Risk Management of Storm Damage to Overhead Power Lines

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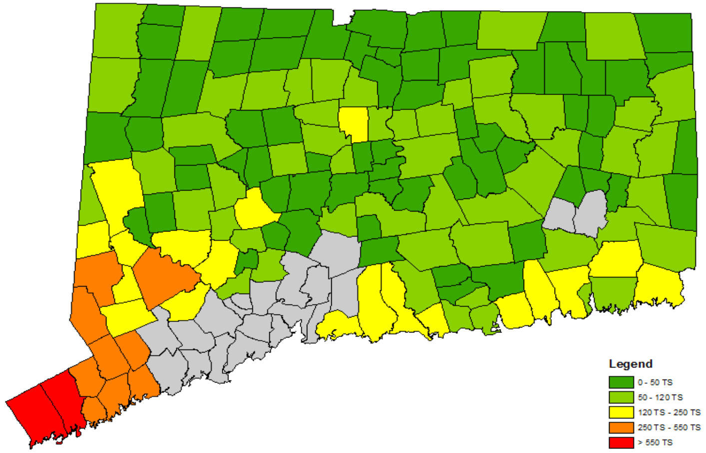
Why is risk management important?

Estimated Drive Time for Outside Line and Tree Crews

Source: K. Bowes, CL&P

Storm Sandy: Predicted TSs per town



Emergency Preparedness Decisions		Prediction Model Outputs/Information
Number of local crews Need for outside crews to be called in	←	Total predicted damages (and associated length of outages) for the entire service territory
Deployment of resources Staging of equipment	←	Spatial distribution of damage occurrences (what areas will be hit hardest from winds and flooding?)
Timing of staffing (when to call in crews)	←	Regional weather/damage predictions (what other service territories will be impacted by the same storm?)

1. Damage Prediction

Our main deliverable to the utilities

Data and Deliverables

Modeling Framework

Inputs

Weather
- Sustained Winds
- Wind Gusts
- Wind Stress
- Precipitation Rate
- Snow Water Content
- Soil Moisture Content
- Air Temperature

Infrastructure
- Count of isolating devices
    - Fuses
    - Switches
    - Reclosers
    - Transformers
- Length of circuit miles
    - Percentage of backbone vs. lateral circuit

Geography
- Land Use Per Town (percentage)
    - Developed
    - Forested
        - Coniferous
        - Deciduous
- Per capita income

Damage Modeling

>10 years of Historical Storm Data
- Trouble spot locations
- Number of customers affected
- Device failure codes
- Seasonal calibration (summer, winter, transition months)

Outputs

Quantitative Estimates of Damage
- Trouble spots per town
- Estimate confidence

Weather Data

- Mean and max of weather variables are captured on a 2 km grid overlaying the service territory

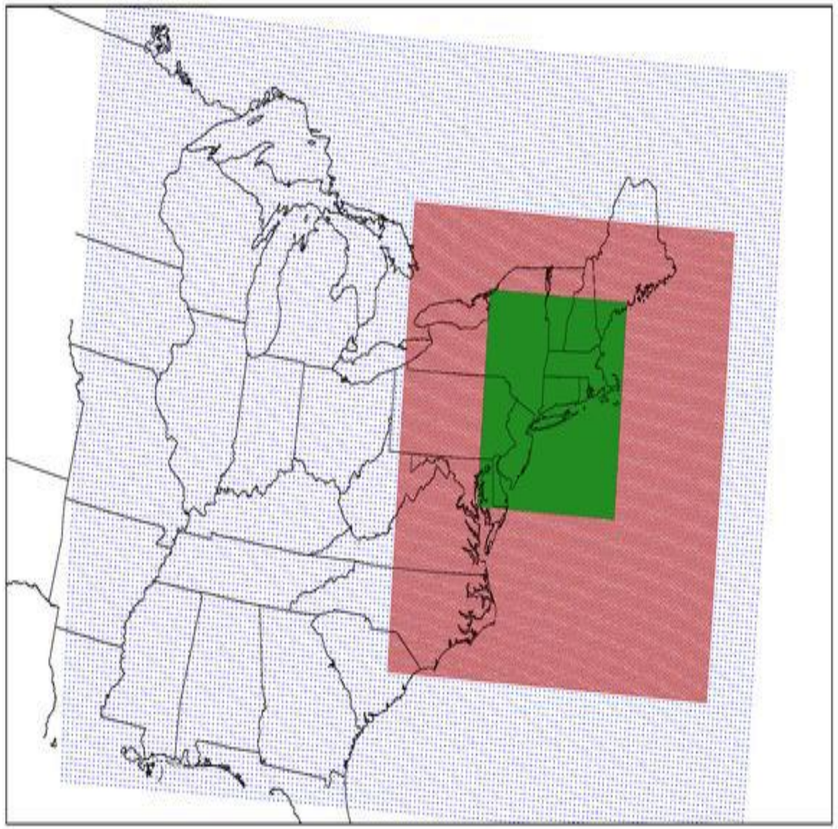


Figure: Nested weather grids (different resolutions)

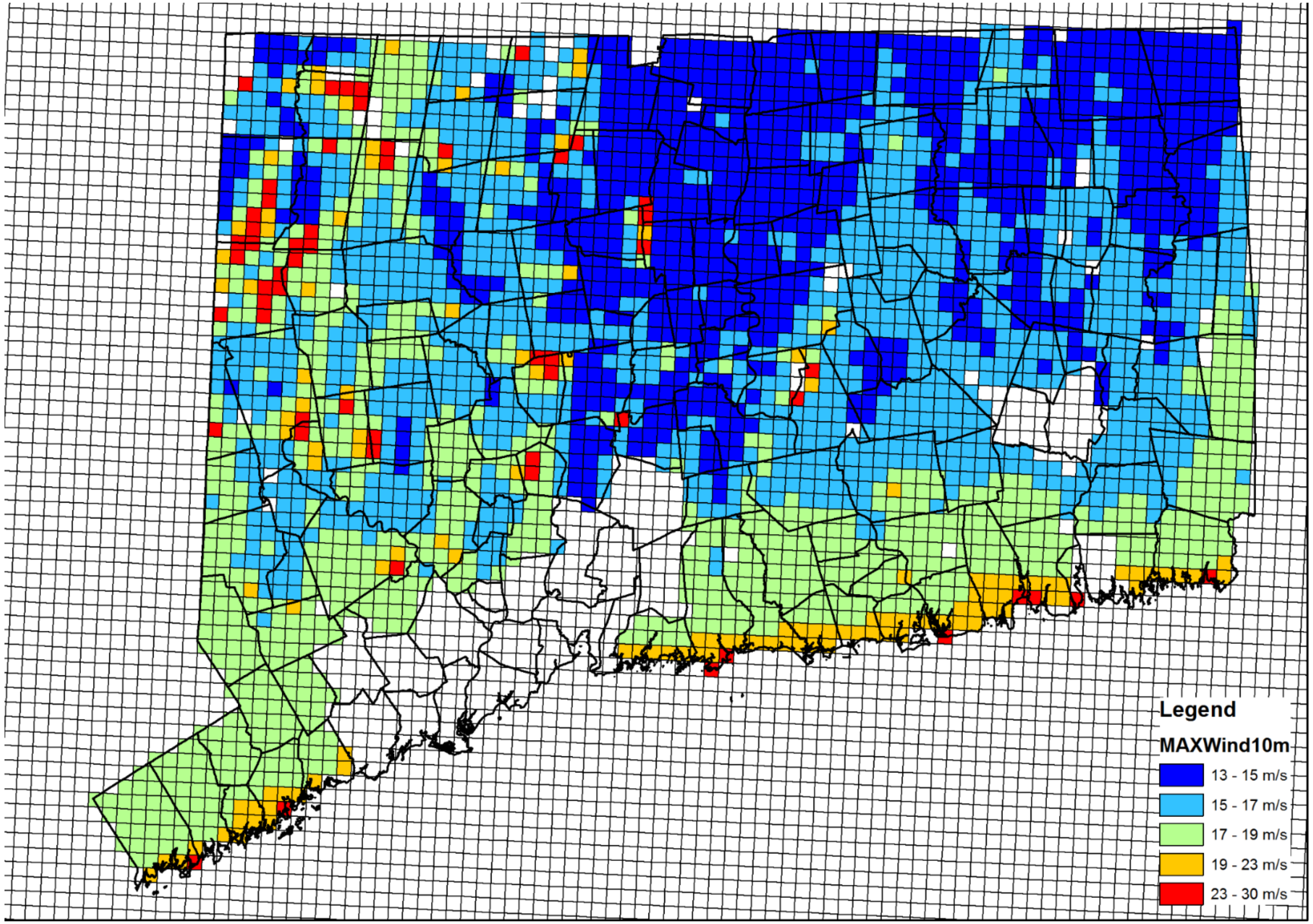


Figure: MaxWind10m during Sandy

TS and Distribution Infrastructure

- Daily trouble spot data for CL&P from 2005 - 2013
- Latitude/longitude of all distribution infrastructure (poles, transformers, reclosers, switches, fuses)
- Count of circuit miles per town (backbone and lateral)
- Count of customers per town

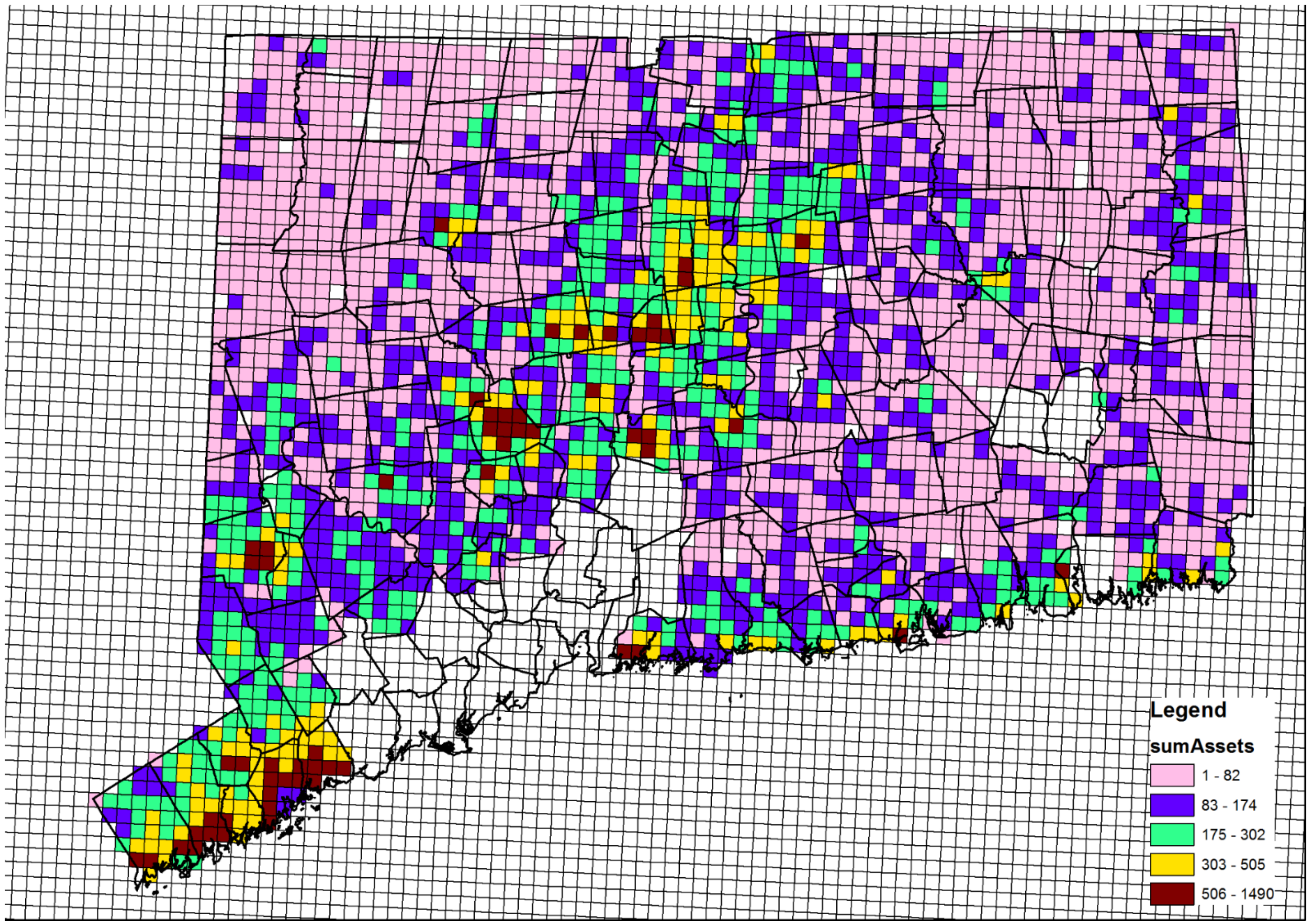
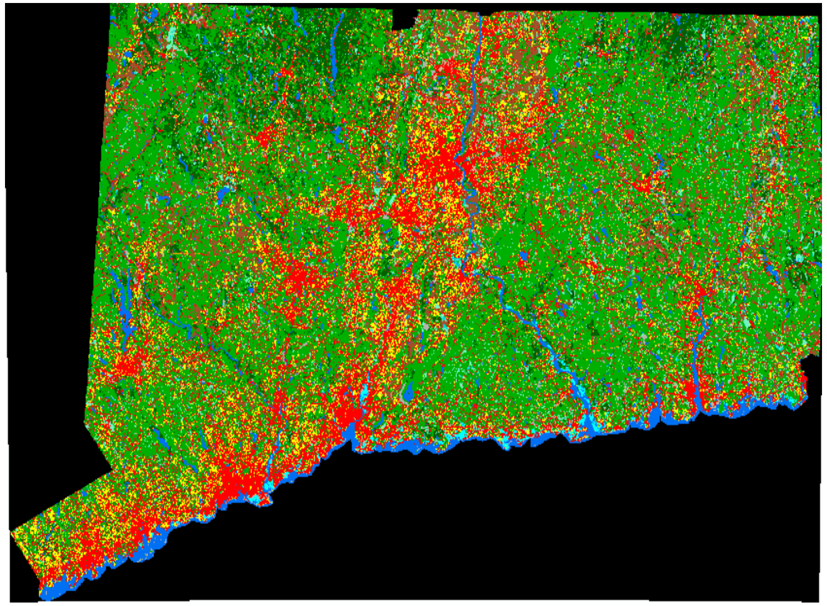


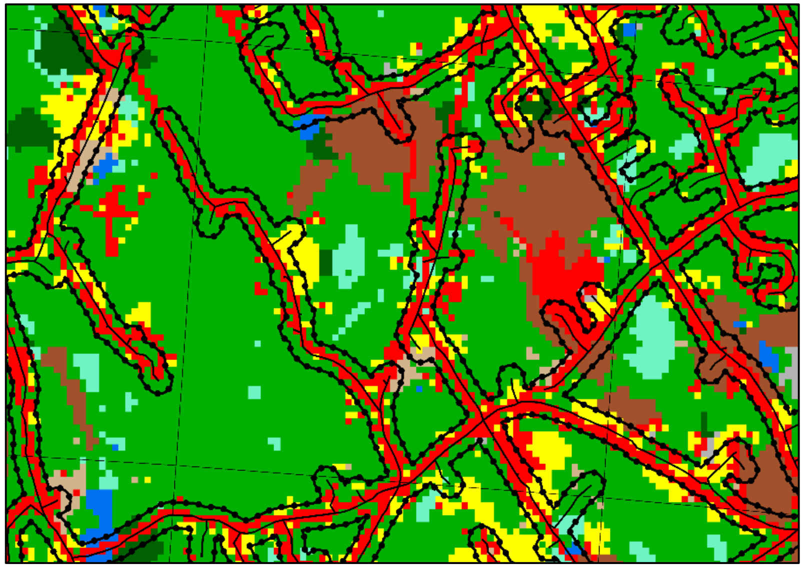
Figure: Assets per 2 km pixel

Data Blending – Infrastructure & Land Use

- 2 km grid overlaying the entire CL&P service territory
- Same grid used by WRF to forecast weather variables (wind, precipitation) during storm events
  - High resolution compared to town areas
  - One town has many 2-km pixels



- 30 m pixels overlaying the State of Connecticut
- Developed by the UCONN Center for Land Use Education and Research
- 12 land use categories (forest, developed, grass, wetlands)



- Power lines follow the road, can’t just use the closest pixels to the power lines!
- Created 30 m and 60 m buffers around CL&P distribution power lines, created points every 30 m each buffer, spatially joined to land use category
- 30 m points along 60 m buffer is **most representative** of field conditions

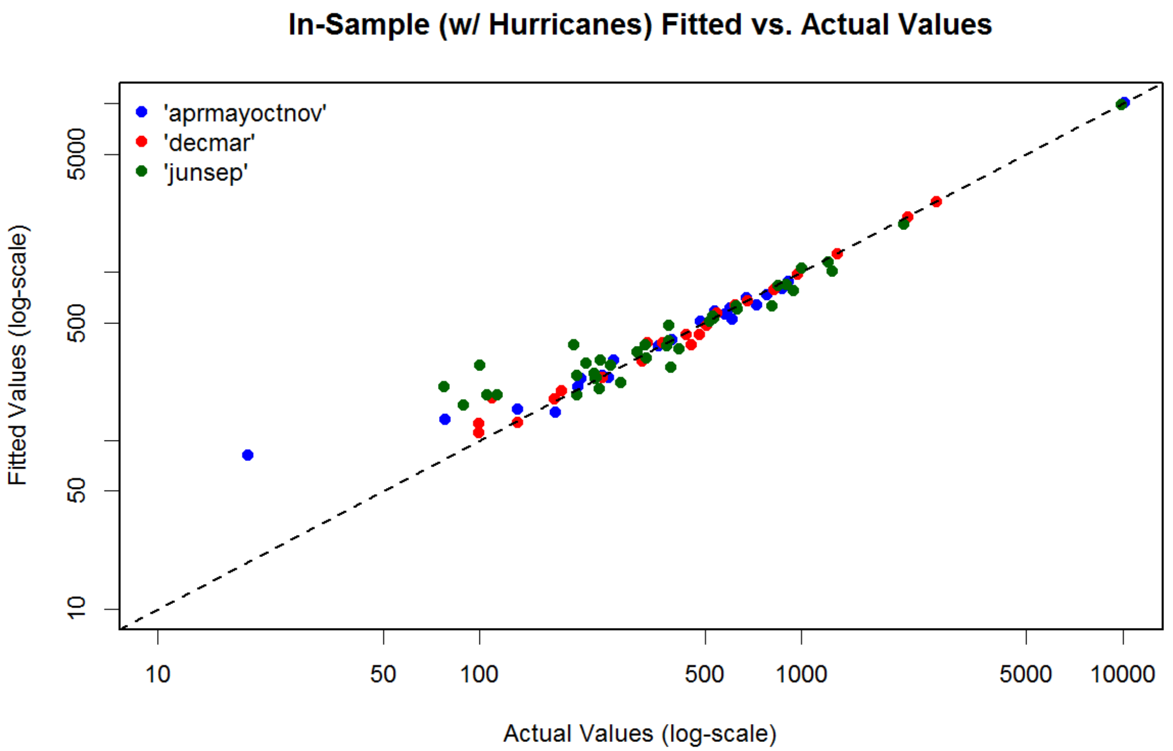
Damage Prediction Model

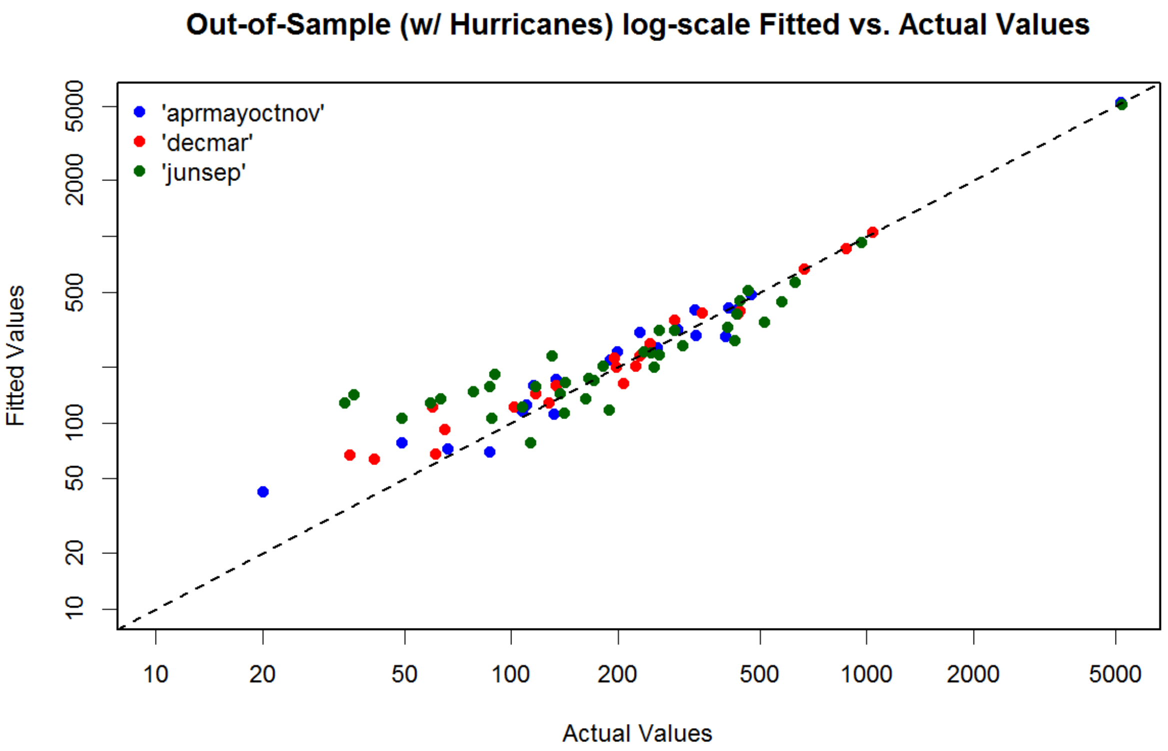
The BART model (Bayesian additive regression trees) is a statistical model based on sum of regression trees, combining the advantages of multiple tree learning and Bayesian inference:

- Prediction power from regression tree learning
- Resistant to overfitting (like random forests)
- Robust to extreme response values

BART models are applied by season at the 2 kilometer grid level.

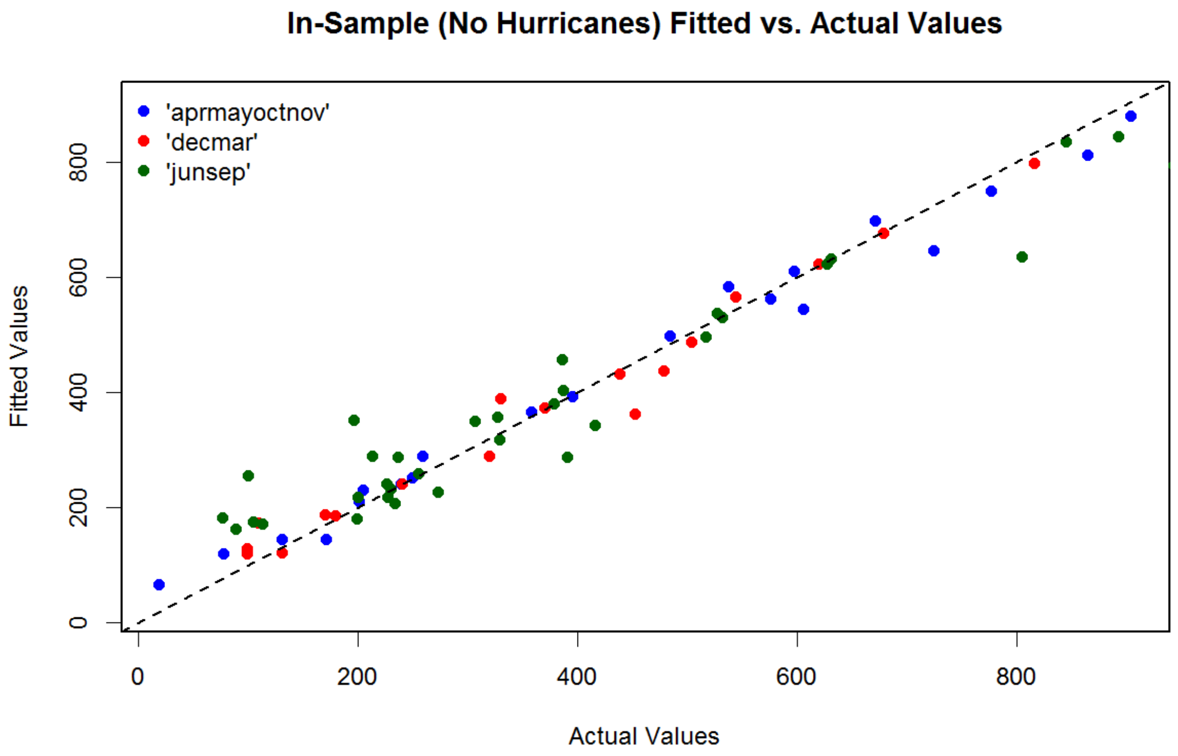
Actual vs. Predicted (BART)

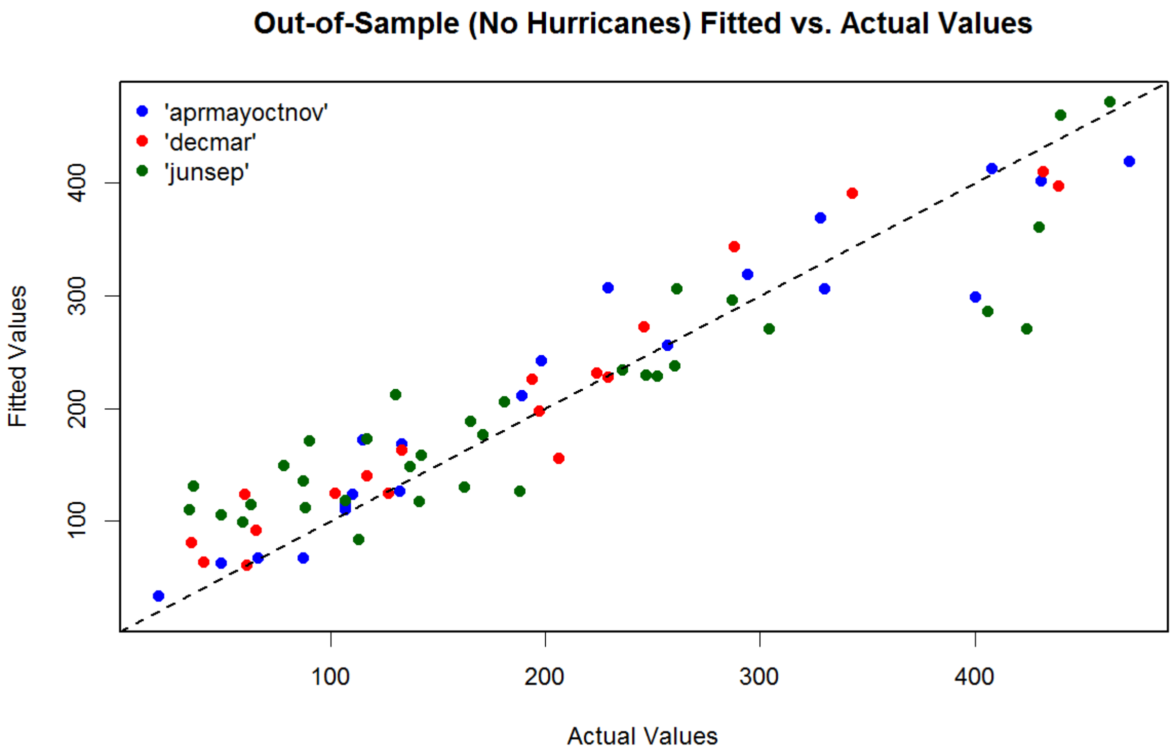




- Transition
- Winter
- Summer

Actual vs. Predicted (BART) – no hurricane cases





- Transition
- Winter
- Summer

2. Vegetation Management

Effect of vegetation management on outages based on damage model results

Vegetation Management Data

Standard Maintenance Trimming (SMT)

- Most utilities strive to trim circuits on a 4 year cycle
- SMT features were recorded by NU as line features, Dissolved to 2 km grid, then sum length

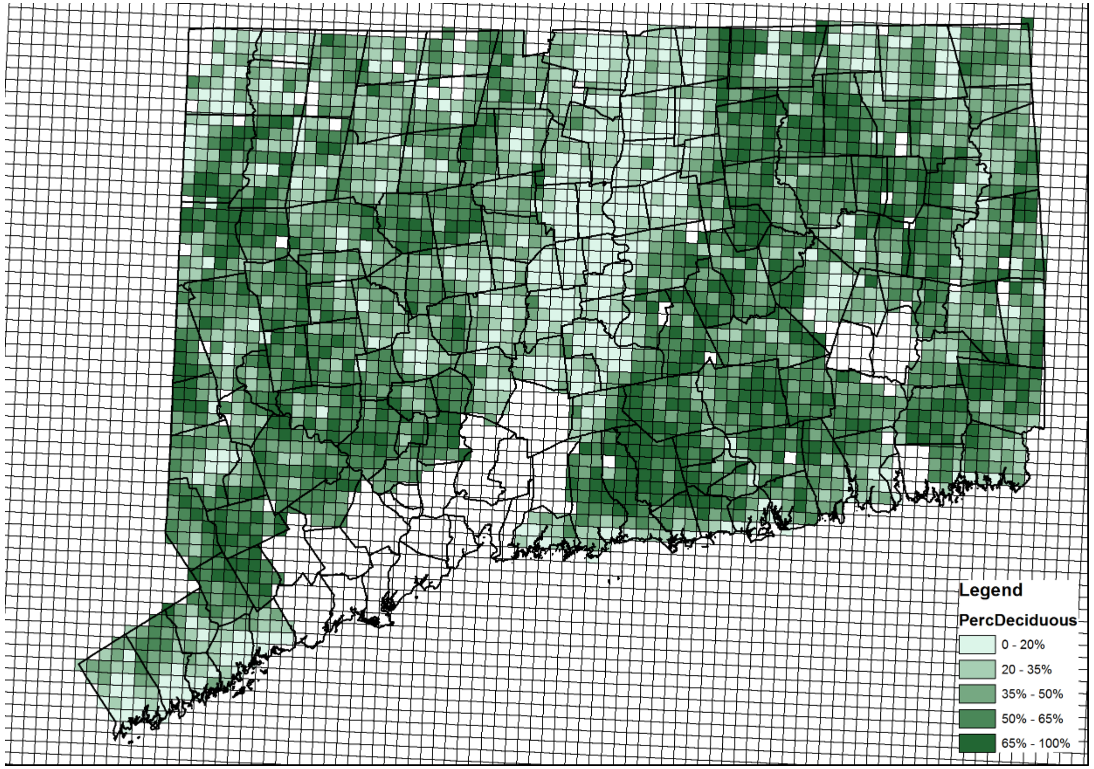
Enhanced Tree Trimming (ETT)

- Most utilities strive to trim circuits on a 4 year cycle
- ETT features were recorded by NU as polygon features, needed to dissolve power line shapefile and spatially join power lines to polygons, then sum
- ETT is more sparse than SMT

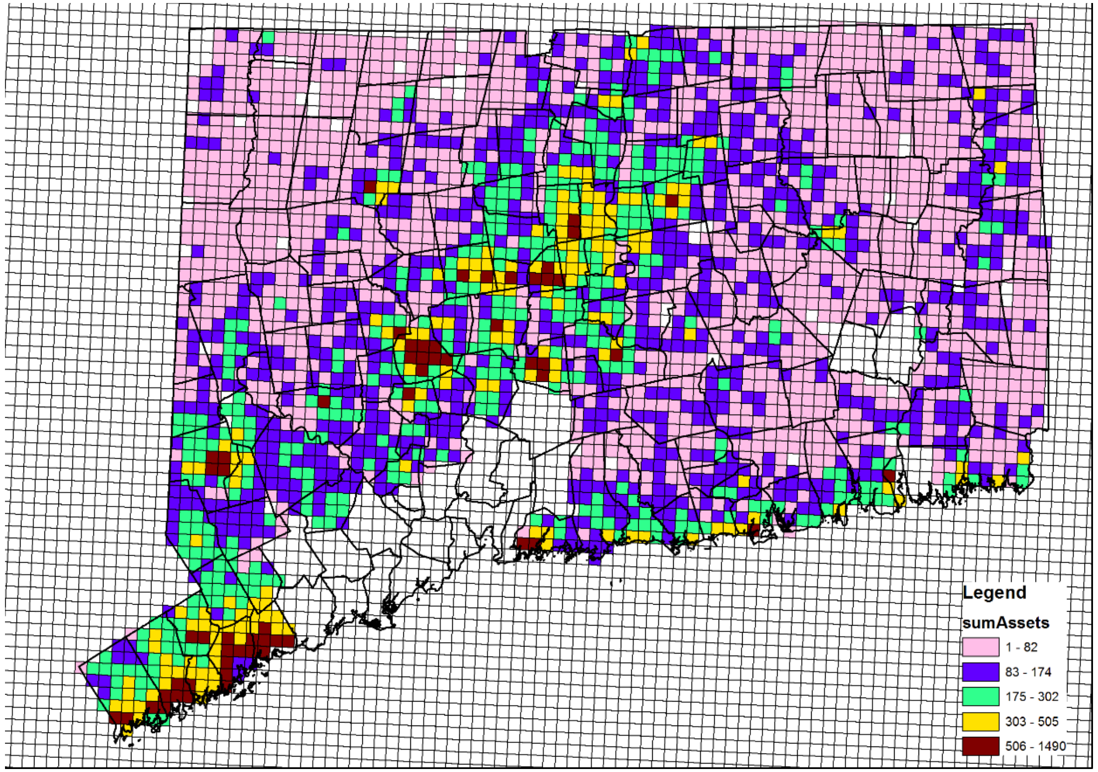
**spatial join preferred to other joins/queries, because circuits can change names over time (difficult to update)*

PercForest and Asset Data per Pixel

PercForest (computed around OH lines)



Count Assets



Overview – DT model analysis

Models Evaluated

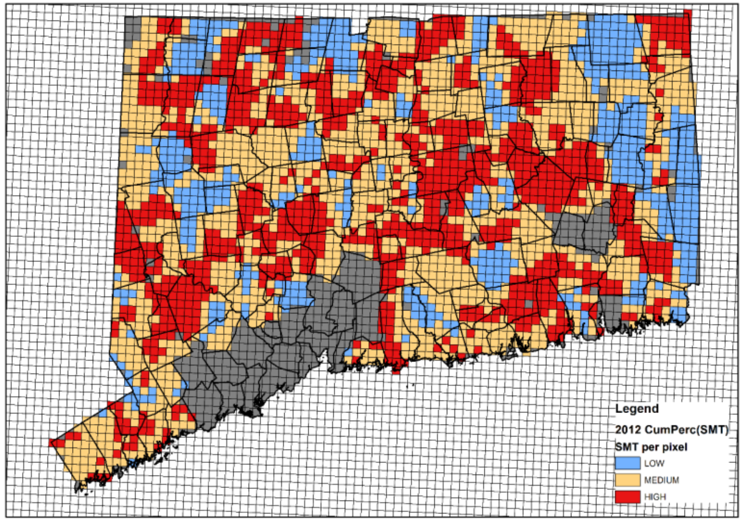
- ETT > 0 ONLY Calibration
- ETT and SMT > 0 Calibration
  - Change SMT and ETT in scenarios
- Scenarios evaluated
  - 10%, 33%, 66% trimming
  - Trimming benefit is relative to a 10% trimming baseline for all scenarios

Methodology

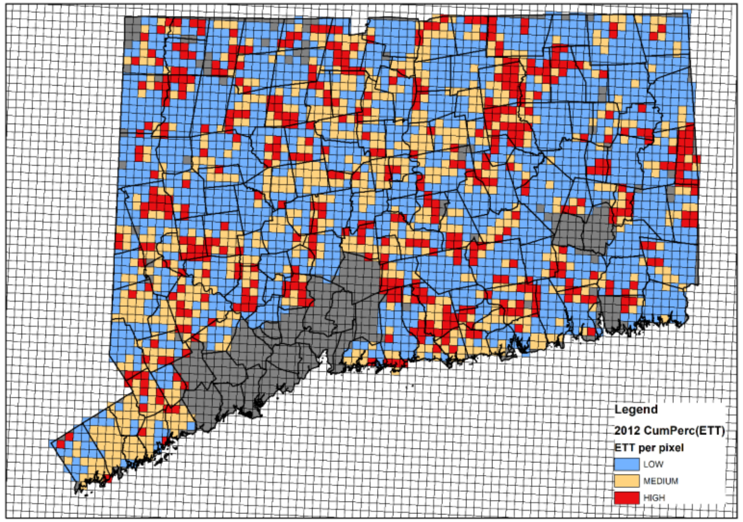
- Bootstrap DT forest analysis calibrated on pixels with ETT and SMT > 0
- BART model analysis calibrated on pixels with ETT and SMT > 0:
  - Variable importance: The % usage of a specific variable on tree branch splitting
  - Partial dependence: Expected response based on all other variables given fixed values.

Other Notes

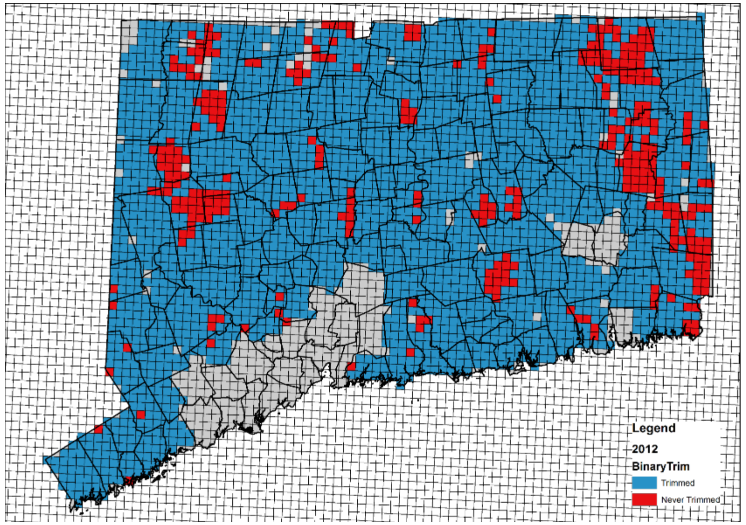
- 18 storms from 2011 – 2013 (excludes October 2011 nor'easter)
- 2,851 pixels cover the State (2 km grid)
- ETT is cumulative for all years (additive)
- SMT is cumulative, but has a 25% decay per year since trimming occurred



Cumulative PercSMT (linear decay)



Cumulative PercETT (2009 – 2012)



Pixels never trimmed (2009 – 2012)

Results - Bootstrap DT forest analysis

ETT > 0 Model

- Range (relative difference)
  - 33% Trim: 5% - 15% decrease
  - 66% Trim: 8% - 24% decrease
- Mean (relative difference)
  - 33% Trim: 9% decrease
  - 66% Trim: 13% decrease

Note: 18,020 pixels used for calibration

SMT and ETT > 0 Model

- Range (relative difference)
  - 33% Trim: 7% - 24% decrease
  - 66% Trim: 11% - 32% decrease
- Mean (relative difference)
  - 33% Trim: 15% decrease
  - 66% Trim: 20% decrease

Note: 13,319 pixels used for calibration

3. HazPix

Leveraging granular Lidar altitude data to improve damage prediction

Field Vegetation Survey and LiDAR Dataset

- Airborne laser scanner determines location and elevation of objects on ground surface.
- Eastern CT LiDAR dataset acquired in November 2010 (leaf-off)
  - Average point density: 1.6 pts/m2
  - Maximum point spacing: 0.7 m
  - Vertical accuracy: 21 cm (forest)
  - Horizontal accuracy: 1 m
  - Bare-earth DEM (1 m resolution) developed by data provider
- Tree heights and positions for validation of LiDAR height model.
- Tree inventory and hazards to characterize roadside forests.

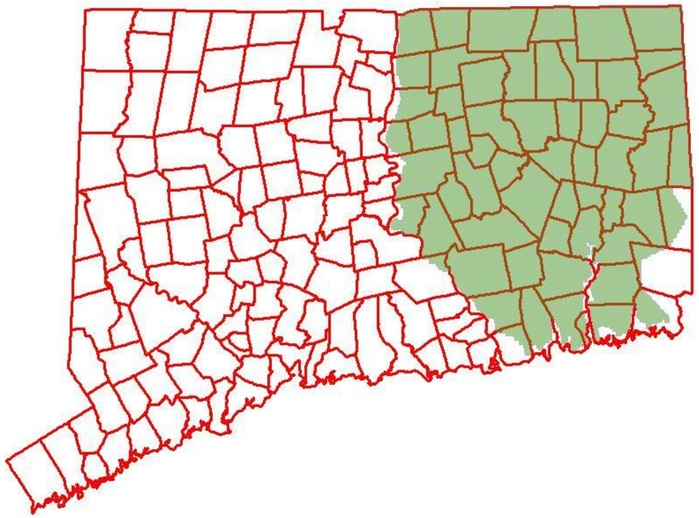
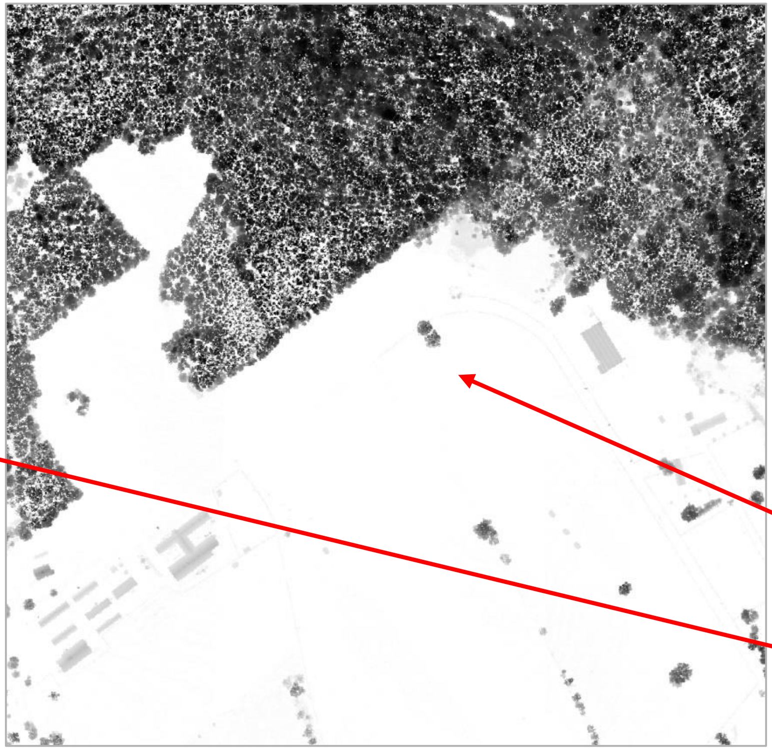


Figure: LiDAR Coverage area

- Survey included…
  - 11 sites
  - 7.6 km of roadside
  - 1650 roadside trees
  - 124 interior forest plots

LiDAR Height Model Example



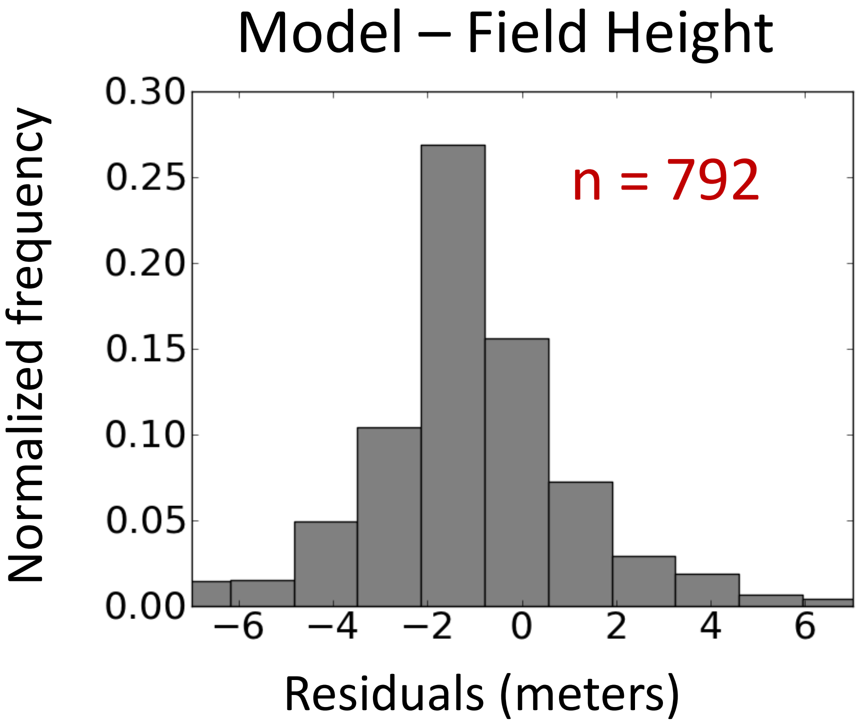
Trees

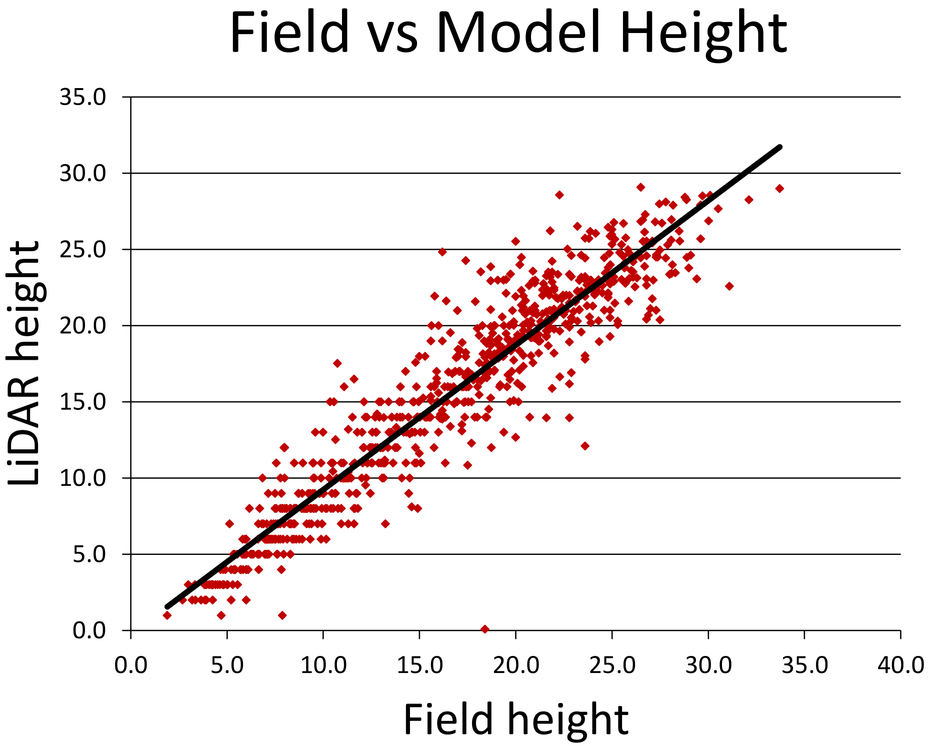
- Pixel height = max elevation – ground elevation
- 1 x 1 meter pixel size

White – low elevation
Black – high elevation

LiDAR Model Validation

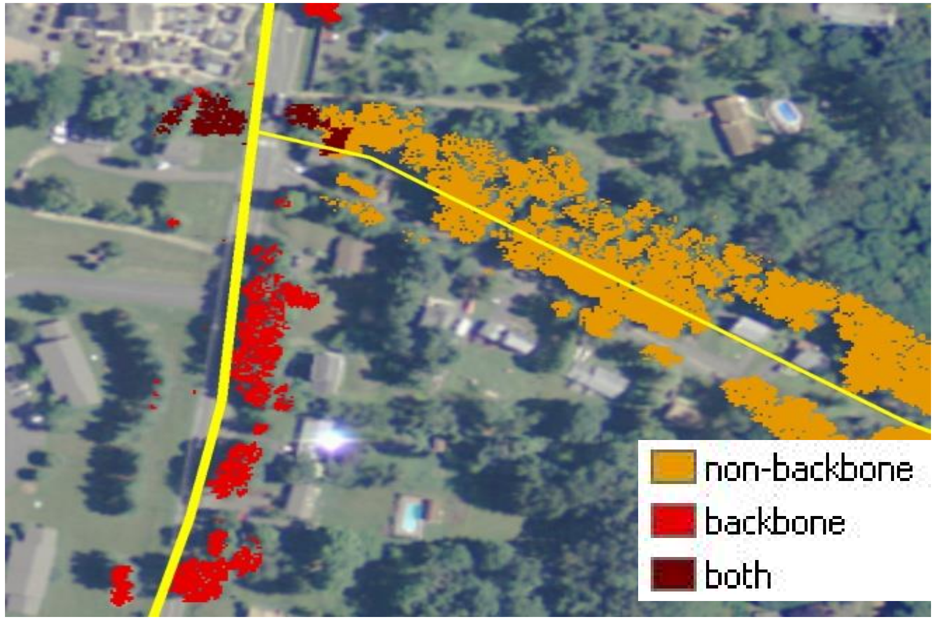
- Field heights compared with heights from LiDAR model to assess accuracy.
- Model underestimated heights by 1.1 meters on average.





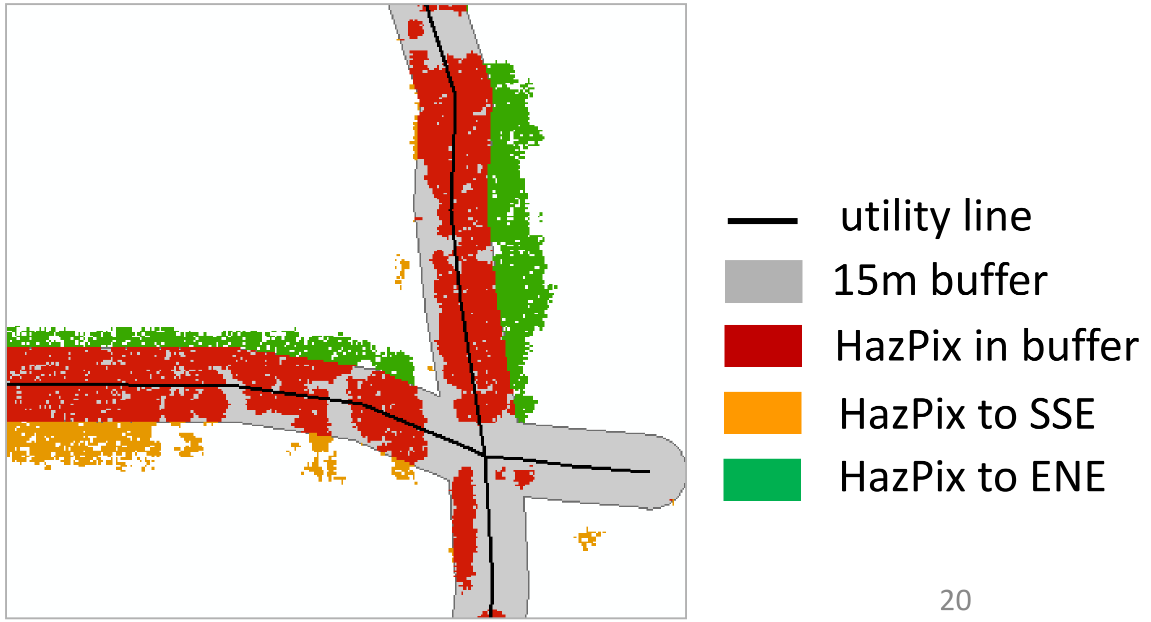
Hazard Pixels

- Pixels tall enough and close enough to strike lines in event of a tree failure.
  - pixels are a proxy for trees
- Classified based on type of lines they can reach…
  - backbone or non-backbone.



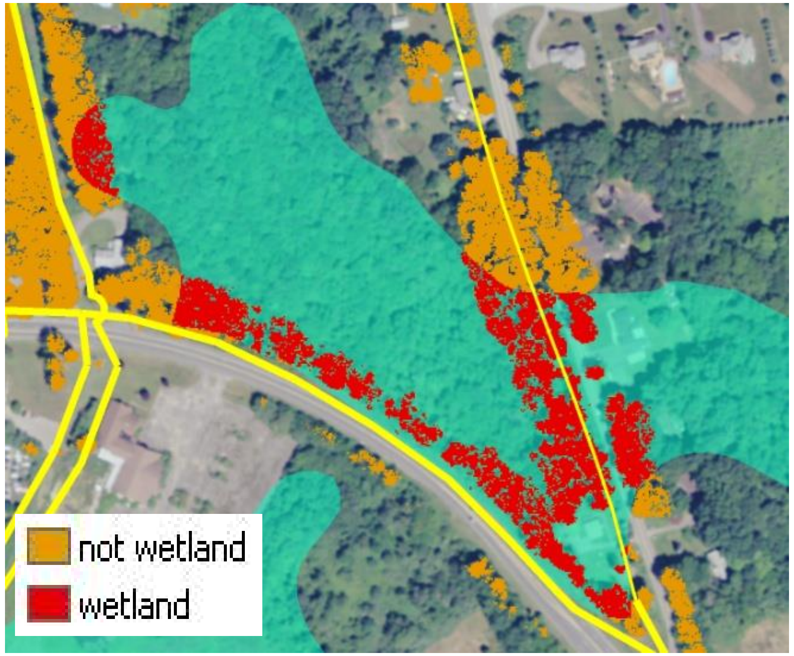
Position of Hazard Pixels

- Upwind hazard pixels likely to be of greater risk to power lines.
- Pixels classified by position relative to lines
  - within 15 meters
  - direction to lines (i.e. NNE, ENE, etc.)
- Metric can be matched to predicted wind direction



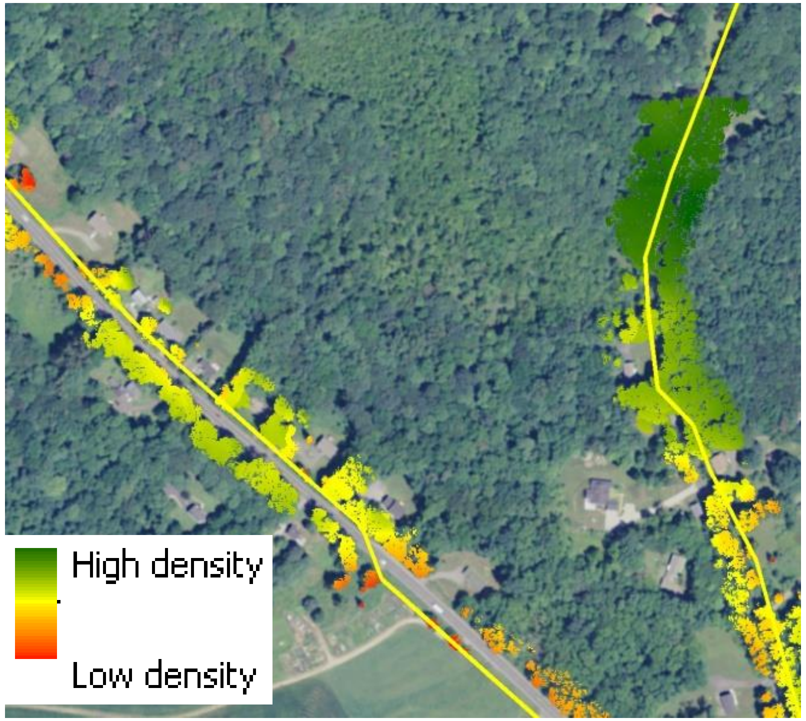
Soil Conditions

- Wet soils increase potential for windthrow.
- Hazard pixels classified by presence of wetland soils (DEEP GIS data).

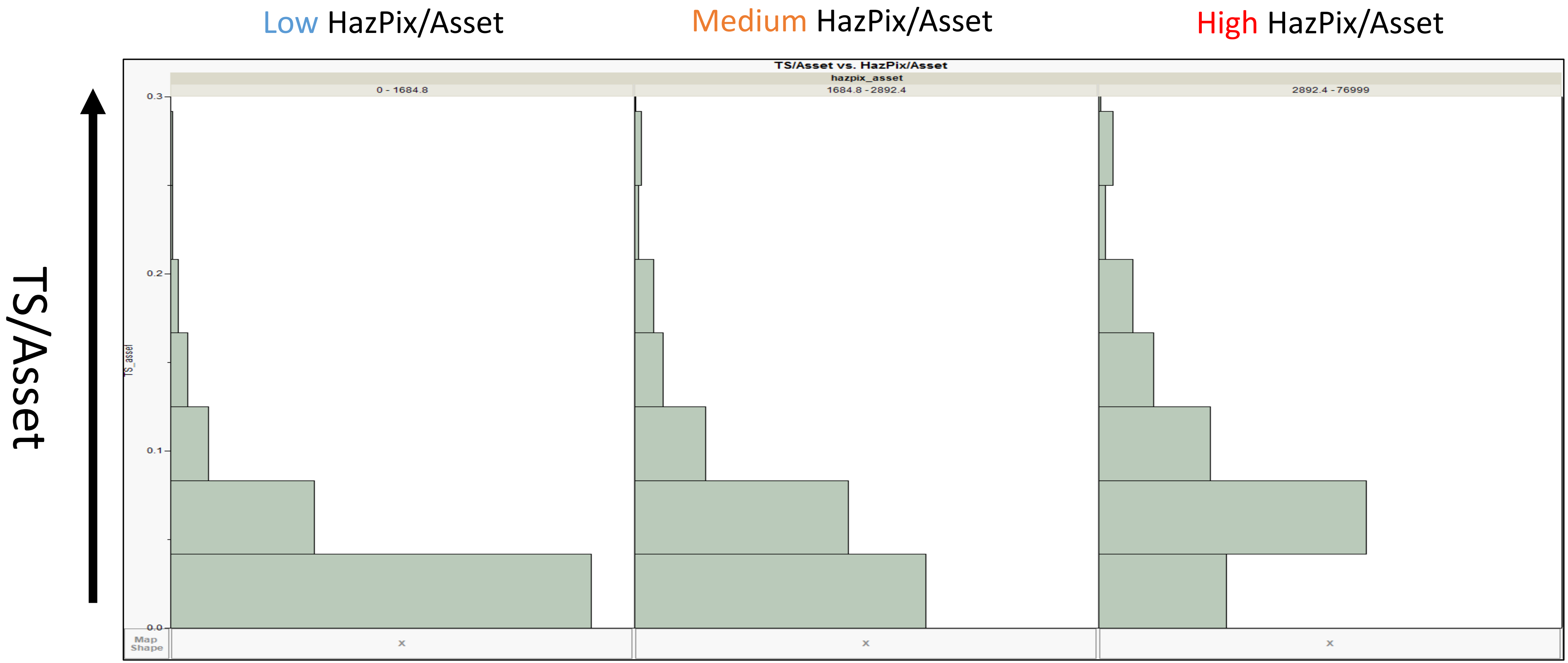


Forest Canopy Density

- Canopy density influences tree wind exposure and thus wind adaptation.
- Canopy density calculated for hazard pixels

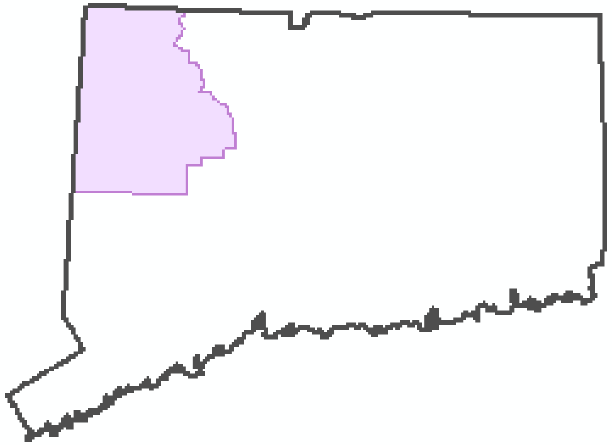


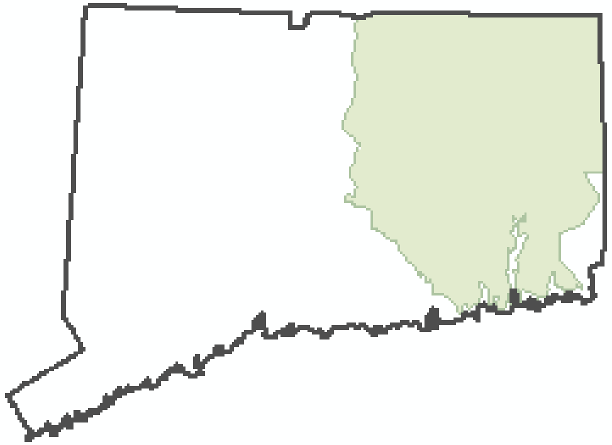
Histogram: TS/Asset by HazPix

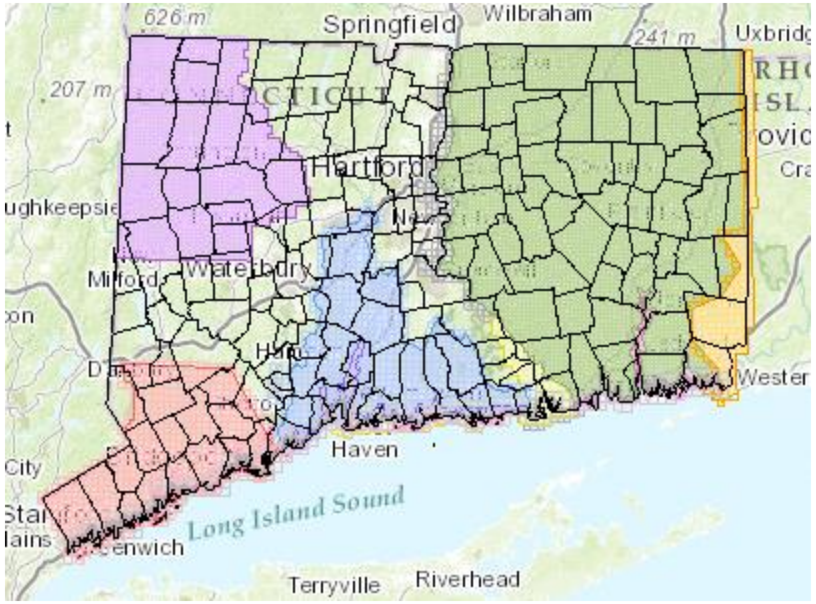


Future Work on HazPix

http://cteco.uconn.edu/help/info_lidar.htm







- Repeat HazPix analysis for Northwestern Connecticut (LiDAR data captured December 2011 data)
- Compare the relationship between Eastern CT
- Expand HazPix grid to other parts of CT
- Incorporate trimming data with HazPix into the DPM

Conclusions

- Both DT and BART models performed well in predicting CL&P service territory total number of TSs
  - Two-model calibration is needed: with and without hurricane cases;
  - Models use seasonal separation, which seems to improve model predictions;
  - Land use and infrastructure data improve model accuracy
- Both models were able to describe well the complex relationship between vegetation management, weather, land use and TSs.
- Calibrated models were used to evaluate impacts from different vegetation management scenarios
  - Up to ~35% reduction of TSs was noted in the case of high (66%) ETT and SMT trimming.

Sound fun? Join our team!

We are currently offering two positions

- Post-doctoral Fellow, starting either Winter or Fall 2015
- Funded PhD studentships in actuarial science, statistics, or environmental engineering currently available

In both cases, we are looking for people with a strong statistics/analytics background who are interested in learning more than you ever thought you would about weather and trees

Contact me with questions or interest, brian.hartman@uconn.edu

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