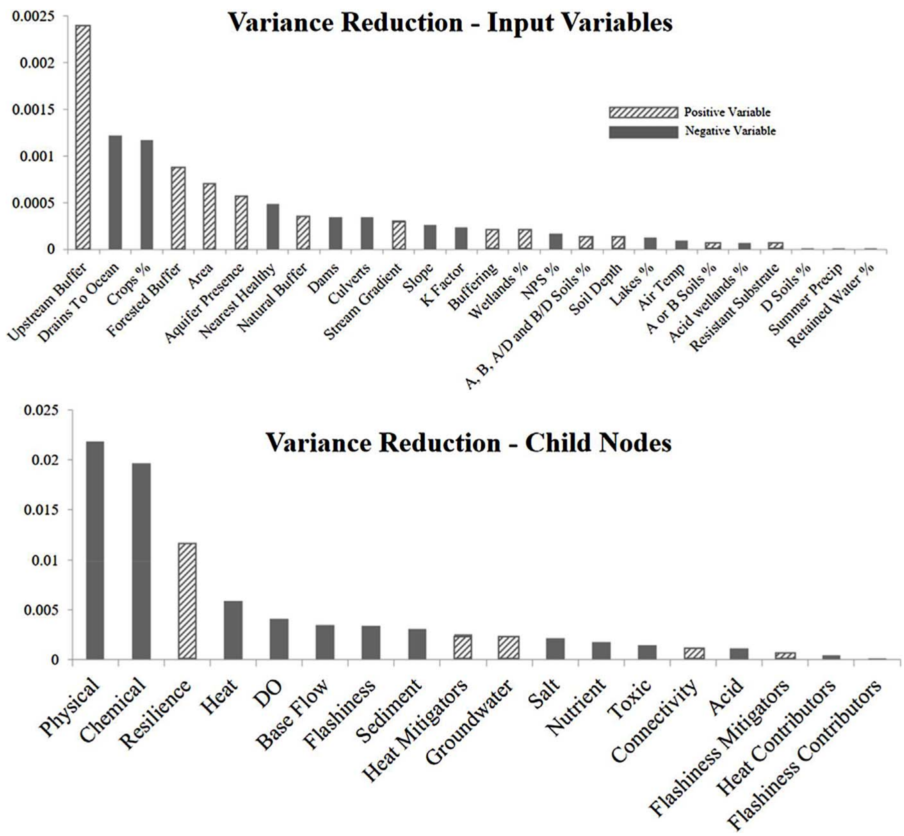


Fig. 5. Sensitivity analysis based on variance reduction; bars show the direction of influence of input variables and child nodes. Positive variables and nodes decrease the probability of stream vulnerability; all other variables and nodes increase the probability of vulnerability.

Based on our BN-GIS land cover model, we selected all pixels that were classified in the top quartile of development suitability in each of the two watersheds. This procedure identified 41,768 ha in LPRW (representing 4% of the land area) and 244,616 ha in CBLA (equal to 38% of the land area) that were predicted to have the highest probability of suitability for future development. A GIS query was then performed to determine which of those pixels with a high probability for future development were located in catchments in the highest quartile of vulnerability (Fig. 7). Using that final set of pixels, we screened catchments to determine which ones could potentially attain a future urban footprint of 6% IC, a level of impervious cover that corresponds with the Maine DEP IC threshold associated with streams that no longer attain statutory Classes AA/A or B (Danielson et al., 2016). Because algorithms for converting development to IC generally indicate that

Table 3
(a) Model validation analysis showing which attaining and non-attaining streams above or below the IC impairment thresholds have the expected vulnerability scores from BN model predictions. Table entries show IC impairment thresholds by statutory class (e.g., > 3% IC for statutory class A) vs. quartile of vulnerability (Q1 through Q4). (b) The lower table summarizes the results from part (a). The 108 streams in this analysis met the selection criteria described in the methods section and were characterized using macroinvertebrate community data.

a.

	Statutory Class A			Statutory Class B			Statutory Class 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
									Sum	108

b.

	Attaining with High IC	Not Attaining with Low IC
Total number of streams	9	3
Number in correct quartile	5	1
Percent in correct quartile	56	33

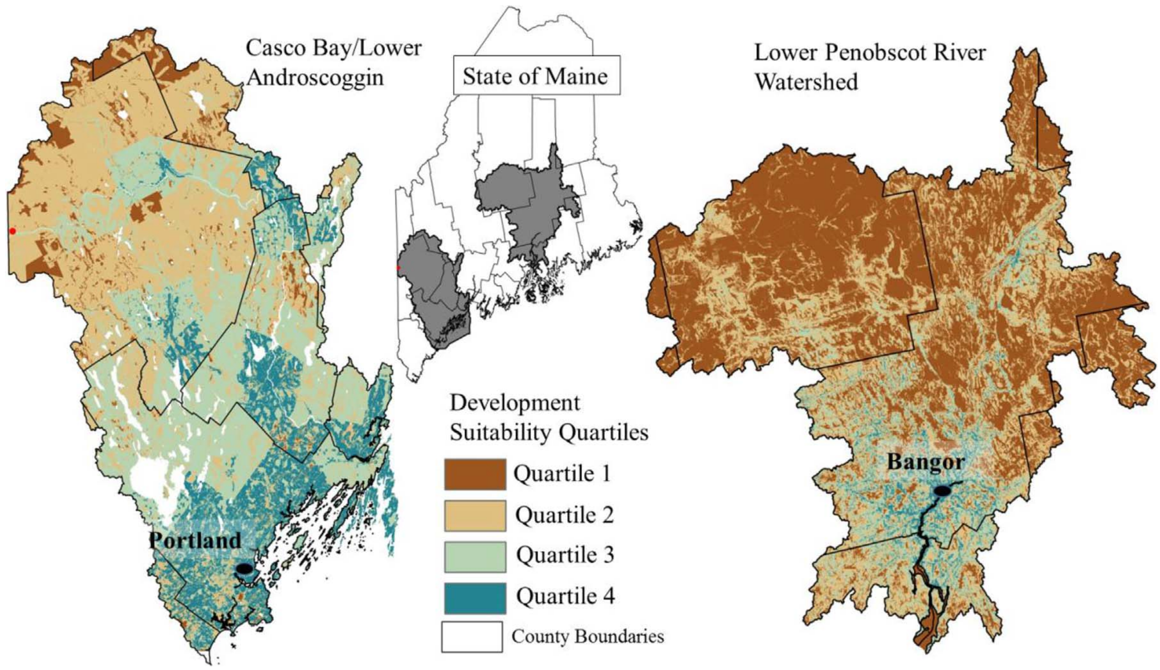


Fig. 6. The Casco Bay/Lower Androscoggin (CBLA) and Lower Penobscot River Watershed (LPRW) study areas. Development suitability in each watershed is displayed by quartile, with Quartile 4 representing areas with the highest probability of suitability for development. Areas in white are unavailable for development (e.g., conserved land).

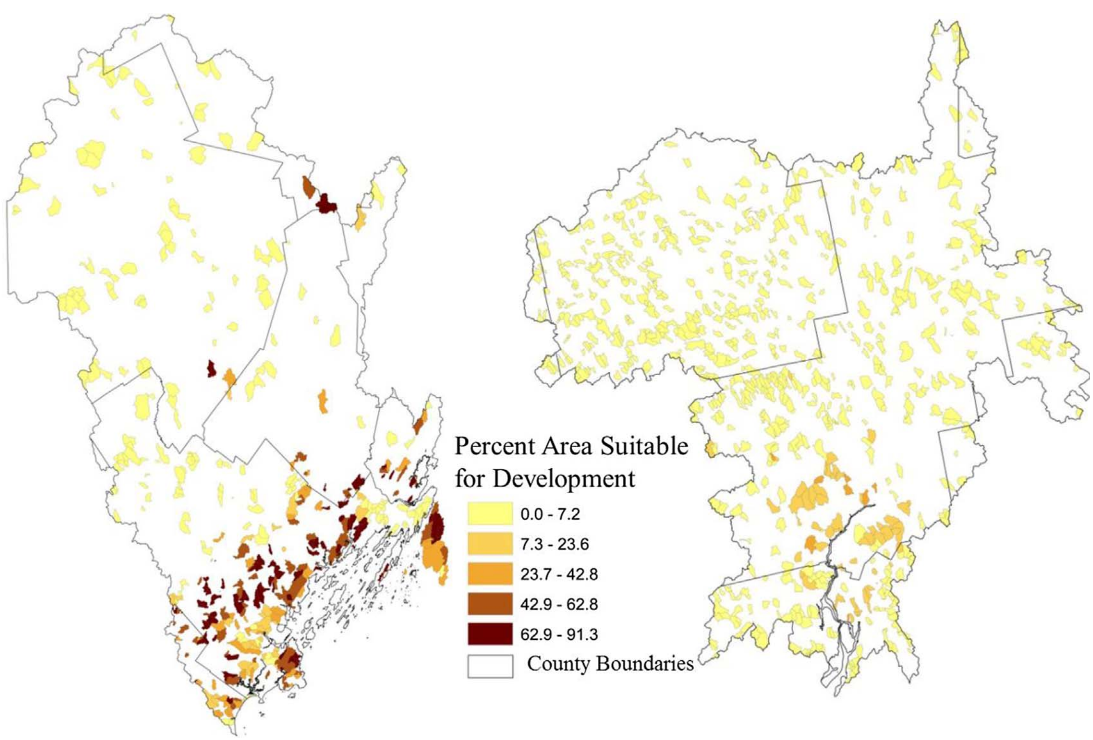


Fig. 7. Catchments in the CBLA and LPRW that are classified in the top quartile of BN vulnerability to urbanization (Quartile 4). Colors show the percent of total area in a vulnerable catchment that is classified in the top quartile of development suitability (Quartile 4 in Fig. 6).

only 25–80% of developed land can be classified as IC (Danielson et al., 2016), we computed projected future IC in the study catchments as current IC + (area with high development suitability/2), which assumes that areas with high suitability will eventually be fully developed and that half of that urbanized area will become actual IC. Results indicated that 415 streams in the LPRW and CBLA watersheds met our criteria for an elevated risk of future impairment based on their location in catchments with projected future IC levels greater than 6%, combined with vulnerability scores in the uppermost or 4th quartile of the BN model probability distribution (Fig. 8). Those streams represent 5% of the sub-catchments in the LPRW and CBLA watersheds. For perspective, there are currently 29 waterways listed as 303 (d) urban-impaired streams (Maine DEP, 2012b) in the LPRW and CBLA study areas.

5. Discussion

In this investigation, we worked with a team of aquatic resource experts to develop a BN spatial model for predicting stream

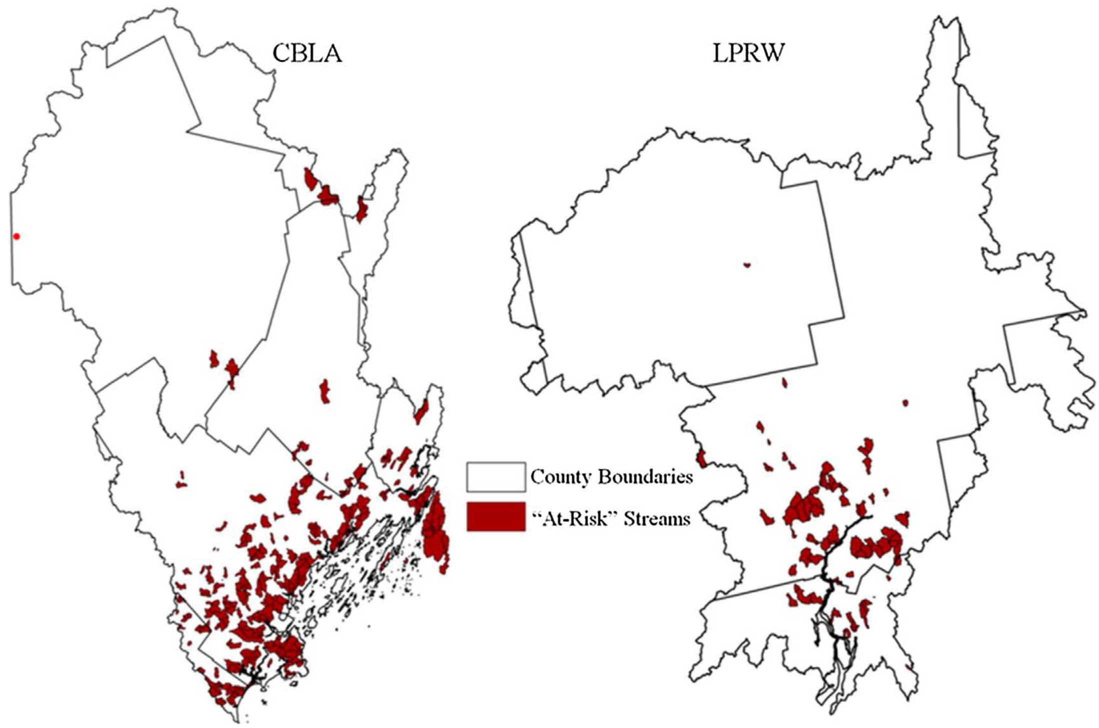


Fig. 8. Spatial distribution of 415 "at risk" catchments in the CBLA and LPRW watersheds. The at-risk catchments exhibit both high BN vulnerability (Quartile 4) and a projected future impervious cover greater than 6%.

vulnerability to urbanization stress. By integrating outputs from our BN watershed vulnerability model with the development suitability model of Meyer, Johnson et al. (2014), we identified over 400 streams in the Lower Penobscot River and Casco Bay-Lower Androscoggin River watersheds that have an elevated risk of impairment from future development in their catchments. These vulnerable streams represent key targets for monitoring, proactive growth management, and conservation efforts intended to protect the surrounding watersheds and associated streams from degradation. Model results such as these can be used not only to guide development away from vulnerable watersheds, but also to identify watersheds that are less likely to be impacted by new development – i.e., areas suitable for future growth. As such, this information should allow developers, municipalities, and decision-makers to plan strategically for smart development that will avoid expensive stream restoration costs.

To our knowledge, this is the first investigation to use complementary BN spatial models to identify streams that are not only vulnerable to urbanization, but are also located in watersheds with a high probability of development suitability and future urbanization. In their alternative futures model, Van Sickle et al. (2004) projected how different scenarios of land use change could affect stream biological condition, but did not examine how the impacts of anthropogenic drivers might be mitigated by watershed resilience and resistance factors. McCluney et al. (2014) presented a conceptual model for the potential effects of resistance and resilience factors on river responses to human alterations, but did not develop an actual application of their macrosystems theory.

A major advantage of expert-based BN modeling is the ability to gain an improved understanding of the knowledge base for a particular model topic (Chen and Pollino 2012; Marcot et al., 2001; Uusitalo 2007), especially in instances when the state-of-science is incomplete or is inconsistent. Throughout our modeling process, we encouraged discussion among the experts regarding the variables and structure in our BN model. 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 areas of agreement and disagreement on the state-of-science.

One focus of ongoing discussion throughout the modeling process was the effect of soil drainage class (i.e., class A or B soils vs. D soils) on vulnerability to urbanization. Some experts argued that well-drained A or B soils allow infiltration of water surrounding urban IC, which tends to increase stream health. Others thought that a watershed with poorly draining D 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 in a watershed with well-draining soils. This debate caused CPT surveys to be completed in different ways by each expert, depending on which opinion the expert held. The lack of agreement resulted in soil drainage variables having a relatively low rank in the sensitivity analysis and highlighted this topic as one requiring further research.

The BN vulnerability model was intended to improve on current IC-based models by identifying biophysical factors that modulate stream responses to IC, causing aquatic ecosystems to be either more or less sensitive to IC and urbanization. Unfortunately, BN model outputs only partially agreed with our validation benchmarks based on stream attainment of statutory class. One explanation for the inconclusive model performance is that the empirical data set was too small to provide a robust number of streams meeting our criteria for the validation analysis. This made it difficult to judge the accuracy of the BN model predictions. Besides the constraint of a small sample size in our validation test, there were at least four other factors that introduced uncertainty regarding the performance characteristics of the model. The lack of adequate spatial data on groundwater influences meant that this important factor was not well represented in the model. Another source of variability arose because our expert panel members represented a range of disciplines and often disagreed on their CPT surveys, which made it difficult to generate a strong consensus and sharply defined probabilities in BN model. As a result, several child nodes had relatively high standard deviations. For example, the road salting parameter in the model reflected disagreements in both the direction of the relationship and the strength or magnitude of influence by that parameter. Vulnerability to salt stress has two input variables: percent class

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; however, experts disagreed on the effect of well-drained soils. Other potential sources of uncertainty in the BN model were related to the subjective discretization of data variables and the conversion of Likert scores to probability distributions. A future version of this model would benefit from addressing those technical issues.

Our use of an expert panel in model development was a source of critical insights and valuable wisdom, but it also introduced complications that could have affected the accuracy of the final model. Because our definition of vulnerability was difficult for several experts to grasp, there were differences in fundamental understanding of the BN model. Ease of use was a priority in designing the CPT survey, yet some experts were uncomfortable with the survey process. We mitigated this problem by working in small groups to fill out the CPTs, reviewing responses, and communicating with experts when their responses seemed unintended or counterintuitive. A final concern was the length of the surveys; because CPT surveys covered 27 pages and required 419 Likert scale responses, expert exhaustion may have compromised the process to some extent.

One purpose of this study was to facilitate better proactive policy responses to the issue of stream impairment. By identifying the locations of at-risk watersheds, we hoped to provide communities with information to be used in setting priorities to protect streams. Within the two watersheds that were examined (CBLA and LPRW), we found numerous at-risk watersheds in dozens of municipalities. Because this impairment risk is concentrated in suburban-style towns and adjacent rural areas that are only a subset of the state, we suggest an initial policy response aimed at producing a model watershed protection ordinance that focuses on avoiding over-development in vulnerable catchments. Such an ordinance could be developed at the state level, and then offered to local municipalities to adopt or to tailor to local conditions as appropriate.

6. Conclusion

A major research theme in sustainability science is the analysis of vulnerability in coupled social-ecological systems. Communities and ecosystems with high vulnerability and low resilience are regarded as important targets for conservation protection and management for long-term sustainability (Kates et al., 2001; Wu 2013). Turner et al. (2003) have argued that vulnerability analyses must use a place-based approach that incorporates multiple interacting stressors, accounts for the sensitivity of the system to those stressors, and results in development of metrics and models for measuring vulnerability.

Our study used expert knowledge and a BN modeling framework to assess the complex relationships influencing stream responses to catchment urbanization in the northern temperate landscape of Maine. By combining a BN model for stream vulnerability to urbanization stress with a complementary BN model of development suitability, we developed a process for predicting the spatial distribution of streams that are at higher risk of impairment from future land use changes. Our analysis identified over 400 streams and associated small watersheds in the Maine landscape that are at increased risk of degradation from future human development activities. Further, we developed a framework that can be used to identify catchments where aquatic ecosystem services may be less vulnerable to development pressure. This information provides a probabilistic basis for more informed decision-making and proactive watershed management focused on sustaining aquatic resources. Overall, our BN vulnerability model provides a new application of spatial land use planning aimed at mitigating human development impacts on both natural ecosystems and ecosystem services.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.landurbplan.2017.11.001.

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