Information for Climatic Adaptation and Restoration of Ecosystem Services (ICARES) for urban and agricultural landscapes of Massachusetts

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Project Report

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1. Introduction

1.1 The Problem

Healthy natural resources form the foundation of the well-being of the Commonwealth of Massachusetts. This is mainly due to the multiple ecosystem services that nature provides. Information on these ecosystem services is critical to effective decisions toward protecting and enhancing land and water resources. With the increasing loss of natural processes in human-dominated landscapes, primarily urban and agricultural land, it is imperative to develop a tool to identify and restore these areas to their original ecosystem service potential. In developing land and for guiding conservation, much of the decisions made on natural resources are made at private and some public levels with guidance from local and state laws. Sometimes, these decisions are not based on scientific information related to the nature of the ecosystem and dynamic processes that are part of the land resources. For example, what are some regional benefits of forest cover to stormwater mitigation and reduction in climate change impacts?
Decisions related to land protection, land-use changes, forestry, stormwater, agricultural soil conservation practices, and climate adaptation need assessment that uses location information and regional flow information within watersheds, ecological regions, and administrative boundaries. A spatially explicit support system is required to accurately assess these changes to help decisions made by communities and agencies. In the Commonwealth of Massachusetts, communities face decisions requiring accurate and timely spatial information about their community. With impending climate change, the need for local-level information on impacts and adaptation opportunities is becoming critical to communities. There is a need for developing scientific information on landscapes that can help in land use and water use decisions.

1.2 Research Questions

Specific research and management questions relevant to conservation needs in the Commonwealth of Massachusetts are: What is the role of the urban forest in adapting to climate change? How can urban trees mitigate stormwater resulting from impervious cover and climate change? The role of trees in augmenting and protecting local water supplies? Can urban trees achieve regional benefits in ecosystem services? What are some benefits of urban trees in mitigating the urban heat island effect at a regional scale? How can farms benefit from timely cover cropping to improve soil health, thereby increasing environmental health and adapting to climate change?

1.3 Research Needs

These questions need careful assessment of the local ecosystem using Geographic Information Systems (GIS) and spatial models to simulate ecosystem services and potential climate impacts. These assessments need to be integrated into a decision support system that communities use, especially with location-specific information and must be accessible through available technology.

1.4 Conceptual Model

Climate impacts on urban areas are many that include stormwater flooding, droughts, water supply disruption, heat waves, soil erosion/ loss, groundwater depletion, soil ecosystem deterioration, and variable rainfall and temperature patterns. These impacts are stormwater flooding, droughts, water supply disruption, nutrient contamination, soil erosion/ loss, groundwater depletion, soil ecosystem deterioration, and variable rainfall and temperature patterns in rural areas. This is presented in the conceptual model shown in Figure 1 and is quantified as resilience characteristics.

1.5 ICARES

Rapid urbanization and changing temperature and precipitation patterns are putting severe strain on the health of local ecosystems. To assist communities in developing resilience to these changes, the Information for Climatic Adaptation and Resilience for Ecosystem Services (ICARES) presents a suite of assessments that model specific ecosystem services under current and future climate scenarios. The primary purpose is to evaluate the role of vegetation, especially urban trees in mitigating vulnerability to stressors like urban heat islands, stormwater runoff, and impacts to water supplies for a spatially explicit decision support tool. This online tool enables communities to identify risk areas, understand risk contributing factors, and devise plans for restoration using scientifically grounded information and models. In addition, this spatially explicit decision support tool is easily accessible and spatial in assessment enabling the evaluation of benefits and costs of land decisions, nature of ecosystem services, and map attributes on a landscape. This tool will support and improve decisions made by communities and agencies.

2. Methods

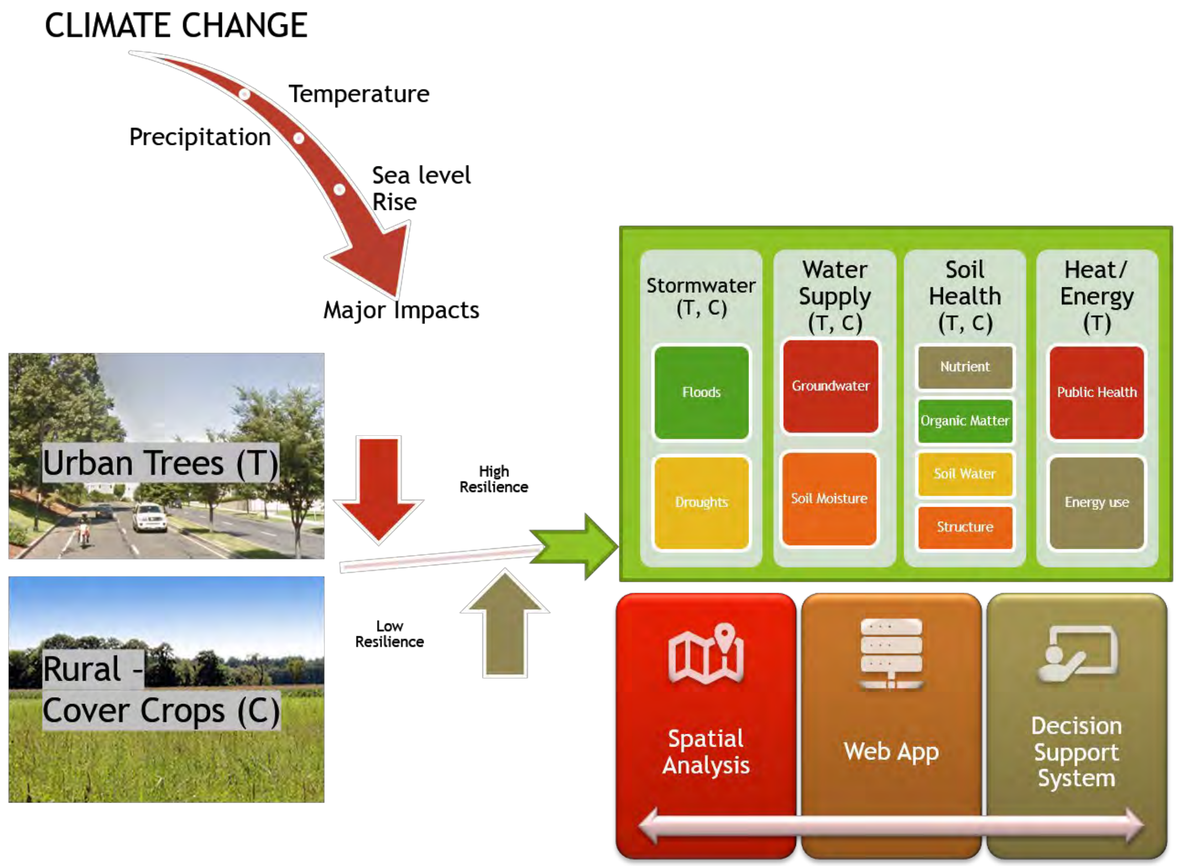


Figure 1. Conceptual Model of the analysis

As depicted in the conceptual representation (Figure 1), the analysis included four subcomponents: climate scenarios, landscape features (urban forests and agricultural cover crops), benefit assessment, and spatial decision tools.

2.1 Baseline

This study developed a baseline assessment of the landscape conditions at current conditions. This baseline level is critical to evaluate changes in ecosystem services under alternative scenarios.

Representation is in cell-based units (Rasters), common in Geographic Information Systems (GIS) to analyze landscapes. Model of landscapes and sites and their linkages are presented in Figure 2.

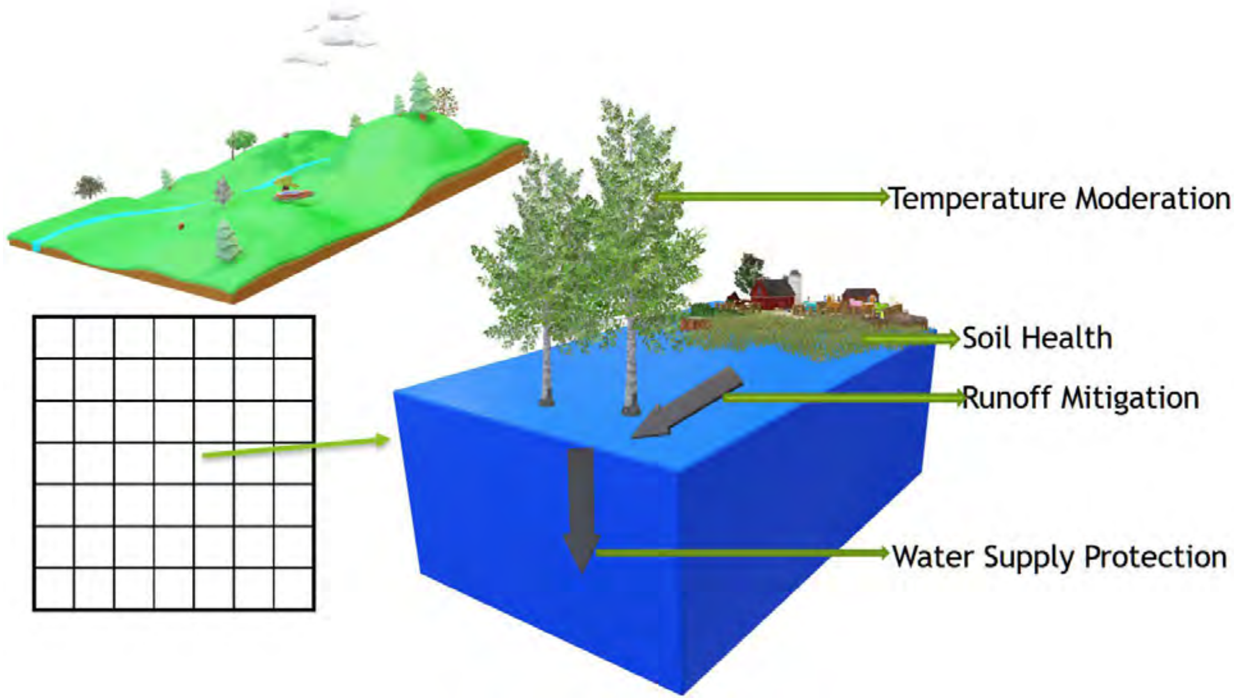
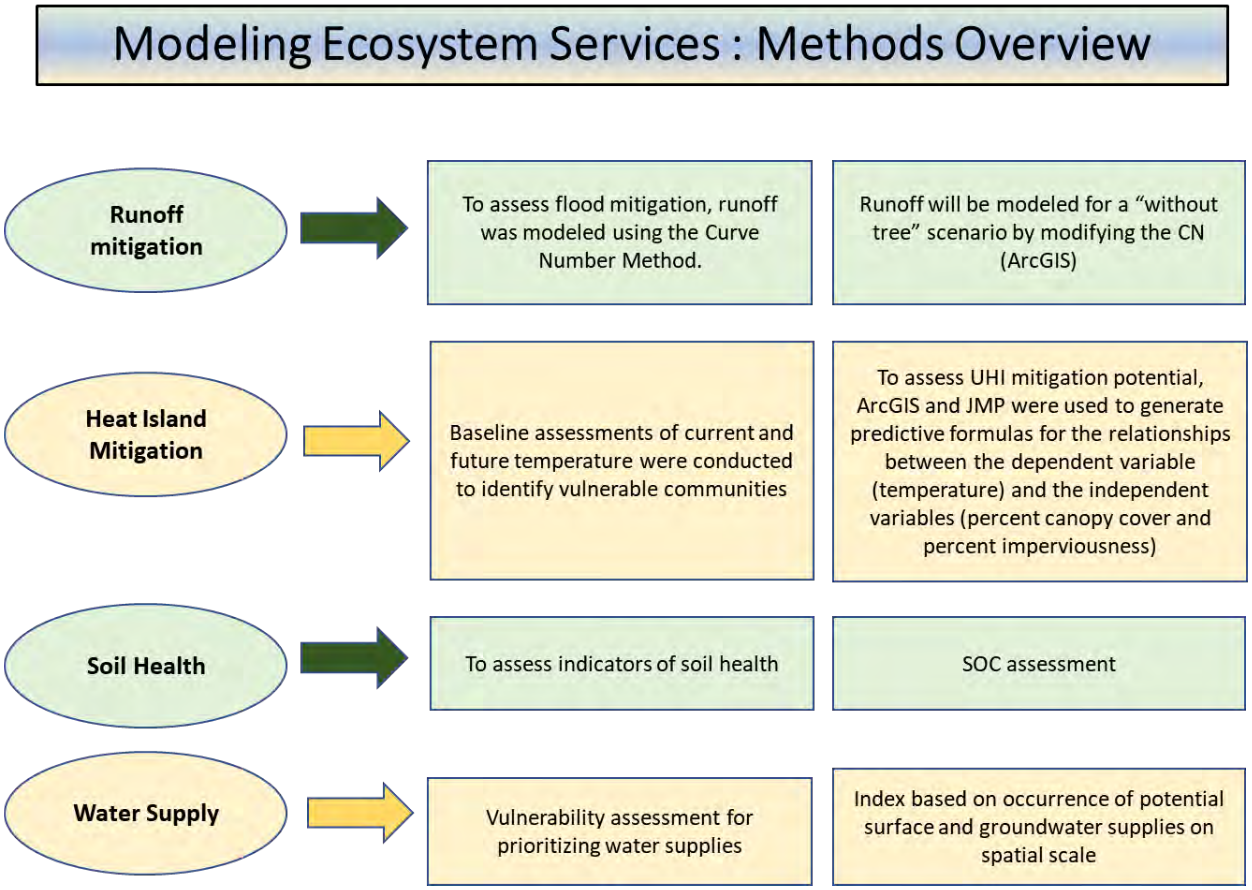


Figure 2. Representation of model units and quantification of processes.

BASELINE ecosystem services:



2.1.1 Water Supply: For water supply protection, proximal and downstream water supply bodies were identified and weighed to assess vulnerability.

Data Sources:

1. Runoff mitigation potential dataset
2. Aquifer data for Massachusetts
3. Water supply protection data for Massachusetts
4. SSURGO-Certified Soils data for Massachusetts
5. Soils hydrological groups data

Data Preparation Process:

- A ranking system for runoff mitigation potential was generated by subtracting minimum values from maximum values and dividing by the difference and multiplied by 5
- Aquifers were ranked based on yield with low yielding receiving a score of 1 and high yielding receiving a score of 5
- Water supply protection area were assigned a 0 if they fell outside of a watershed or a 1 if within. Values were multiple by 5
- For wellhead protection areas, each zone type was assigned a separate rank (Zone II was assigned a 3, IWPA and Zone I were assigned a 5). Overlapping regions were summed to receive additional weight in creation of the subindex.
- SSURGO-Certified soils data was modified and joined to soils hydrological groups and received a rank based on infiltrative properties
- Each data set was converted to a raster file and map algebra was executed to compute the statewide index ranging from 0 to 100
- Natural breaks were used to classify the Water Supply Index into quintiles

2.1.2 Flood Mitigation: For flood mitigation, the runoff was modeled from each raster (using the CN method) and compared with and without scenarios. Values were aggregated for the project to evaluate benefits.

Data Sources:

1. 2016 Land Cover/Land Use dataset from MassGIS
2. Soils dataset from STATSGO2
3. Digital elevation model from MassGIS
4. Annual precipitation values for the period between 1981 and 2010

Process:

- Curve Number Method
- Developed using high resolution state-wide 2016 land cover/land use and soils data
- Cross tabulations were created to find all land use and soil combinations and designate curve numbers
- Potential maximum retention was calculated as a function of the curve numbers using the raster calculator
- The output raster was used in the algorithm for runoff
- The cells were aggregated by their membership to sub-basins in the state to assess runoff patterns
- Effect of greening was calculated using changes in runoff volume under a broadleaf deciduous tree with medium growth modeled for Northeast by Hynicka and Caraco (2017)

2.1.3 Heat Island: For the heat island effect, the average summer temperature during past years and in the future was computed. Ecosystem service provided by canopy cover through heat mitigation was evaluated using spatial models and data mining methods.

Data Sources:

1. NLCD 2016 USFS Tree Canopy Cover (CONUS)
2. NLCD 2016 Percent Developed Imperviousness (CONUS)
3. 30-year average maximum temperature data for June, July and August between 1981 and 2010 obtained from PRISM Climate Group
4. Massachusetts feature polygon layer obtained from MassGIS
5. Shapefile of urban places in MA from the United States Department of Agriculture Forest Service

Data Preparation Process:

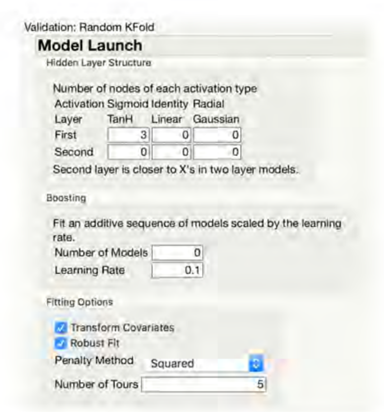
- Averaging temperature using the raster calculator
- Reprojection, clipping, resampling, and natural neighbor interpolation
- Preparation of percent tree canopy and percent developed imperviousness layers
- All layers clipped to the urban places shapefile
- Raster to point conversion
- Extraction of values to points
- Same process repeated for each individual Gateway City and Boston, West Springfield, Pittsfield, and Cambridge for intracity analysis

Ordinary Least Squares Regression in ArcGIS (Linear Model)

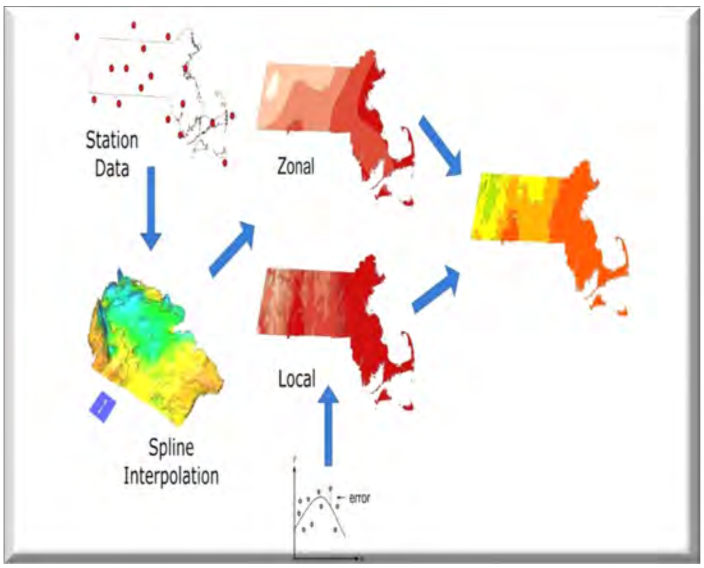
❖ OLS provides a linear model for a dependent variable that is to be explained or predicted by one or more explanatory variables
❖ The summary OLS output report file provides the coefficients, intercept, measures of statistical significance, and measures of multicollinearity for each explanatory variable
❖ The OLS diagnostic section provides information on model performance and significance, consistency of the relationship, and model bias

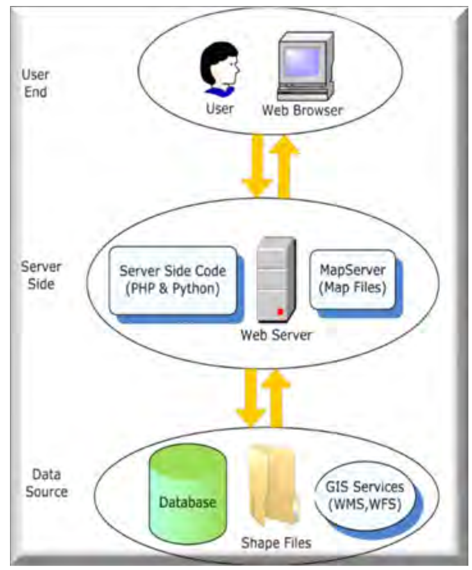
Dependent variable: average maximum summer temperature
Independent variables: percent canopy and percent developed imperviousness

Neural Networks in JMP (Predictive Non-Linear Model)



2.1.4 Cover crop: Cover crop's potential benefits in agricultural farming were assessed using cumulative Growing Degree Days to accumulate enough plant biomass for soil health and nutrient uptake. Optimal planting dates were used to evaluate the benefits of cover crops in farms.





2.1.5 Soil Health: Soil health was assessed using Soil Organic Carbon as an indicator for carbon sequestration and health.

Data Sources:

1. A1 scenario and EDCM model from USGS

Data Preparation Process:

- Carbon baseline was assessed at the top 20 cm of soil and by calculating the average carbon stock in gram of carbon per square meter or land from 2010 to 2020
- Carbon flux was estimated by subtracting 2020 data from the predicted 2050 data divided by 30 years
- Yearly flux was used to estimate 2100 soil carbon
- Carbon flux was multiplied by 80 years and added to the 2020 carbon stock to obtain carbon estimate for 2100
- Carbon stock data for 2010, 2020, 2050 and 2100 were converted to point data and interpolation was performed using Spline with borders in ArcGIS

2.2 Climate change scenarios

Two climate scenarios were assessed: Mid-century (2050) and late-century (2100) scenarios from GCM simulations. For each scenario, projected temperature and precipitation were calculated as differences from Baseline (2010). An RCM model prediction was used for these estimates. The raster layer from climate results was Spline -interpolated to match the rasters in the project.

2.3 Benefits under vegetation

The benefits of trees for each ecosystem service were used in mitigating the impacts of climate change, for both preserving tree cover and adding new cover.
From evaluating these benefits, raster and aggregated values (subbasin) were used to assess the relative strength of each project for climate benefits.
Each project evaluation was done visually as well as using change evaluation - [[climate impacts (without trees)]- [Climate impacts (with trees)]]/ [climate impacts (without trees)]. The range of benefits was evaluated for each parcel and was further aggregated to the project or regional scales. These spatial values are useful as a ranking mechanism for conservation for soils, water, land, and heat effects.

2.4 Spatial Decision Tool

Spatial data on the baseline and climate scenarios are added to a web-based decision support tool (ICARES-DS) for easy access by communities and users. This is based on ArcGIS Online interactive tools.

3. Results and Discussion

3.1 MA Climate Change

3.1.1 Baseline Climate and Temperature

The baseline precipitation and temperature data are shown in Figure 3 and Figure 4. Baseline data was determined as the yearly average for the period between 1981 and 2010.

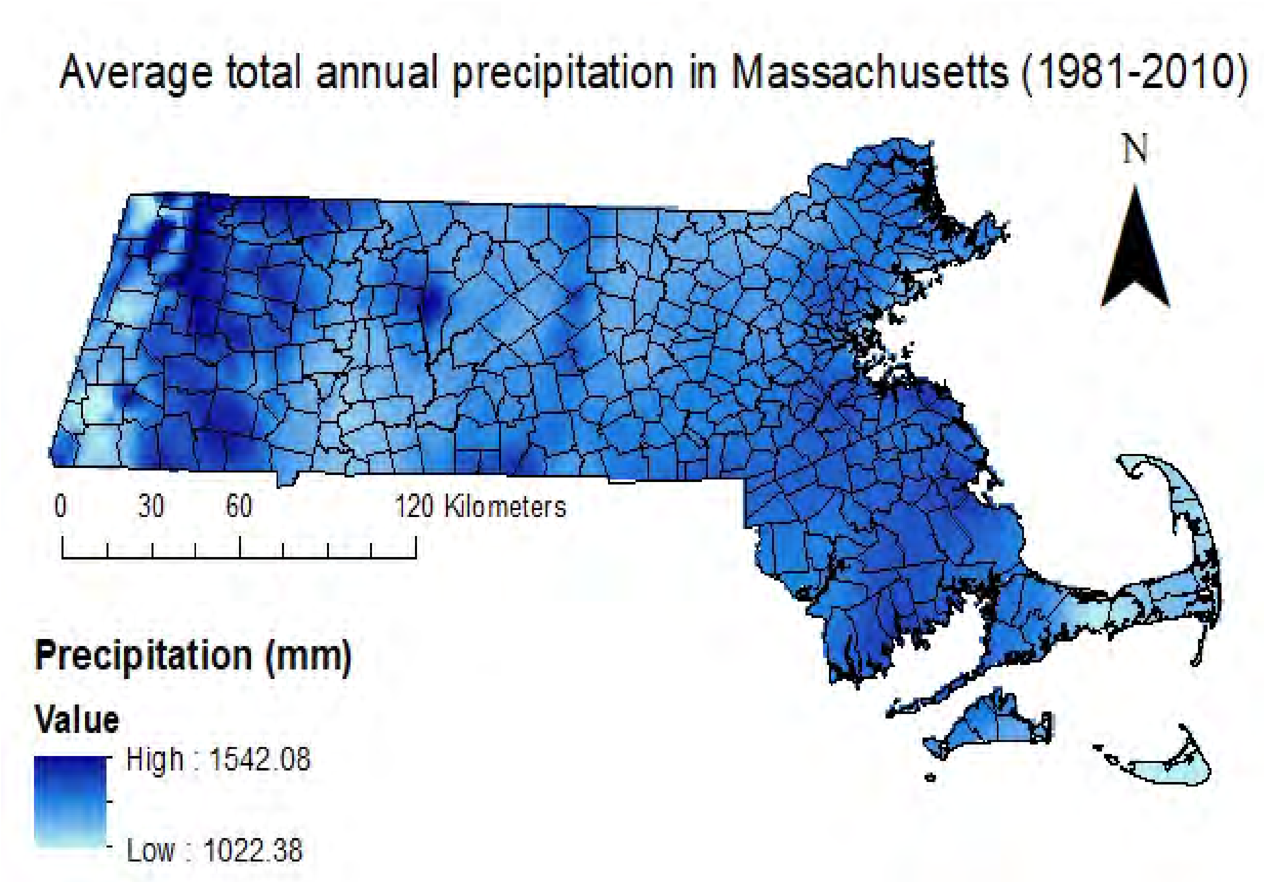


Figure 3: Average total annual precipitation in Massachusetts (Current)

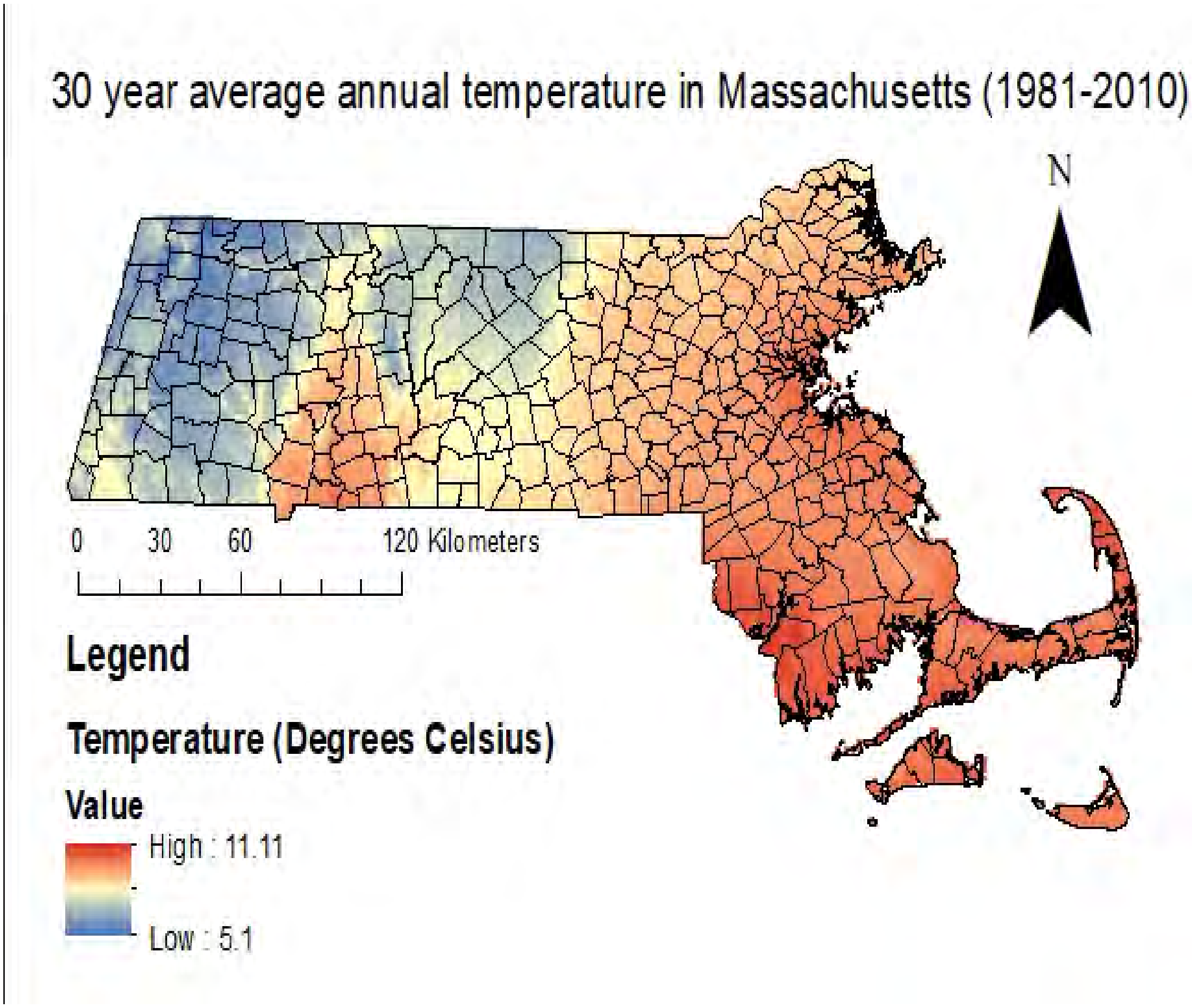


Figure 4: Average annual temperature in Massachusetts (Current)

3.1.2 Future Climate Data

Future temperature (Figures 5 and 6) and precipitation (Figures 7 and 8) data were compiled for the Commonwealth of Massachusetts for 2050 and 2100. The projections were developed by the Community Climate System Model (CCSM-5) for the 5th Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC). The data was sourced from the NCAR GIS Program. The following data presents ensemble averages under the RCP 4.5 scenario. Predictions are not available for the Cape Cod area.

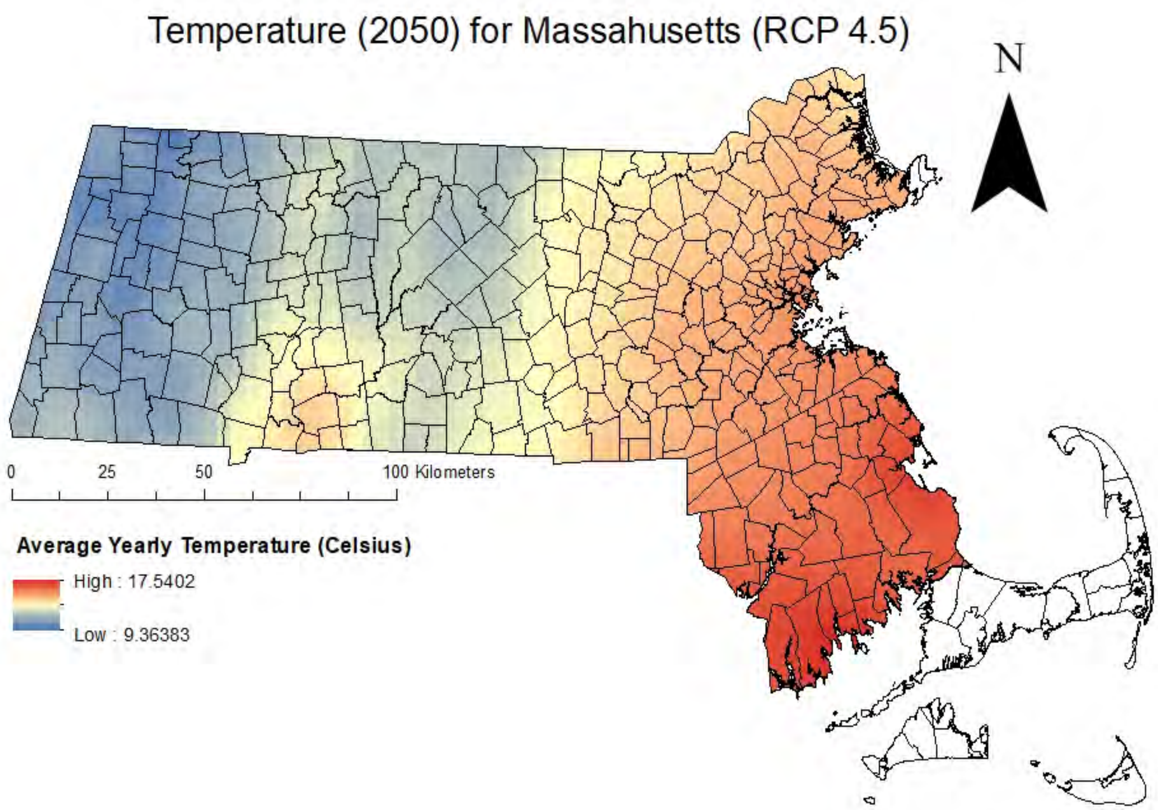


Figure 5: Temperature Predictions (2050)

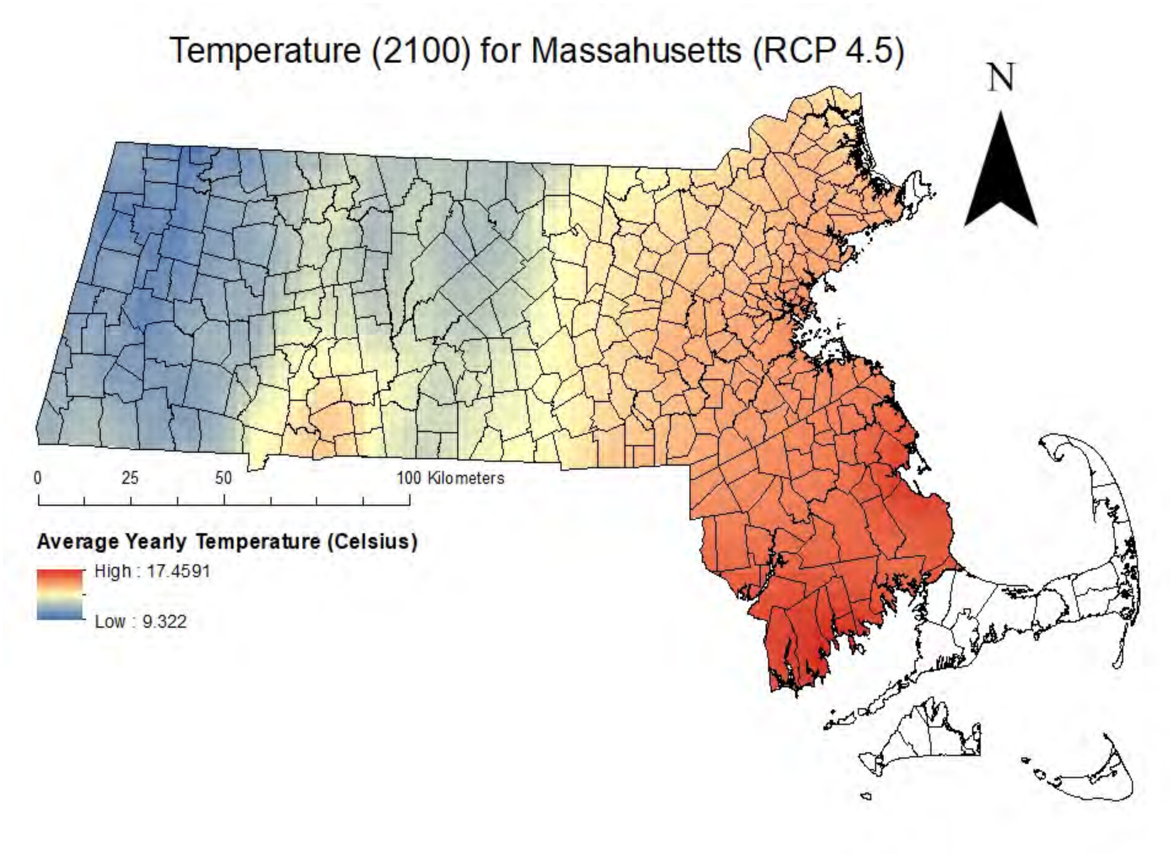


Figure 6: Temperature Predictions (2100)

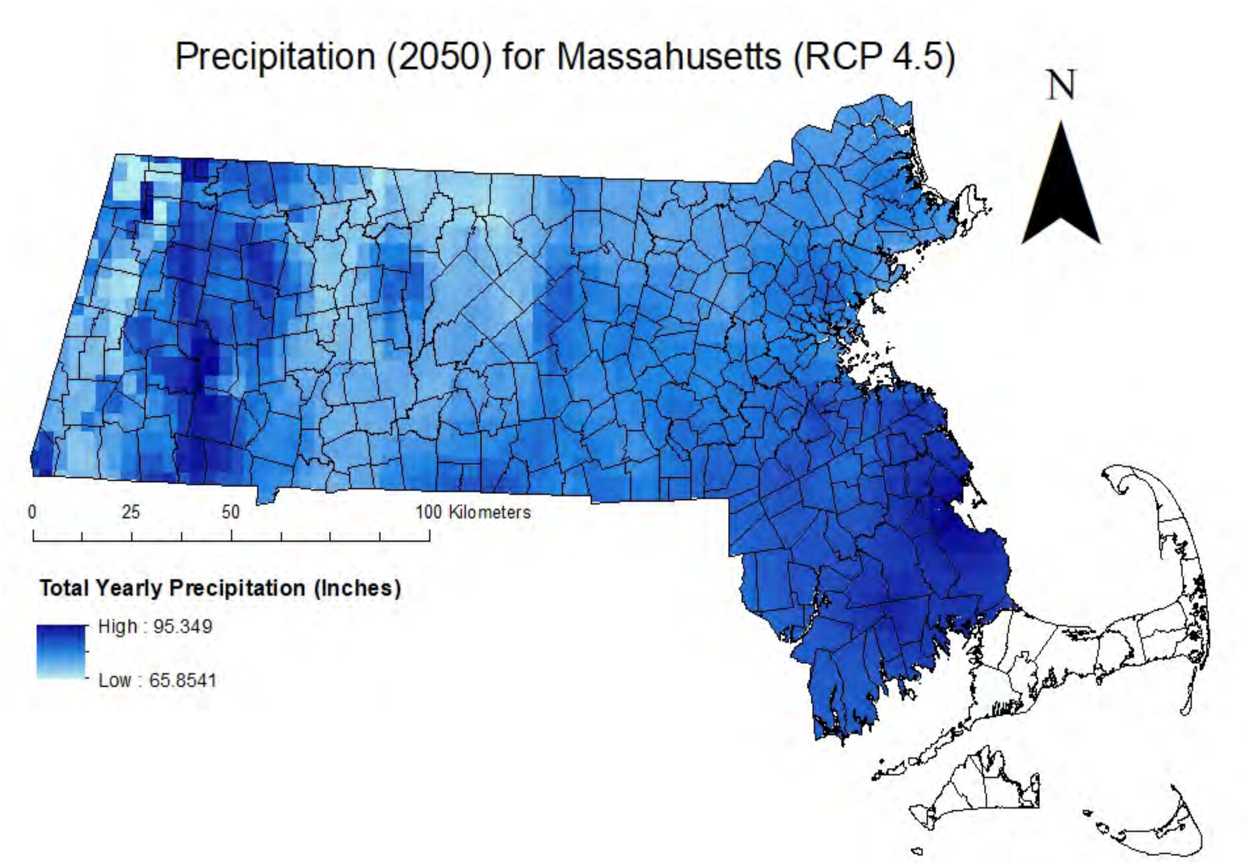


Figure 7: Precipitation Predictions (2050)

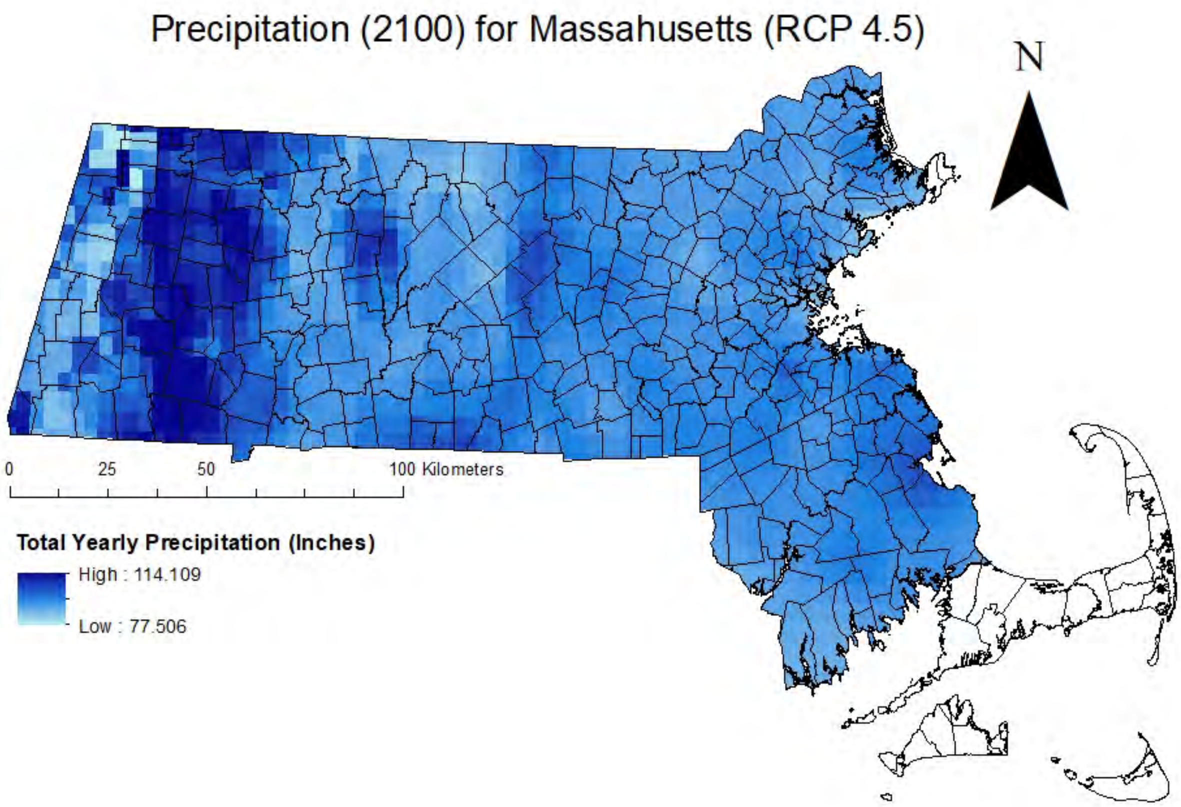


Figure 8: Precipitation Predictions (2100)

3.2 Urban Areas and Gateway Cities

Massachusetts Urban Areas (Figure 9) and the 26 Gateway Cities of Massachusetts (Figure 10) used in the analysis are presented below.

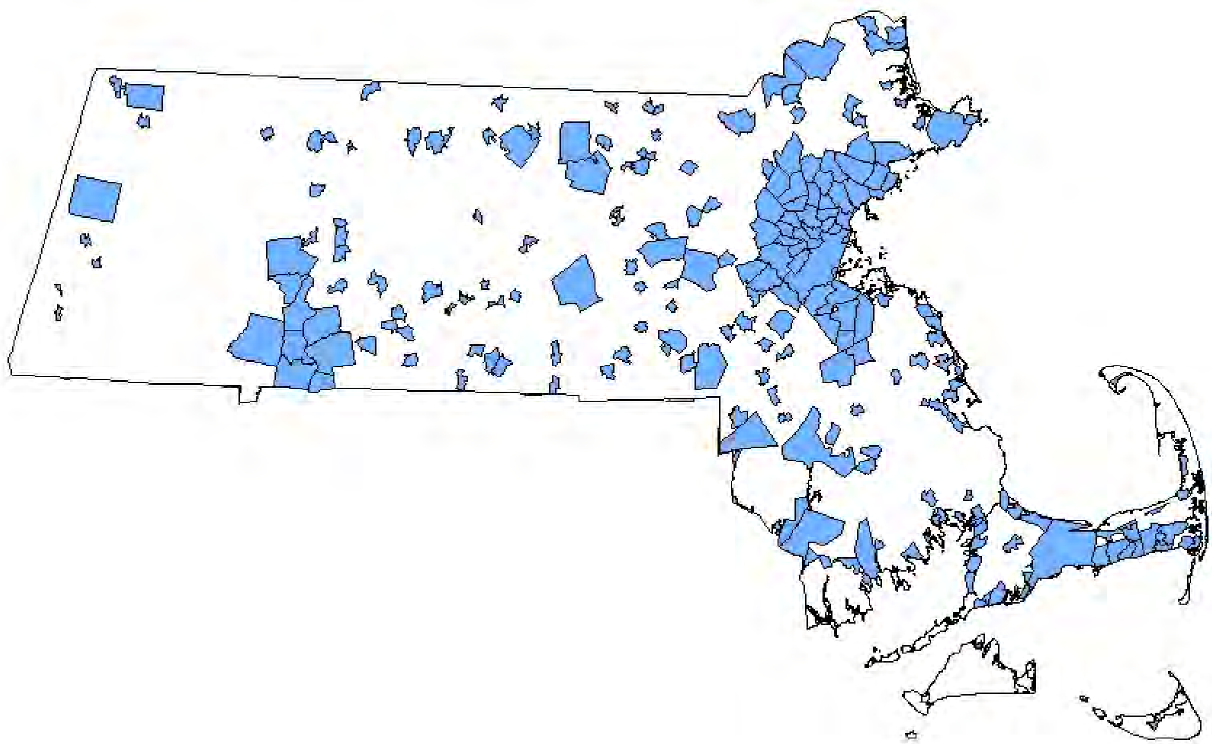


Figure 9: Massachusetts Urban Areas

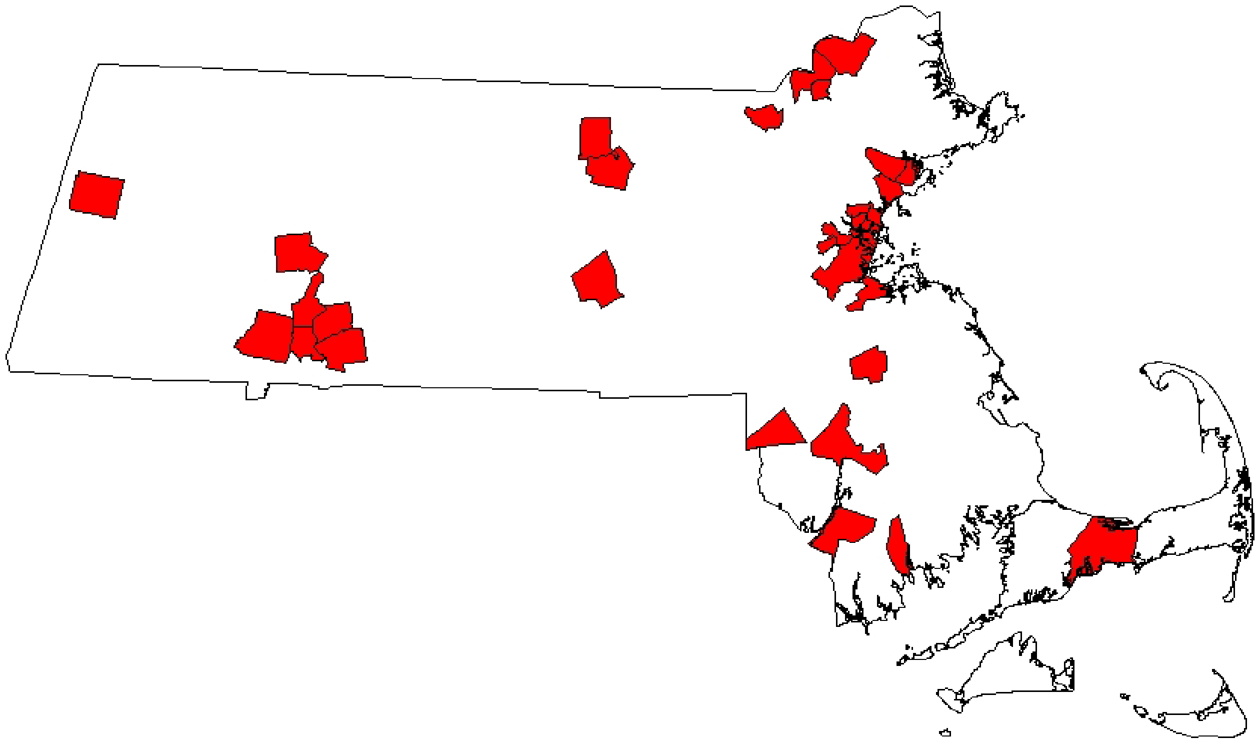


Figure 10: The 26 Gateway Cities in Massachusetts and Boston, Pittsfield, West Springfield, and Cambridge

3.3 Ecosystem Services

3.3.1 Cover crop Planting Date

Weather data were collected from National Oceanic and Atmospheric Administration (NOAA) website and used for extracting daily maximum and minimum temperature for each year. Then for each day, GDD was calculated using the following formula:

$g=(t_{max}+t_{min})/2-t_{base}, g\geq 0$

Where g is daily Growing Degree Day (GDD), t_{max} is the maximum temperature of the day (◦ C), t_{min} is the minimum temperature of the day (◦C), and t_{base} is rye base temperature which is 0 ◦C for winter rye (Stoskopf 1985). Also, total GDD from planting date to each sampling date was calculated as the total summation of daily GDDs in that time:

$t_s=\sum_{i=p}^{s} g_i$

Where p is planting date (day of the year), s is sampling date (day of the year), t is accumulated GDD from planting date to the specific sampling date, and g is daily GDD. Details of methods are presented in Farsad et al. (2011).

ICARES-DS - Cover Crop

Figures 11-14 show the online decision support tool for cover crops and how it can be utilized and customized to fit the needs of the community. Figure 11 and Figure 12 depict the Hybrid Model, and Figures 13 and Figure 14 show the Zonal Model. The tool itself can be accessed using the following link:
https://arcg.is/1mvmPC

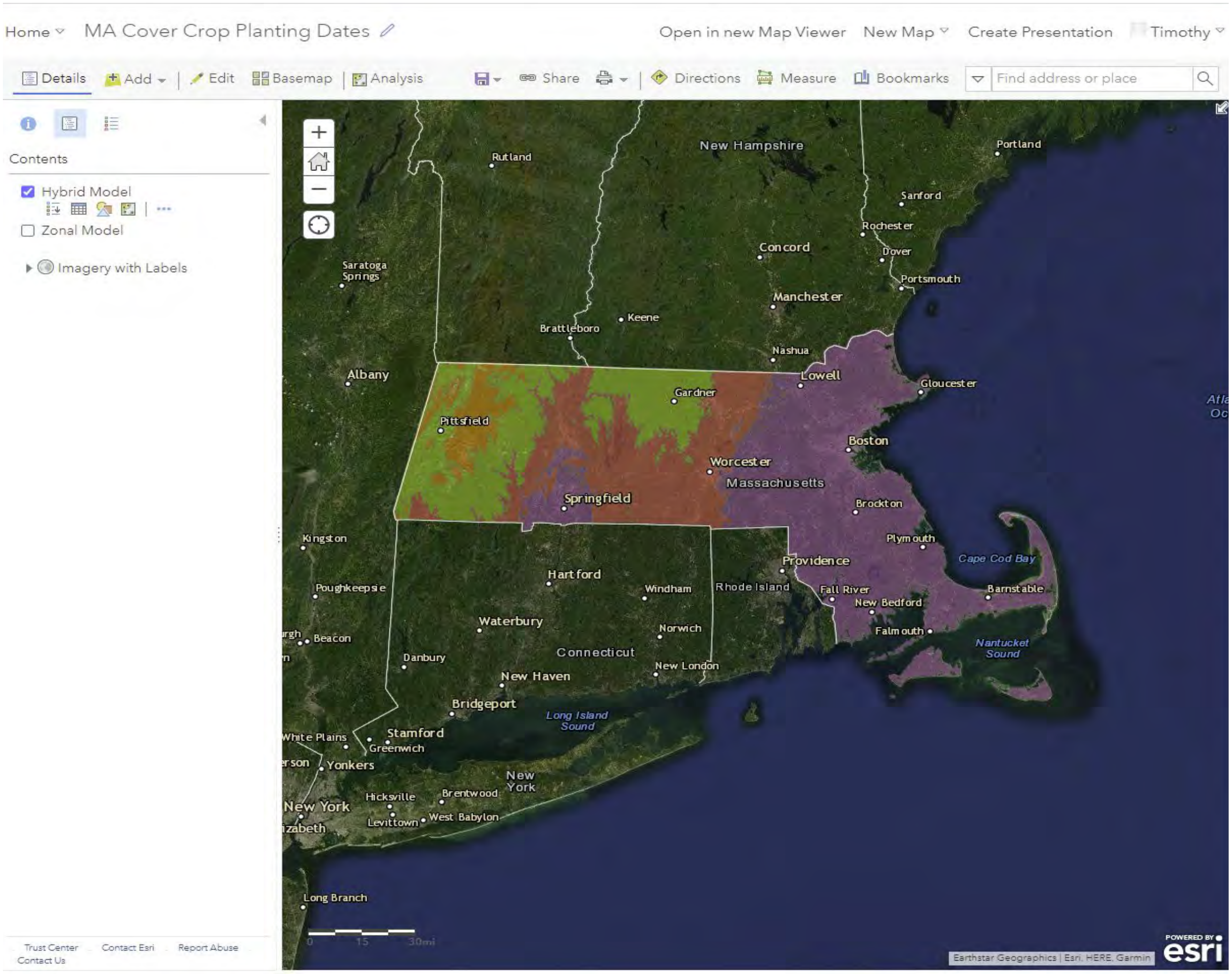


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Figure 11: MA Cover Crop Planting Dates (Massachusetts view)

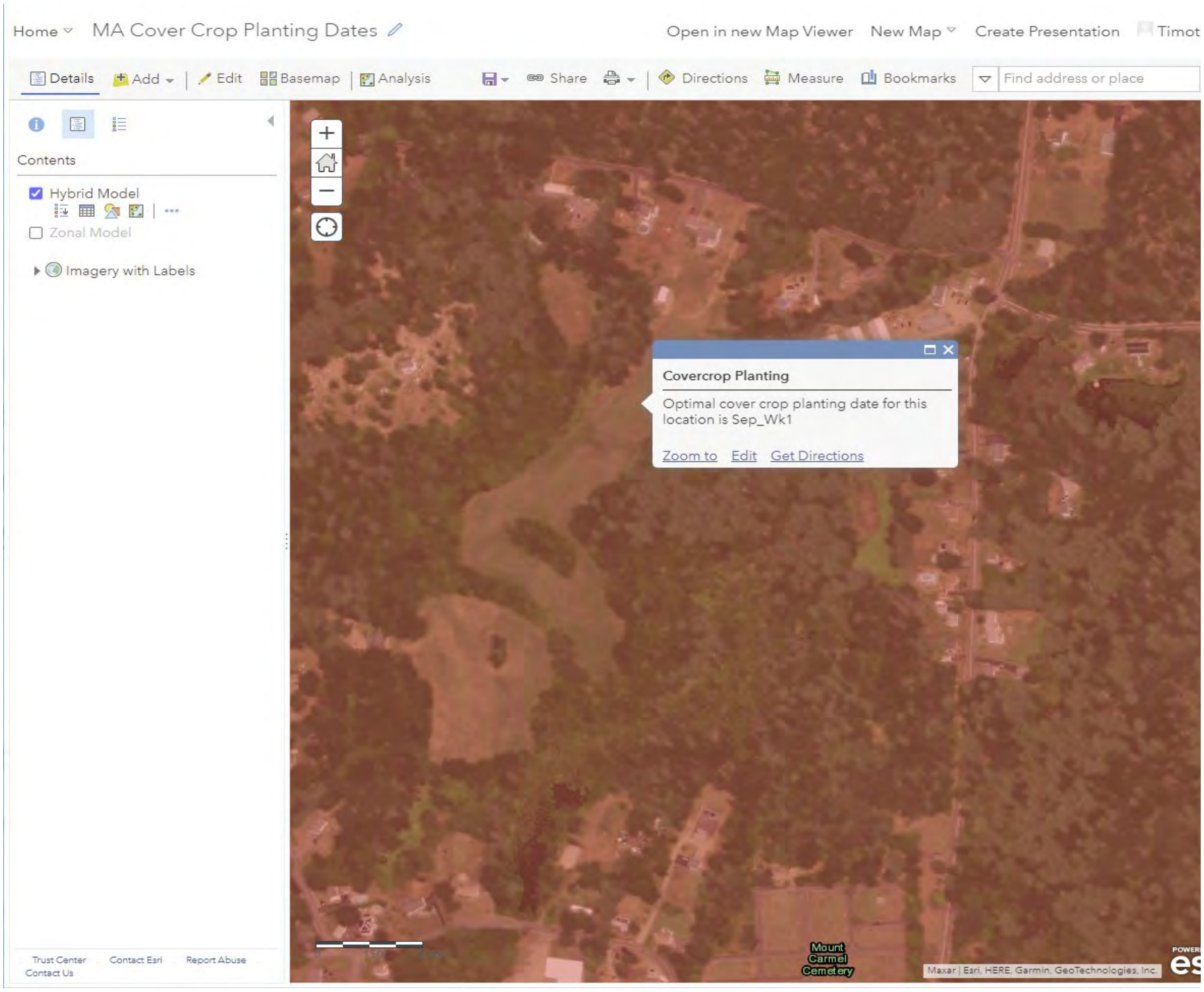


Figure 12: Example of pop-up indicating the optimal planting time for region selected

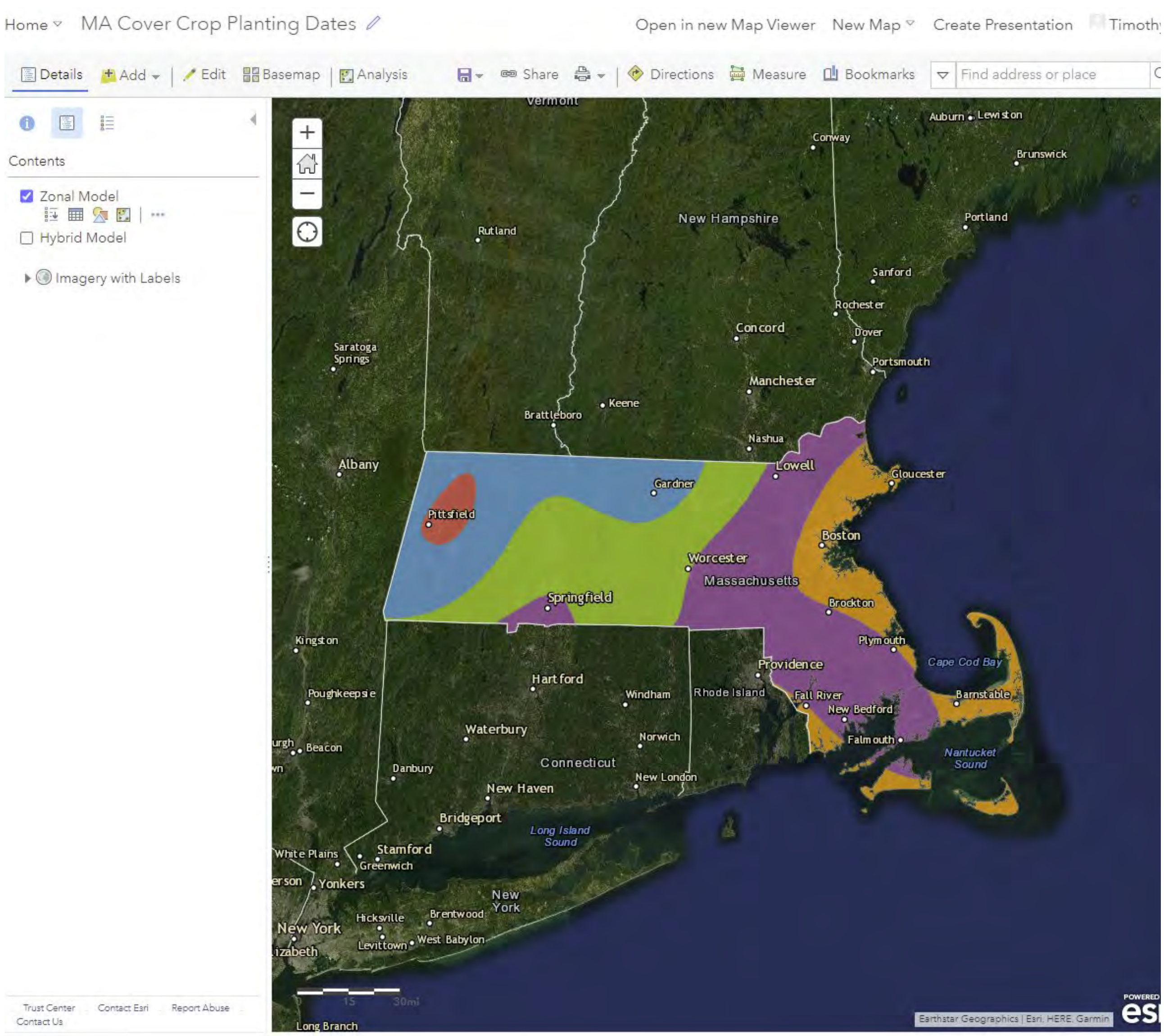


Figure 13: Zonal model view of the cover crop tool for Massachusetts

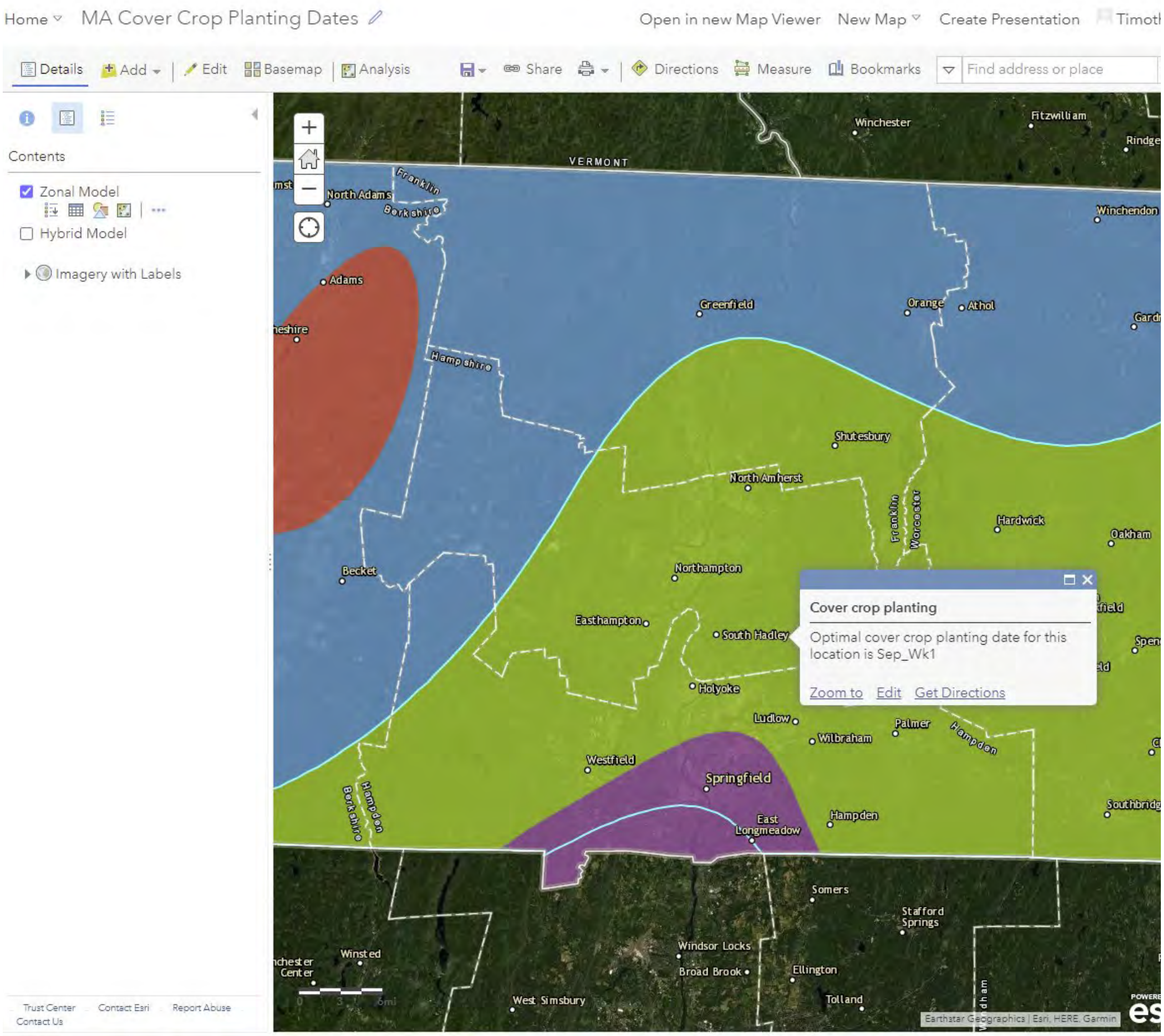


Figure 14: Zoomed in sample of the zonal model view of the cover crop tool for Massachusetts with pop-up indicating optimal cover crop planting date

3.3.2 Canopy Cover

The NLCD 2016 USFS Tree Canopy Cover (CONUS) data was used to determine the canopy cover for Massachusetts. The data was processed using the ArcGIS Data Management toolbox to match the extent, pixel size, and projection of the Massachusetts polygon feature layer. The output is shown in Figure 15.

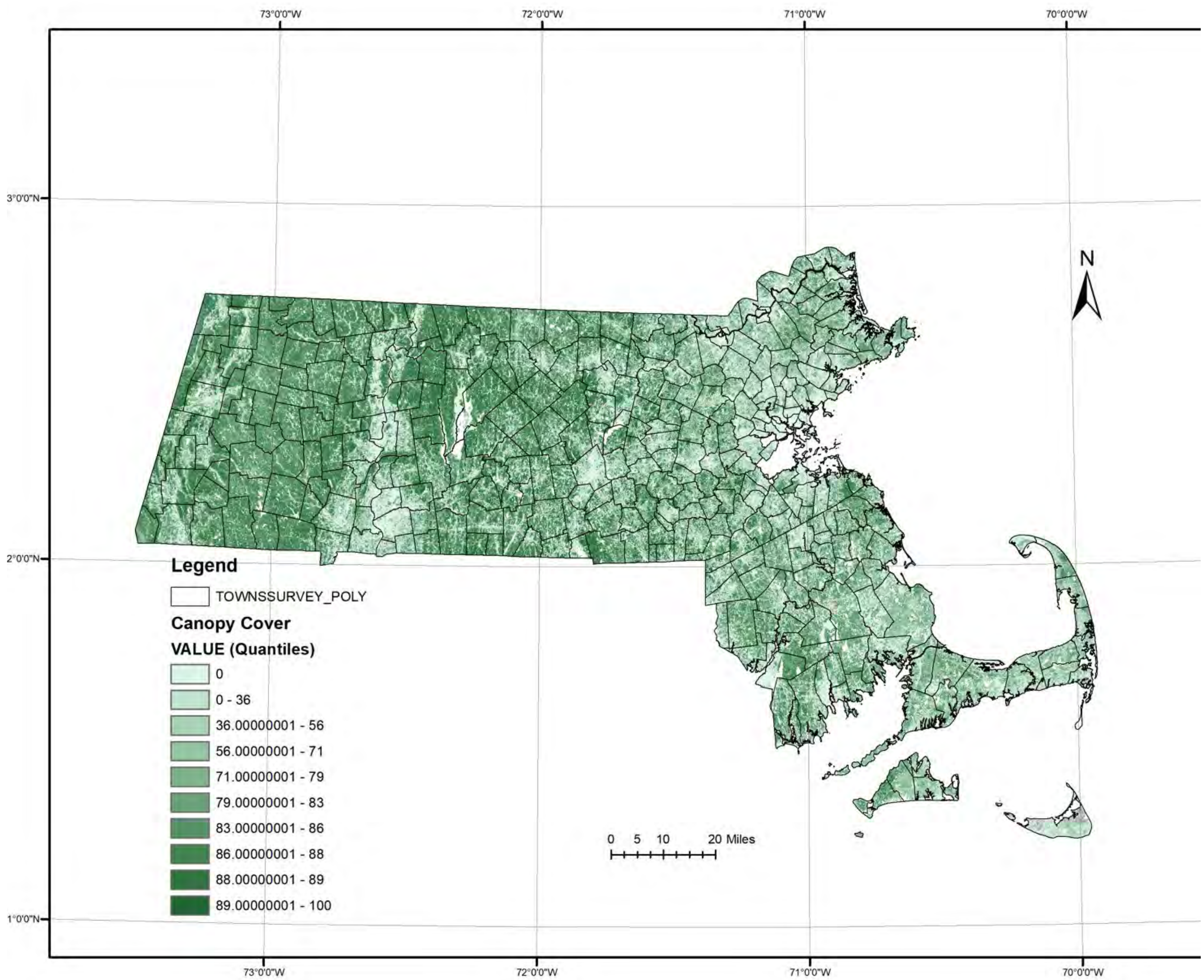


Figure 15: Canopy Cover (%) in Massachusetts

3.3.3 Stormwater Runoff Mitigation Potential

3.3.3.1 Stormwater runoff modeling

Climate change is negatively affecting the hydrological cycle, exacerbating flooding conditions in many urban communities worldwide. Excessive runoff from intense precipitation causes devastating property damage, foul water flooding, and leaching of contaminants and nutrients. These contaminants can cause adverse effects on the human body, such as developing cancers and dysregulation of endocrine functions. Similarly, these chemicals cause severe environmental stress and public health concerns such as acidification of water systems. In addition, runoff can erode the soil causing alteration of microbial activities and geochemical processes, causing additional challenges for farmers, landowners, conservation policies, and city planners. In Massachusetts, precipitation is following an upward trend, stressing the importance of generating scientifically grounded information and models that can assist communities in building resilience.

The stormwater runoff was modeled for every 30-meter raster cell in Massachusetts using the Curve Number Method. High-resolution state-wide land use and land cover data and a soils dataset were used to generate cross-tabulations and determine all land use/land cover and soil combinations within the state as depicted below (Figure 16). The unique combinations were used to assign proper curve numbers for each pixel. Outputs were aggregated by sub-basin to assess runoff patterns and determine high-risk communities in Massachusetts.

To evaluate the effect of greening, runoff reduction was calculated using changes in runoff volume under a broadleaf deciduous tree with medium growth modeled for the Northeast by Hynicka and Caraco (2017). The medium, broadleaf assumption is based on a typical tree in urban areas, which are roughly 45' in height and 20 to 30" in DBH (averaging 25") (Bloniarz (USFS)- consultation).

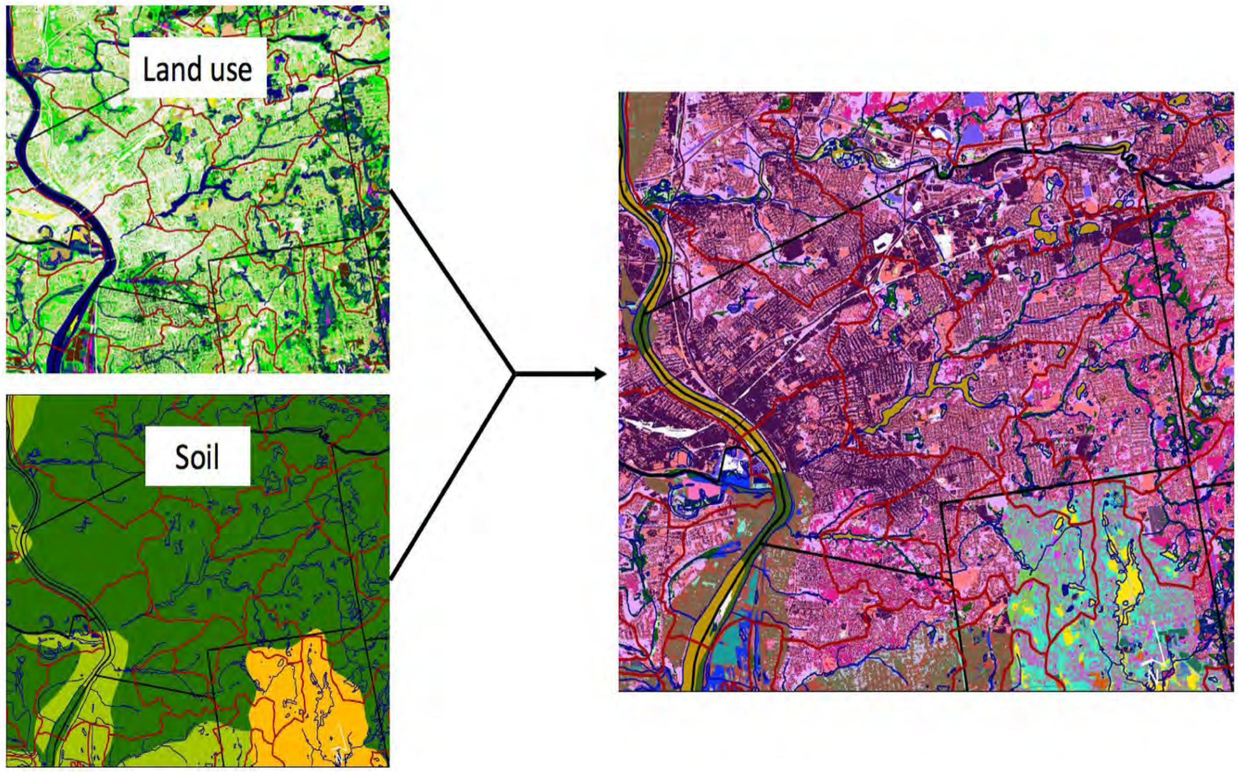


Figure 16: Generation of the high-resolution land use and soil combinations dataset

Runoff patterns and high-risk communities as determined by the models are depicted in the maps below (Figures 17-24). High-risk communities fall along the coast in the Greater Boston region, as well as the Berkshire, Franklin, Hampden, Middlesex, Barnstable, Lower Essex, and center Hampshire counties.

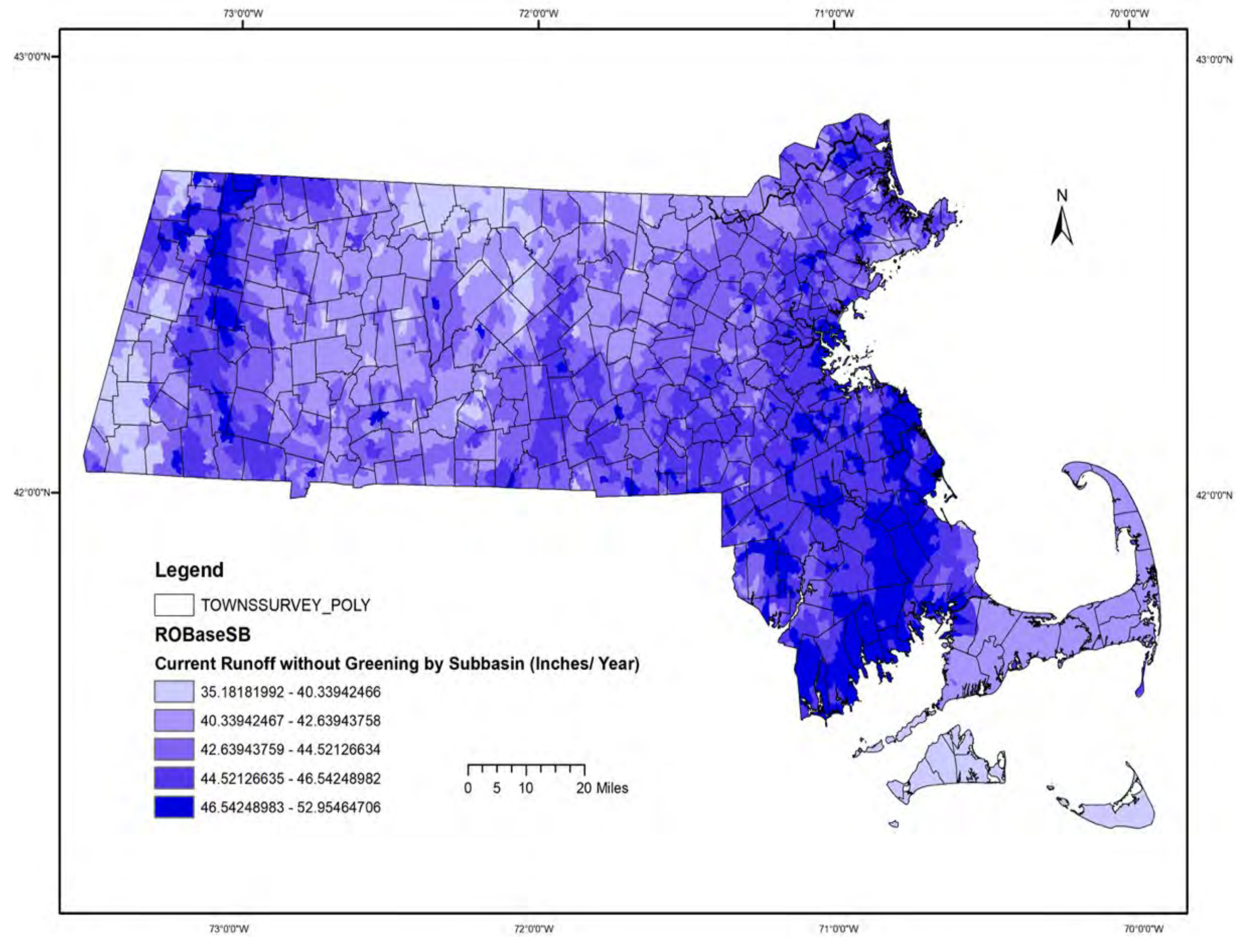


Figure 17: Current Runoff without Greening (By Subbasin)

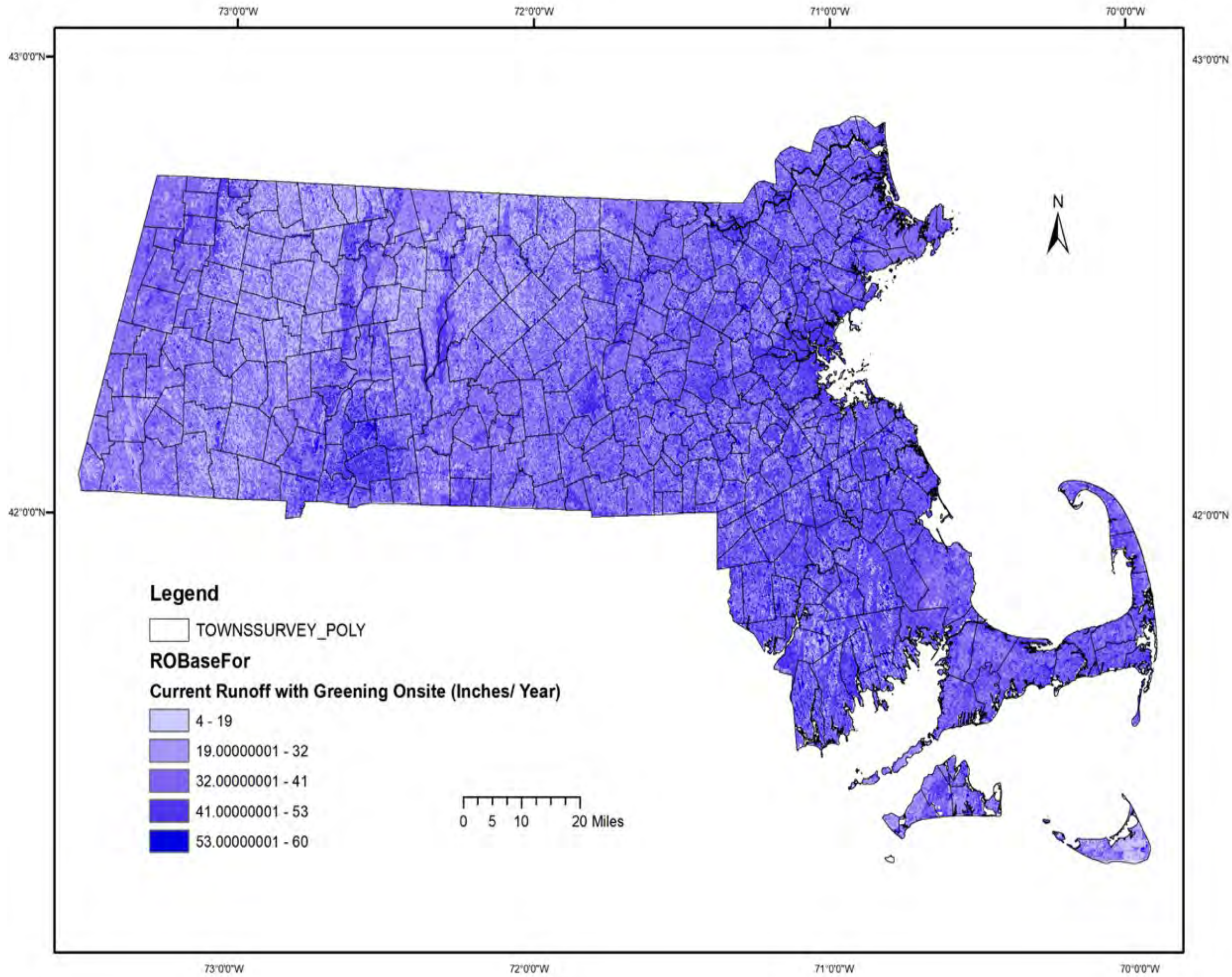


Figure 18: Current Runoff with Greening Onsite

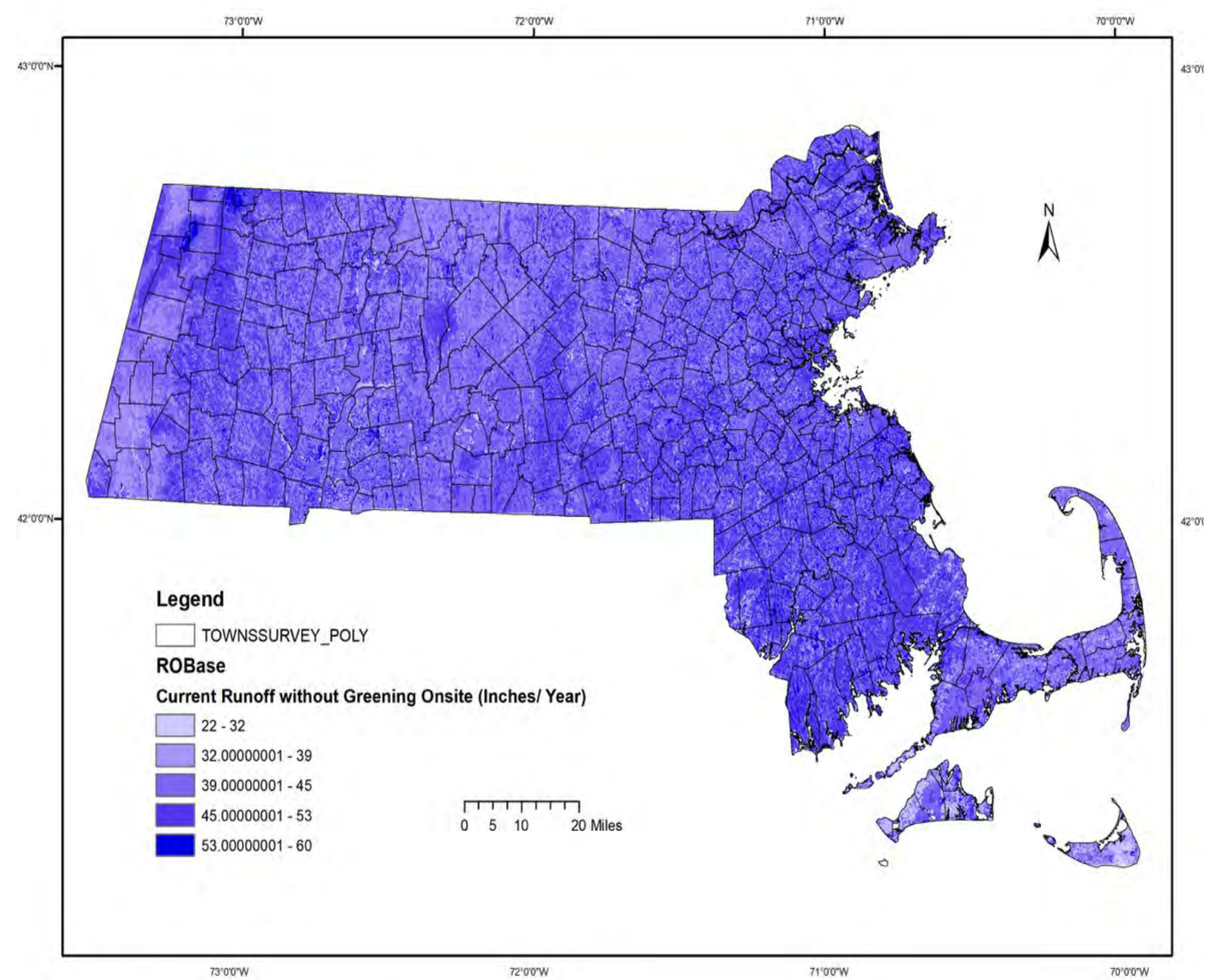


Figure 19: Current Runoff without Greening Onsite

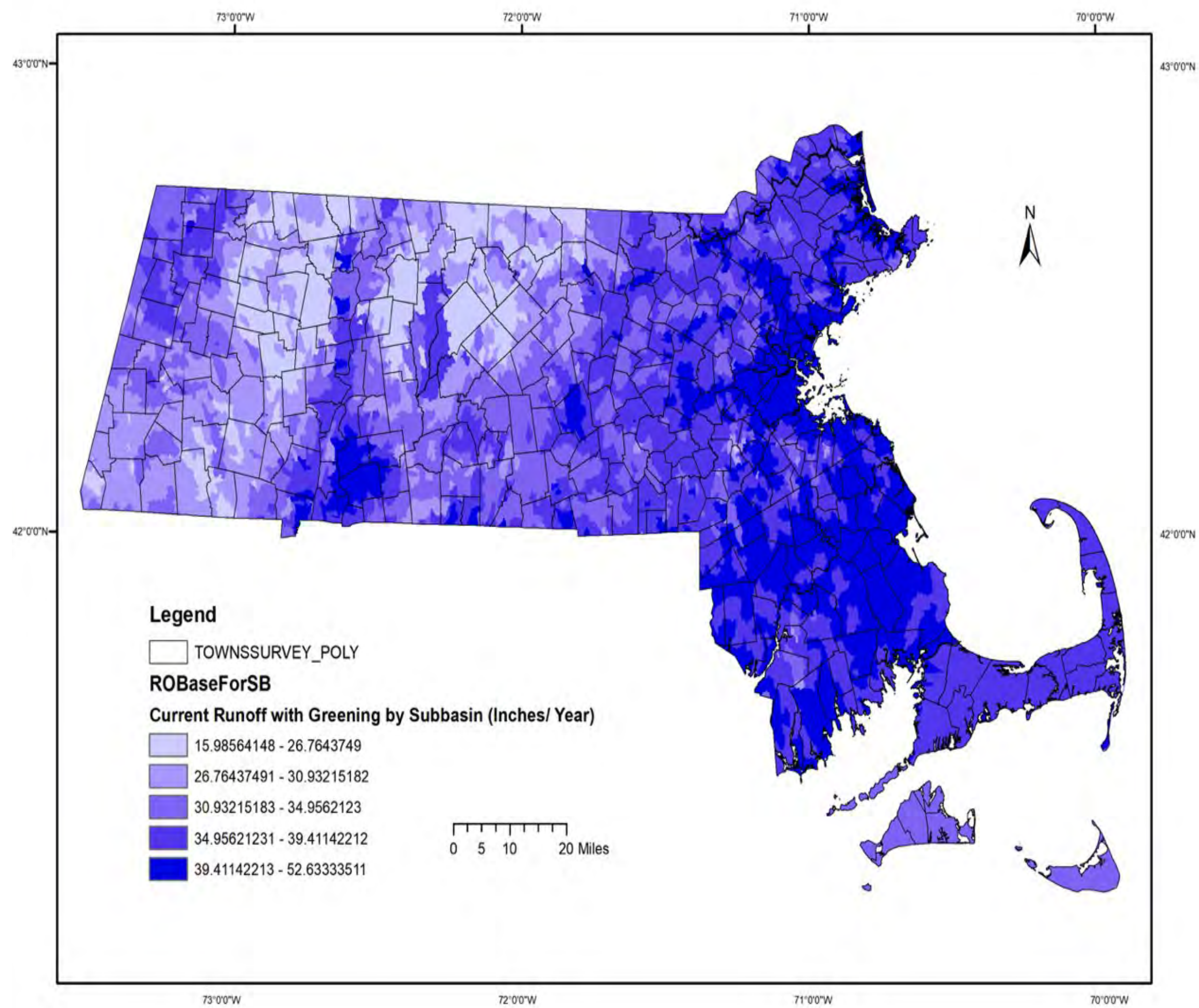


Figure 20: Current Runoff with Greening (By Subbasin)

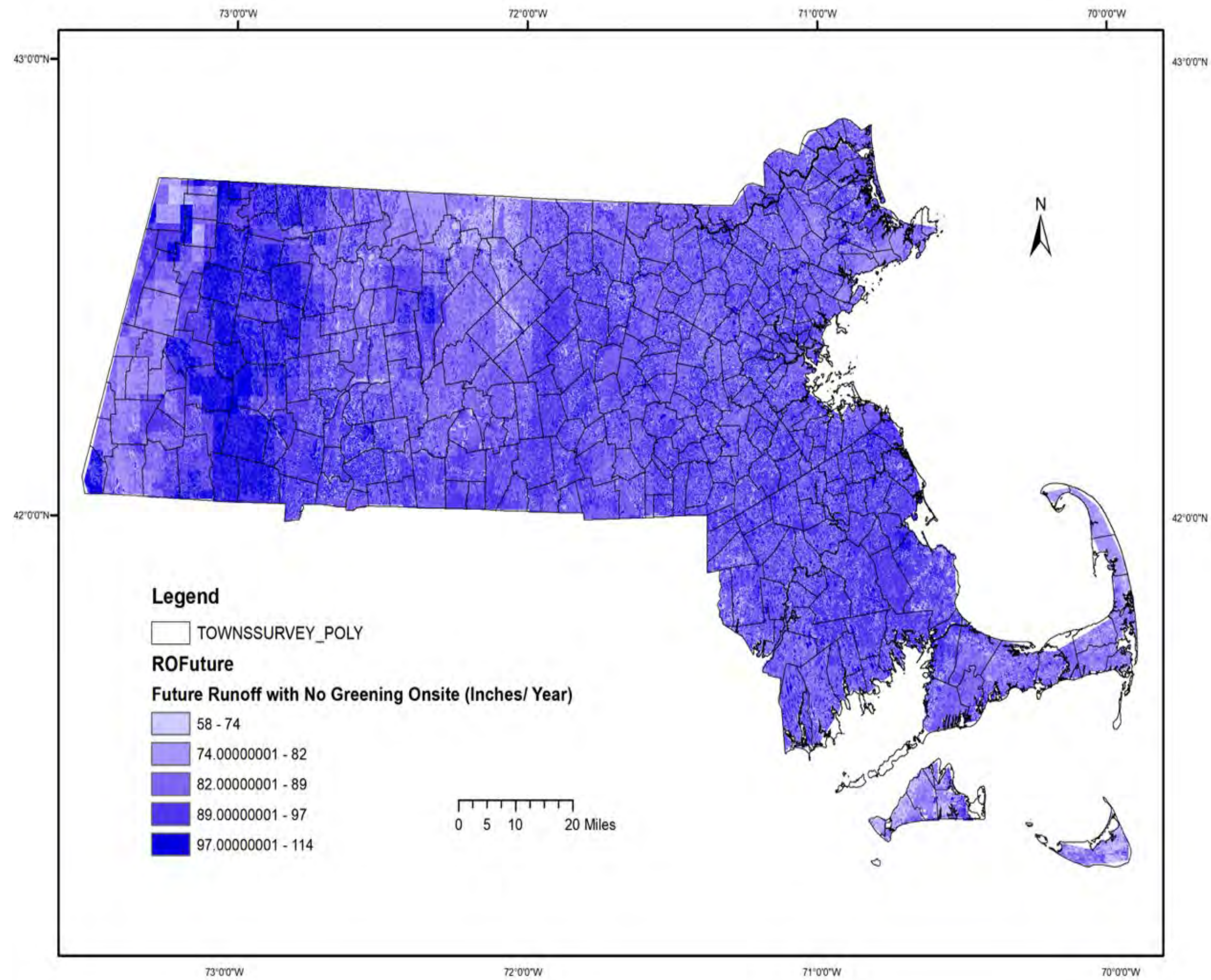


Figure 21: Future Runoff without Greening Onsite

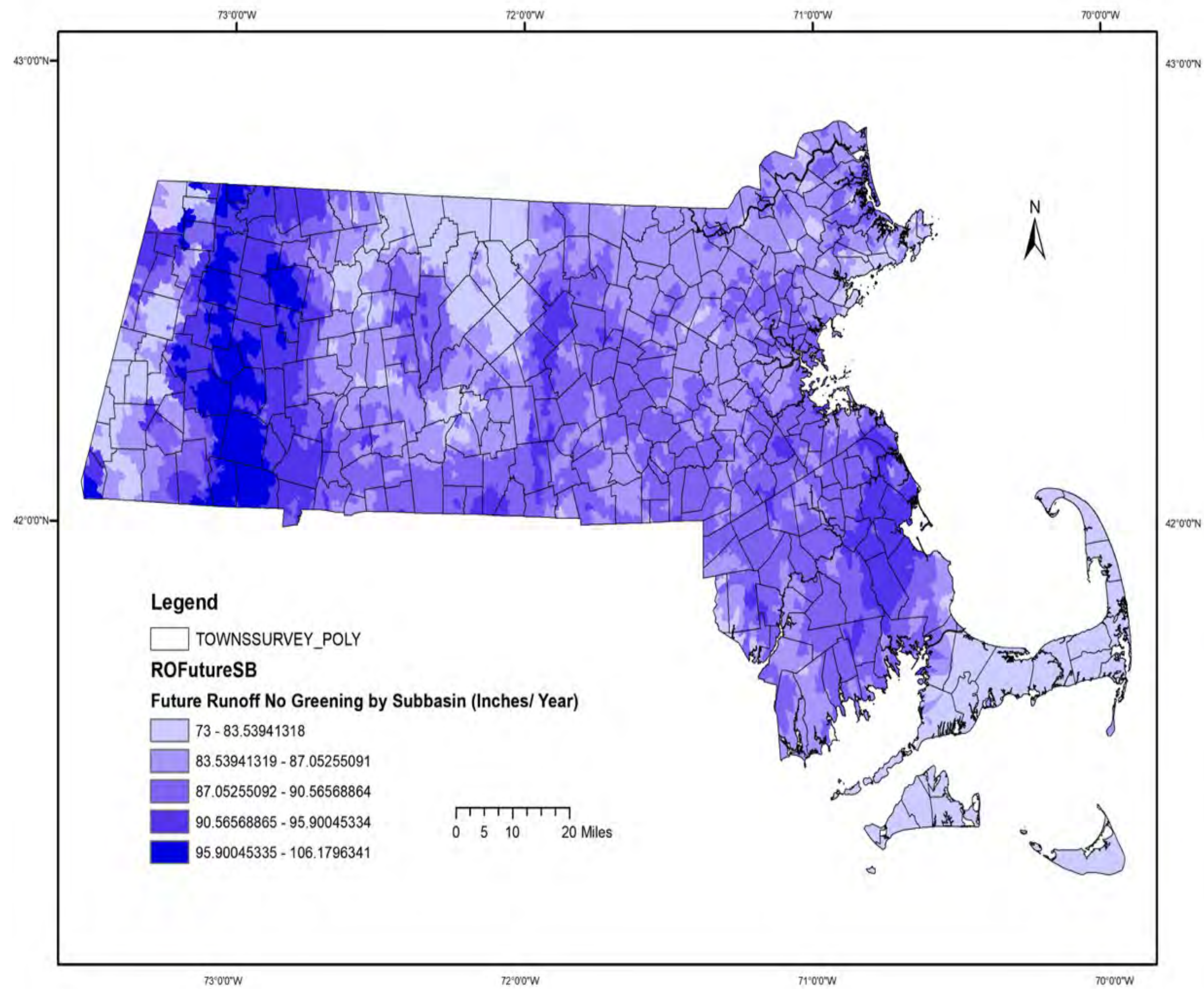


Figure 22: Future Runoff without Greening (By Subbasin)

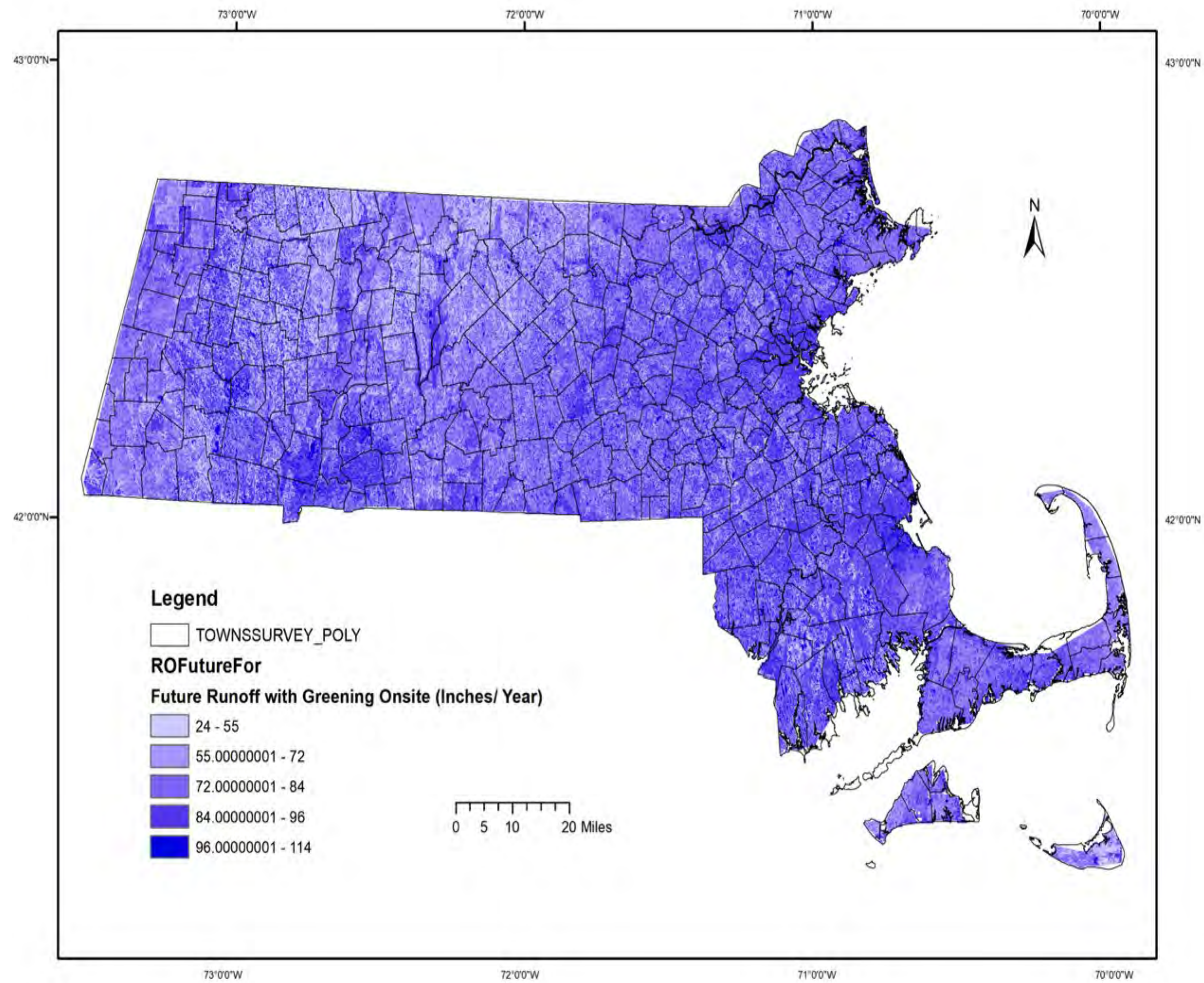


Figure 23: Future Runoff with Greening Onsite

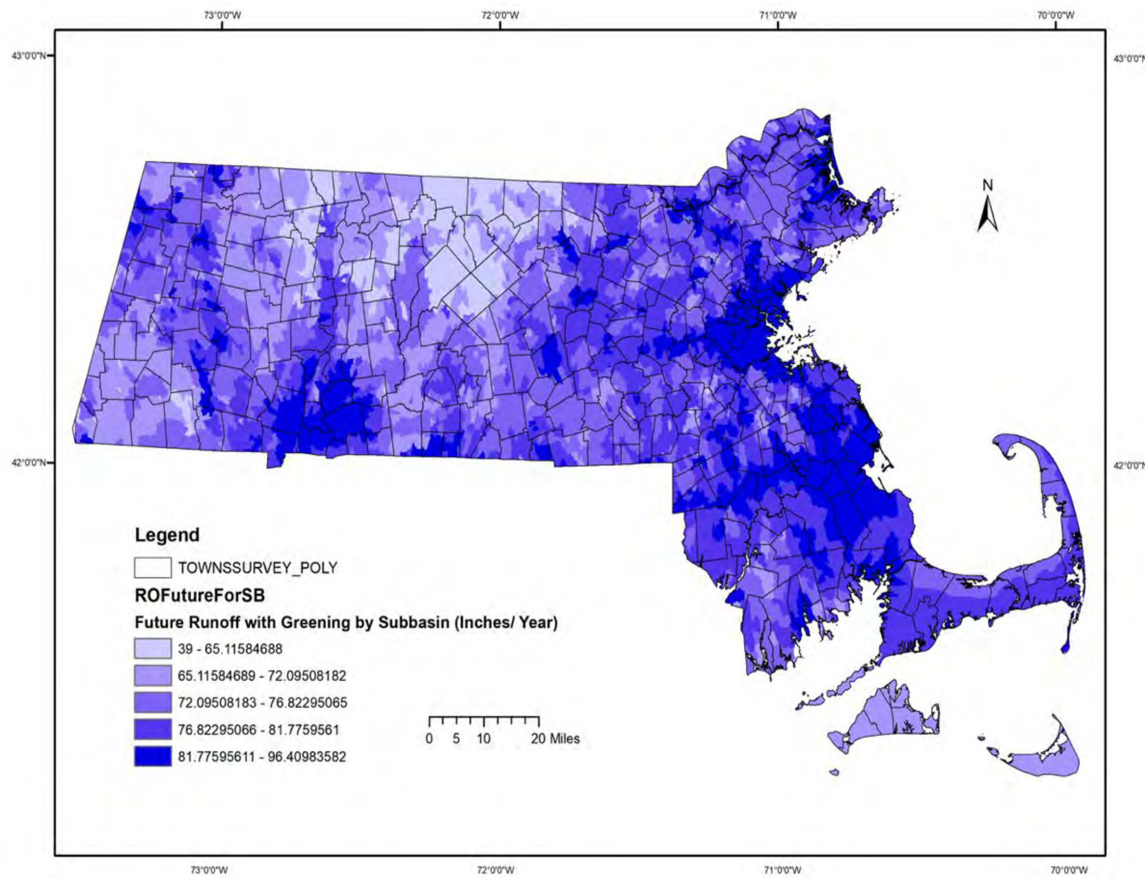


Figure 24: Future Runoff with Greening (by Subbasin)

3.3.3.2 ICARES-DS - Stormwater Runoff

Stormwater runoff calculations use the Runoff Curve Number Method with coefficients adapted to Massachusetts conditions. Greening scenarios are implemented using methods suggested by Hynicka and Caraco (2017) with greening with typical medium-sized, broadleaf trees. These stormwater runoff models (ICARES_StormwaterNow for the current climate and ICARES_Stormwater Future for future climate) are accessible from the following two links:

ICARES_Stormflow Now: https://arcg.is/1y4HC4
ICARES_Stormflow Future: https://arcg.is/1PGDH10

Start by searching for an address or Zoom to the region you are interested in. Click on the location, and information on the estimated runoff in inches per year will be displayed in the pop-up window. The model is being improved to add specific benefits of urban forests in mitigating stormwater runoff in urban areas. Sample maps are shown in Figures 25-28. The ICARES modules will be compiled on an ICARES website. Screenshots of both models at state and city scales are presented in the following pages.

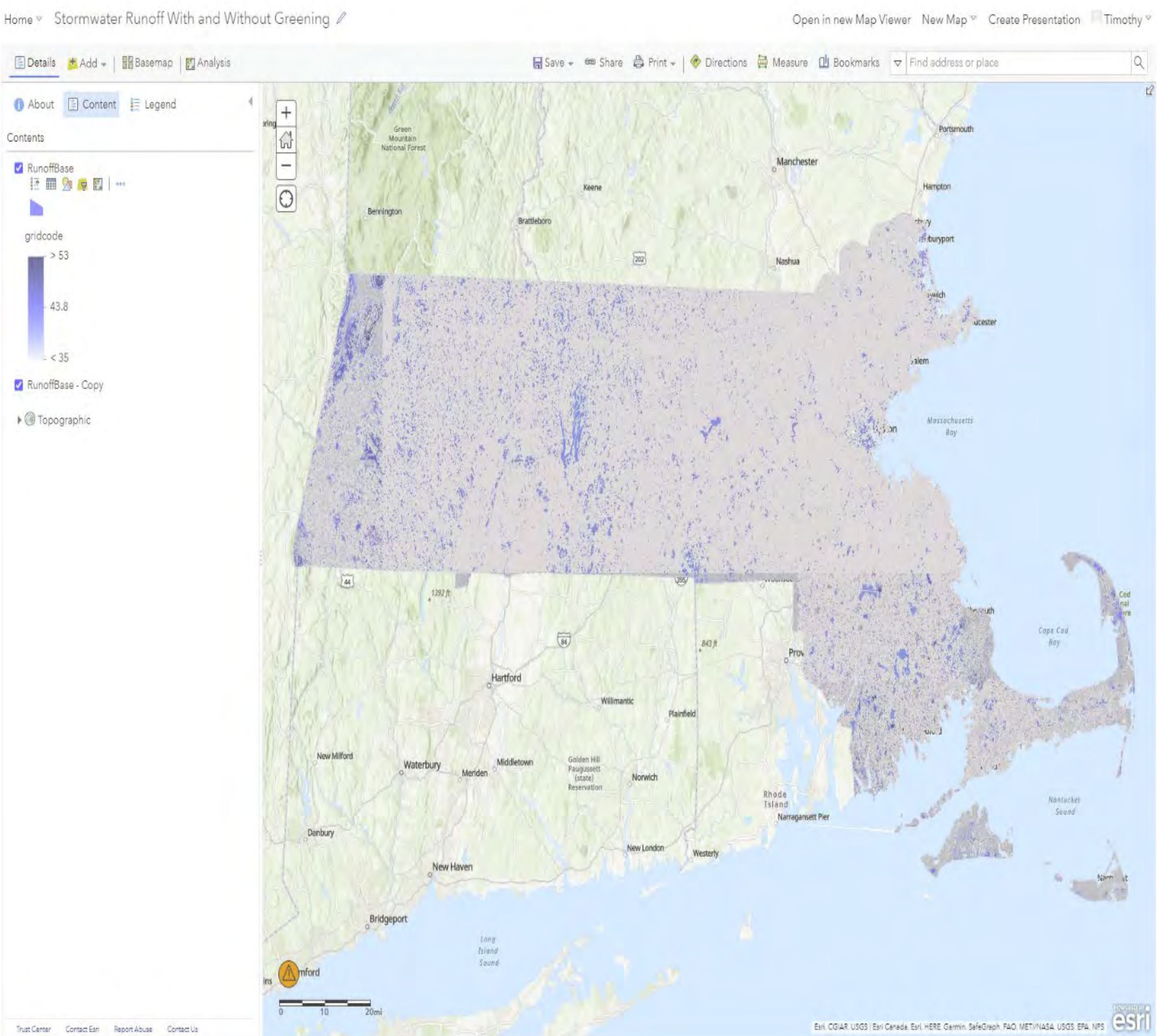


Figure 25: ICARES Stormwater Runoff current Baseline

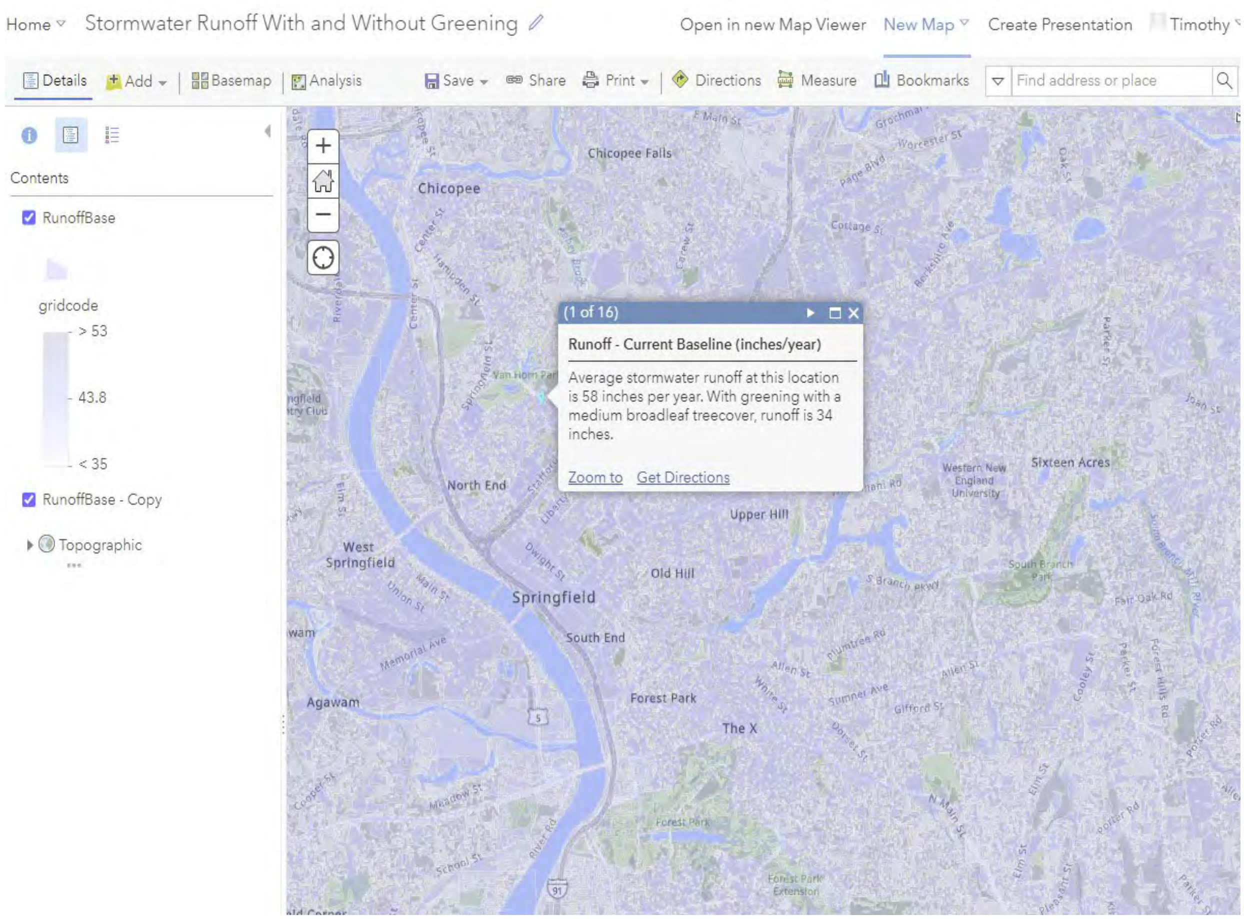
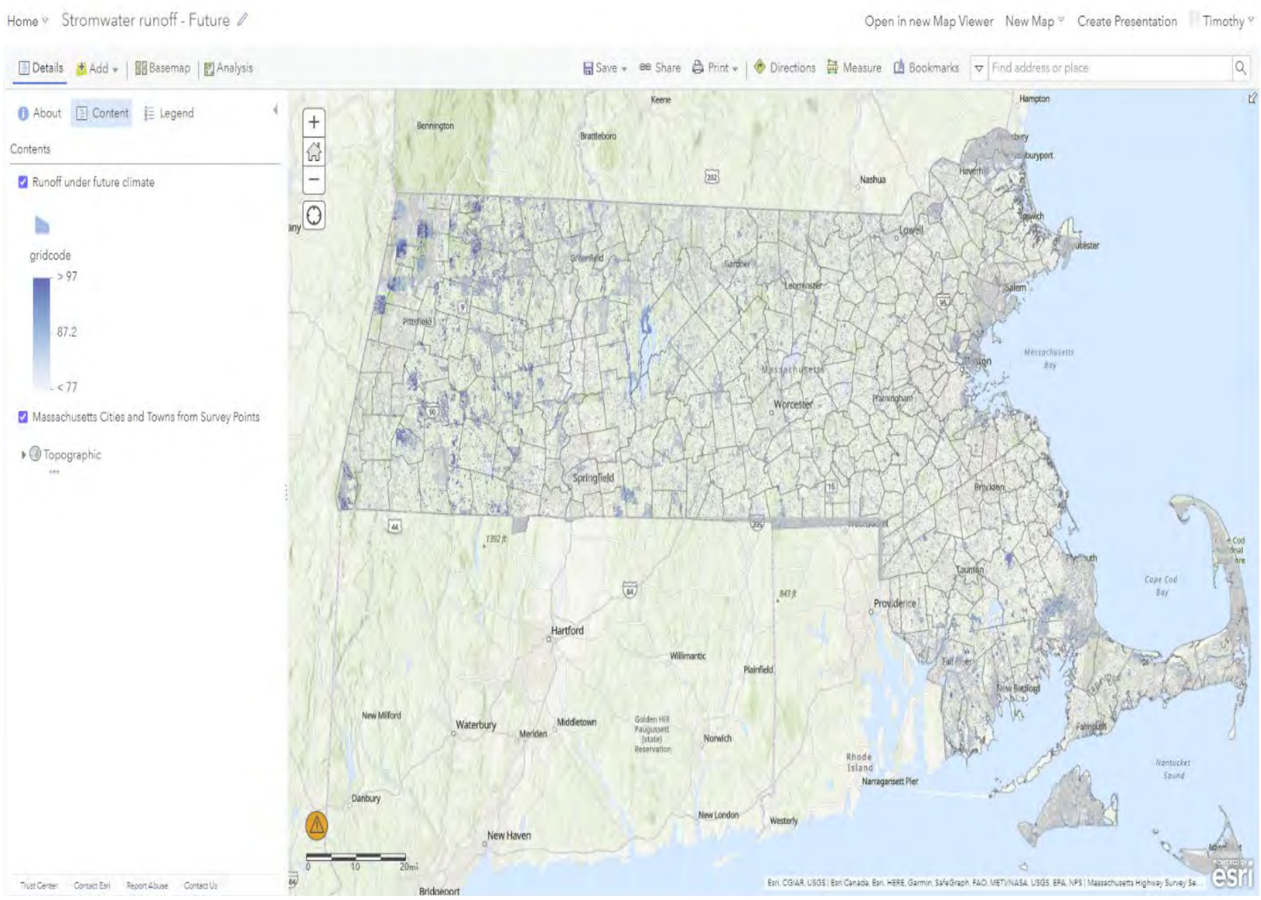


Figure 26: ICARES Stormflow zoomed in to location with pop-up of the current Baseline for region



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Hartford
Providence
Waterbury
New Haven

Figure 27: Future runoff for Massachusetts

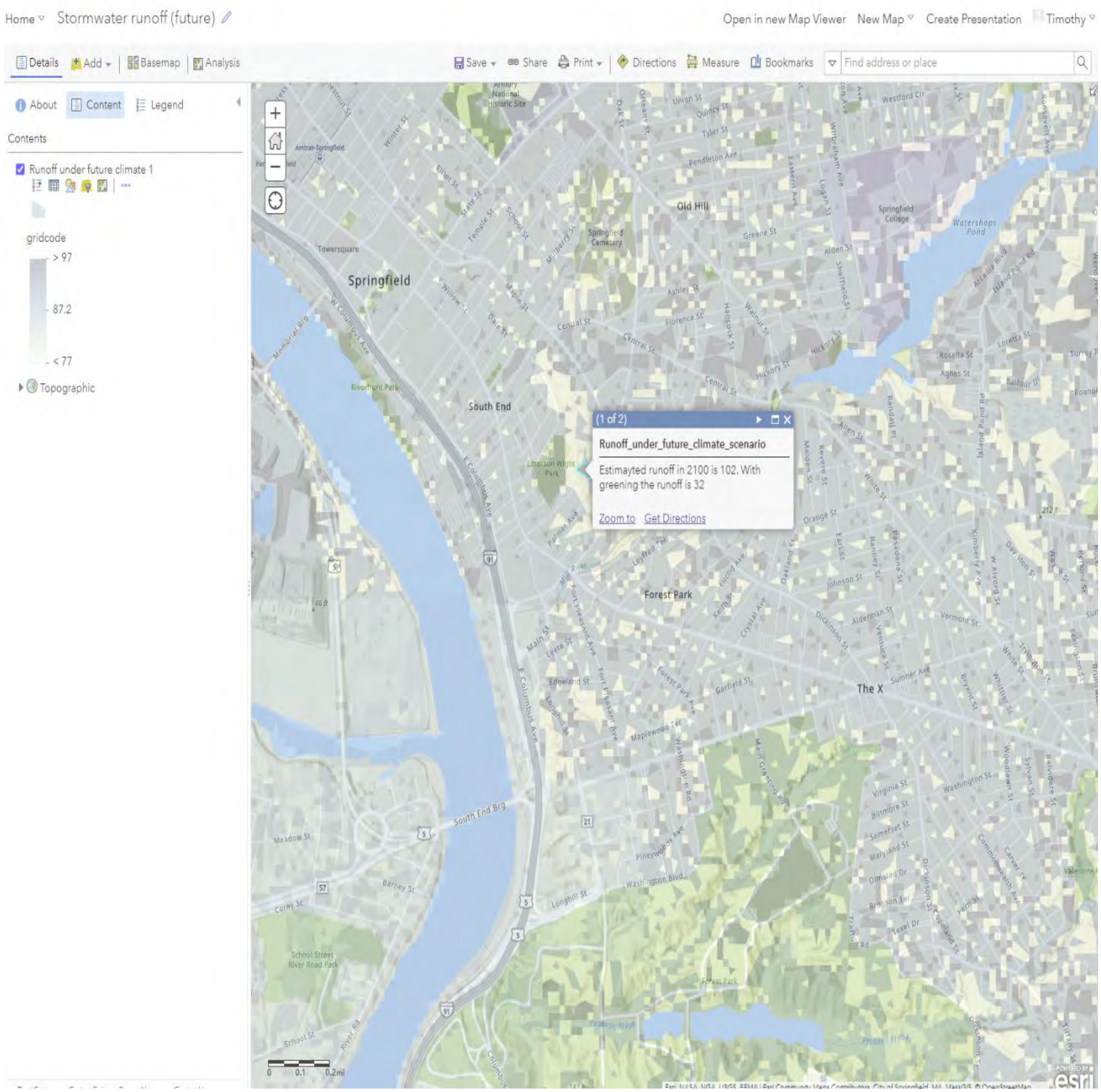


Figure 28: Future runoff for Massachusetts zoomed in to sample location with a pop-up indicating estimated runoff

3.3.4 Urban Heat Island Mitigation Potential

3.3.4.1 Urban Heat Island Modeling

Global temperatures have increased by 1.14^{o}C over the last 40 years, with a projected additional increase of 0.2^{o}C every decade. In urban communities where there are levels of impervious cover, solar energy is absorbed and re-radiated in the form of heat, causing average urban air temperatures that are substantially higher than surrounding communities. Temperatures that began to exceed normal community levels resulted in excess heat-related morbidity and mortality, exacerbation of mental health disorders and cardiovascular diseases, and disruption to the productivity and quality of landscapes. In addition to these severe implications for public health and conservation, energy demands and cooling costs have increased, placing many vulnerable communities at disproportional risk.

The following tools were developed using extensive climate data in Massachusetts over the past 30 years and GCM climate projections from CCMP4-AR5. The datasets were used in combination with Spatial Analysis tools in ArcGIS to compute the distribution of current and future heat islands in Massachusetts. The data were subdivided into 16 quintiles. The current heat island for Massachusetts is shown in Figure 29. Future trends are depicted in Figure 30.

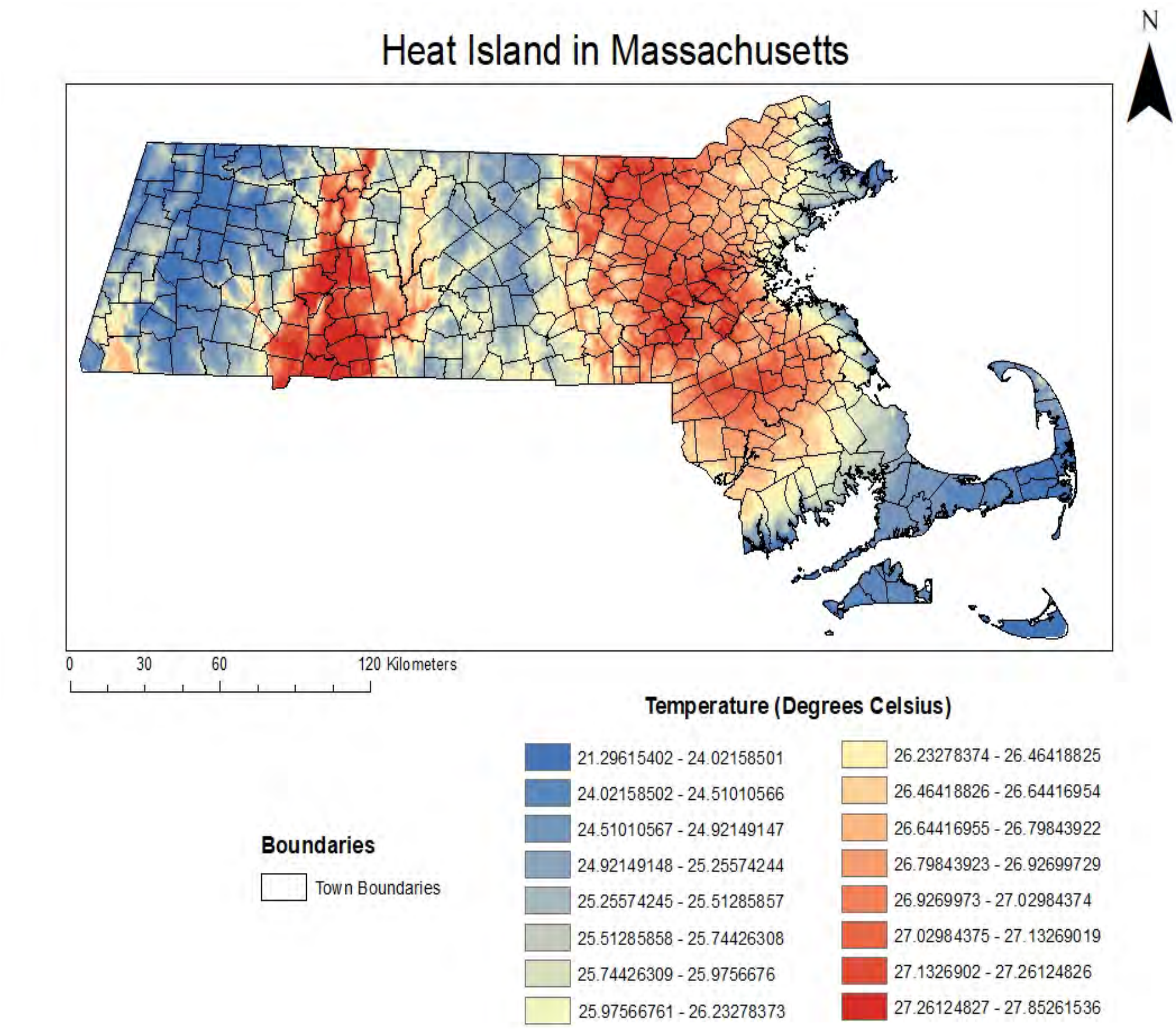


Figure 29: Current heat island in Massachusetts

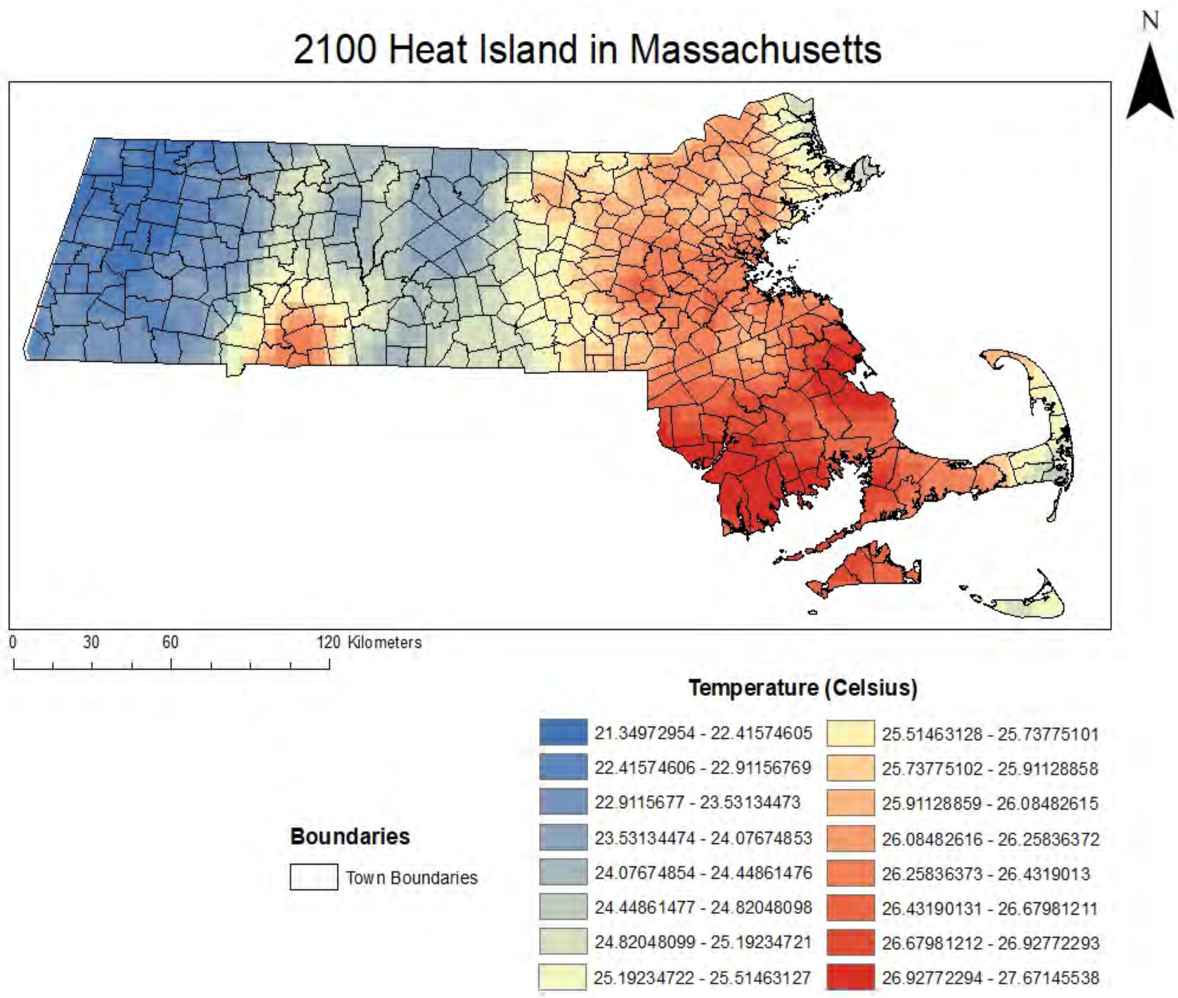


Figure 30: Future Heat Island in Massachusetts

To determine current and future sites with top 25% vulnerability in Massachusetts, the top four quintiles were selected to depict the top quartile of vulnerability and are presented in Figure 31 and Figure 32. Current communities in Western Massachusetts with elevated risk fall within the Greater Springfield, Hampshire, and Franklin counties. These regions have high percent imperviousness compared to surrounding communities. Similarly, on the Eastern side of Massachusetts, the current heat island spans primarily across the Middlesex, Norfolk, Plymouth, Bristol, and Suffolk counties, with some communities in the Essex and Worcester regions also falling within the top quartile of vulnerability. By 2100, the heat island is projected to shift South and affect other communities in the Barnstable and Dukes counties.

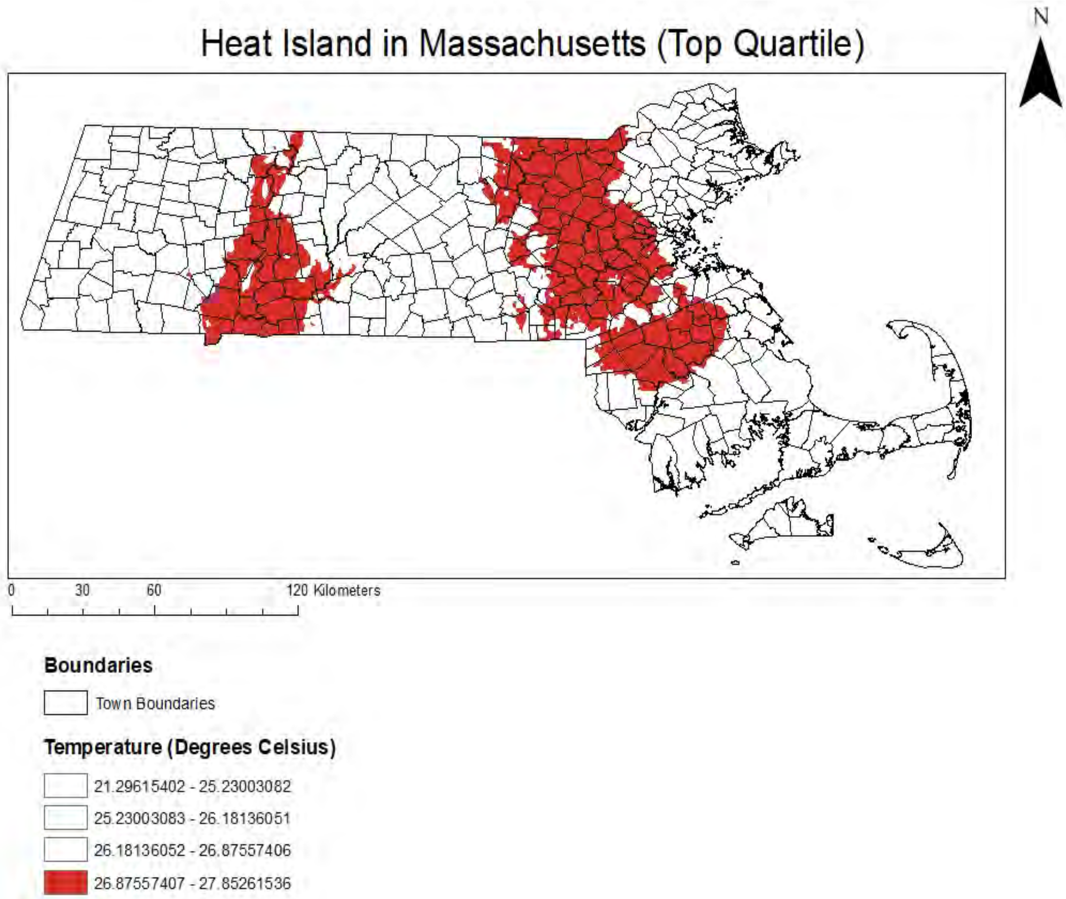


Figure 31: Current top quartile of vulnerability

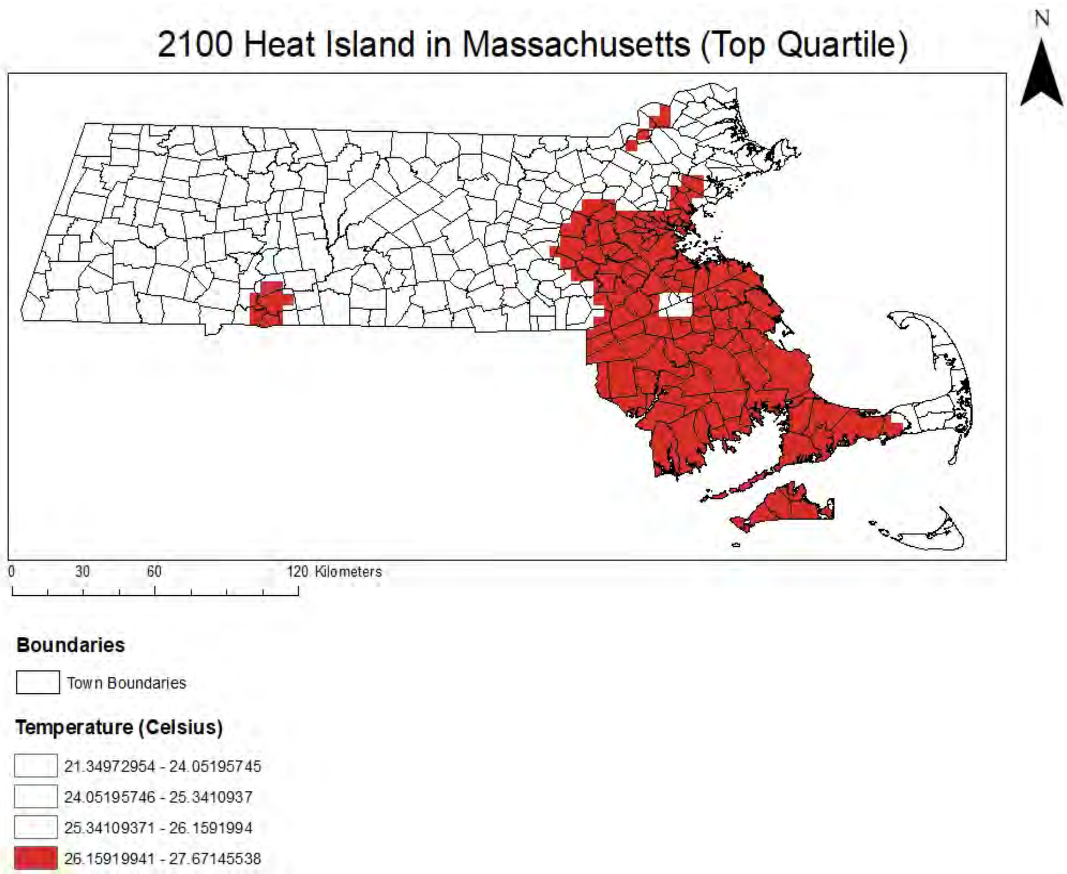


Figure 32: Future progression of vulnerable communities Massachusetts

3.3.4.2 ICARES-DS HEAT ISLAND

In addition, in support of the online decision support tool, these heat map models (ICARES_HeatNow for current climate and ICARES_HeatFuture for future climate) are tentatively accessible from the following two links:
ICARES_HeatNow: https://arcg.is/1zuz0S
ICARES_HeatFuture: https://arcg.is/DzH5W
Start by searching for an address or Zoom to the region you are interested in. Click on the location, and information on the quartile range of the summer heat Island will be displayed in the pop-up window. The model is being improved to add specific benefits of urban forests in mitigating the heat island effect in urban areas. The ICARES modules will be compiled on the ICARES website. Screenshots of both models at state and city scales are presented on the following pages (Figures 33-36).

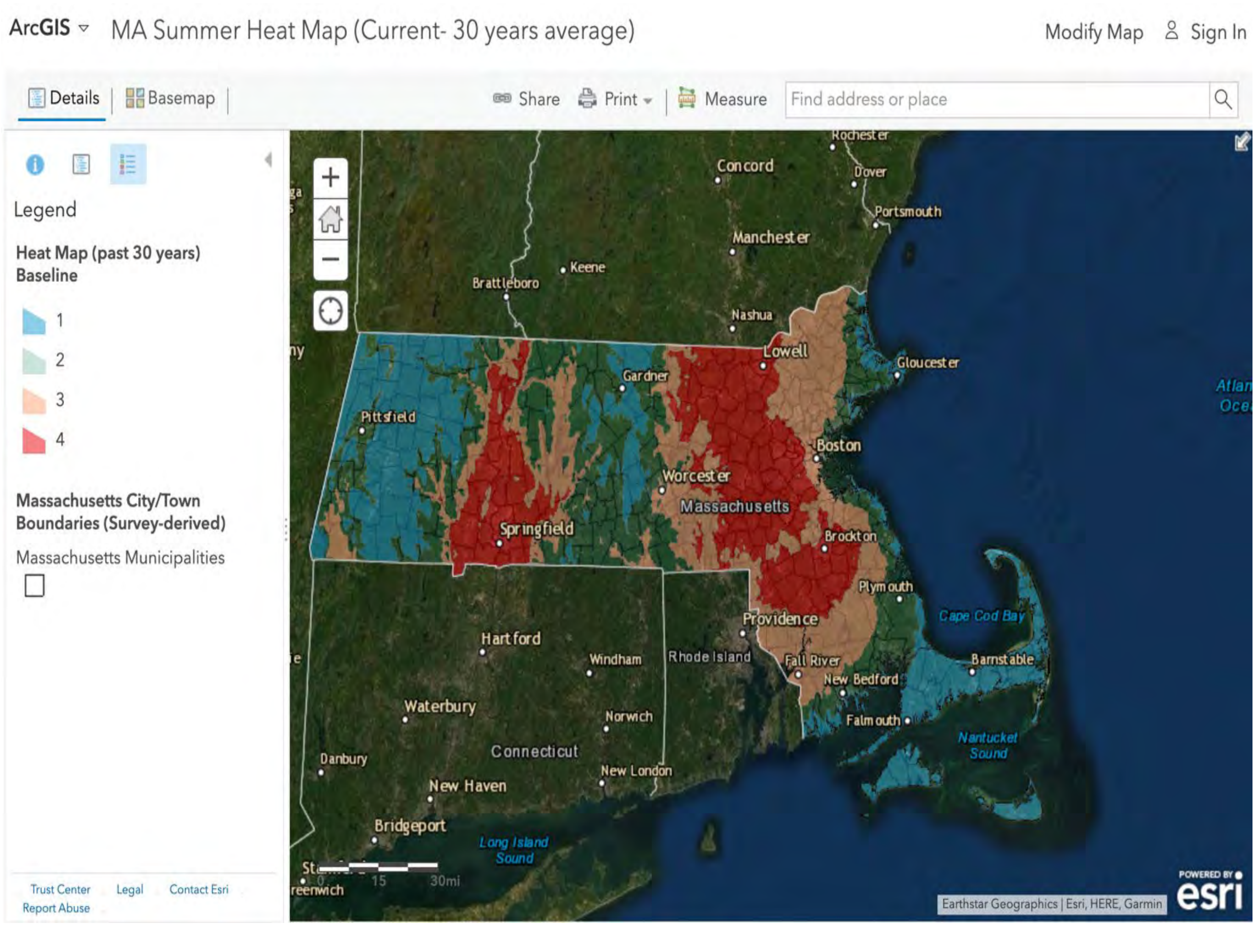


Figure 33: ICARES_HeatNow - Massachusetts

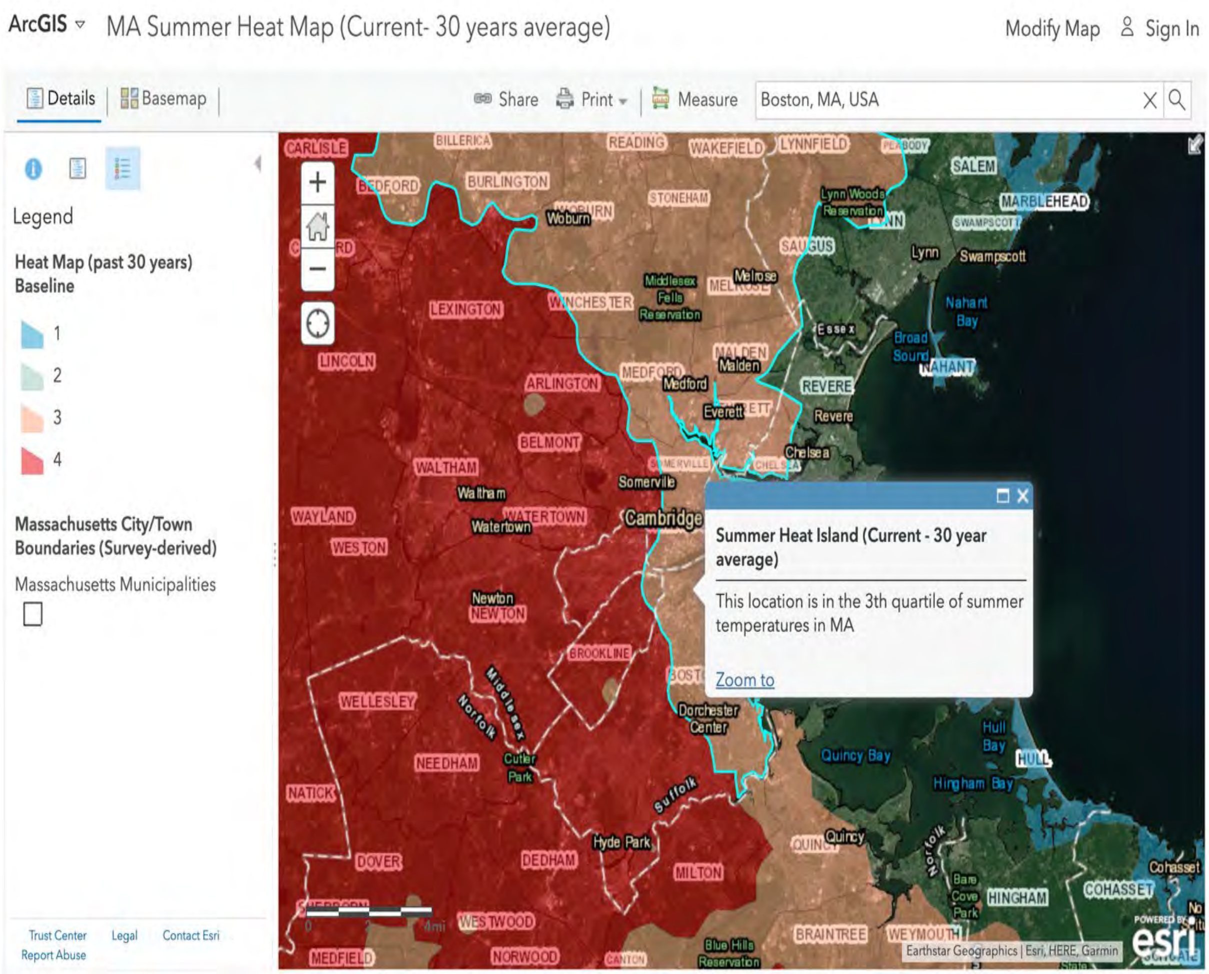


Figure 34: ICARES_HeatNow - Zoomed

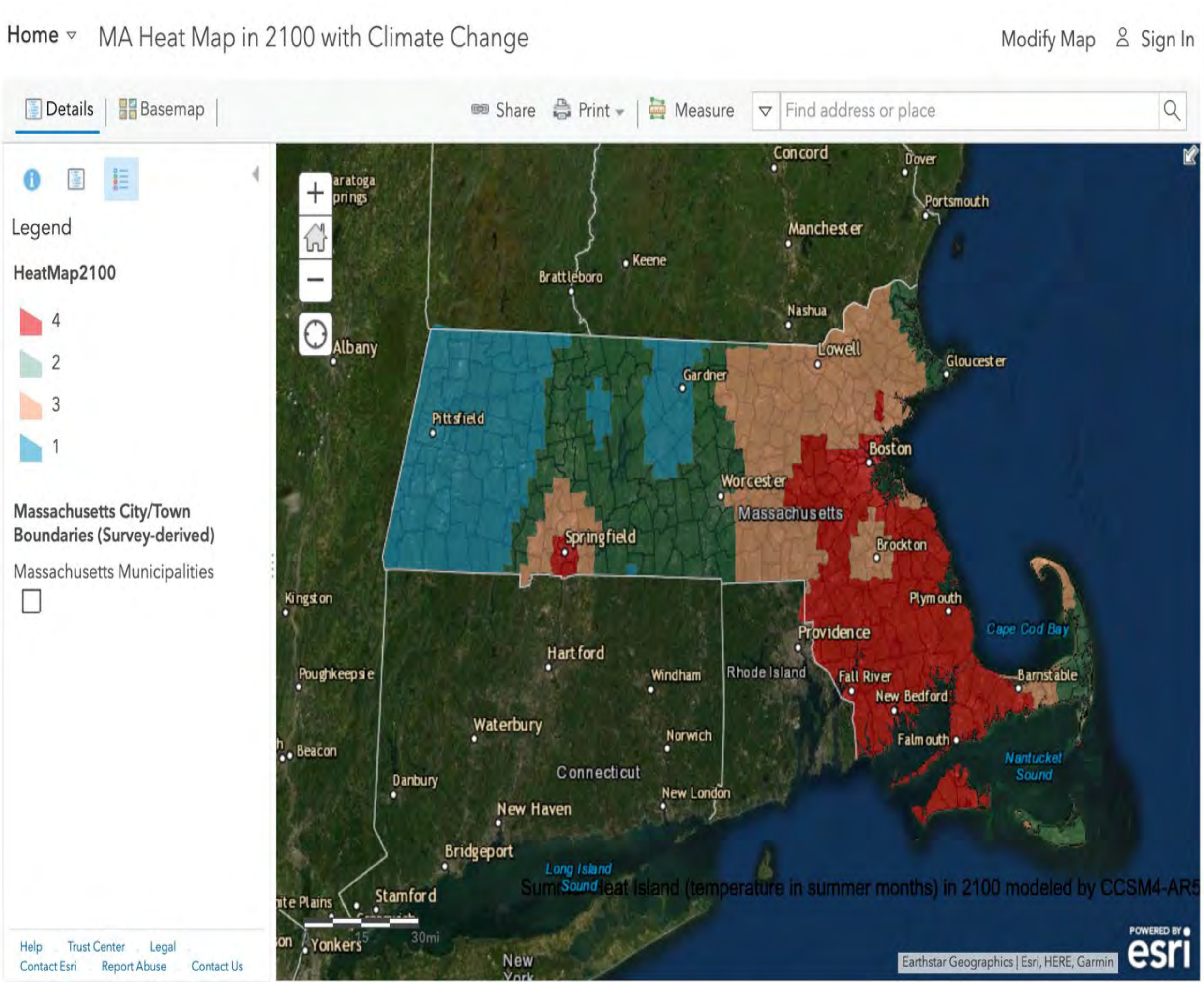


Figure 35: CARES_HeatFuture - Massachusetts

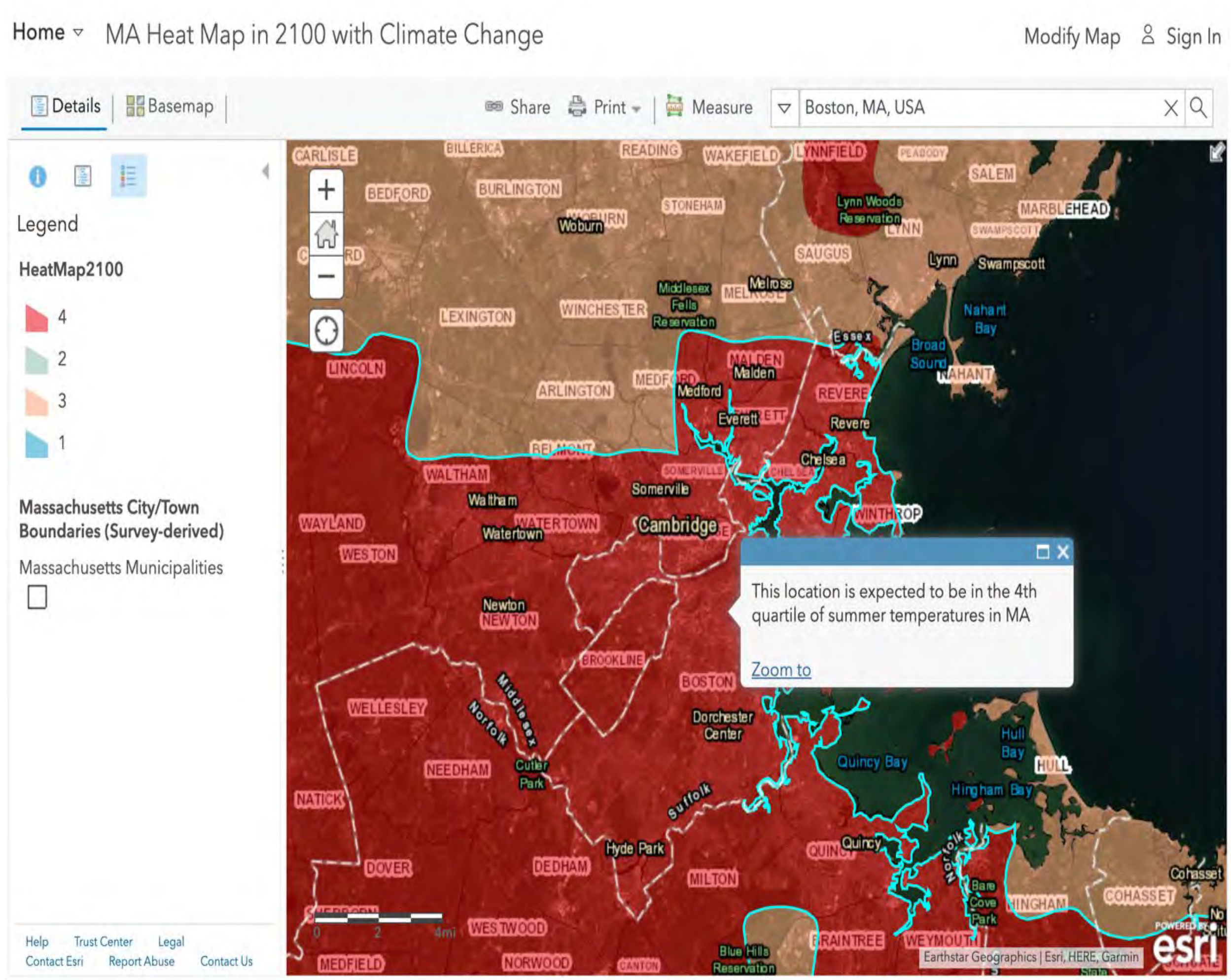


Figure 36: CARES_HeatFuture - Zoomed

3.3.4.3 PREDICTIVE MODELING

To quantify the relationship between temperature and tree canopy and determine the mitigative properties of urban forests, a combination of linear regression analyses in ArcGIS and neural networks in the JMP platform was employed. High-resolution temperature data for Massachusetts urban areas were joined with the NLCD tree canopy and percent imperviousness datasets. Analyses were run at the intercity and intracity levels. The intercity level analysis included all Massachusetts urban areas as presented in the first map below. Intracity analyses focused on the 26 Gateway cities of Massachusetts (Attleboro, Barnstable, Brockton, Chelsea, Chicopee, Everett, Fall River, Fitchburg, Holyoke, Haverhill, Lowell, Lynn, Lawrence, Leominster, Malden, Methuen, New Bedford, Northampton, Peabody, Quincy, Revere, Salem, Springfield, Taunton, Westfield, and Worcester) as well as Boston, West Springfield, Pittsfield, and Cambridge.

Ordinary least-squares linear regression algorithm was performed with intercity level data first. The model could be represented as follows: $Y = 26.300305 + 0.002743X1 – 0.000099X2$, where Y represents the temperature in degrees Celsius, X1 represents percent imperviousness, and X2 represents percent canopy cover. The probability and robust probability were statistically significant for all terms ($p<0.01$). However, the adjusted R-squared for the model was 0.008046. This indicates that the model could only explain less than 1% variability in the dependent variable. It is possible that these results are because the temperature is a regional phenomenon rather than a local phenomenon. In addition, site-specific differences cannot be detected on a state-wide scale.

Therefore, the regression algorithm was used to assess intracity differences in the 30 individual Massachusetts cities. The OLS model results varied substantially across cities. For example, adjusted R-squared values ranged from 0.002465 for the city of Taunton and 0.505652 for the city of Lynn. These results show that a linear regression model can explain up to 50% of the variability in intracity analysis for the state of Massachusetts.

Non-linear predictive modeling was performed using neural networks, as represented below. The diagram depicts the structure of the best fit neural model featuring one layer of 3 TanH nodes. The neural network model for the predictive modeling is shown in Figure 37.

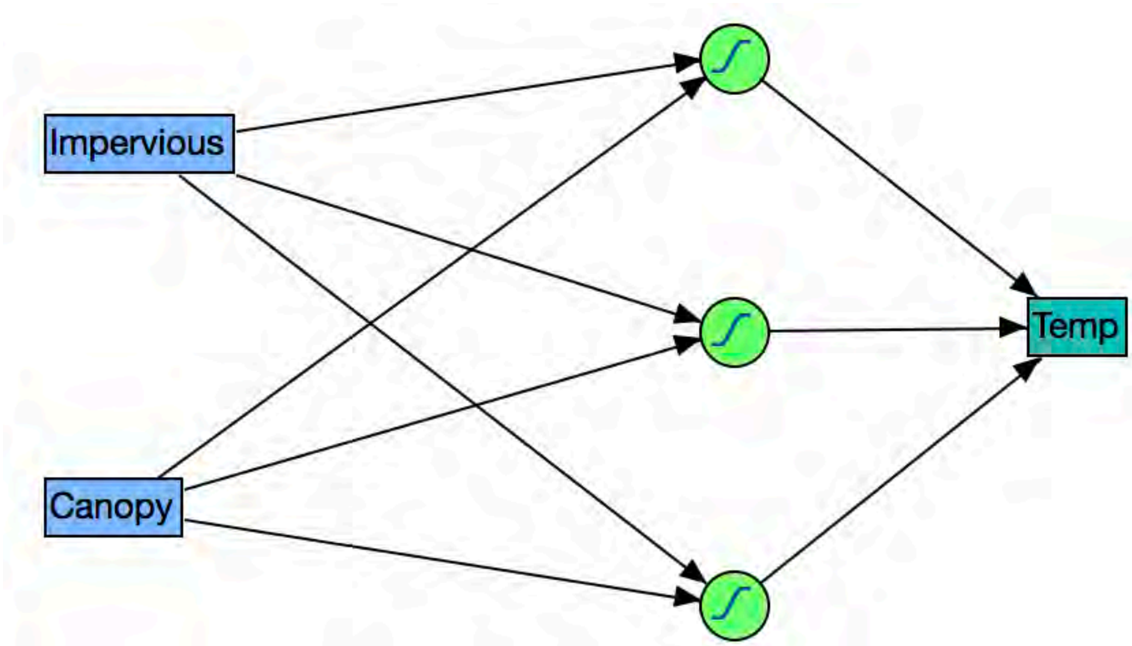


Figure 37: Neural Network Model

Non-linear predictive modeling was found to explain greater variability in temperature than linear regression. The R-squared values at the intracity level ranged from 0.0324916 for Taunton to 0.6530902 for Lynn, indicating that a non-linear predictive model can explain up to 65% of the variability in the dependent variable. The prediction profilers and contour profilers for Massachusetts Urban Areas are presented below in Figure 38 and Figure 39.

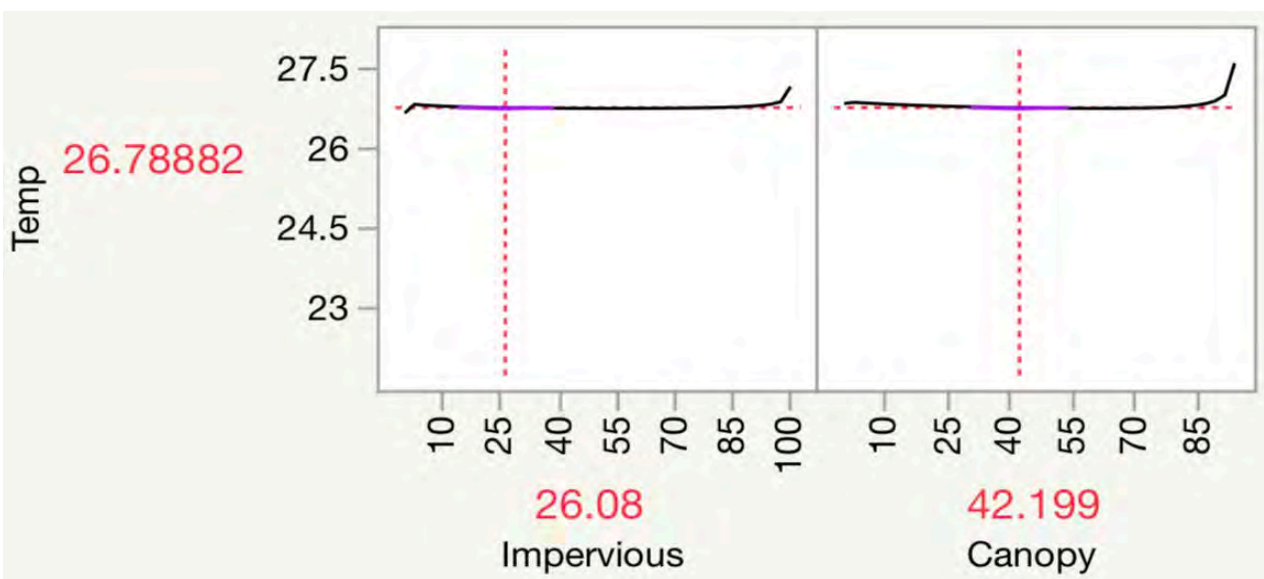


Figure 38: Massachusetts Urban Areas Prediction Profiler

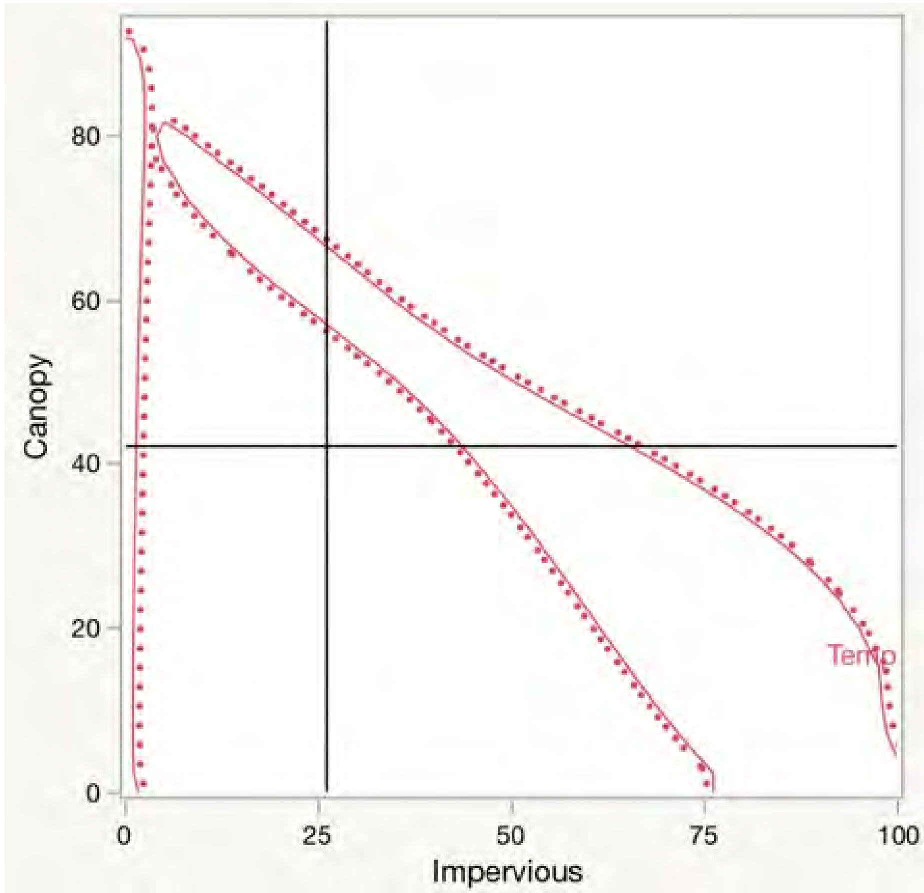


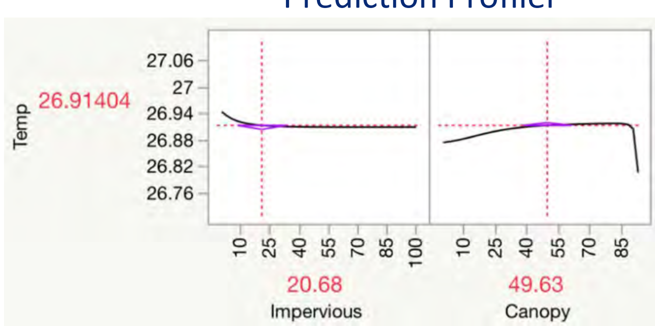
Figure 39: Massachusetts Urban Areas Contour Profiler

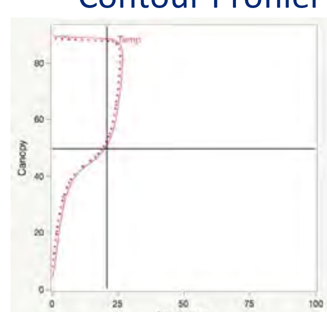
The outputs for the non-linear predictive modeling at the intracity level data have been compiled into separate PDF documents. Each PDF document includes model inputs and outputs for each city and information on the model's performance. The prediction profilers and contour profilers for each city are included below in Figure 40.

Prediction Profiler

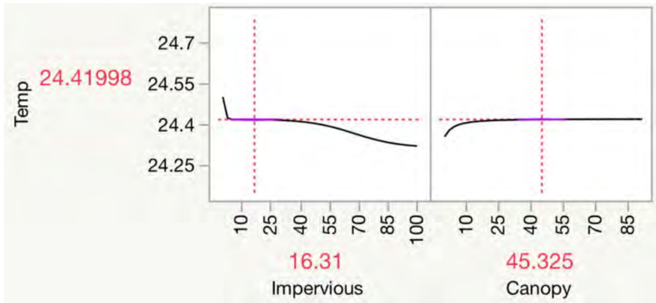
Contour Profiler

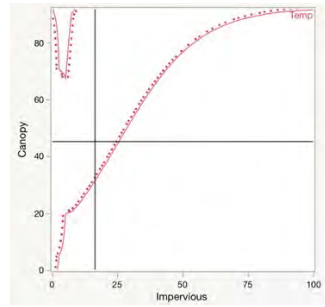
Attleboro



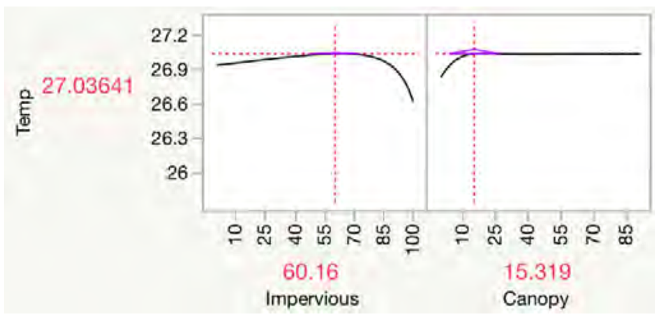


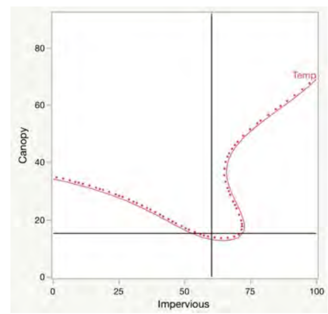
Barnstable



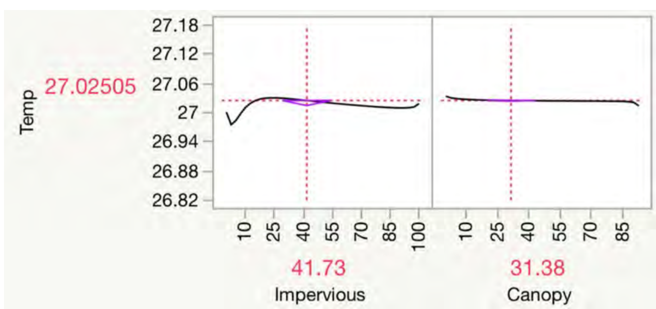


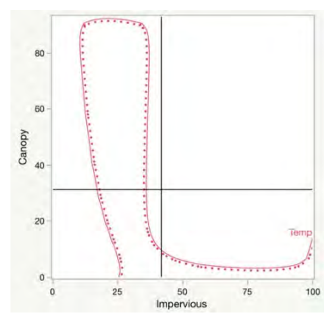
Boston



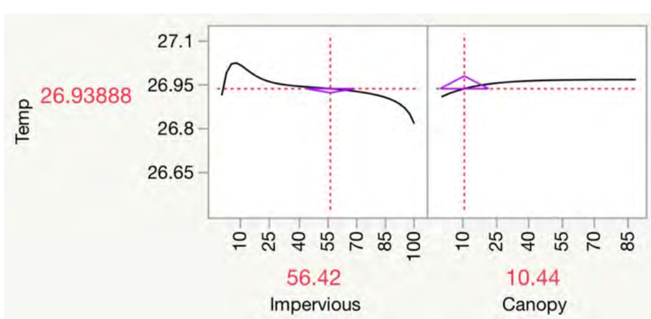


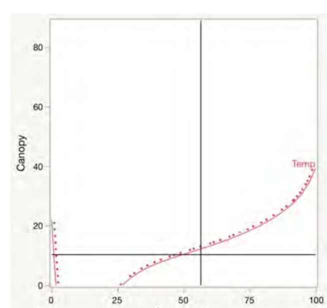
Brockton



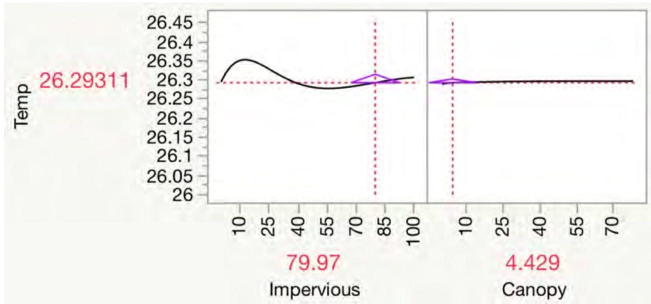


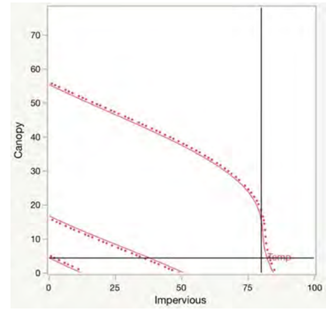
Cambridge



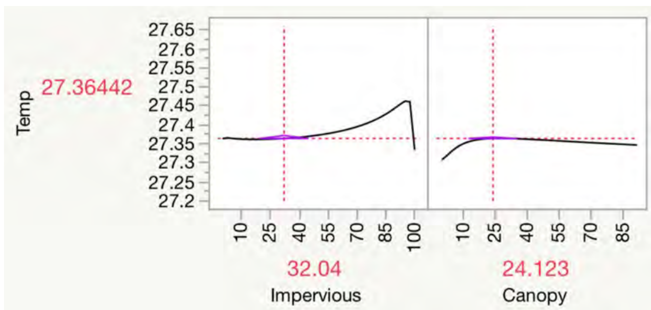


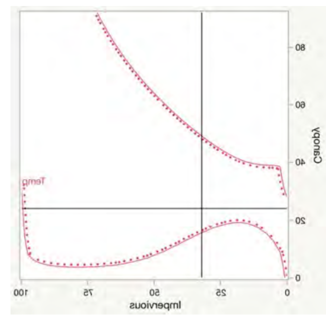
Chelsea



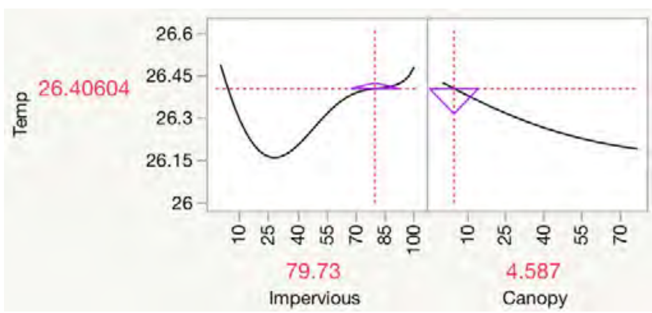


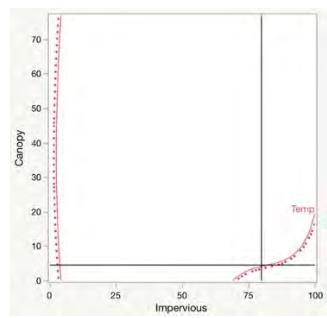
Chicopee



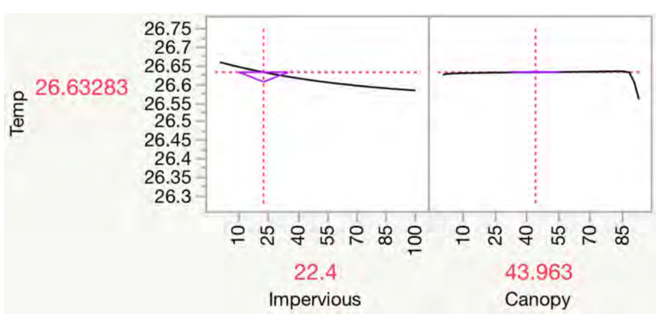


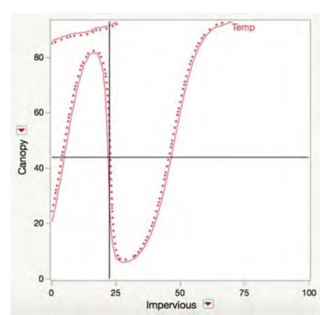
Everett



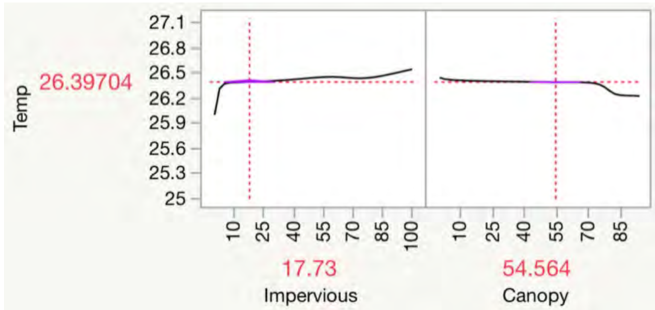


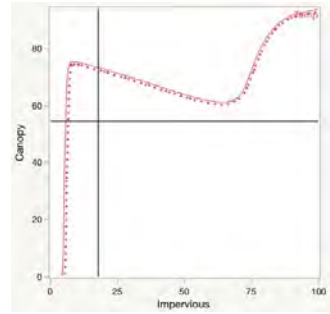
Fall River



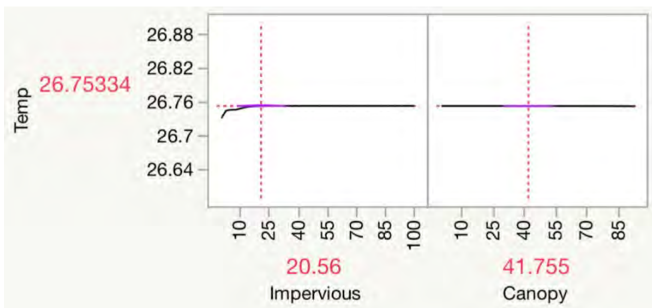


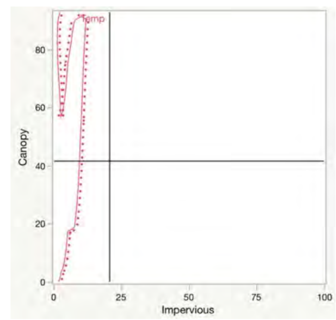
Fitchburg



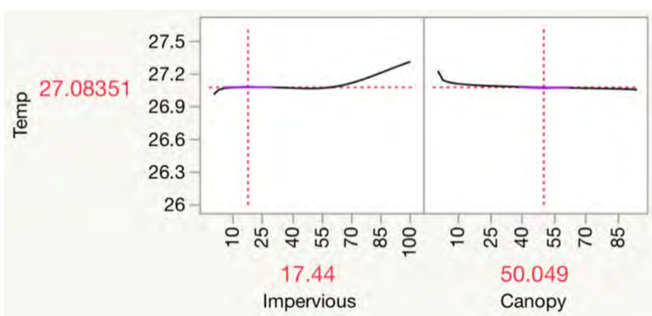


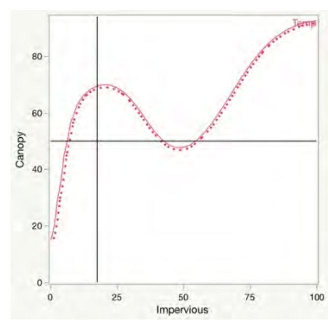
Haverhill



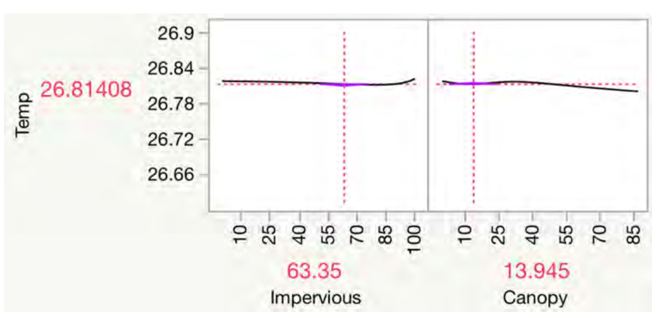


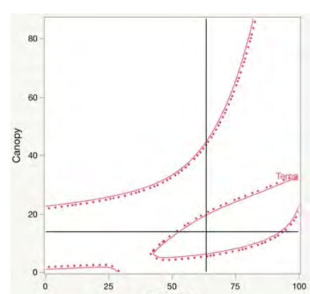
Holyoke



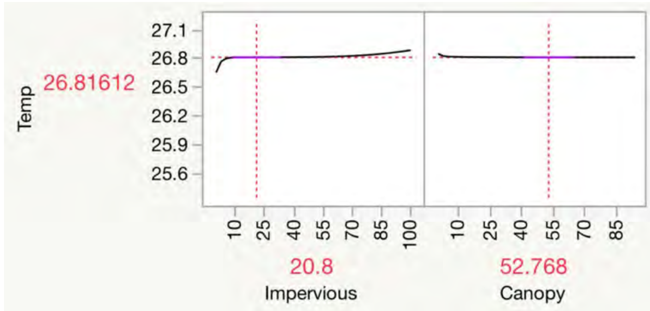


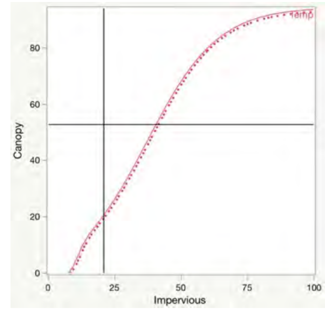
Lawrence



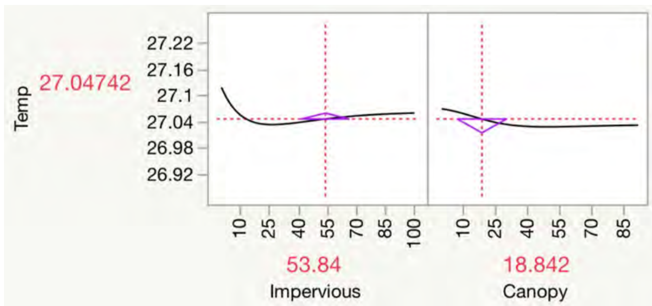


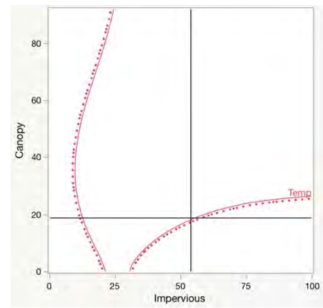
Leominster



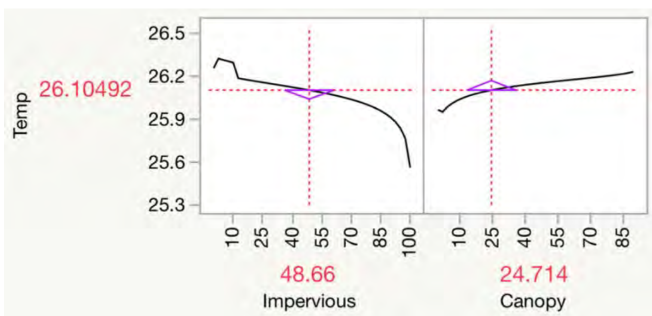


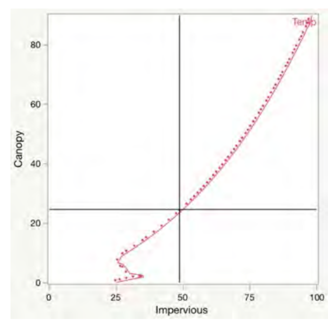
Lowell



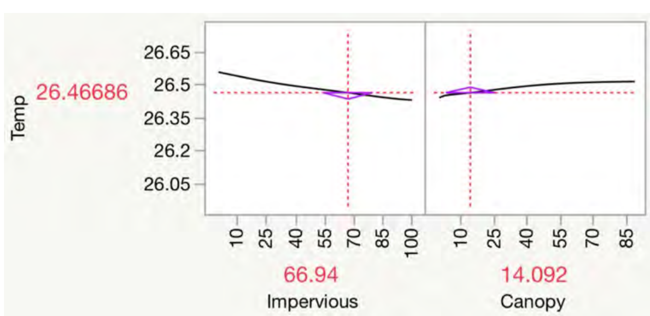


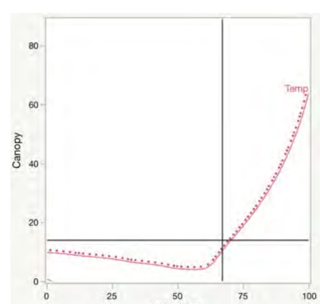
Lynn



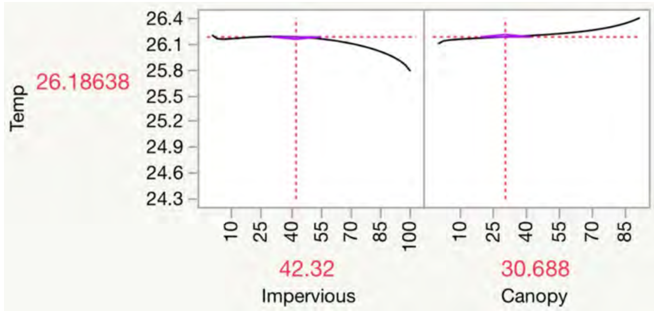


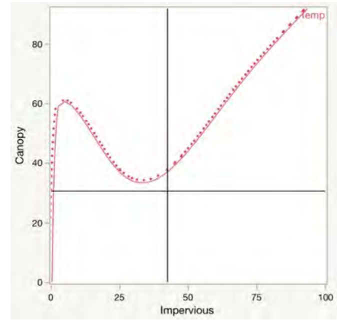
Malden



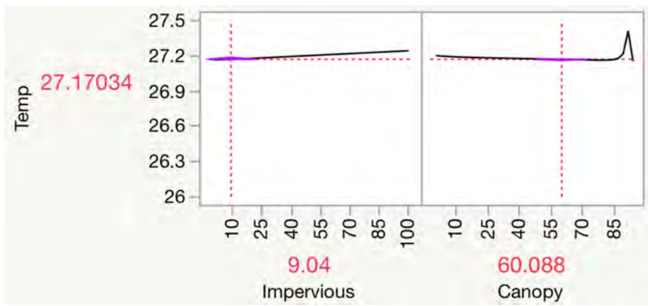


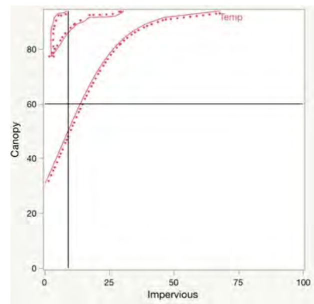
New Bedford



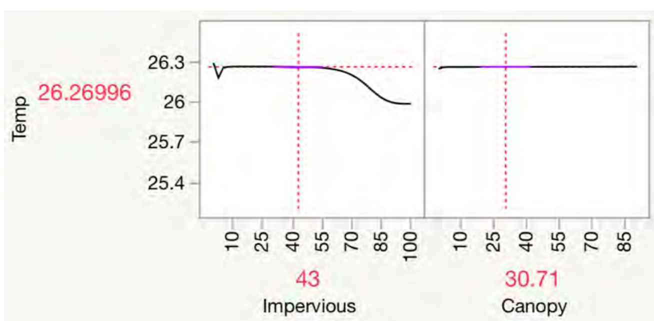


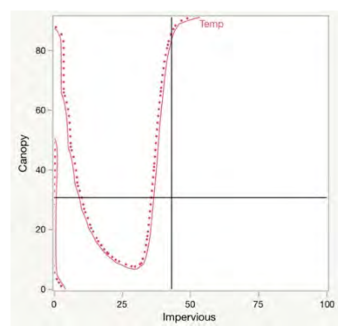
Northampton



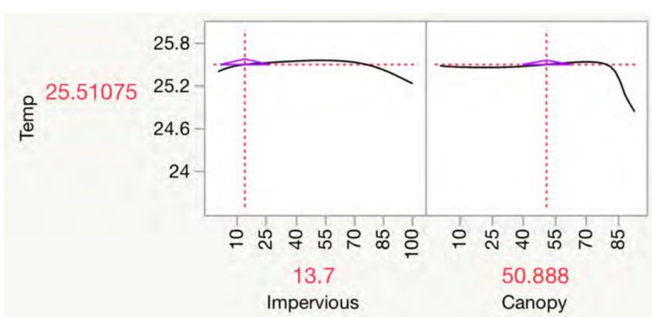


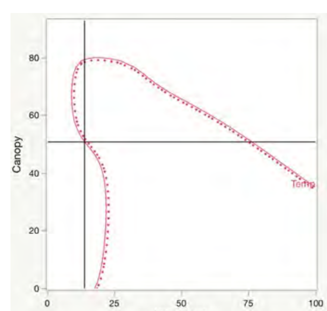
Peabody



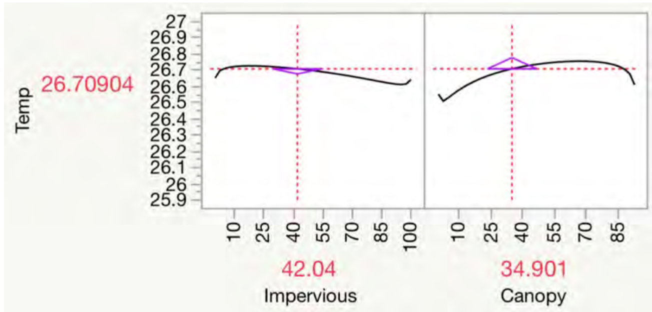


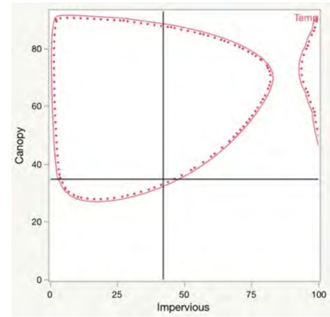
Pittsfield



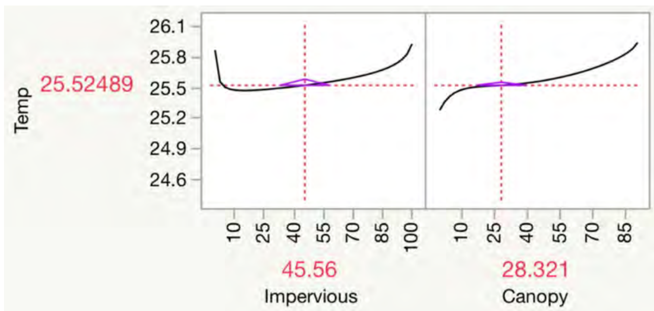


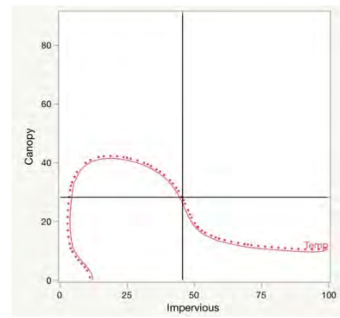
Quincy



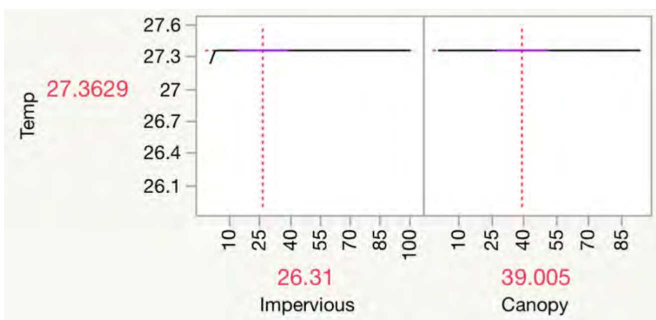


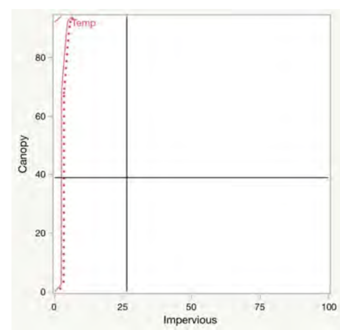
Salem



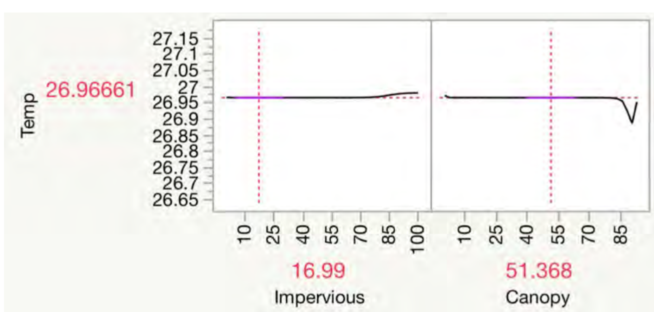


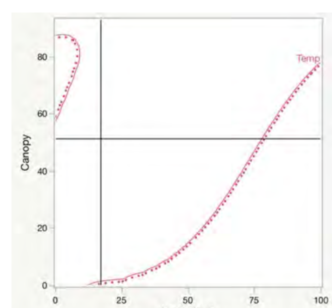
Springfield



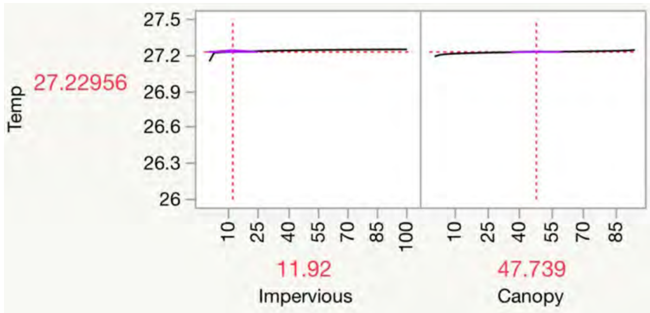


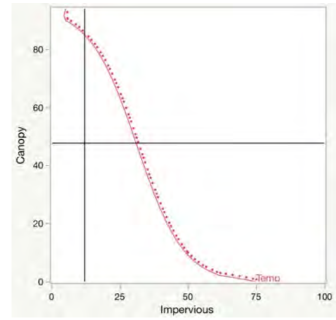
Taunton



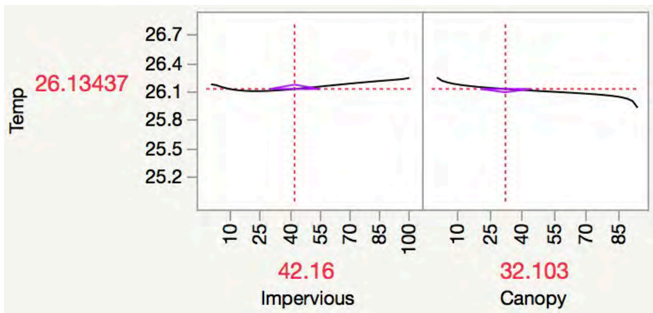


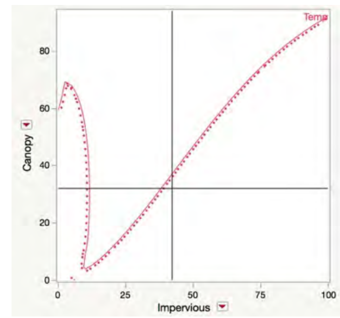
Westfield



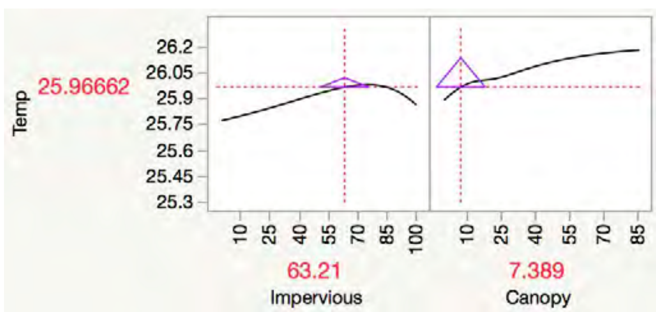


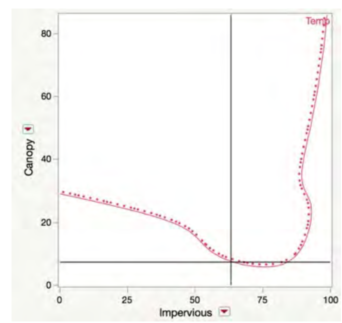
Worcester



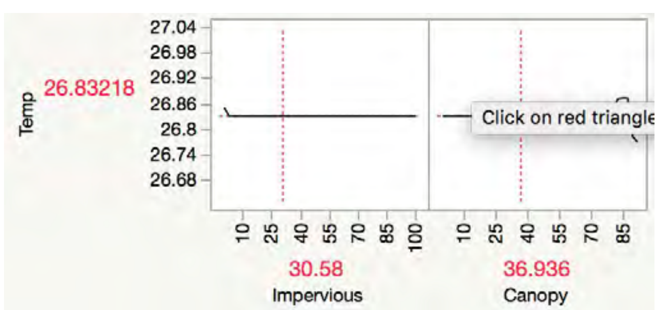


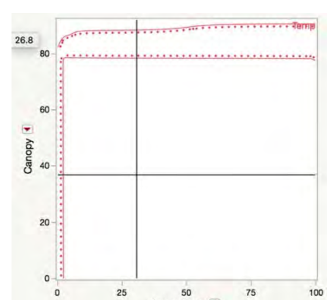
Revere



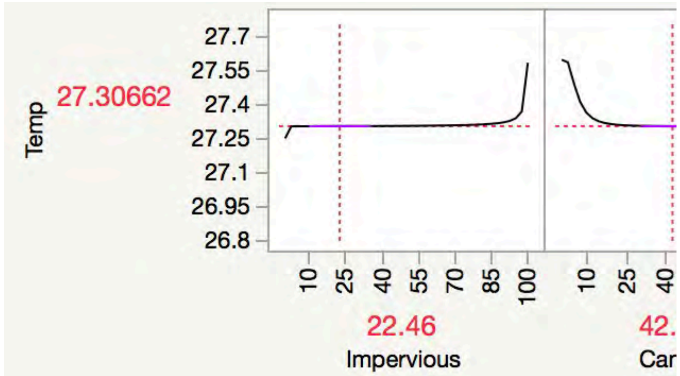


Methuen





West Springfield



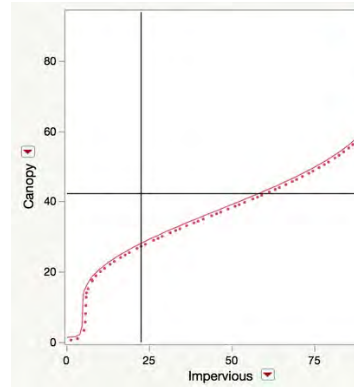


Figure 40: Prediction profilers and contour profilers from intracellular analysis

3.3.5 Water Supply Protection

The Water Supply Index was developed using a combination of high-resolution data on runoff mitigation potential, soil hydrological groups, aquifers, wellhead, and surface water supply protection areas in the Commonwealth of Massachusetts. Each data set was processed separately to formulate subindexes that were then used in the final calculation of a state-wide water supply index. The datasets that were used in the calculation of the water supply index are shown below in Figures 41-44.

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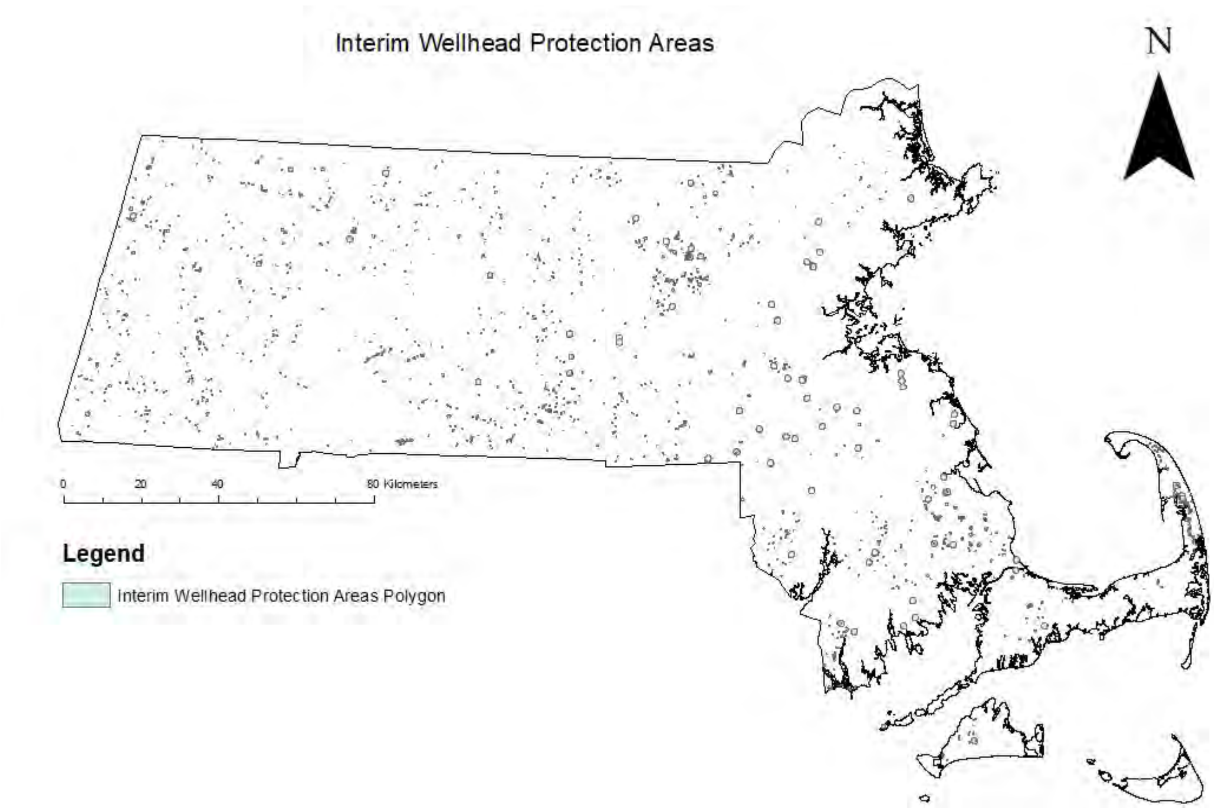

Figure 41: Interim Wellhead Protection Areas

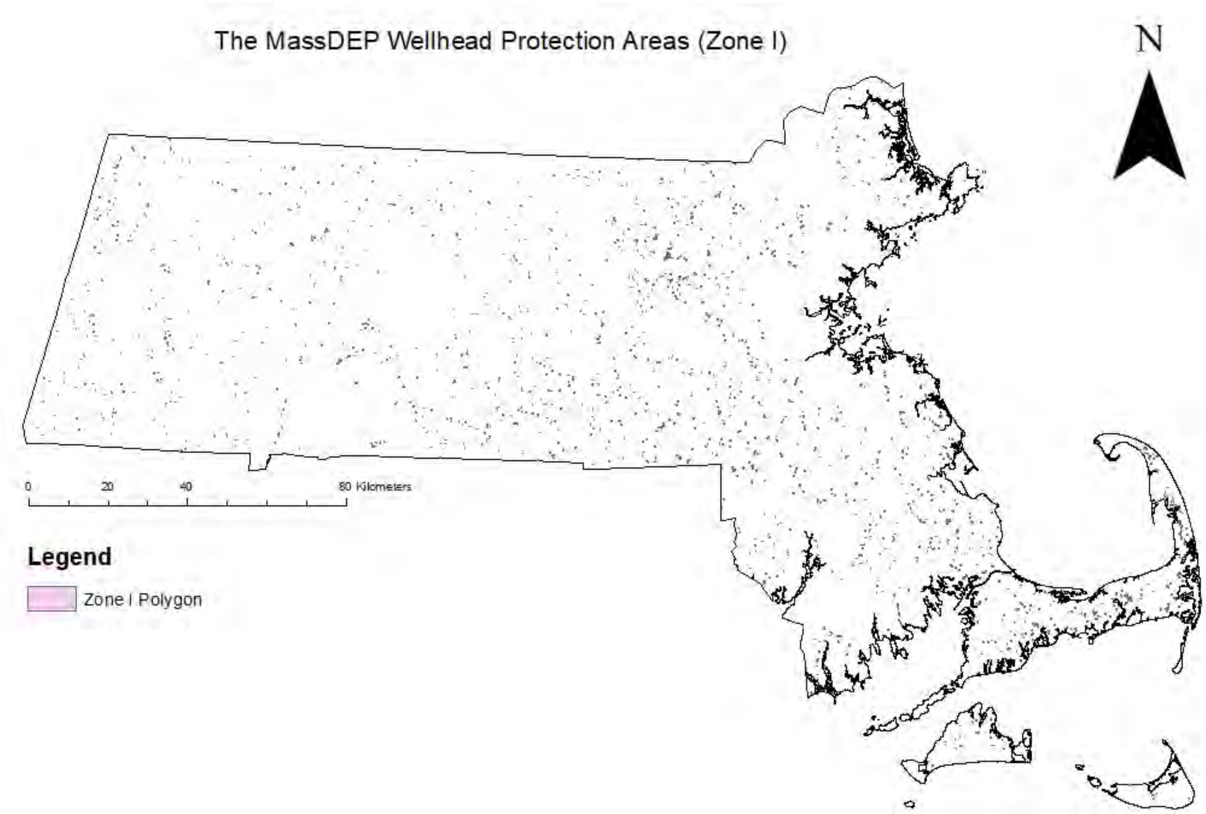

Figure 42: MassDEP Wellhead Protection Areas (Zone 1)

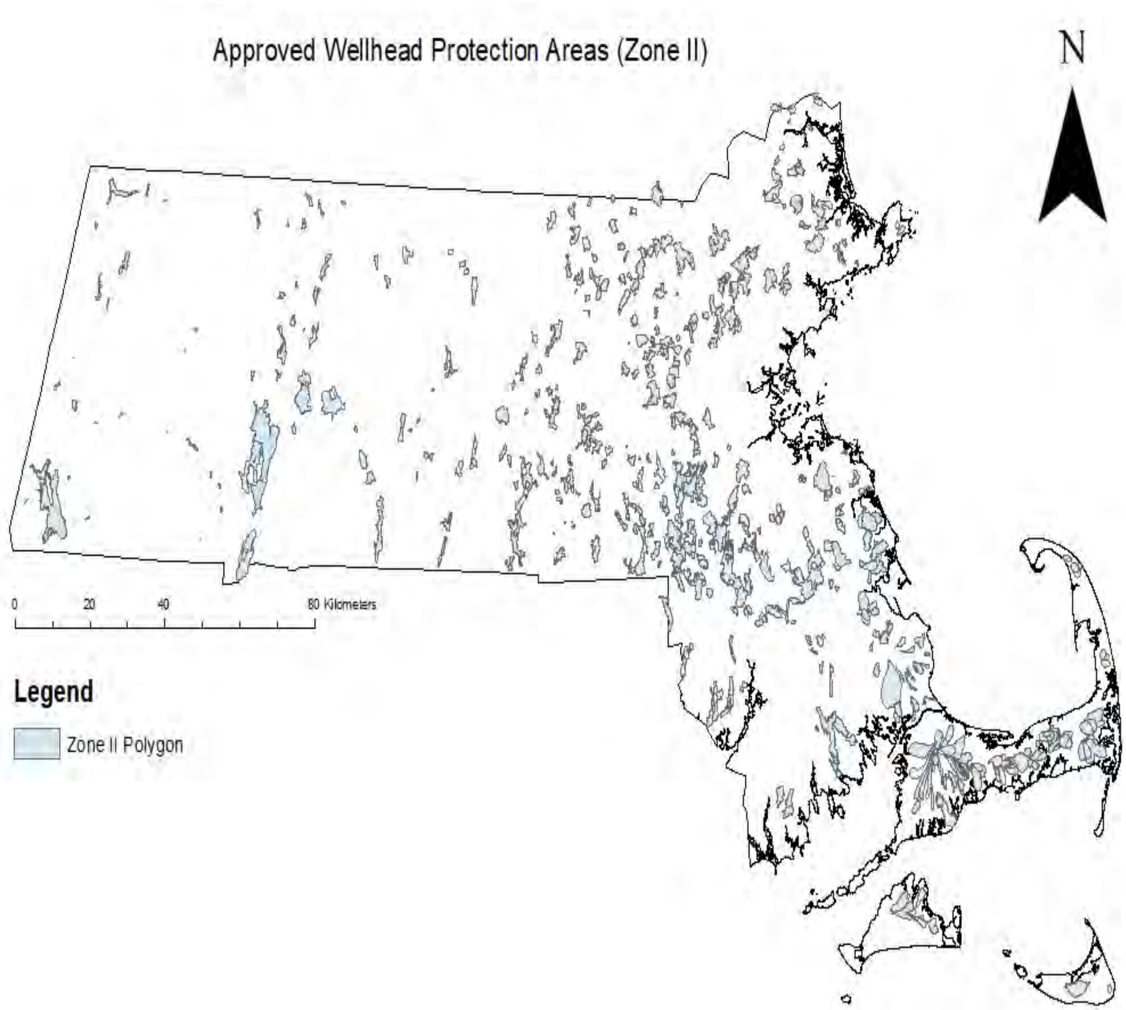

Figure 43: Approved Wellhead Protection Areas (Zone II)

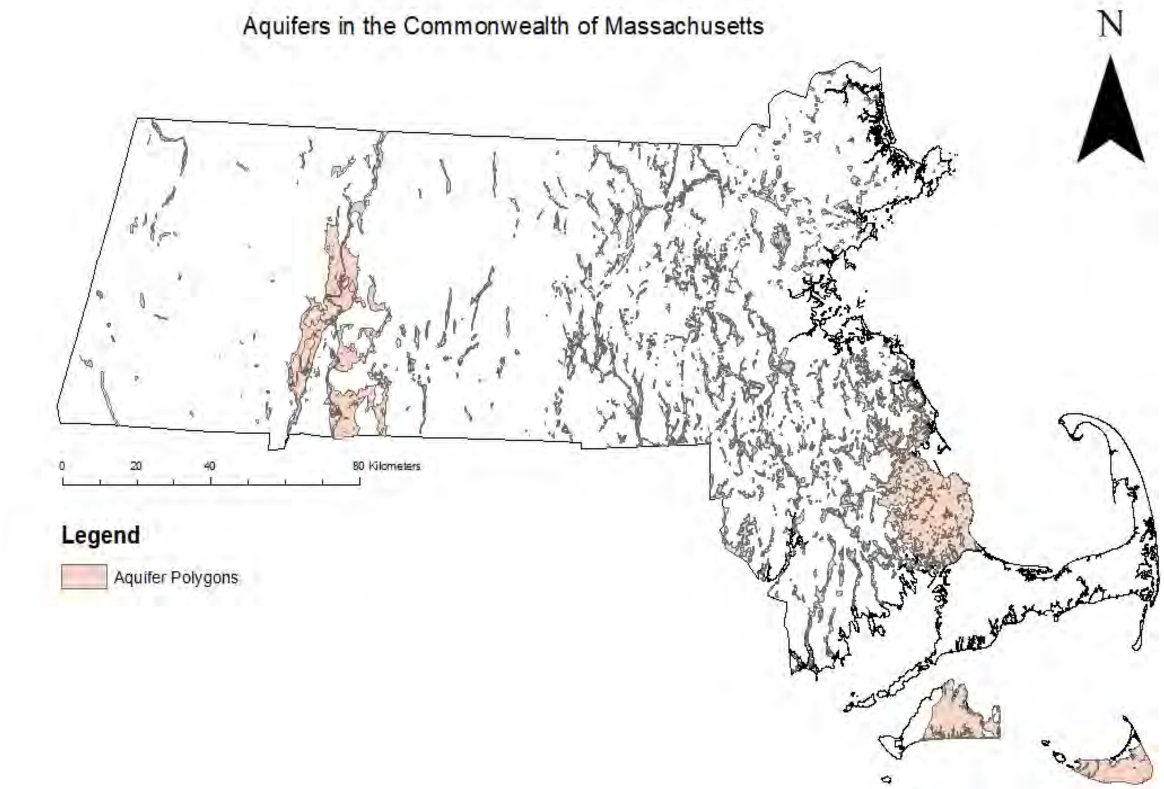

Figure 44: Aquifers in the Commonwealth of Massachusetts

Starting with the runoff mitigation potential dataset formulated earlier in this report, a ranking system for runoff mitigation potential was generated by subtracting the minimum values from the maximum values and dividing by the difference between the two. This process was carried out at a state-wide level to achieve a value between 0 and 1 for each 30 by 30-meter unit. The score was then multiplied by five to generate a runoff subindex ranging from zero to five as depicted in Figure 45.

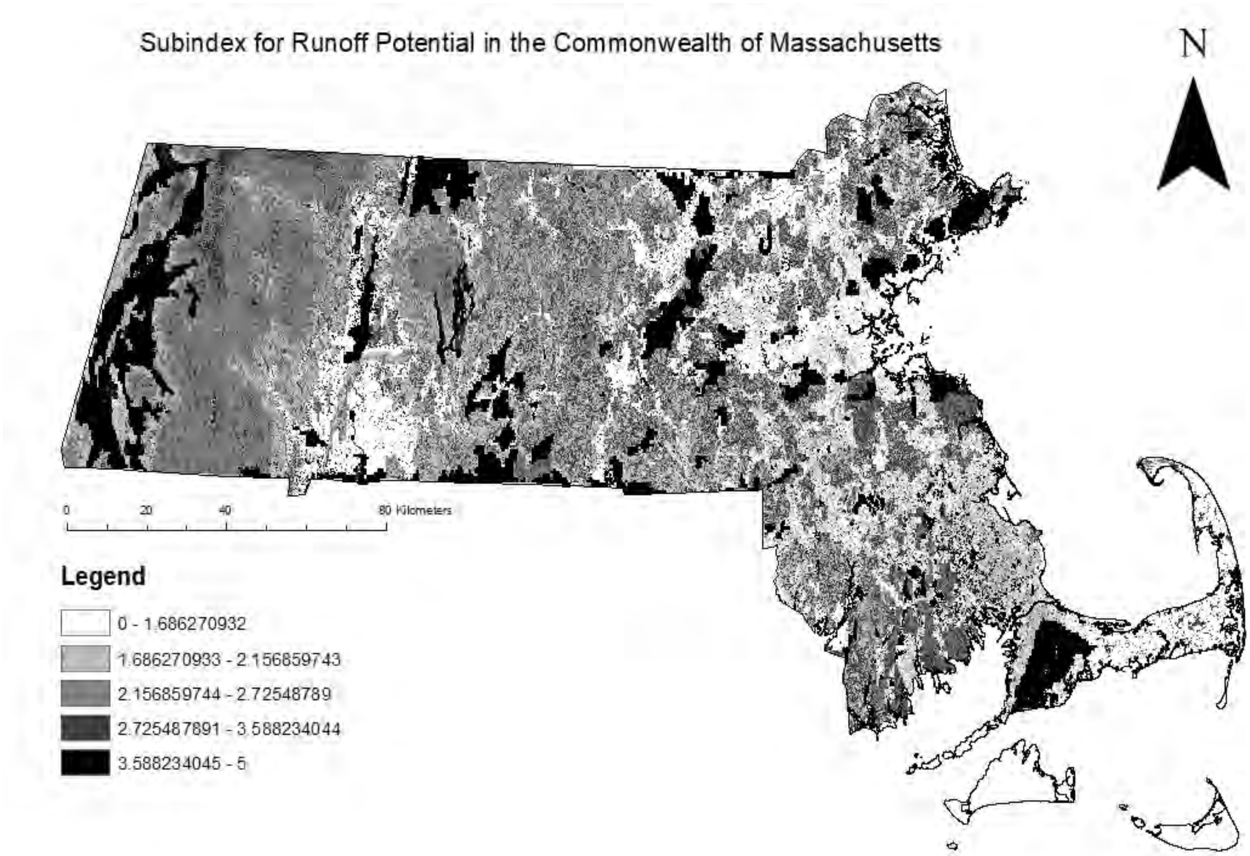

Figure 45: Subindex for Runoff Potential

Aquifers were ranked based on their yield using ArcGIS. Aquifers that were low yielding were ranked a 1, aquifers with medium yield were assigned a 3, and aquifers that were high yielding were assigned a 5. This process was conducted at a state-wide level to generate a subindex, as depicted in Figure 46.

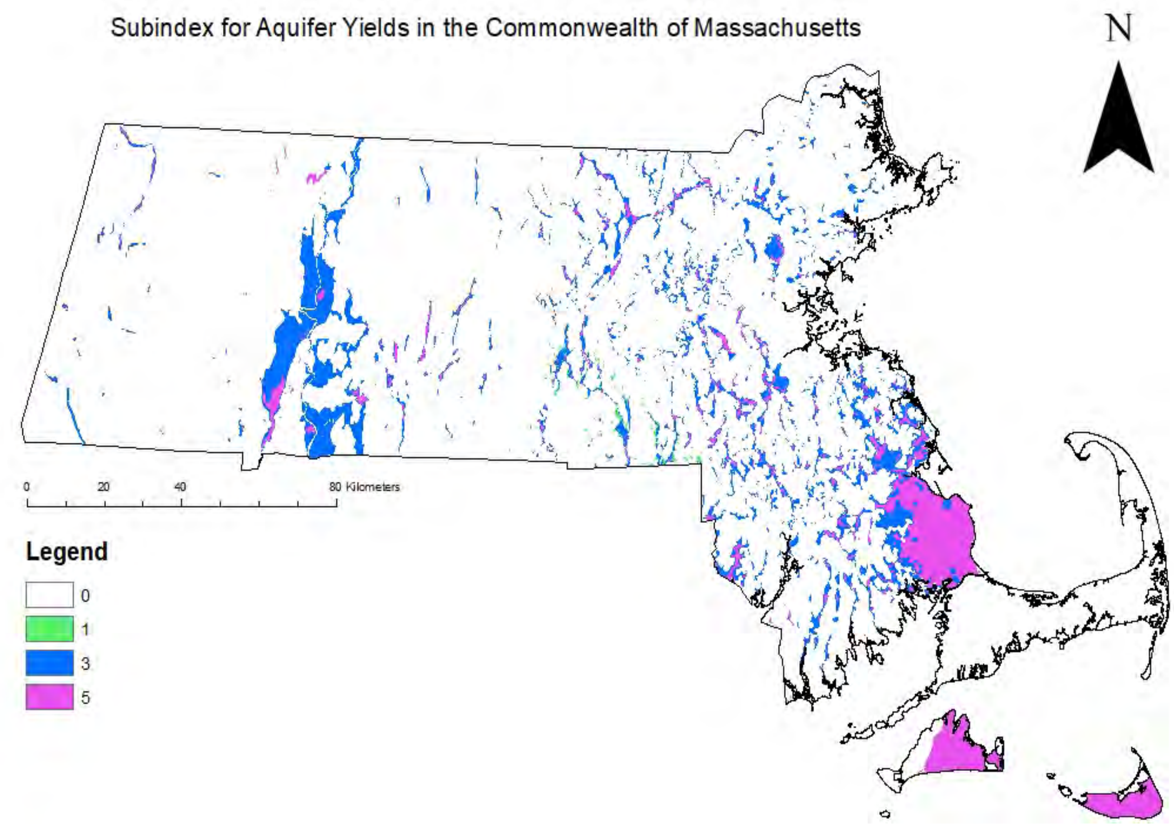

Figure 46: Subindex for Aquifer Yields

Data on surface water supply protection areas were assigned either the value of 0 if the pixels fell outside of a watershed or a value of 1 if the pixels fell within a watershed. The shapefile output was then multiplied by 5 to create a subindex with values ranging from 0 to 5, as shown in Figure 47 and Figure 48.

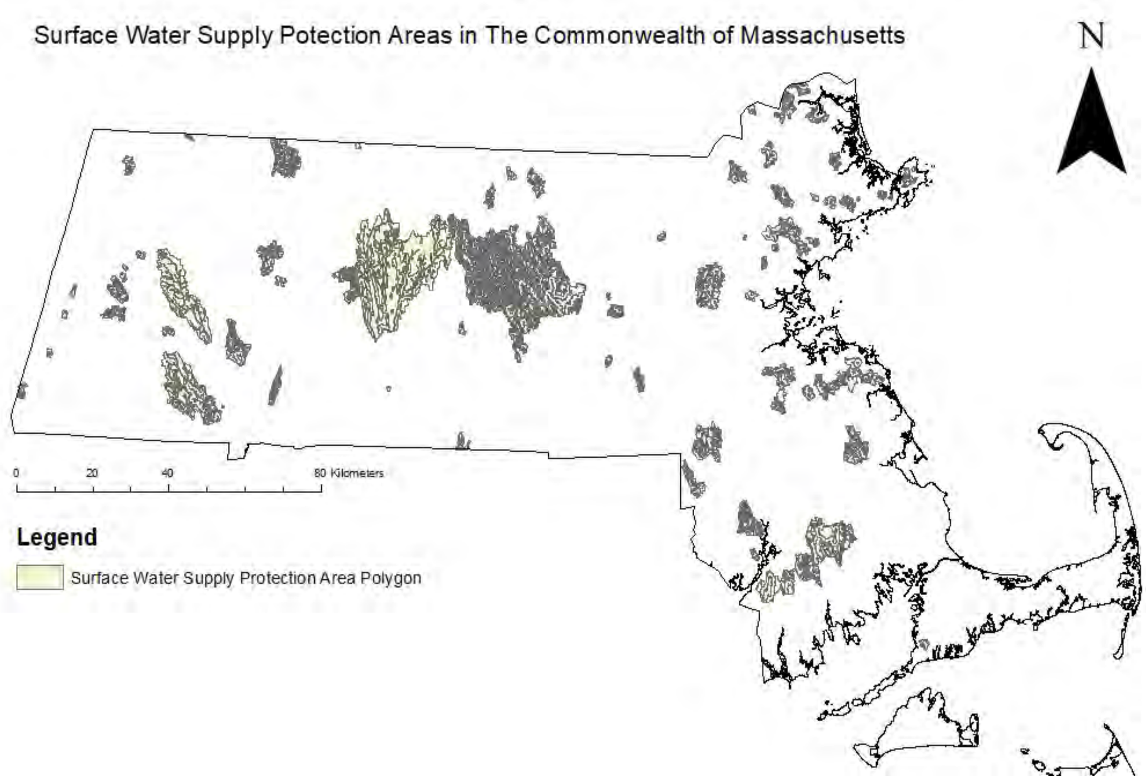

Figure 47: Surface Water Supply Protection Areas

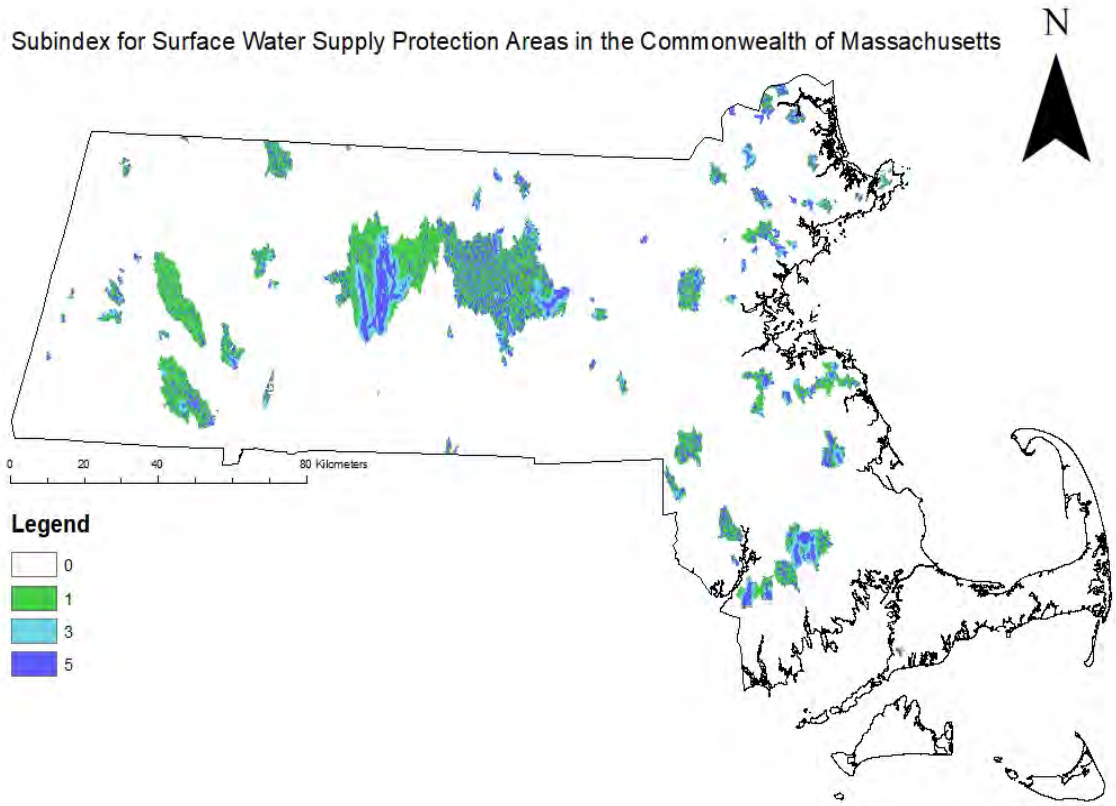

Figure 48: Subindex for Surface Water Supply Protection Areas

The processing of wellhead protection areas data required several additional steps. First, each zone type was assigned a separate rank. Zone II (approved wellhead protection areas) were assigned a 3, while Interim Wellhead Protection Areas (IWPA) and Zone I (MassDEP wellhead protection areas) were assigned a rank of 5. Overlapping regions were summed to receive additional weight in the creation of the subindex. A shapefile containing values of 0, 3, 5, 8, 10, and 13 was computed and reclassified to a subindex ranging from 0 to 5. The output is shown in Figure 49 and Figure 50.

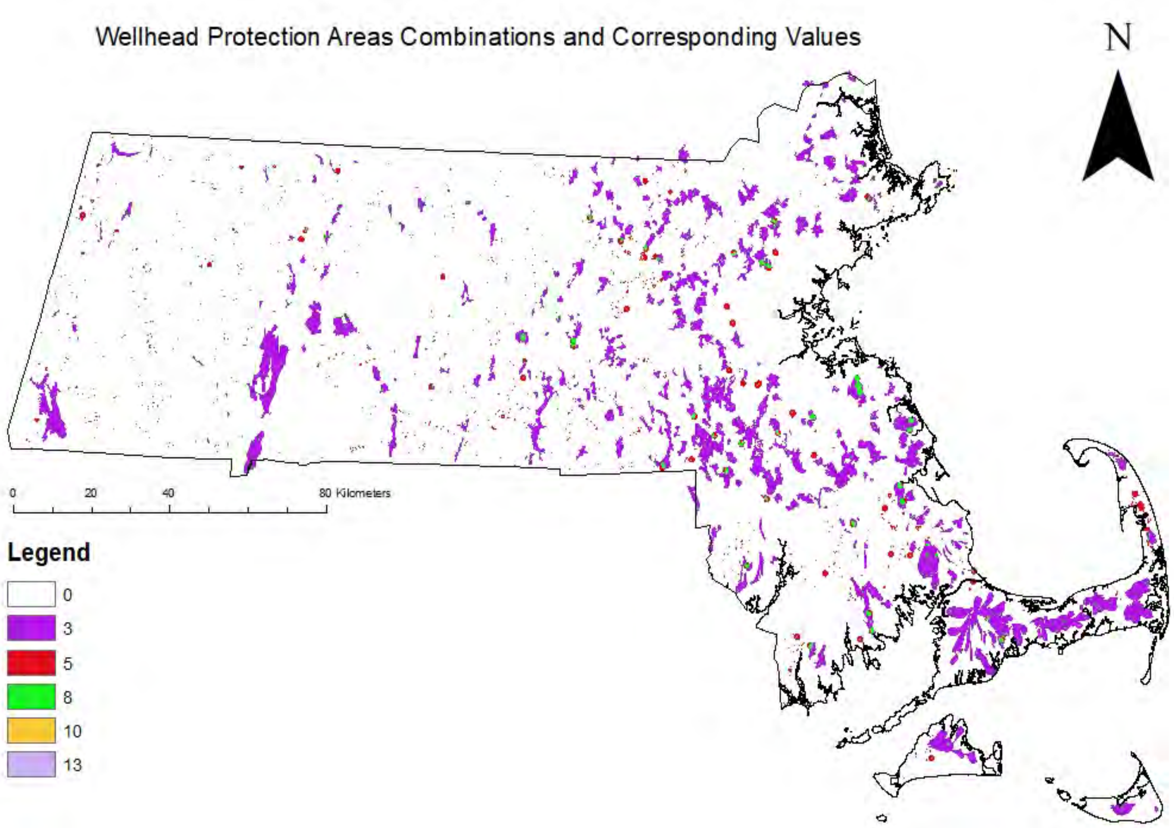

Figure 49: Wellhead Protection Areas Combinations and Corresponding Values

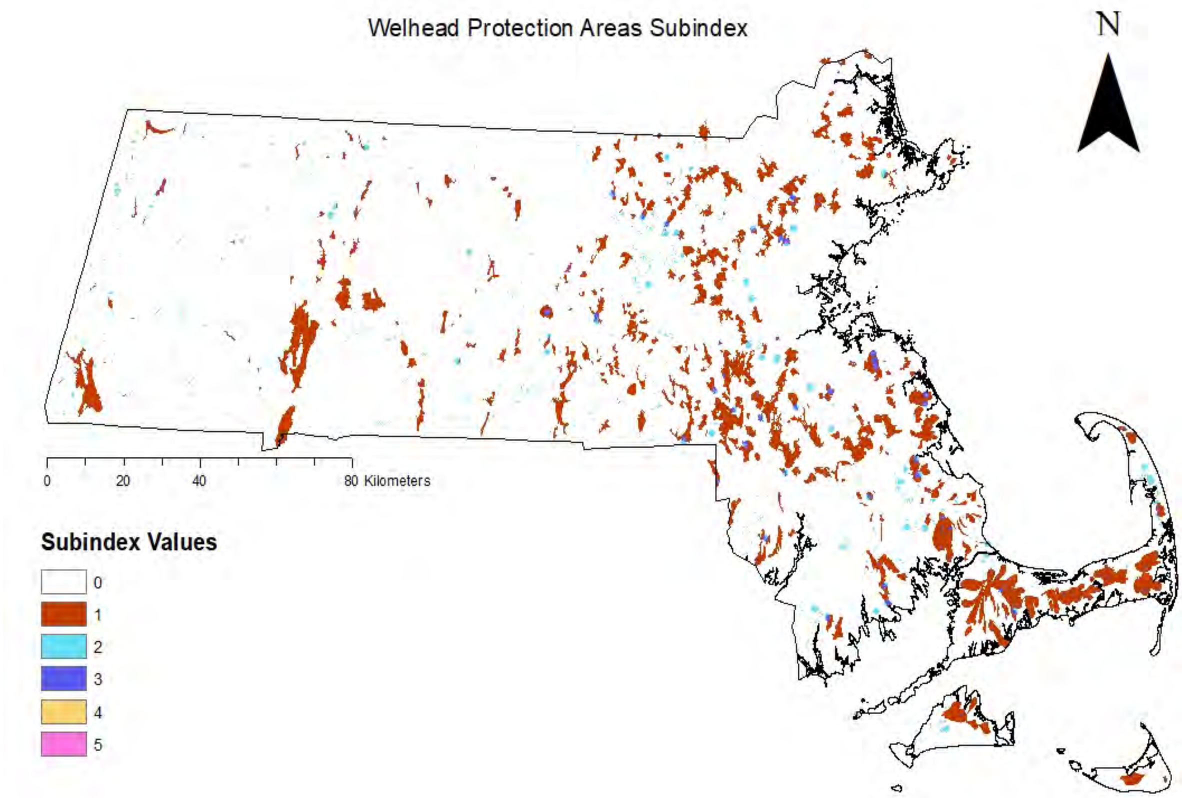

Figure 50: Wellhead Protection Areas Subindex

Lastly, soils data were subindexed and went into the creation of the final water supply index for the Commonwealth of Massachusetts. High-resolution SSURGO-Certified soils data was modified and joined to data of soil hydrological groups in the Commonwealth of Massachusetts. Soils with excessive or somewhat excessive drainage received a rank of 5 due to high infiltrative capacities. Soils that were well-drained were assigned a rank of 3. Soils with moderately well-drainage were assigned a rank of 1, and soils with somewhat poor, poor, or very poor drainage were assigned a rank of 0 due to the poor infiltrative capacity and predominantly clay constituents. The output can be observed in Figure 51.

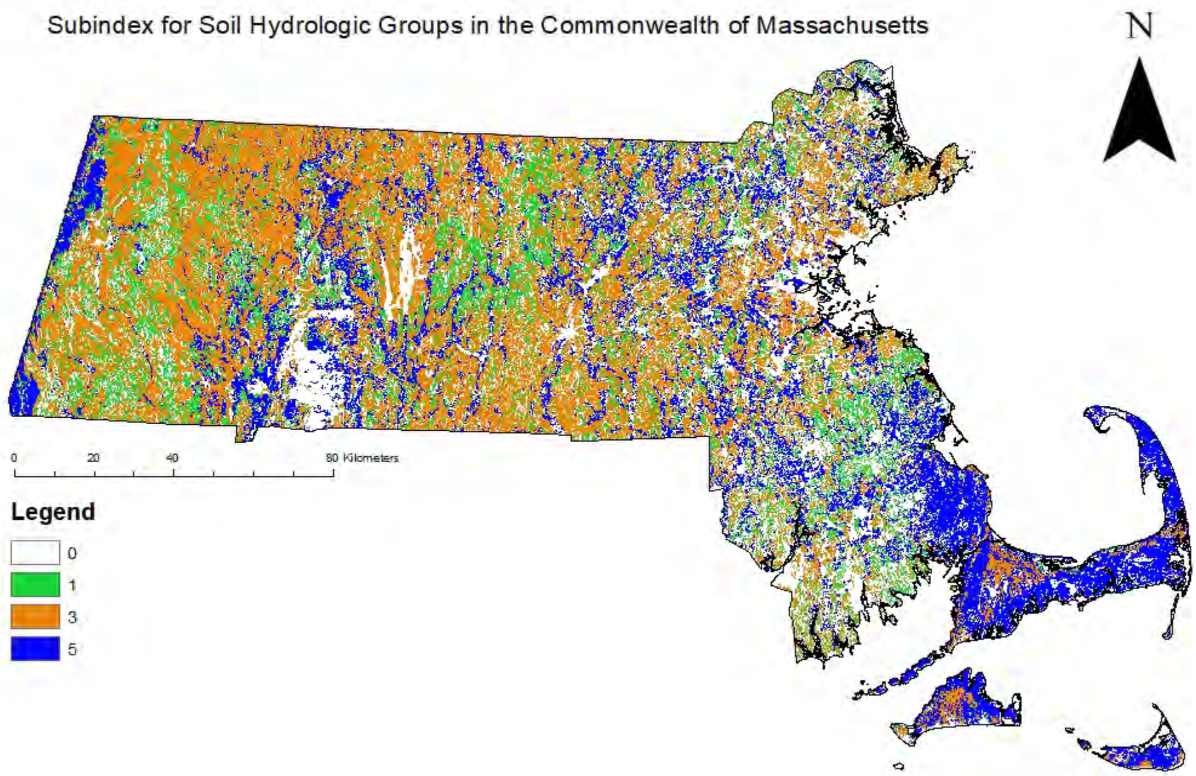

Figure 51: Subindex for Soil Hydrologic Groups

Each data set was converted from a polygon to a raster layer, and map algebra was executed to compute the state-wide index ranging from 0 to 100. Natural breaks were then used to classify the Water Supply Index into quintiles. The outputs are shown in Figures 52 and 53. .

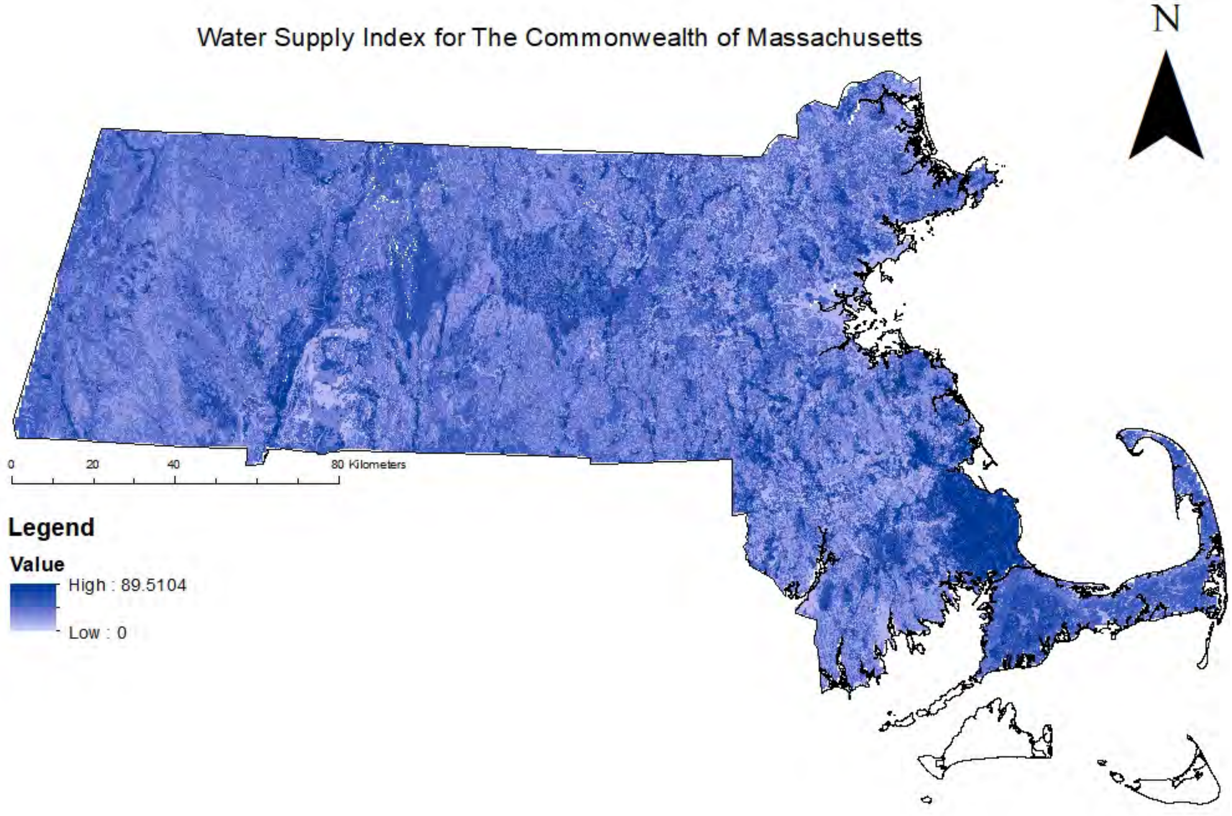

Figure 52: Water Supply Index

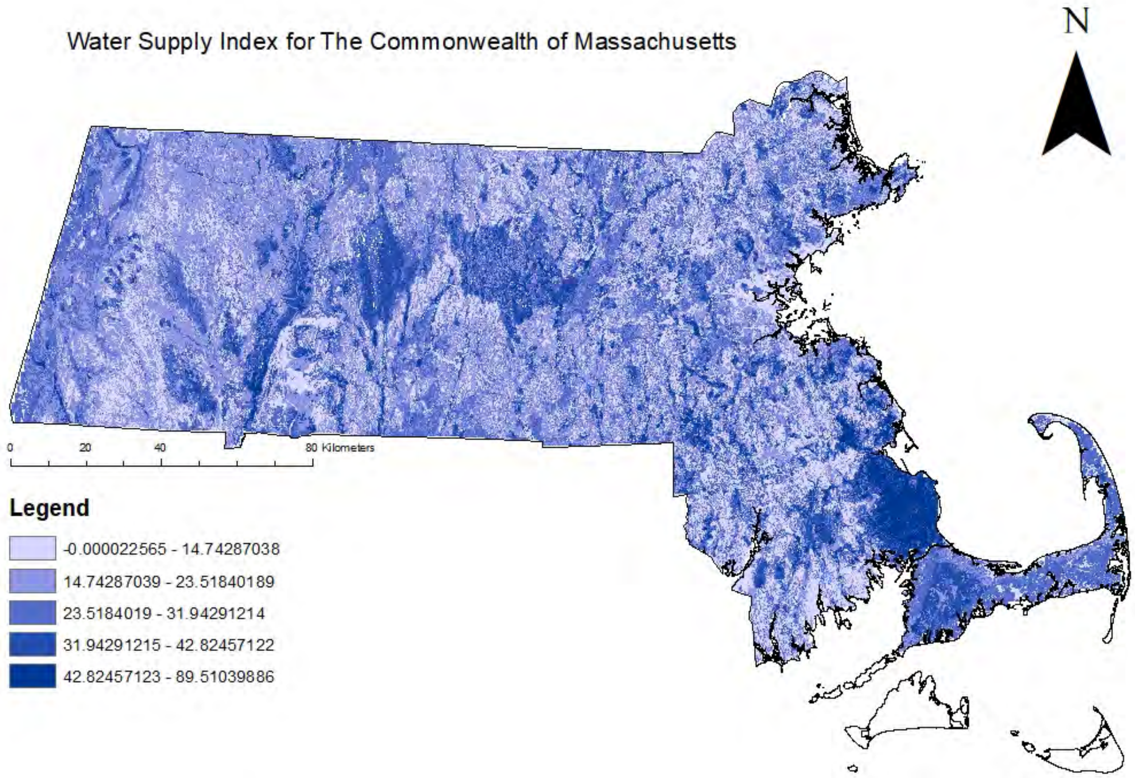

Figure 53: Water Supply Index Categorized

It can be observed from the following outputs that areas with the highest Water Supply Index in the Commonwealth of Massachusetts are located near the coast or near large water body supplies, including the Quabbin Reservoir, the Connecticut River, and the Wachusett Reservoir.

3.3.6 Soil Organic Carbon

3.3.6.1 Soil Organic Carbon Modeling

Soil organic carbon was estimated using The A2 scenario and EDCM model data from USGS (Zhiliang et al., 2011). The spatial processing was done using the raster calculator in ArcGIS. A carbon baseline was assessed at the top 20 cm of soil USGS (Zhiliang et al., 2011) and by calculating the average carbon stock in grams of carbon per square meter (gC/m2) of land (Zhiliang et al., 2011) from 2010 to 2020. The carbon flux was also estimated by subtracting 2020 data from the predicted 2050 data, then dividing the difference by 30 years, then using the yearly flux to estimate 2100 soil carbon. The carbon flux was multiplied by 80 years and added to the 2020 carbon stock to obtain a carbon estimate for 2100. Carbon stock data in 2010, 2020, 2050, and 2100 were converted to integers then to point data. Data interpolation was conducted using Spline with borders tools in ArcGIS using Massachusetts state boundaries. It can be observed from the maps that soil organic carbon is expected to decrease by 2100 drastically. Areas most strongly impacted are in the Eastern part of the Commonwealth of Massachusetts. Figure 54-

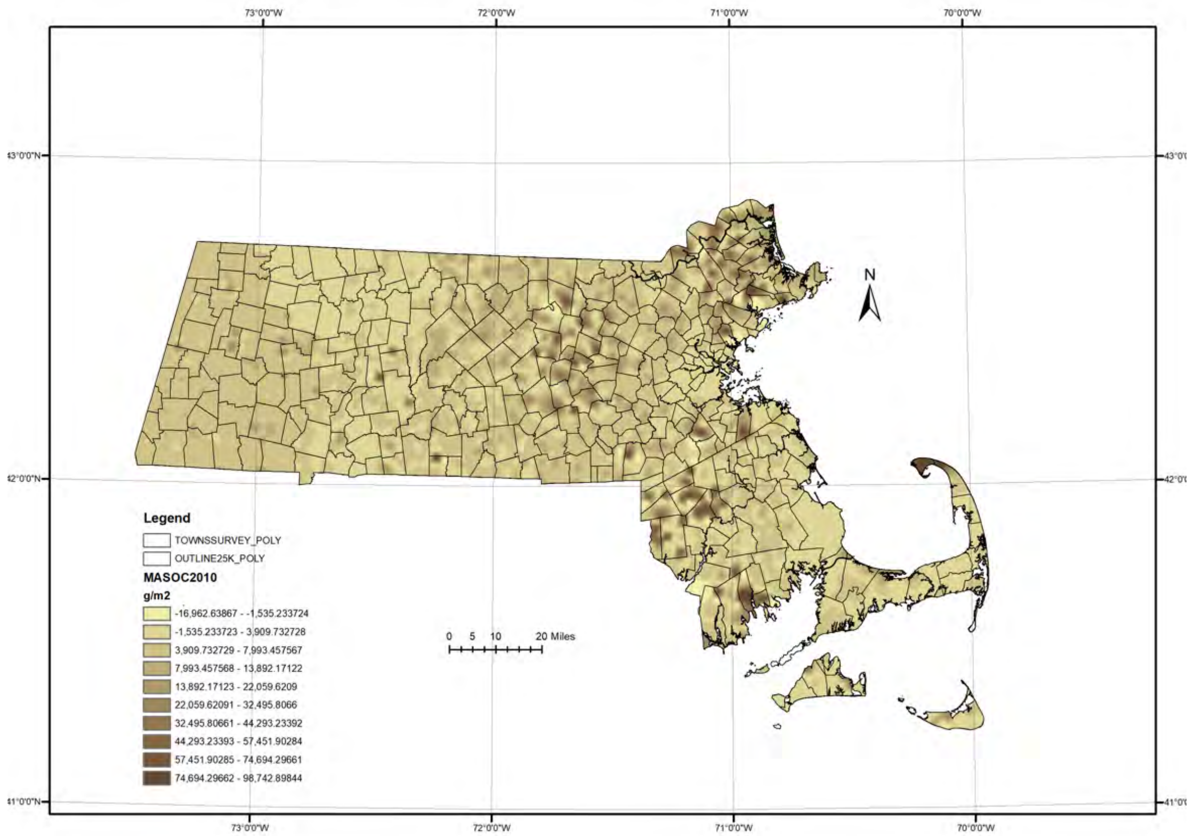

Figure 54: Soil Organic Carbon for 2010

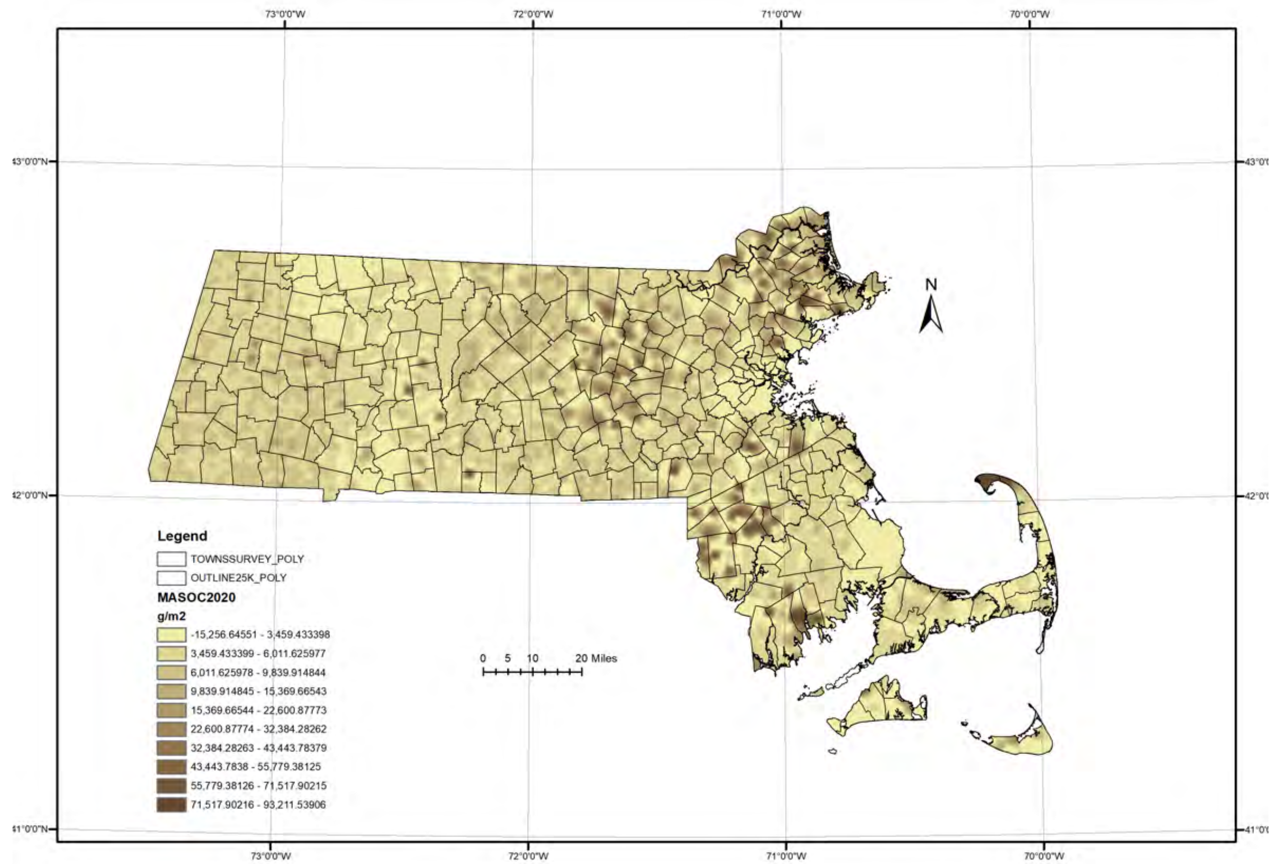

Figure 55: Soil Organic Carbon for 2020

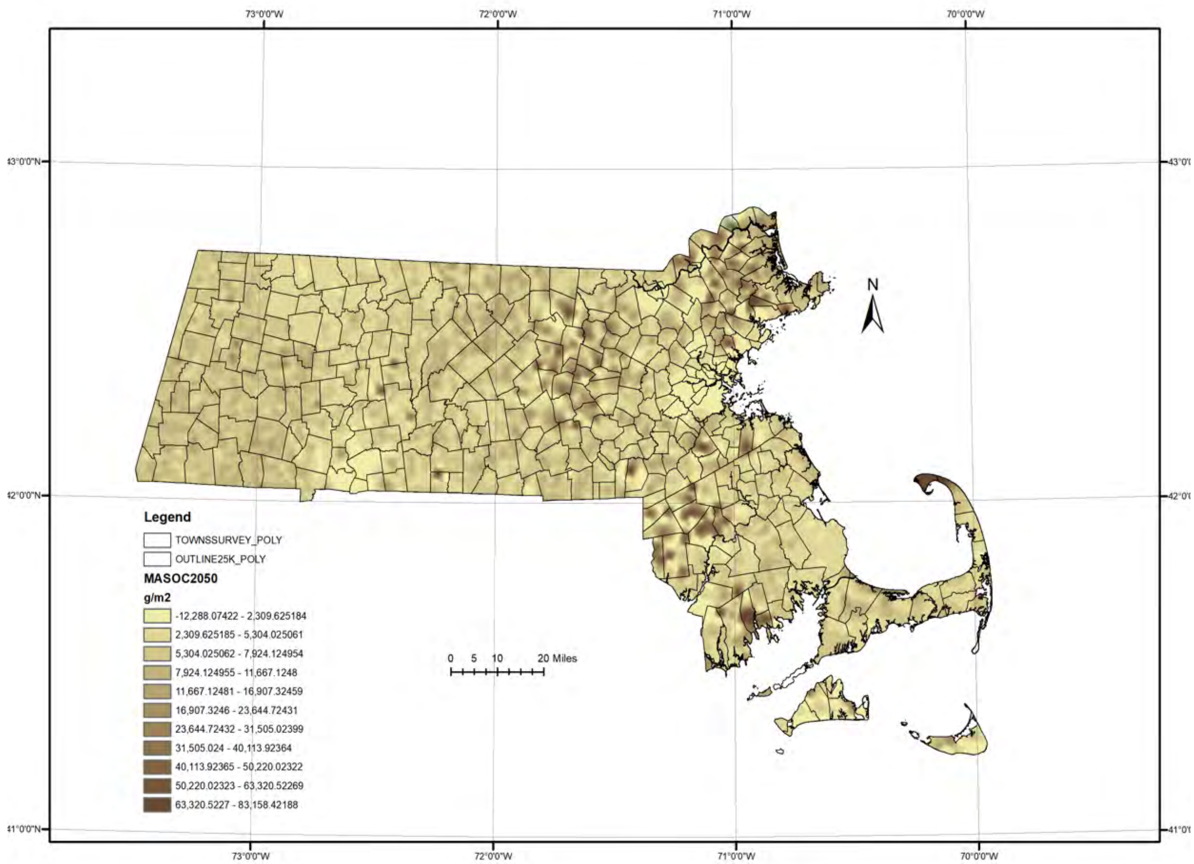

Figure 56: Soil Organic Carbon for 2100

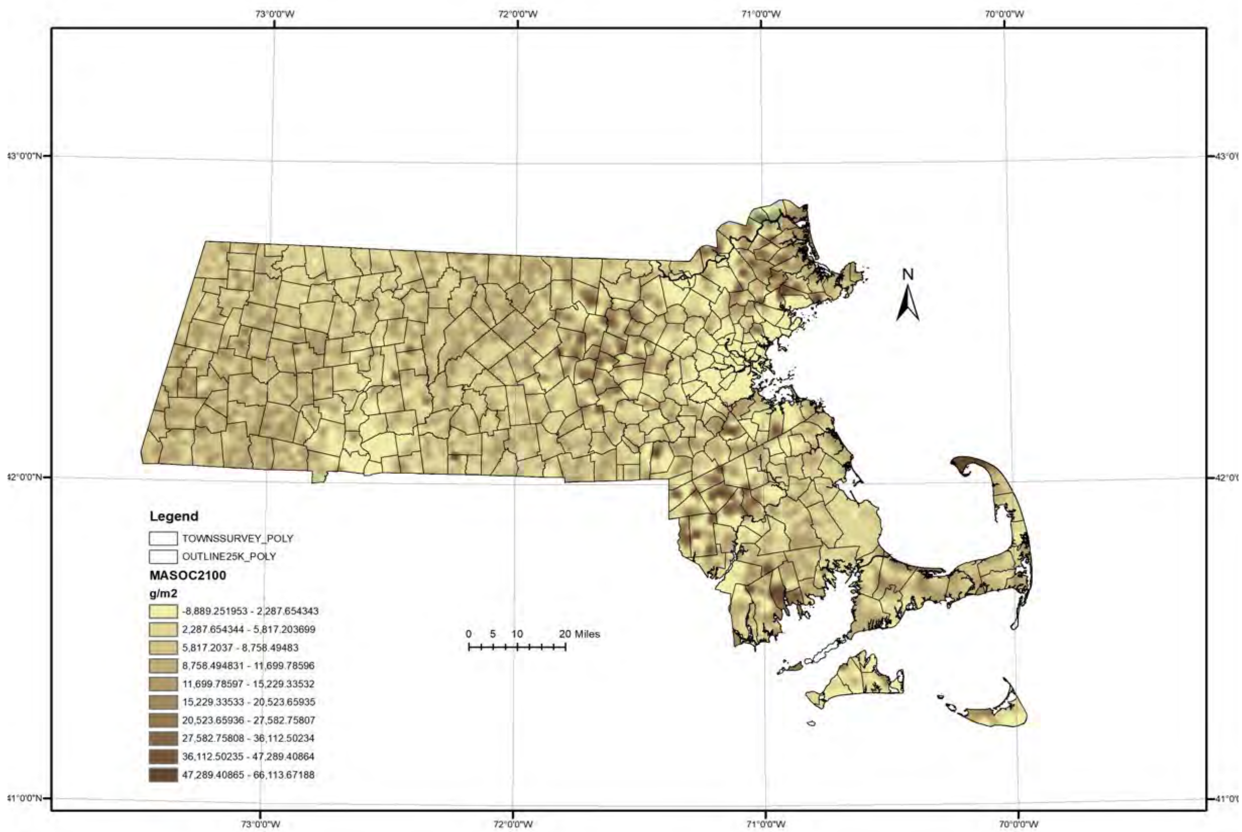

Figure 57: Soil Organic Carbon for 2050

3.3.6.2 ICARES-DS - Soil Carbon

Soil organic carbon (SOC) was estimated using The A2 scenario and EDCM model data from USGS (Zhiliang et al., 2011). The spatial processing was done using a raster calculator in ArcGIS. A carbon baseline was assessed at the top 20 cm of soil USGS (Zhiliang et al., 2011) and by calculating the average carbon stock in grams of carbon per square meter (gC/m2) of land (Zhiliang et al., 2011) from 2010 to 2020. The carbon flux was also estimated by subtracting 2020 data from the predicted 2050 data, dividing the difference by 30 years, then using the yearly flux to estimate 2100 soil carbon. The carbon flux was multiplied by 80 years and added to the 2020 carbon stock to obtain a carbon estimate for 2100. These SOC models (ICARES_SoilCarbonNow for the current climate and ICARES_SoilCarbon Future for future climate) are accessible from the following two links:

ICARES_ SoilCarbon Now: https://arcg.is/1u5Lny
ICARES_ SoilCarbon Future: https://arcg.is/11nvGr
Start by searching for an address or Zoom to the region you are interested in. Click on the location, and information on the estimated runoff in inches per year will be displayed in the pop-up window. The model is being improved to add specific benefits of urban forests in mitigating stormwater runoff in urban areas. The ICARES modules are compiled on the ICARES website. Screenshots of both models at state and city-scale are presented in Figures 58-61.

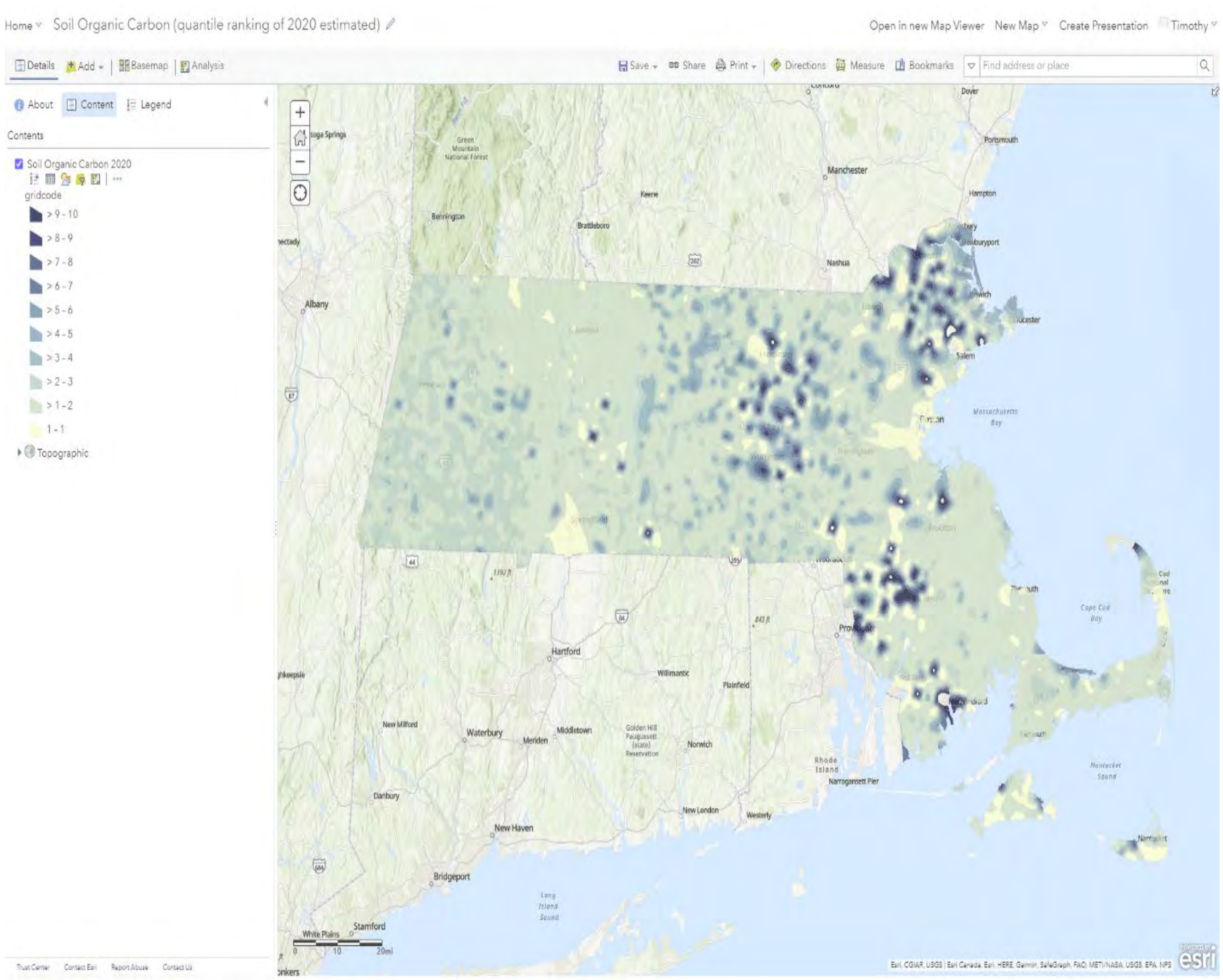

Figure 58: Full View of ICARES_ SoilCarbon Now

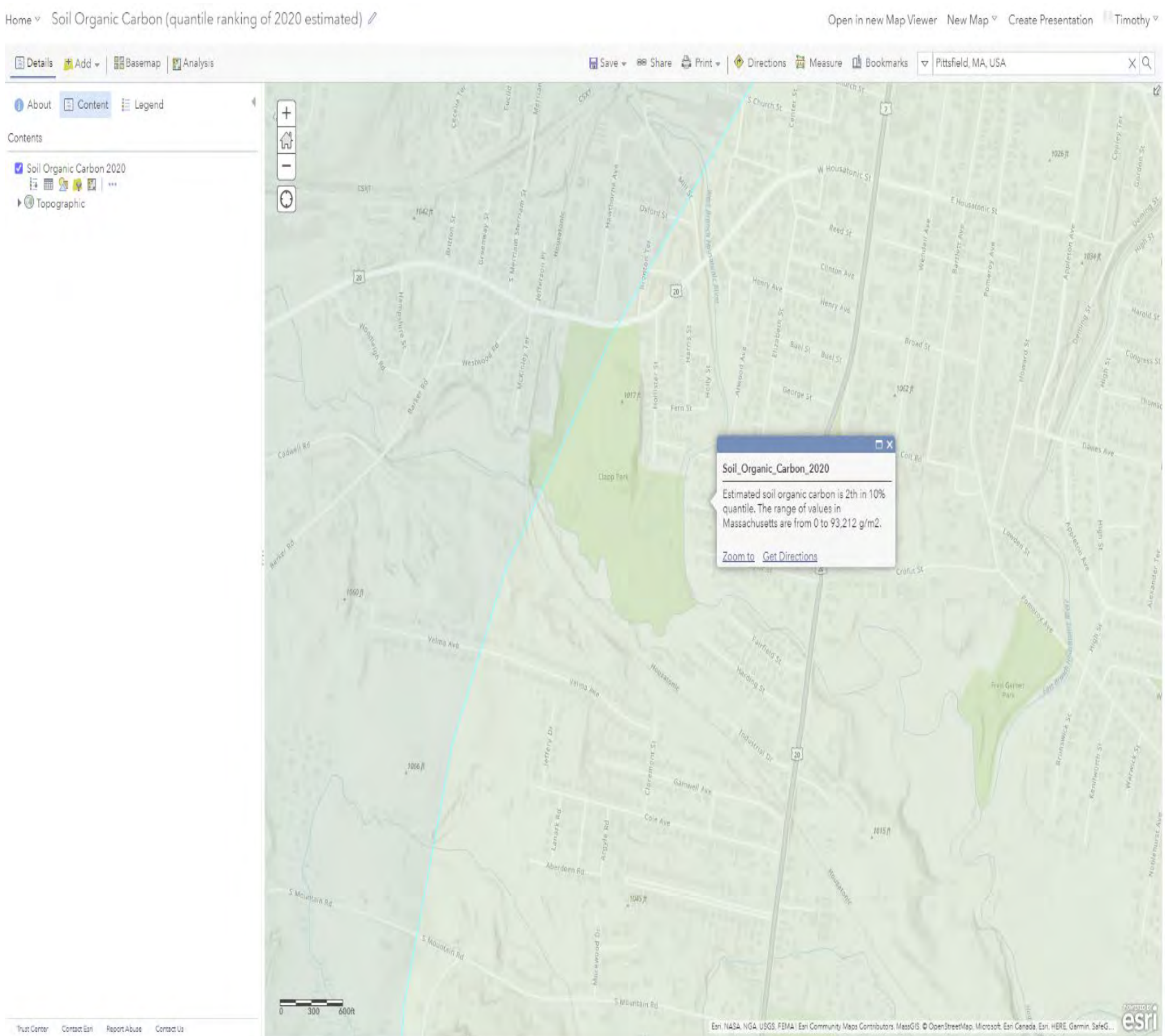

Figure 59: Zoomed View of ICARES_ SoilCarbon Now

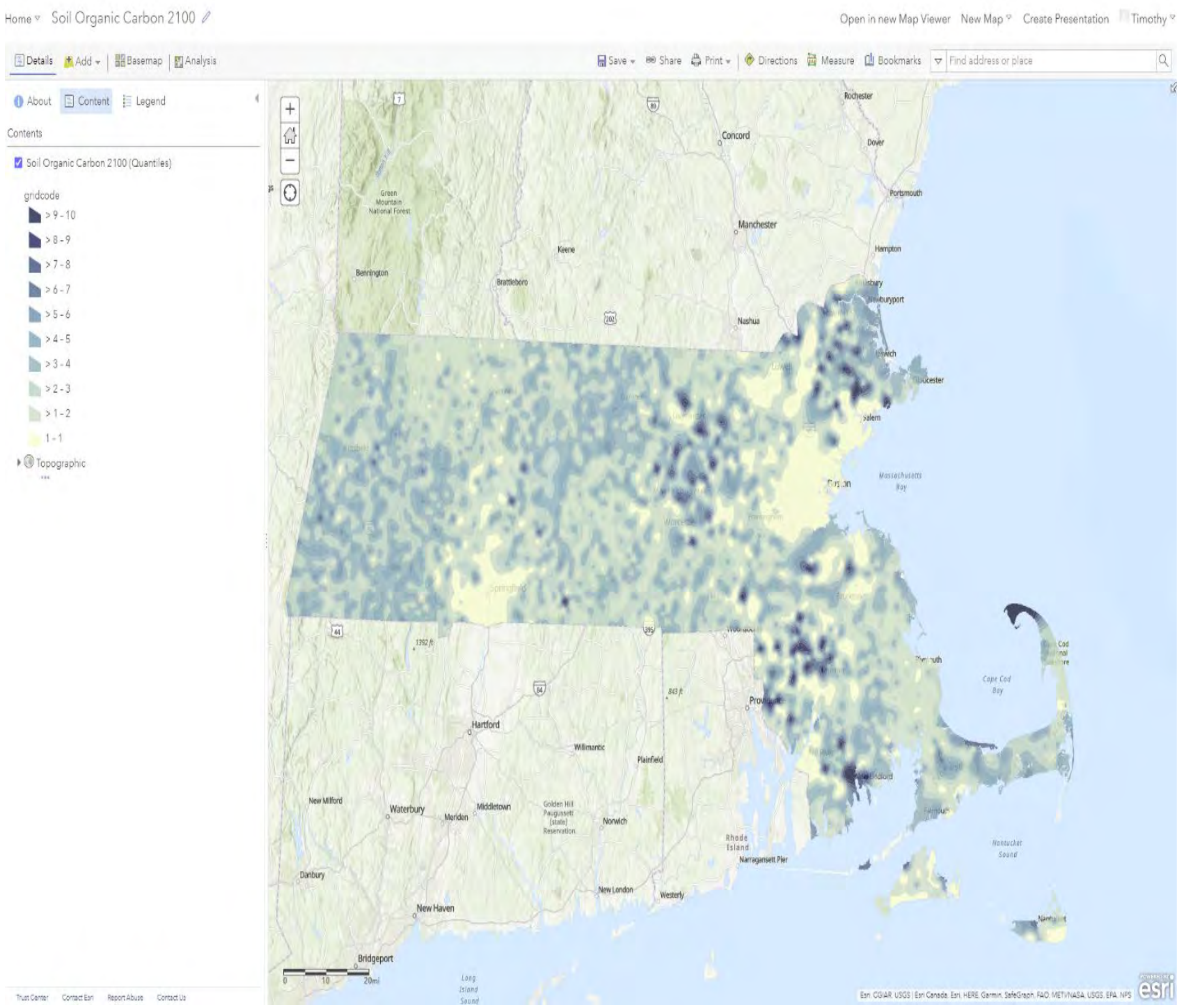

Figure 60: Full view of ICARES_ SoilCarbon Future

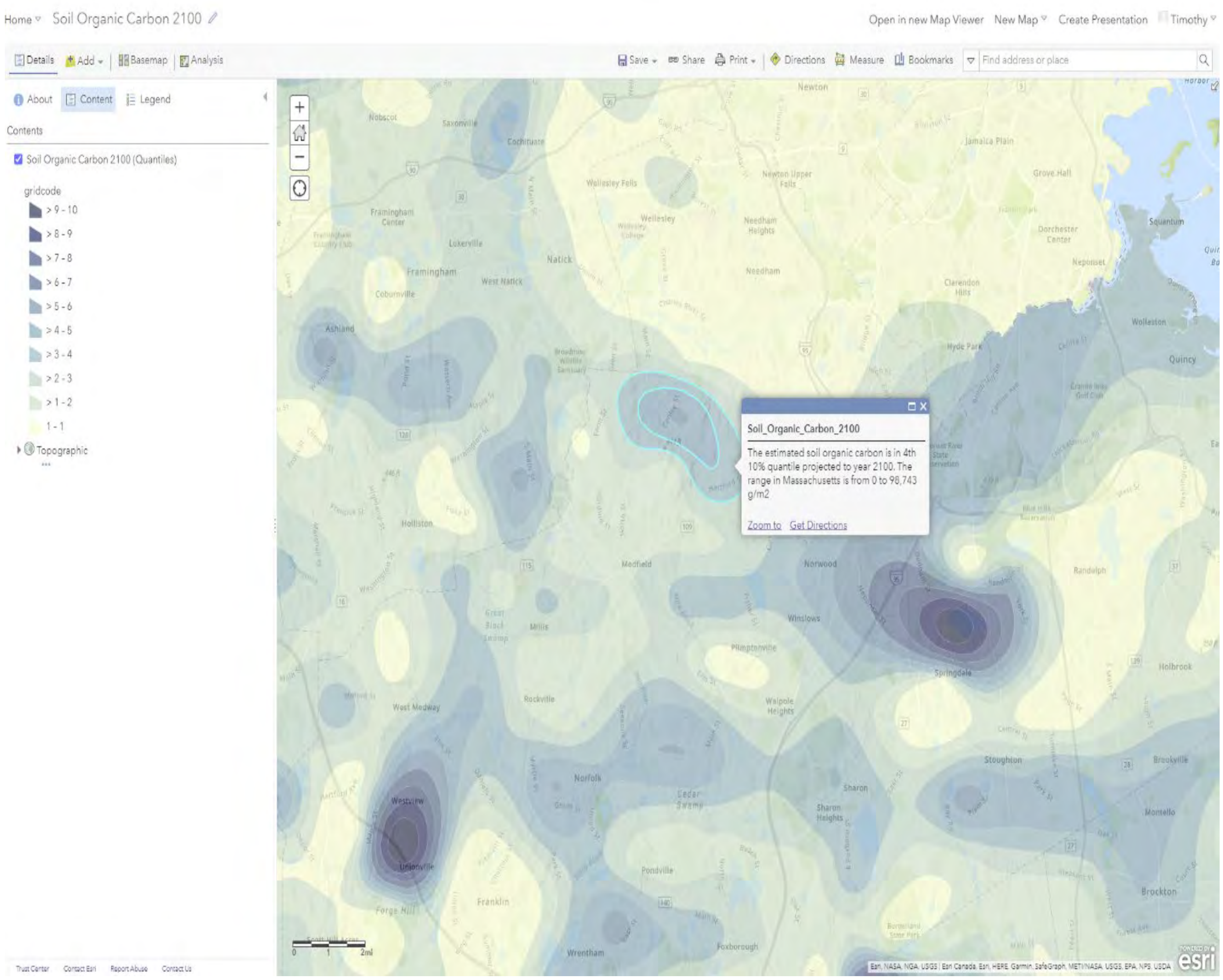

Figure 61: Zoomed view of ICARES_ SoilCarbon Future

3.4 Landuse Predictions

Three models of land use were selected for the project. The models are the ICLUS model of USEPA, the USGS-EROS predictions, and the Massachusetts land use predictions based on scenarios by Harvard Forest. The ICLUS model of USEPA and the USGS-EROS models offer future predictions for 2050 and 2100, while the Massachusetts land use predictions are based on scenarios by Harvard Forest models predictions for 2050 alone. For the USGS-EROS model, the B2 IPCC SRES scenario was selected. The IPCC SRES scenarios provide variations in key features of future population developments, including technology, economic development, and demographic changes. The B2 scenario focuses on environmental sustainability with intermediate levels of economic and technological development. The models were re-projected, clipped to the Commonwealth of Massachusetts, and are shown in 30 meters by 30 meters resolution below. The ICLUS model of USEPA was developed under SSP2 and SSP5 scenarios. The SSP2 scenario was used for ICARES. The outputs are presented in Figures 62-

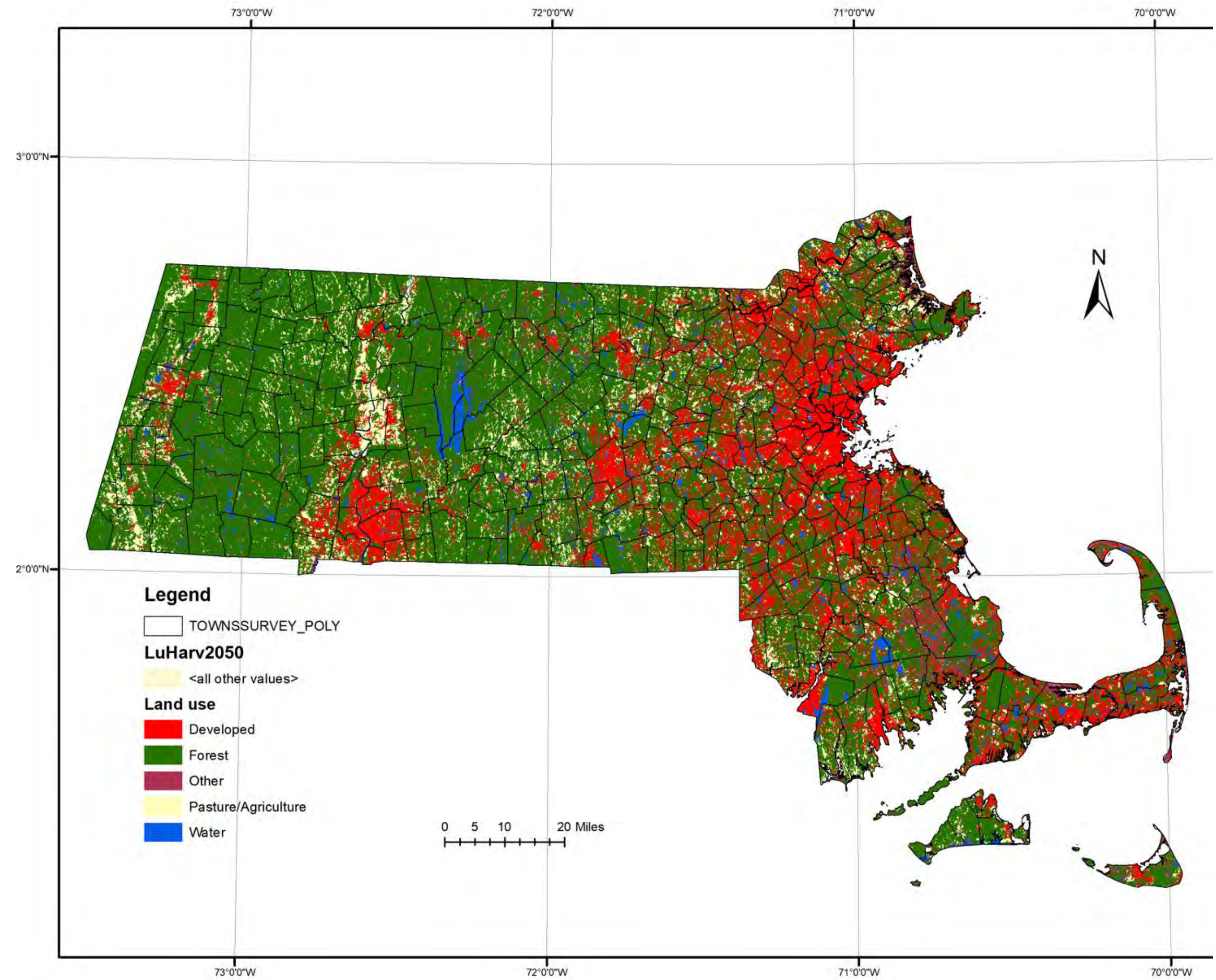

Figure 62: Harvard (HP1) Landuse 2050 Prediction Models

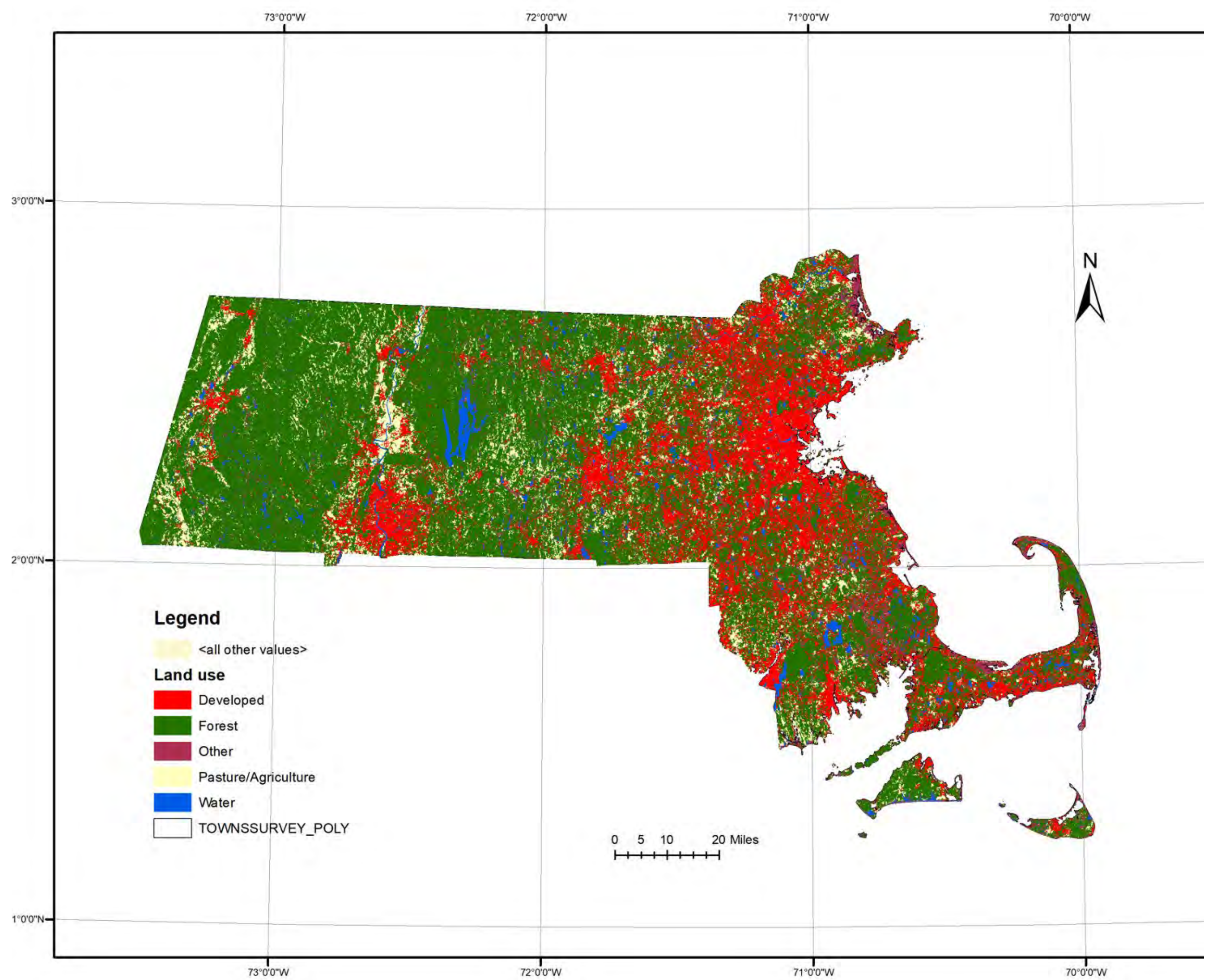

Figure 63: Harvard (HP2) Landuse Prediction 2050

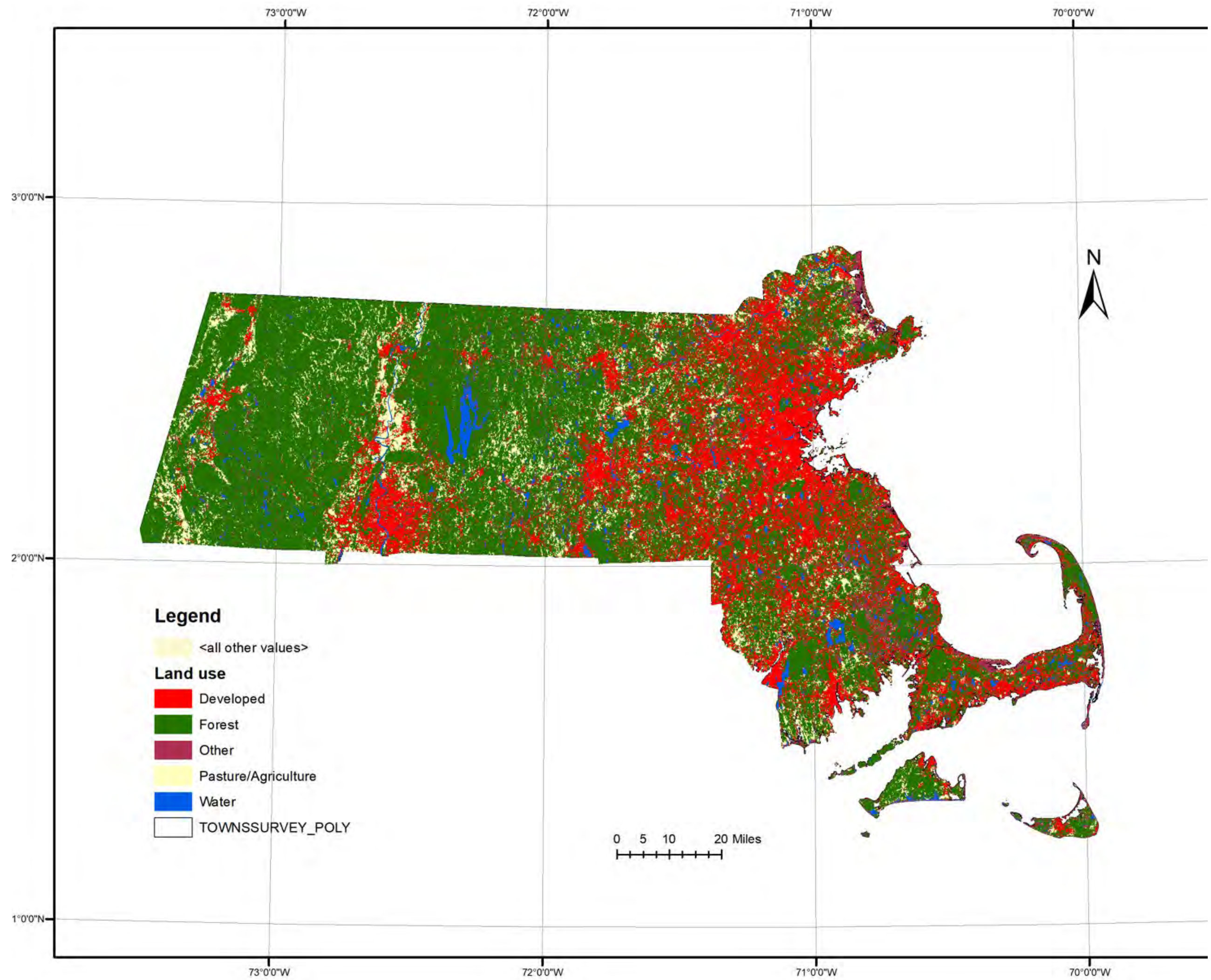

Figure 64: Harvard (HP3) Landuse Prediction 2050

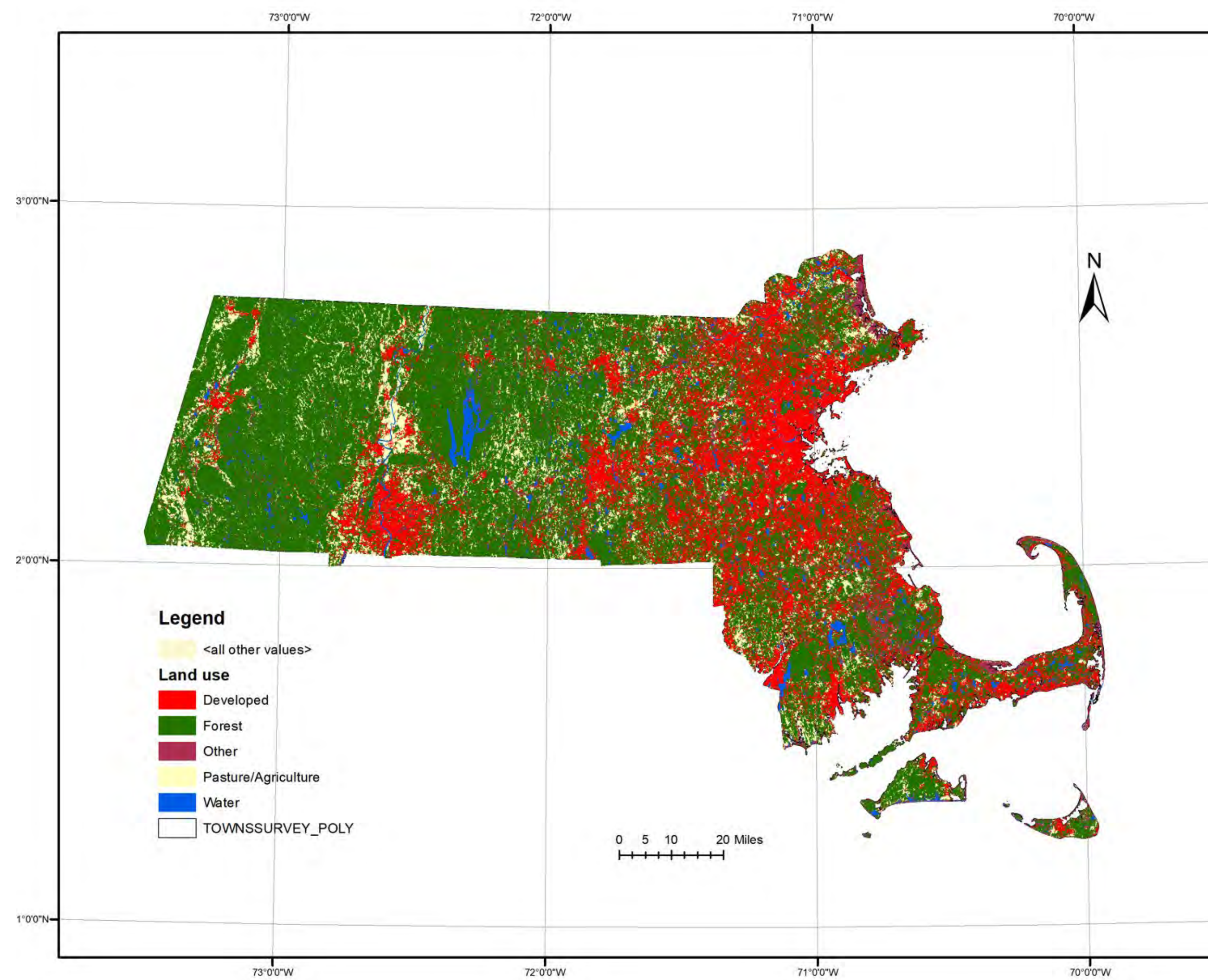

Figure 65: Harvard (HP4) Landuse Prediction 2050

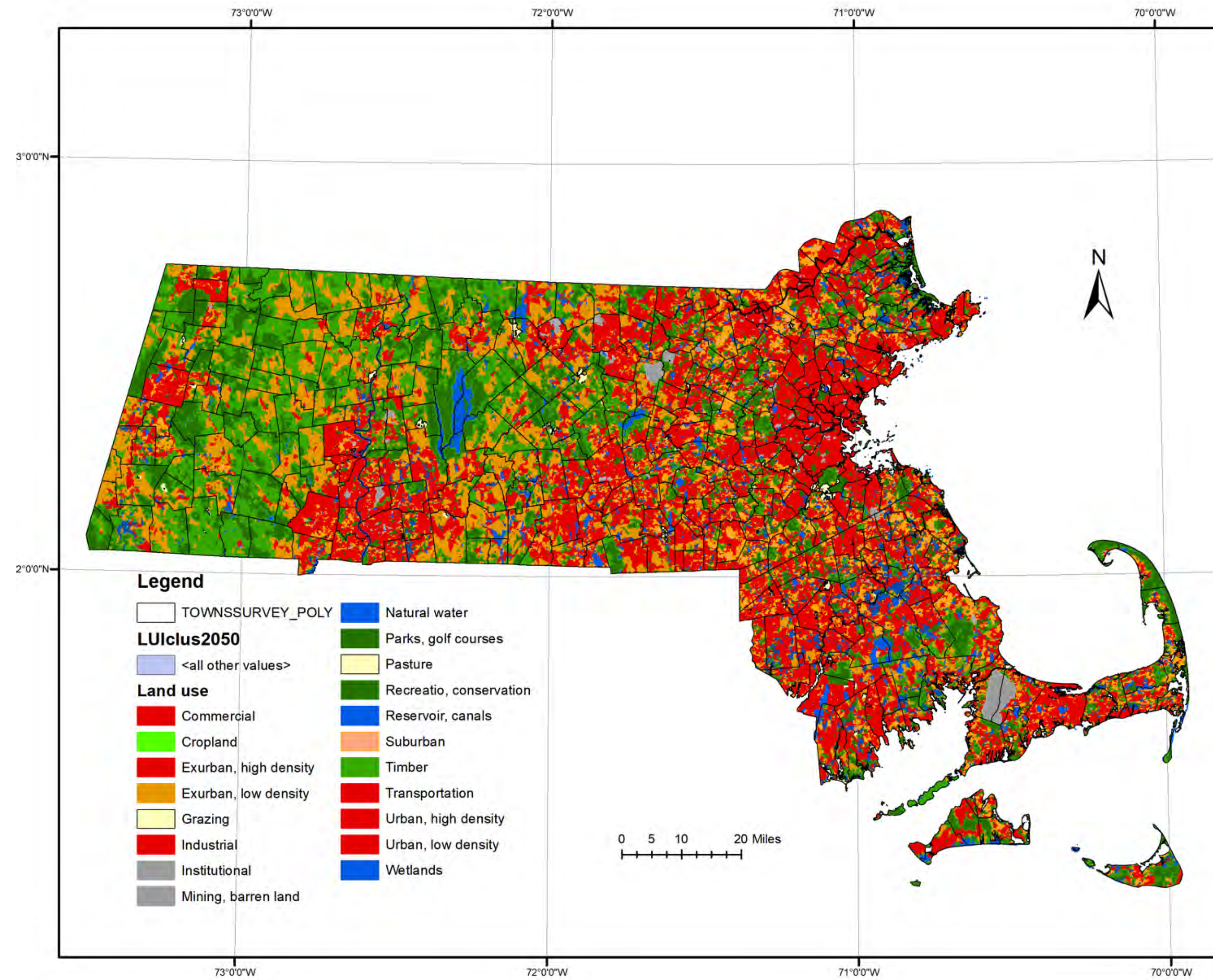

Figure 66: ICLUS (2050) Prediction Model

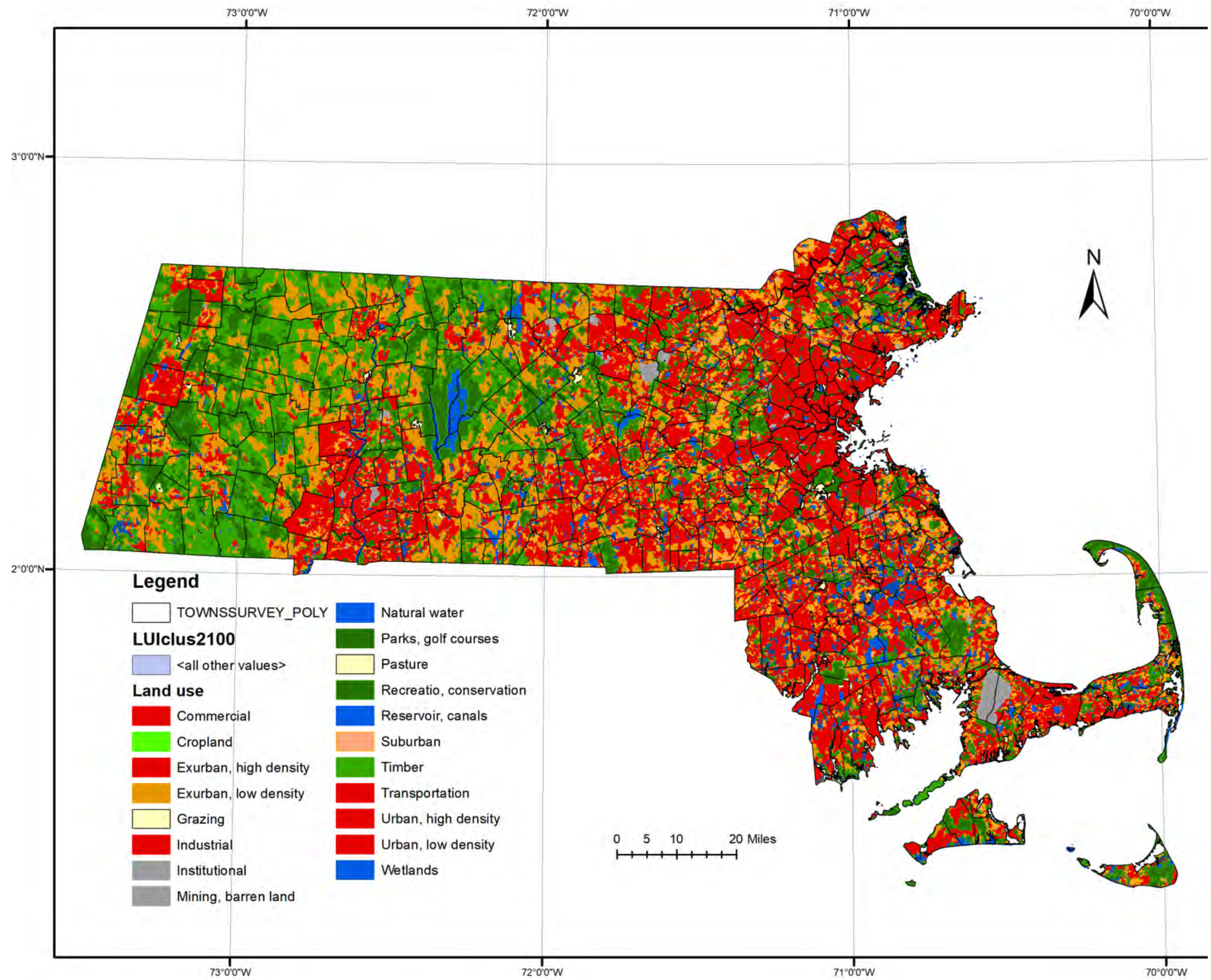

Figure 67: ICLUS (2100) Prediction Model

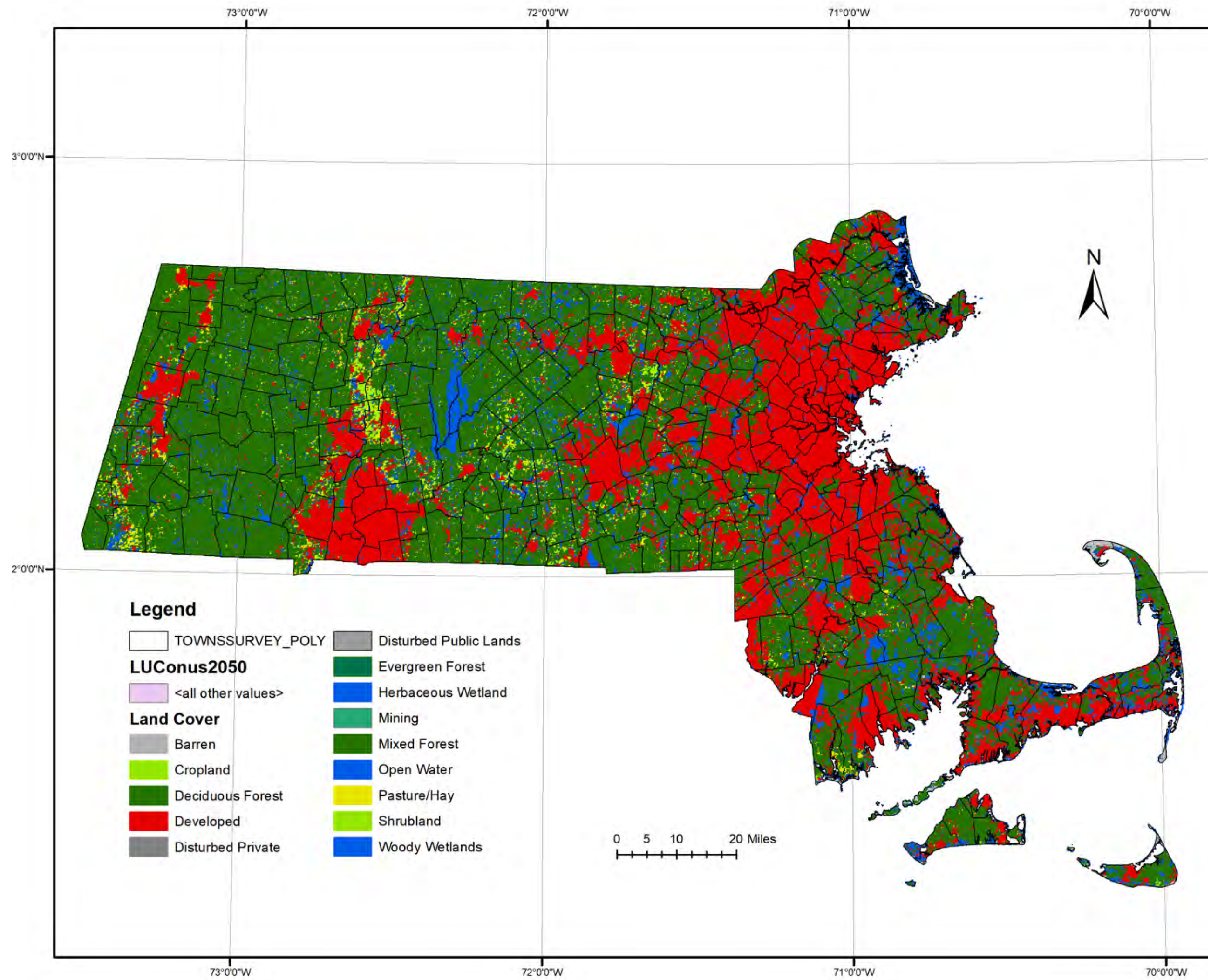

Figure 68: CONUS (B2) 2050 Landuse Model Prediction

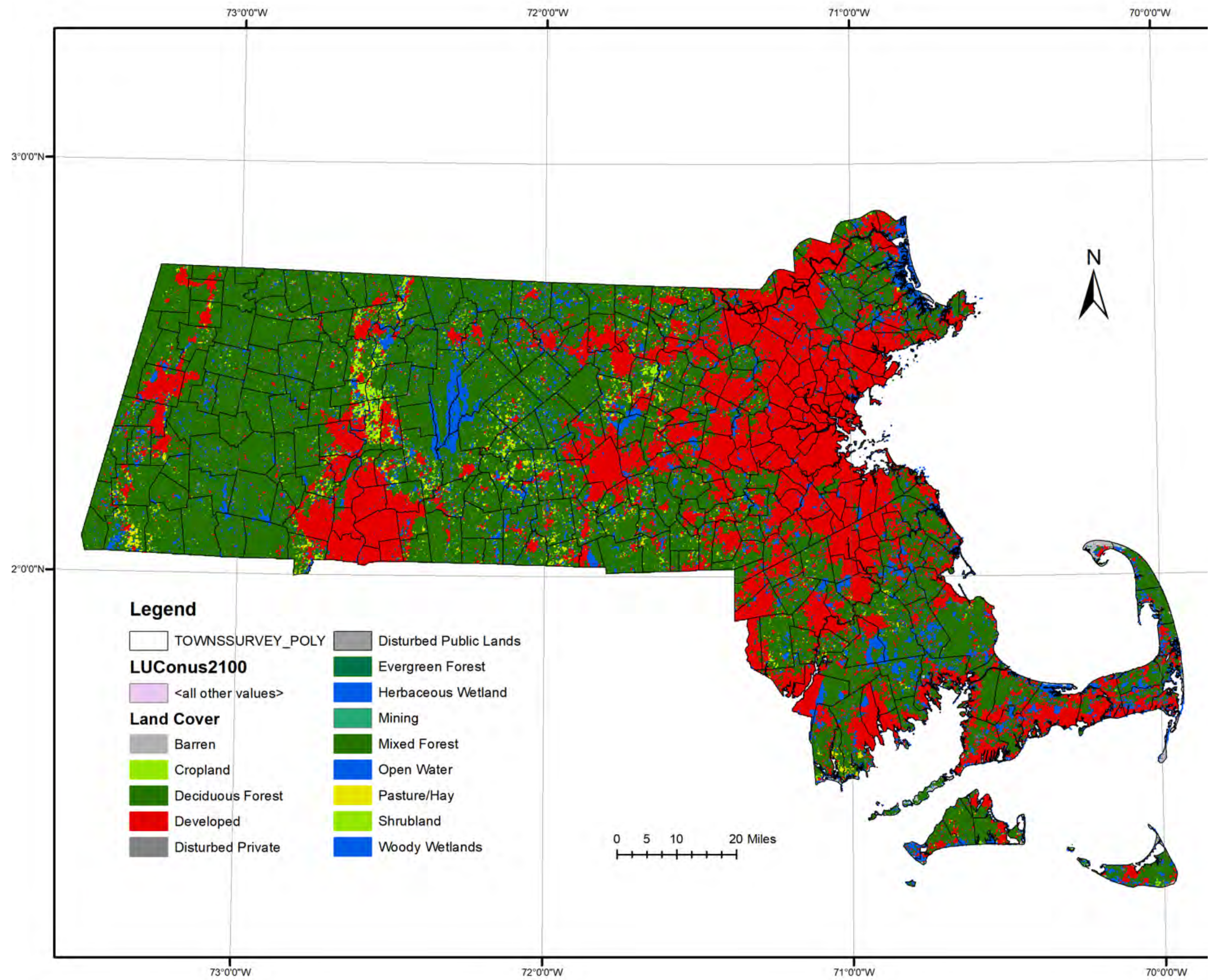

Figure 69: CONUS (B2) 2100 Landuse Model Prediction

4. References

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Hynicka, J. and D. Caraco. 2017. Relative and Absolute Reductions in Annual Water Yield and Non-Point Source Pollutant Loads of Urban Trees. Crediting Framework Product #2 for the project Making Urban Trees Count: A Project to Demonstrate the Role of Urban Trees in Achieving Regulatory Compliance for Clean Water. Center for Watershed Protection, Ellicott City, MD.

Zhu, Zhiliang, ed., Bouchard, Michelle, Butman, David, Hawbaker, Todd, Li, Zhengpeng, Liu, Jinxun, Liu, Shuguang, McDonald, Cory, Reker, Ryan, Sayler, Kristi, Sleeter, Benjamin, Sohl, Terry, Stackpoole, Sarah, Wein, Anne, and Zhu, Zhiliang, 2011, Baseline and projected future carbon storage and greenhouse-gas fluxes in the Great Plains region of the United States: US Geological Survey Professional Paper 1787, 28 p. (Also available at http://pubs. usgs.gov/pp/1787/.)