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A geospatial biomass supply model adjusted for risk from natural disasters

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ABSTRACT

Potential risk for disruption to supply of raw materials for bio-based industrial sites from natural disasters has received little attention in site evaluations even though these risks may be significant. Biomass supply in the form of roundwood, forest and agricultural residues, or dedicated short rotation plantations are especially subject to disruptions from meteorological disturbances such as floods, wind and ice storms. The objective of this study was to account for risk from natural disasters in assessing the economic supply of biomass for the Eastern United States in a geospatial context, at the sub-county level (5-digit ZIP Code Tabulation Area). The Presidential Disaster Declaration database was used to identify risk zones where natural disasters frequently exceeded the response capability of State and local governments. Risk levels were estimated from exposure (the combination of the extent of natural hazards and the biomass assets at risk) and adaptive capacity (comprised of economic, social, and environmental factors). Of the 25,044 geospatial polygons in the 33-state study region, 43.8% were located in low risk regions, 26.8% were considered at moderate risk for disruption, and 29.4% were considered at high risk for disruption. The lowest risk locations were in southern Georgia, South Carolina, and Texas.

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Geospatial economic supply; biomass; risk assessment; vulnerability

Introduction

The world witnessed rapid growth and increased prosperity from the early 1900s through the early 2000s (Krausmann et al. 2009). Even with a global economic recession in 2008/2009, the world's energy demand in 2020 is forecast to be 40% higher than it is today ([EIA] 2016) with a substantial contribution from renewable sources including biomass. Meeting the expected bioenergy demand will require an estimated 2200 million m^3 of harvested wood or residues ([IEA] 2013; Sikkema et al. 2017). Abundant research has focused on use of cellulosic feedstocks for energy and fuels; however, replacing oil-derived energy and co-products with bio-based energy and products presents numerous technical, economic, and research challenges (Cherubini 2010; Fiorentino et al. 2017). Formation of markets and industrial supply chains involves managing many contingencies (Altman and Johnson 2008). As markets develop, assessing the economic capability and stability of evolving supply chains is necessary for market organization. A significant issue is the reliable supply of biomass feedstock (Elbehri 2007). Better understanding is needed of potential supply limitations of biomass feedstocks that include the productive capacity of land, production costs, logistics, transportation, and the risk of disruptions to the supply chain from natural disasters (Elbehri 2007).

Determining the factors that govern decisions about siting industrial facilities has long been a topic of theoretical and empirical research (Guimaraes et al. 2004; Arauzo Carod 2005). Factors affecting biobased facilities have included available quality labor, feedstock supply, proximity to markets, taxes, infrastructure, local policy and environmental regulations, and incentives. The recent recognition of the power of geographic information systems has put these factors into a spatially explicit perspective (e.g. Noon and Daly 1996; DiFulvio et al. 2016). In general, risk has not been a major determinant and specifically, potential risk from natural disasters to the raw material supply or market disruption for products has received little attention in evaluating processing sites even though these risks may be significant.

Natural disasters globally affected or destroyed more than 800 million hectares of forested area between 1996 and 2015 ([FAO] 2015). The United States has an assortment of natural disasters that threaten the safety and economic well-being of its bio-based supply chain and natural resources. To minimize disruption to the supply chain for bio-based natural resources, businesses and communities need a clear understanding of where and what they are vulnerable to, in order to reduce risk to these assets. Vulnerability is determined by more than just disaster prone landscapes. Other factors affecting vulnerability include socioeconomic conditions, land use, and local community understanding and willingness to manage for risk. Vulnerability is the concept that explains why people are more or less at risk with a given level of physical exposure (Pielke et al. 2013). In theory, vulnerability is modified by coping capacity and adaptive capacity, which encompasses the idea of a community's ability to prepare for, respond to, or recover from a disaster (Brooks et al. 2005; Adger 2006; Smit and Wandel 2006). Sustainable

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solutions involve the assessment of the local interrelationships among the environmental, social, economic, and risk conditions linked with broader regional characteristics.

The goal of this research was to account for risk from natural disasters in assessing the economic supply of biomass for the Eastern United States in a geospatial context. Despite an abundance of literature on the economic availability of biomass (Young et al. 1991a, 1991b; Lunnan 1997; Walsh 1998; Walsh 2000; Ugarte et al. 2000; Ugarte et al. 2006, 2007; Biomass Research and Development Board 2008; Western Governors' Association 2008; Kumarappan et al. 2009; Perez-Verdin et al. 2009; Galik et al. 2009; Young et al. 2011; [USDOE] 2016) risk from natural disasters, with the exception of risk of fire damage in Europe (Duguy et al. 2012; Ioannou et al. 2018) has not been documented in relation to biomass supply. For example, recent reports by the U.S. Department of Agriculture and Department of Energy did not adjust for risk in the estimate of the 1.3 billion tons of biomass supply needed to meet energy goals (United Nations Development Program 2004; Perlack et al. 2005). Our objective was to improve the cellulosic feedstock decision tool BioSAT by accounting for economic vulnerability of biobased assets in the 33 eastern US states to supply chain disruptions from natural disasters. The **Bio**mass **S**upply **A**ssessment **T**ool (**BioSAT**) is a web-based system http://www.biosat.net/ (Perdue et al. 2011) that assesses the economic comparative advantages of biomass supply at the regional, inter-state, and intra-state levels in a spatially explicit visualization.

Our approach to assessing risk was to estimate the probability of natural disasters in the 33-state region using a conservative measure of the frequency and extent of natural hazards such as hurricanes, windstorms, and floods: the frequency of *Presidential Disaster Declarations under the Stafford Act* (Lindsay and McCarthy 2015; Federal Emergency Management Agency 2018a, 2018b). We assessed vulnerability on two dimensions, exposure (the combination of the extent of natural hazards and the biomass assets at risk) and adaptive capacity (comprised of economic, social, and environmental factors). We combined available datasets for land-use, forest biomass, road density, and population levels within BioSAT, augmented by natural hazards defined as Presidential Disaster Declarations to produce an aggregated risk impact map that shows the degree of natural disaster risk associated with decisions for locating biomass-using facilities.

Materials and Methods

BioSAT data sets

This study used the BioSAT database collected from numerous sources ([USDA] 2008; [USEPA] 2011; [USDA] 2009; [USCB] 2010a, 2010b; [USGS] 2010; Perdue et al. 2011). The BioSAT application encompasses transportation, harvesting, and resource cost models that provide spatially referenced biomass economic supply curves at 30-meter resolution within the 33 eastern U.S. states. BioSAT output provides sub-county, spatially-defined groupings and comparisons of environmental, economic, and societal factors that impact landscape capability and biomass access (Perdue et al. 2011). Spatial resolution of BioSAT is based on the 5-digit ZIP Code Tabulation Area (ZCTA) developed by the US Census Bureau (https://www.census.gov/geo/reference/zctas.htmlaccessed; last accessed 12 February 2016). The average area for 5-digit ZCTAs in the 33-state study region was approximately 169 km^2. The 5-digit ZCTAs provide 25,307 potential analytical polygons or site locations.

Probability of natural hazard

The Presidential Disaster Declaration dataset was used as an established natural disaster risk metric to identify the frequency of extreme events and the areas affected. Presidential Disaster Declarations are authorized under the Stafford Act (Lindsay and McCarthy 2015; Federal Emergency Management Agency (FEMA) 2018a, 2018b) and coordinated by the Federal Emergency Management Agency (FEMA). A Presidential Disaster Declaration is the process by which FEMA validates that damage is of such severity that it is beyond the response capabilities of state and local government and determines where supplemental federal emergency assistance is necessary. A major disaster declaration provides a wide range of federal assistance programs for individuals and public infrastructure, including funds for both emergency and permanent work. The President can declare a major disaster for any natural event, including any hurricane, tornado, storm, high water, wind-driven water, tidal wave, tsunami, earthquake, volcanic eruption, landslide, mudslide, snowstorm, or drought, or, regardless of cause, fire, flood, or explosion (Federal Emergency Management Agency (FEMA) 2018b). Presidential Disaster Declarations activate supplemental federal emergency financial and physical assistance to save lives, protect property, public health and safety (Federal Emergency Management Agency (FEMA) 2018a).

Presidential Disaster Declarations are increasing in frequency; the long-term average of 35.5 annually from 1953 to 2014, increased to an average of 46 annually in the decade of the 1990s, and 56 annually from 2000 to 2009 (Lindsay and McCarthy 2015). Severe storms, floods, hurricanes, and tornadoes were the primary causes. Notably, Presidential Disaster Declarations do not include resources for suppression of wildfires, an increasingly serious disturbance (Liu et al. 2010; Liu et al. 2013a, 2013b) that could be related to increased severe weather incidents (Karl et al. 2009; Wehner et al. 2011; Vose et al. 2012). We examined the frequency of Presidential Disaster Declarations over two intervals; the short-term (2000–2011) and long-term (1964–2011). County-level data were not available prior to 1964. The main types of natural disasters included coastal storm, drought, earthquake, fire, flood, freezing, hurricane, mud land slide, severe ice storm, severe rain storm, snow, tornado, and tropical storms (Table 1).

Biomass assets at risk

The physical exposure of biomass cultivated land is where hazardous events can occur. Specifically, forest land and crop cultivated land are areas where forest residues and

Table 1. Frequency of Presidential Disaster Declarations in study area for the time periods from 1964–2011 and 2000–2011 (Federal Emergency Management Agency (FEMA) 2012).

Disaster type	2000–2011	1964–2011
Coastal Storm	905	2042
Drought	0	1820
Earthquake	130	130
Fire	4785	5876
Flood	3624	68851
Freezing	1108	1108
Hurricane	19703	33145
Mud Land Slide	0	70
Severe Ice Storms	5359	5543
Severe Storms	71377	106557
Snow	10984	25807
Tornado	1406	11185
Tropical Storm	1566	1566
Total	**120947**	**263700**

agricultural biomass occur and may be used for bioenergy and where dedicated bioenergy plantations could be developed (Perlack et al. 2005). Forestland and agricultural land were identified using digital raster map data from national land cover data ([USDA] 2008). Each pixel represented a particular land cover class, *i.e.* forest, cropland, water, or urban, etc. on the digital raster map. The numbers of pixels for all land cover classes in each 5-digit ZCTA were estimated by overlaying each area with the land cover image layer. The ratio of forest and agricultural land pixels to all pixels in a ZCTA provided the estimate of biomass assets potentially at risk. By proportionally allocating land cover data at the 5-digit ZCTA level, the resolution of the U.S. Census data was maintained, and also included other socio-economic factors such as urban areas, road network density, park boundaries, waterways, etc. ([USDOE] 2016; Perlack et al. 2005; Perdue et al. 2011; Huang et al. 2012). This improves upon previous research that aggregate U.S. Census data to a lower resolution such as the county boundary.

Vulnerability

Vulnerability (or susceptibility to supply disruptions) here refers to different variables that make biomass-using facilities less able to absorb the impact of a disruption in supply and recover from a disaster event. These include economic (such as potential economic damage of production, transportation and consumption), social (such as different population groups' coping capability to the disaster), and environmental (such as the fragility of ecosystem) dimensions.

The economic dimension of vulnerability represents the risk to the production, transportation, and consumption of the facility using biomass; vulnerability implies higher risk to increased costs and disruptions in the supply chain. Road density here is used to measure ability to transport biomass from the field to the facility, which is defined as:

$$D_R = L_R/A_L, \tag{1}$$

where D_R = road density, L_R = road length, *and* A_L = land area.

Average road density by 5-digit ZCTA, within a 129-km one-way driving distance (Young et al. 2017a, 2017b) was calculated to represent its regional impacts, and is grouped into five levels by its quartile distribution with assigned vulnerability probability (Table 2) (Jongman and Pungetti 2004; McDonald et al. 2008). Quartiles are typically the starting point for reporting risk probabilities in medical and some environmental studies. These probabilities are arbitrarily assigned and may be changed to better suit local conditions.

Table 2. Average road density levels with assigned vulnerability probability.

Average road density levels	Vulnerability probability
>14 km/square km	1.0
>5.38–14 km/square km	0.75
>2.7–5.38 km/square km	0.50
>1–2.7 km/square km	0.25
>0–1 km/square km	0

The social dimension of vulnerability assesses the effect on different population groups, and the emphasis is on "coping capacity." Cross (2001) argues that "*people in small towns and rural communities are more vulnerable than people in large cities because of weaker preparedness*." In this study, the population density in each 5-digit ZCTA was used as an indicator of the social dimension of vulnerability (Wear et al. 1999; Alig et al. 2004; White and Mazza 2008). We classified the population density in each ZCTA into five levels, and assigned a vulnerability probability to each population density level (Table 3).

The environmental dimension of vulnerability assesses the impact on fragile ecosystems. According to Williams and Kapustka (2000), "*environmental vulnerability can be seen as the inability of an ecosystem to tolerate stressors over time and space*." In this study, all 5-digit ZCTAs containing more than 50% of land area in national parks or national forests area were excluded because of belonging in federal ownership and thus are not considered a reliable biomass supply source. Lands with a slope greater than 45% were excluded because of environmental fragility. ZCTAs classified as U.S. EPA Level III ecoregions are not ecologically suitable for forest production (*e.g.* Chihuahuan Deserts, Blue Ridge Mountains, Southwestern Tablelands, etc.) and were excluded from biomass supply ([USEPA] 2011).

Using these economic, social and environmental indicators, we expressed vulnerability as:

$$V = D_{RM} \times w_E + D_P \times w_S, \tag{2}$$

where V = vulnerability, D_{RM} = mean road length, D_P=population density, and *w is a weight* assigned to the respective economic and social indicator for its contribution to the overall vulnerability.

Table 3. Population density levels with assigned vulnerability probability.

Population Density Level	Vulnerability Probability
0	1.0
>0–19 people/km^2	0.75
≥19–39 people/km^2	0.50
≥39–58 people/km^2	0.25
≥58 people/km^2	excluded*

*A ZCTA with population density ≥ 58 people/km^2 is not feasible for biomass-using facilities (Wear et al. 1999).

Table 4. Degree levels of risk impact.

Risk impacts degree level	Risk impacts value
Severe impacts	≥ 6
High impacts	≥4–6
Moderate impacts	≥2–4
Low impacts	>0–2
No impacts	0

Risk impacts

The study defines risk impacts as the combination of disaster potential to biomass and vulnerability:

$$R = PD \times V, \tag{3}$$

where R = Risk impact and PD = disaster potential.

Disaster potential was estimated for each 5-digit ZCTA level and expressed as:

$$PD = DD \times AF, \tag{4}$$

where DD = number of disaster declarations and AF = is the proportion of crop cultivated and forest land in each ZCTA.

The risk impacts were then calculated as:

$$R = DD \times AF \times (D_{RM} \times w_E + D_P \times w_S). \tag{5}$$

This resulted in five levels of risk impact (Table 4), from severe to no impacts based on the values calculated from equation 5.

Results

The frequency of Disaster Declarations in the short-term (2000–2011) and the long-term (1964–2011) were allocated by ZCTA for estimating risk at the ZCTA-level (Figure 1(a and b)). Combining the vulnerability data with the disaster declarations (exposure) resulted in risk zones. Risks were assessed with and without weighting. Risks were weighted three ways: (1) road and population densities equally weighted; (2) greater weights for road density and (3) greater weights for population density.

Risk zones without weighting

Given that potential users of this information may have their own weighting system for road density and population density, risk was initially allocated without weighting. Note, for this part of the analysis high impacts were contained within severe impacts in the presence of population density ≥58 km^{-2} and EPA level III ecoregions (*i.e.* exclusion zones with these categories could not be distinguished from severe impacts). Using the short-term data, high risk zones emerged along the eastern seaboard, and inland areas of Arkansas, Missouri and Oklahoma (Figure 2(a)). There were some moderate risk zones in Alabama, Indiana, and Iowa. Twenty-two percent of all ZCTAs were assessed to be low risk and approximately twenty percent were assessed to be moderate risk based on short-term declaration data (Table 5).

In the long-term, the high-to-severe risk zones emerged along the eastern seaboard, and inland areas of Arkansas, Missouri and Oklahoma (Figure 2(b)). Moderate risk zones also occurred in Alabama, Indiana, and Iowa. There were also moderate risk zones in Minnesota and Wisconsin. Eighteen percent of the ZCTAs were assessed to be low risk and 23.2% were assessed to be moderate risk based on long-term declaration data (Table 6).

Risk assessment with weights

Assuming equal weights for road and population densities

Using equal weights of $w_E = 0.5$ (*average road density*) and $w_S = 0.5$ (*average population density*), short-term high risk zones were found along the eastern seaboard, Arkansas, Missouri and Oklahoma (Figure 2). The addition of weighting factors for population density create seven categories relative to the five categories reported in Figure 1 that had no weighting for population density. For this portion of the analysis, the data for EPA level III ecoregions and population density greater than 58 km^{-2} were not included because population density influences extreme risk. There were some moderate risk zones in Alabama, Indiana, and Iowa. Preferred locations for biomass supply based on long-term Presidential Disaster Declaration Data appeared to be in southern Georgia, South Carolina, and Texas. The severity of risk was higher for the long-term versus the short-term intervals.

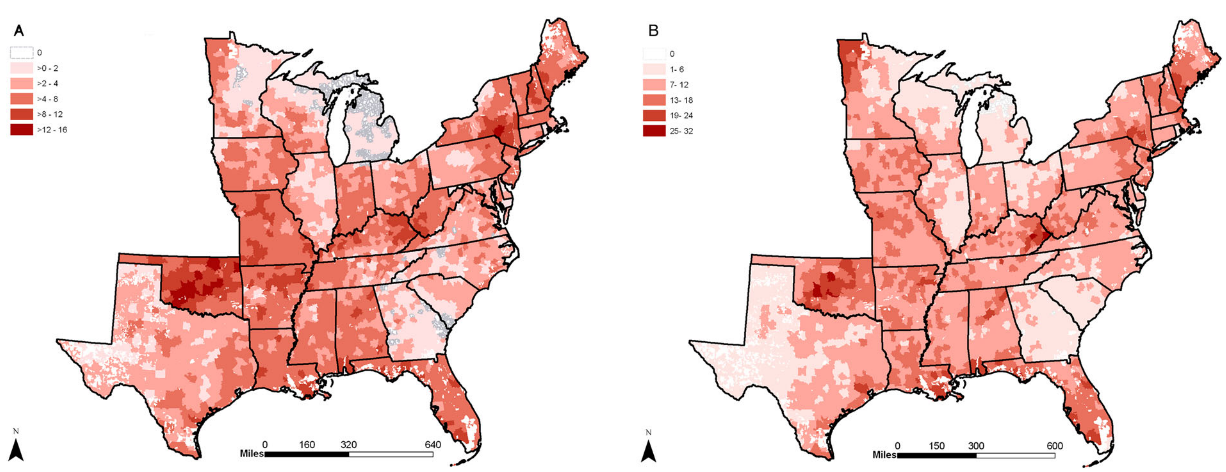

Figure 1. Disaster potential to biomass land in the (a) short-term (2000–2011) and (b) long-term (1964–2011), based on Presidential Disaster Declarations.

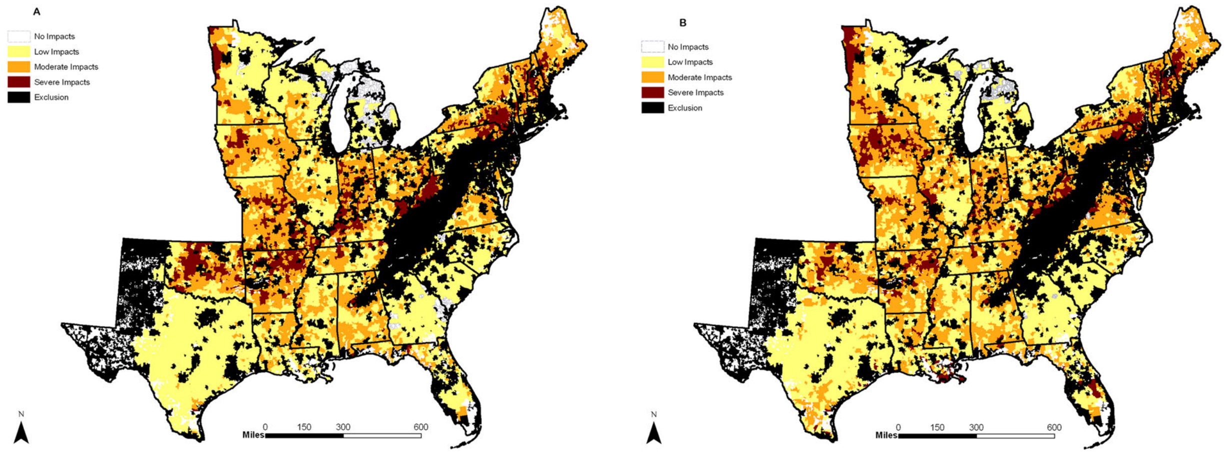

Figure 2. Risk impacts by 5-digit ZIP Code Tabulation Areas (ZCTA) without weights for (a) short-term (2000–2011) and (b) long-term (1964–2011) risk impacts, based on Presidential Disaster Declarations.

Table 5. Risk by category of risk for short-term-term disaster declarations.

Risk Level	Risk Impact Value	ZCTA Counts for Risk	Percent by ZCTA
Severe*	≥6	12,788	51.1%
High	≥4–6	1,578	6.3%
Moderate	≥3–4	5,128	20.5%
Low	≥0–3	5,466	21.8%
None	0	84	0.3%

*All severe impacts were contained within exclusion zones, primarily people ≥58 km^{-2}

Greater weight for road density, less weight for population density

If a greater weight is given to road density (*e.g.* $w_E = 0.7$) and less weight is given to population density (*e.g.* $w_S = 0.3$), there were fewer ZCTAs impacted by overall risk (Figure 3(a and b)). However, even with less weight assigned to population density, risk assessment for the Eastern Seaboard was still highly impacted by population density. High risk areas were in Arkansas, Missouri and Oklahoma for the short-term declaration data. For the long-term declaration data, high risk zones appeared throughout the study area, with the exceptions of southern Georgia, South Carolina, and Texas.

Greater weight for population density, less weight for road density

If more weight is given to population density (*e.g.* $w_S = 0.7$) and less is given to road density (*e.g.* $w_E = 0.3$), there were more ZCTAs impacted by risk for both the short-term and long-term declaration data relative to the previous scenario where the weights were reversed (Figure 4(a and b)). Preferred locations for biomass supply for the weighting scenario of this section again appeared to be in southern Georgia, South Carolina, and Texas.

Table 6. Risk impacts and ZCTAs by category of risk for long-term disaster declarations.

Risk impacts degree level	Risk impacts value	ZCTA counts for risk	Percent by ZCTA
Severe impacts*	≥6	12,788	51.1%
High impacts	≥4–6	1,549	6.2%
Moderate impacts	≥3–4	5,820	23.2%
Low impacts	≥0–3	4,482	17.9%
No impacts	0	405	1.6%

*All severe impacts were contained with exclusion zones, primarily people ≥58 km^{-2}.

Discussion

Bioenergy from lignocellulosic sources has been studied extensively; for such sources to be sustainable, they must come from resources that are accessible. Additionally, the supply must be reliable in the face of disturbances that affect biomass resources directly, or disrupt transportation to processing facilities. Southwide decreases (40%) in hectacres planted, loss of timberland to urbanization, and land fragmentation imply that even under current demand, the future inventory is not likely to follow historical trends (Wear et al. 1999; Wear et al. 2007; Stein et al. 2009). In this study, the objective was to produce an aggregated risk impact map that would show the relative degree of risk from natural disasters for locating biomass-using facilities in terms of potential disruption of the biomass supply chain. The spatially explicit model helped to identify areas that are most prone to natural disaster with a greater need of both short and long-term risk mitigation and where continuous risk may be probable. The maps based on indexed risk indicated the most problematic natural disasters in relation to areas where short-term or long-term degradation of bio-based assets could occur.

Road density, our measure of exposure, is associated with population; higher population, higher road density. While a denser road network could mean there might be alternative routes to transport biomass to a facility, it is more likely that major roads would have priority for clearing and roads to recover biomass would have a low priority for clearing. Other work has shown the importance of "landscape suitability" on mill location; landscapes with a lower slope but abundant forestland, high water area ratios, and high forestland ratio are preferred (Wear et al. 1999; Wear et al. 2007; White and Mazza 2008; White et al. 2009; Wear et al. 2013; Young et al. 2017a; Young et al. 2017b).

The other component of vulnerability, coping capacity, is represented by population density; lower population, denoting rural areas, generally have less ability to withstand and recover from natural disasters (Cross 2001). Admittedly this

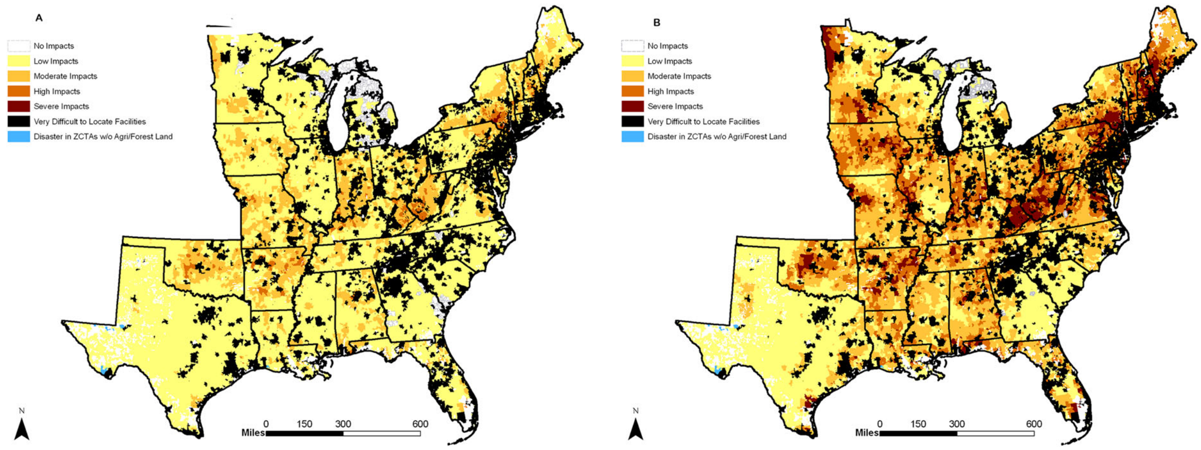

Figure 3. Greater weighting for road density ($w_E = 0.7$) than population density ($w_S = 0.3$) for (a) short-term (2000–2011) and (b) long-term risk impacts (1964–2011), based on Presidential Disaster Declarations.

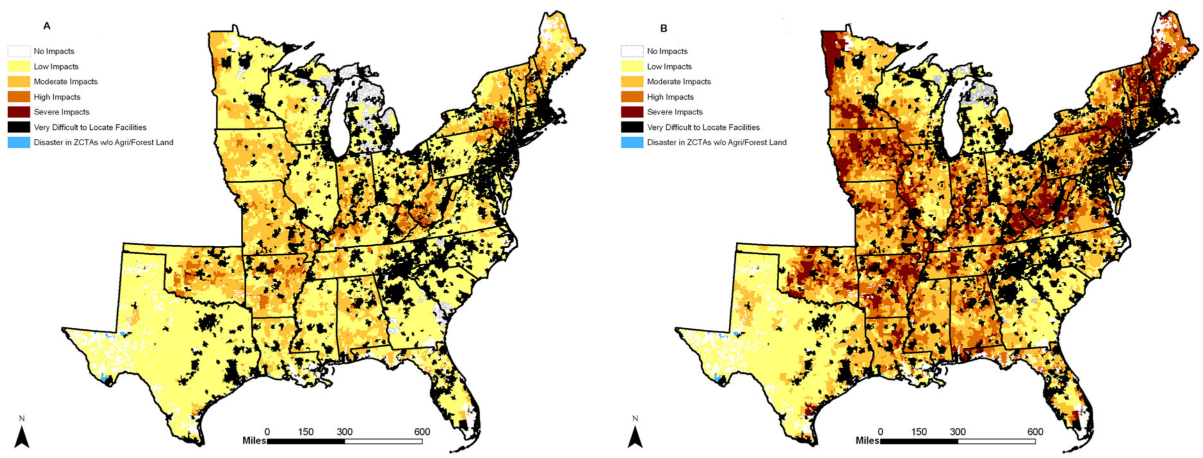

Figure 4. Greater weighting for population density ($w_S = 0.7$) than road density ($w_E = 0.3$) and for (a) short-term (2000–2011) and (b) long-term risk impacts (1964–2011), based on Presidential Disaster Declarations.

generalization is imperfect but other socioeconomic data for the region, not included in this analysis, showed that people in rural areas tended to have lower income than people in urban and suburban areas (Young et al. 2017a). Going forward, analyses for locating specific biomass-using facilities could use socioeconomic data that is also available at the 5-digit ZCTA level. In general, more ZCTAs were affected by risk as population density weighting increased, which is also a scenario supported by the literature (Smit and Wandel 2006; [USDA] 2014; Lindsay and McCarthy 2015).

Risk assessments may give communities the tools to improve disaster preparedness and mitigation plans. Visualizations of risk are generally easier-to-understand than descriptive language. This research advances the study of risk to biomass supply for a large geographic region at a higher level of spatial resolution than previous research. A significant contribution of the research is the addition of major disturbances in a high resolution geospatial database at the 5-digit ZCTA, included in a web-enabled bioenergy siting decision support tool, BioSAT (Perdue et al. 2011). The visualization resulting from kriging reduces the spatial bias introduced by arbitrary jurisdictional boundaries. As far back as 1971, traditional data analysis techniques were questioned because geographic regions such as states and counties in the United States were arbitrarily drawn; therefore invalidating the independence of assumptions resulting in possible bias in the estimates they produced (Kmenta 1971). More recently studies have introduced spatial econometric techniques into location analysis (Lambert et al. 2006).

Future research could use predictive models of the likelihood of occurrence and intensity of different disturbances to refine the impact zones identified in this study, for example the effect of climate change on meteorological disturbances (Rummukainen 2012; Cai et al. 2014). Our approach relied on historical data for disasters to estimate exposure as part of our risk assessment (Alig et al. 2004). Using historical data about natural disasters of significant impact (presidentially declared) allows for some consistency between the type of disaster and the relative ability to compare patterns of occurrence and frequency of damage. Nevertheless, even the long-term dataset of Presidential Disaster Declarations does not fully capture low frequency, high severity events such as hurricanes on the Gulf Coast (Stanturf et al. 2007) and the likelihood that extreme events will increase (Rummukainen 2012; Pielke et al. 2013; Cai et al. 2014). Unfortunately data on frequent low severity events are not readily available;

effects are localized, meteorological models are low resolution, and if affected resources are assessed they are not centrally archived (Peterson 2000; Rootzén and Tajvidi 2001; Bragg et al. 2003; Della-Marta et al. 2009).

Disturbances may temporarily increase supply and disrupt markets, but work following major hurricanes has shown (as discussed in Stanturf et al. 2007), however, that recovery rates are low due to safety issues, the inability to process excessive amounts of wood, and the shortage of harvesting crews who are diverted to higher wage opportunities in clearing roads and urban areas. Longer-term, shortages develop and prices rebound. The area disturbed by smaller events may be too small for cost effective harvesting. In geographic areas with high humidity and ambient temperatures, such as the eastern US, damaged biomass (i.e. on the ground) will decompose quickly, so will be of little value if not removed shortly after a disturbance.

The best geo-referenced data available, the Presidential Disaster Declarations, were aggregates of different types of disturbance; these data excluded other significant disturbances that could affect biomass supply including insects and diseases. For example, our preferred locations of procuring biomass supply in the Eastern United States for all risk factors were in southern Georgia, South Carolina, and Texas but these are areas known to be at risk from major hurricanes (Stanturf et al. 2007). The interpretation of the impacts to bio-based opportunity zones can be improved with further studies to better estimate and establish risk exposure zones with linkages to a wide-range of environmental conditions and specific disturbances. A critical need in this regard is research on the cascading effects of multiple disturbances that interact, possibly synergistically (Buma 2015; Seidl et al. 2017; Frelich et al. 2018). New research should assess risk to supply from especially mega-fires due to management practices (Williams and Hyde 2009; Stephens et al. 2014) and/or given changes in species composition of the forest (Goodrick and Stanturf 2012). One application of these results could be to include risk premiums in interest rates used for economic analysis of dedicated bioenergy plantations such as (Perdue et al. 2017; Stanturf et al. 2017, 2018).

The capacity of local government or communities to cope with natural disasters was not directly assessed. We used the level of the population at risk (exposed) as our measure of social vulnerability without regard for socioeconomic differentiation within communities that could have been improved by incorporating census data (Hahn et al. 2009; Stanturf et al. 2015). Generally, social vulnerability to natural hazards has focused on the ability of people and communities to respond to the effects of events (Cutter et al. 2003; Cutter and Finch 2008). In extreme cases, countries have been indexed based on mortality such as the UNDP Disaster Risk Index (United Nations Development Program 2004). In our case, by definition of Presidential Disaster Declarations, local governments are unable to cope with these levels of disaster severity. Nevertheless, the spectre of increased frequency of extreme events due to climate change has caused a greater focus on building long-term resilience than coping once a disaster has struck (Djalante et al. 2011), efforts that could utilize our results to highlight where significant risk occurs.

Public perceptions and understanding of potential risk are important elements in developing risk scenarios and mitigation plans. Visual results can help communities quickly understand where landscapes and bio-based assets may be a greatest risk and where further analysis is warranted. Our kriged visualizations of risk at the 5-digit ZCTA level provided higher spatial resolution than county-level maps, highlighting the relative risk to biomass supply. Risk and vulnerability models when combined with multiple bio-based assessment systems could improve the ability to derive and generate visual evidence of risk potential to biomass supply/demand, biomass accessibility, landscape suitability, opportunity zones, energy crop production potential, and ecological sustainability.

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Disclosure statement

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