The Big Data Analytics: An Incremental Improvement or a Transformational Change

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M. Kezunovic, P. Pinson, Z. Obradovic, S. Grijalva, T. Hong, R. Bessa, "Big Data Analytics for Future Electricity Grids", Power Systems Computation Conference, Porto, Portugal, July, 2020 (online)

Outline

Example: Outage Management

What is Incremental and what is Transformational?

Transformational Aspects:

- Data Sources and Data Management
- Data Analytics (machine learning)
- Risk Prediction
- Risk Management and Mitigation
- Benefits

Future Decision-Making Framework

Other Examples

Conclusions

How Power Outages Occur?

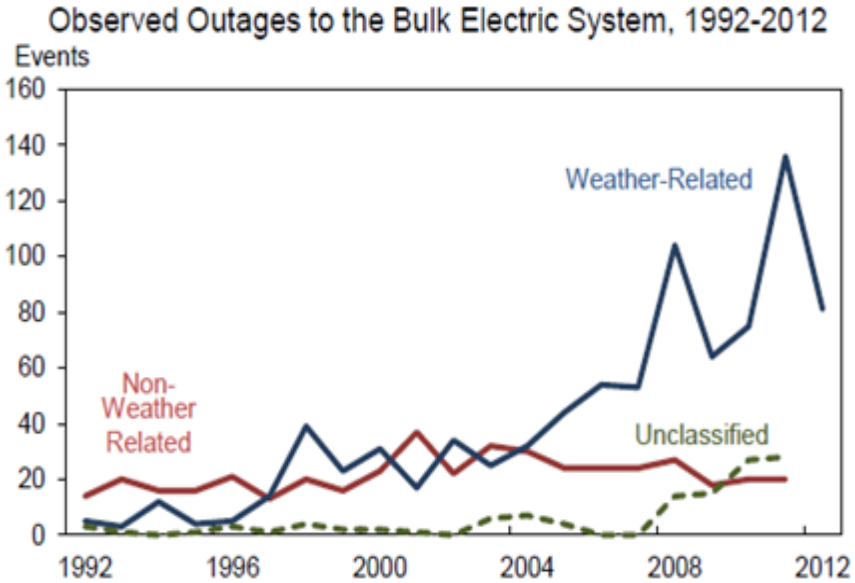
- Lightning damaging insulators
- Trees touching lines/feeders
- Equipment wear and tear
- Animal intrusions
- Infrastructure destroyed due to natural disasters
- Human-caused reasons
- Failure of fault clearing equipment
- Insulation stress going over limits



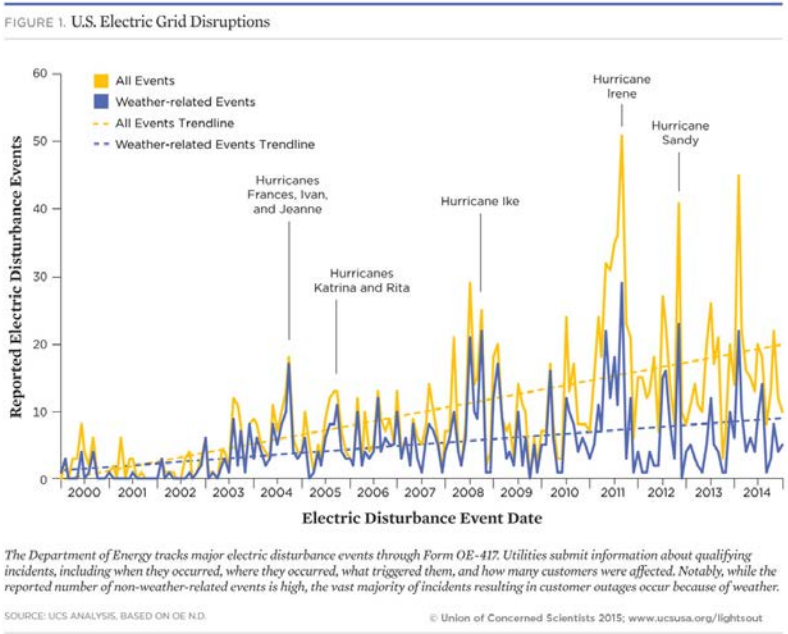




Why Outages are Becoming More Frequent



Source: Energy Information Administration



Outages Affected by Severe Weather

Severe Weather Caused 80% of Large-Scale Power Outages and 88% of Customers Affected by Power Outages From 2003-2012

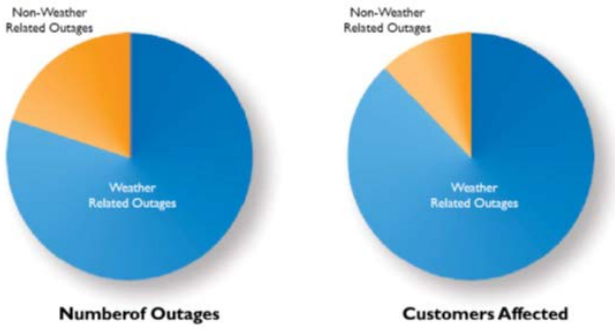


Figure 3. Percentage of power outages and total customers affected caused by severe weather from 2003-2012.

General Storms Caused Nearly 60% of All Weather-Related Outages Between 2003-2012

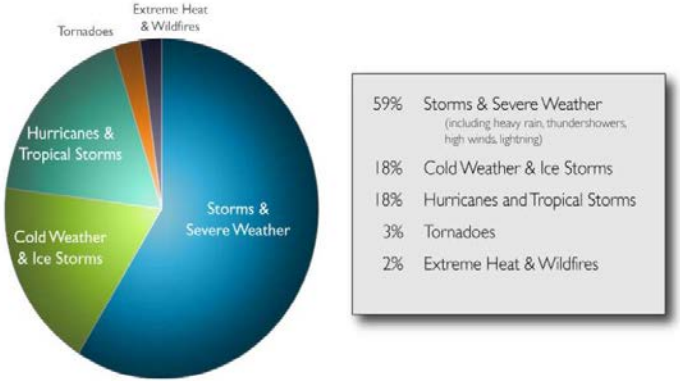
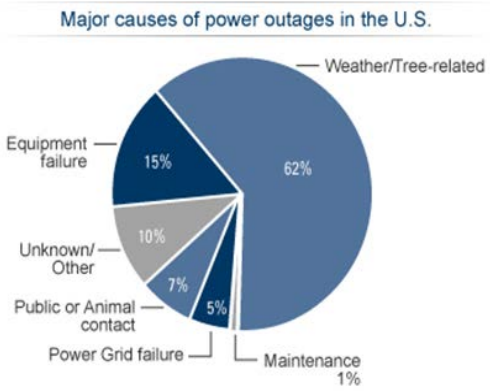
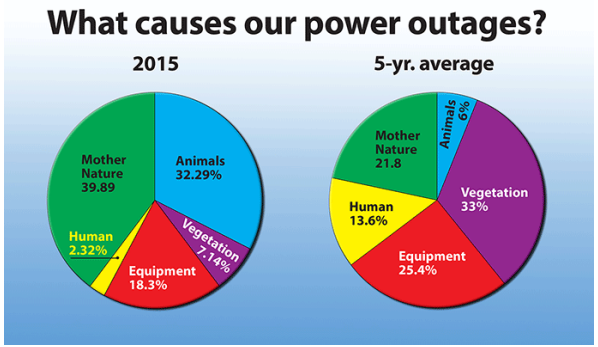


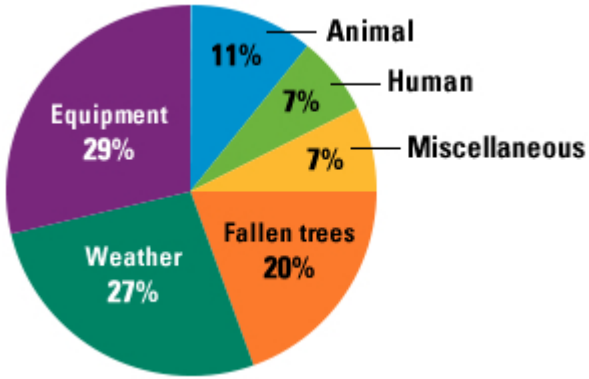
Figure 6. Types of severe weather responsible for all weather-related power outages from 2003-2012.

Outage Causes

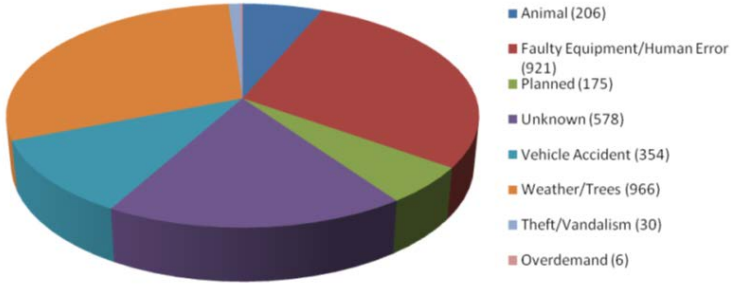




Source: Alaska Electric light and Power Company



Source: We Energies



Source: Annual Eaton Investigation 2013

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What is Incremental and what is Transformational?

Property/method	Incremental	Transformational
Data Sources	Limited to the grid measurements and models	Much more broader data from multiple sources within and outside utilities
Data Management	Use of legacy platforms for field data collection (Digital relays, DFRs, PMUs)	New data platforms allowing data ingestion, curation, cleansing, wrangling, etc.
Data Analytics	Physics-based	Data-based
Results	Corrective	Predictive
Mitigation	Reactive (after the fact)	Preventive

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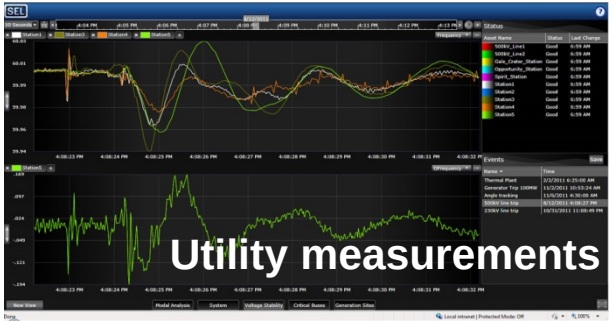
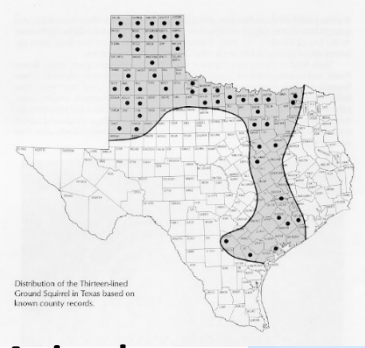
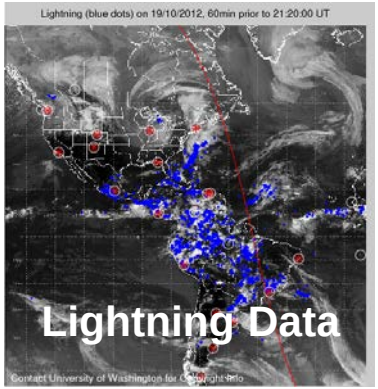
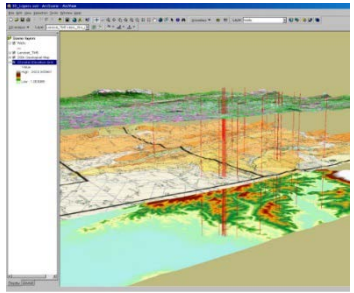




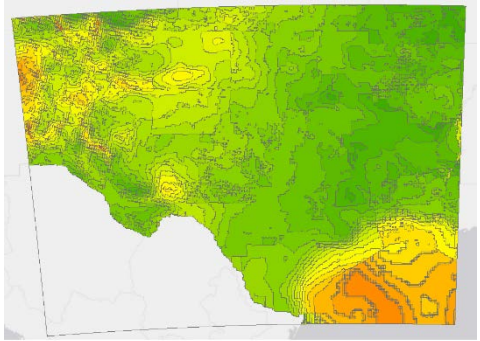
Animals Data



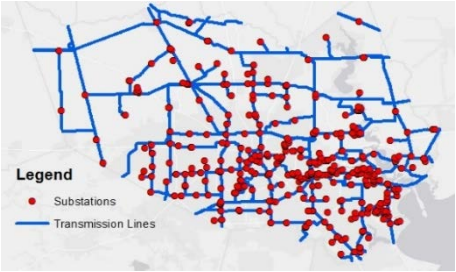


UAS

GIS



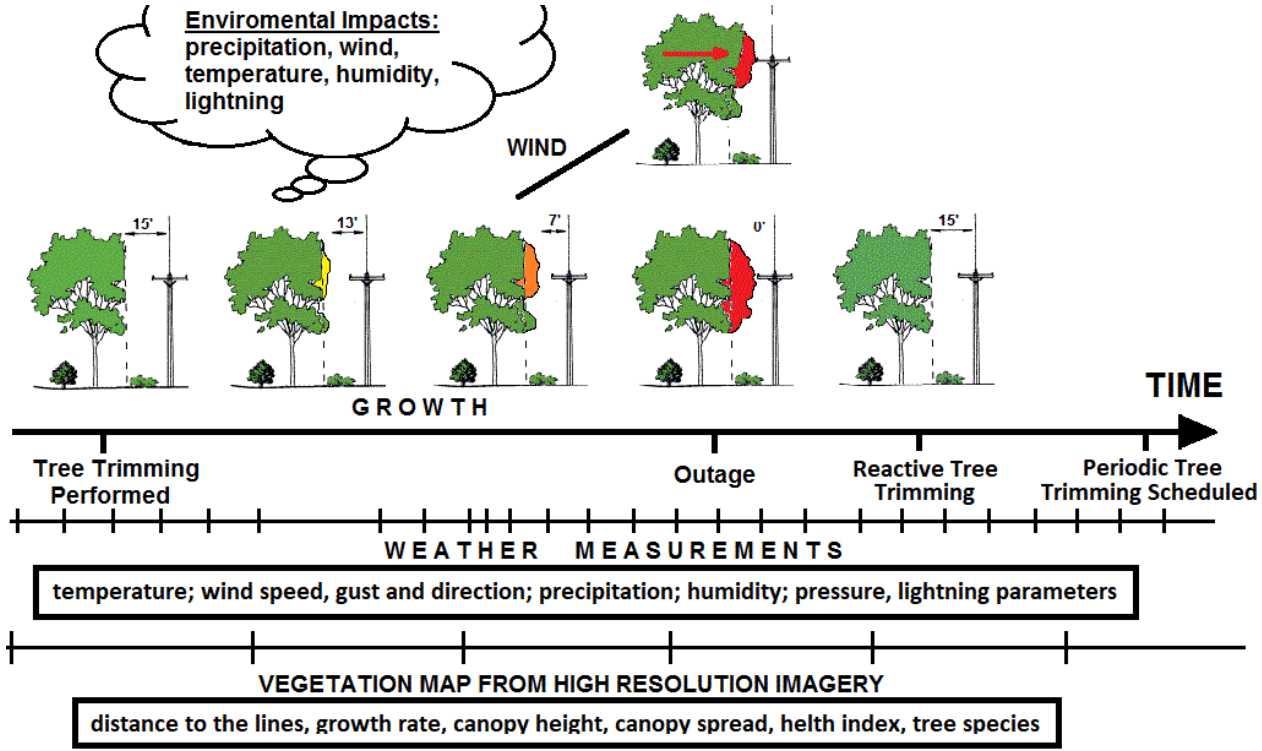
Weather Forecast



Network Assets Data

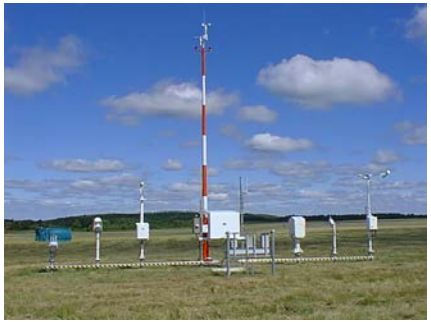
Vegetation Indices

Vegetation Data

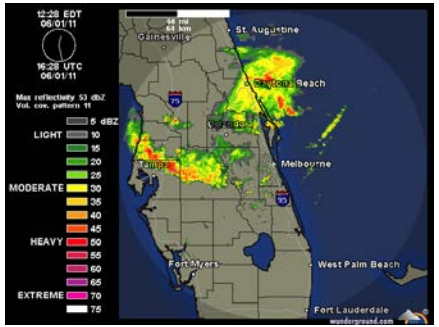


Weather Data

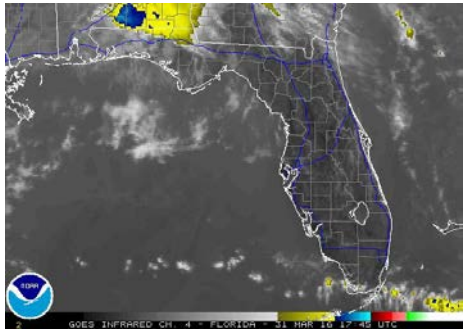
Weather Station



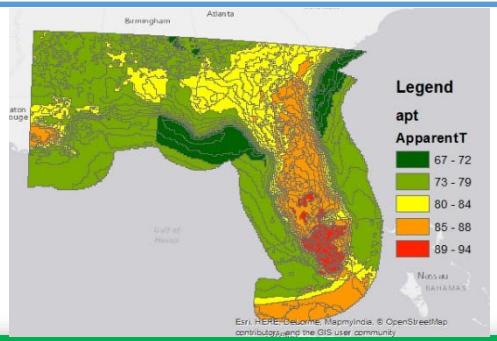
Radar



Satellite



National Digital Forecast Database (NDFD)



Example: Apparent Temperature
Data download: every 3 hours
Forecast for next 3 days
Data resolution: 3 hours

Data Management

Figure 1. Vegetation parameters extraction

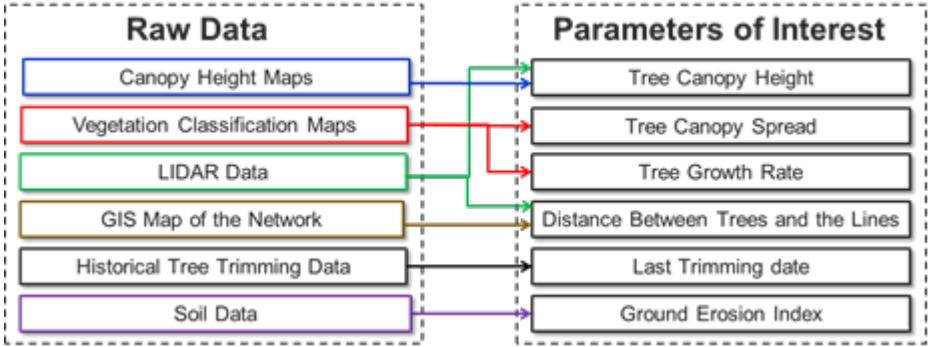


Table I. Vegetation data sources and datasets

Source	Data set name	Spatial res.	Contains
Land Boundary Information System	2004 Digital Orthographic, [11]	1 m	Imagery
National Oceanic and Atmospheric Administration	2010 C-CAP Regional Forest Fragmentation Land Cover, [12]	30 m	Forest fragmentation
Florida Division of Emergency Management	2007 St. Lucie LIDAR, [13]	Vertical 0.6 ft Horizontal 3.8 ft	LIDAR data
National Aeronautics and Space Administration	MODIS - Moderate Resolution Imaging Spectroradiometer, [14]	0.5 km	Vegetation indices
National Cooperative Soil Survey	gSSURGO, [15]	10 m	Soil data

Data Analytics: Risk Formulation

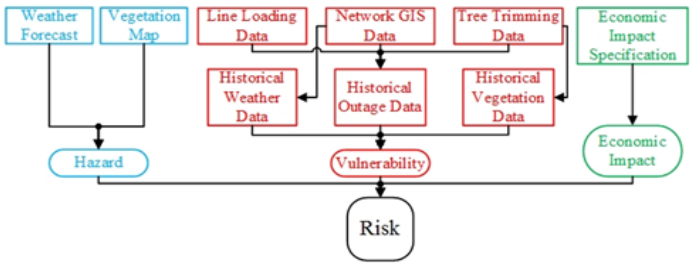
$$R(X,t) = P[T(X,t)] \cdot P[C(X,t)|T(X,t)] \cdot u(C(X,t))$$

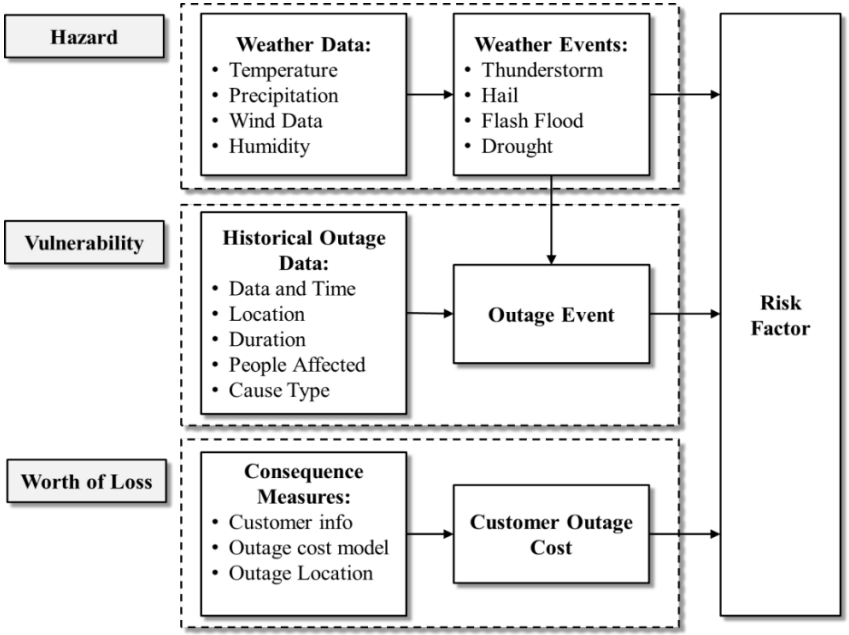
Intensity T – Weather severity

Hazard – Probability of a severe weather impact

Vulnerability – Probability of a vegetation caused outage for a given hazard

Economic Impact – Cost of periodic and reactive tree trimming





T. Dokic, M. Kezunovic, "Predictive Risk Management for Dynamic Tree Trimming Scheduling for Distribution Networks," IEEE Transactions on Smart Grid, Vol. 10, No. 5, pp. 4776-4785, September 2018.

Hazard and Vulnerability

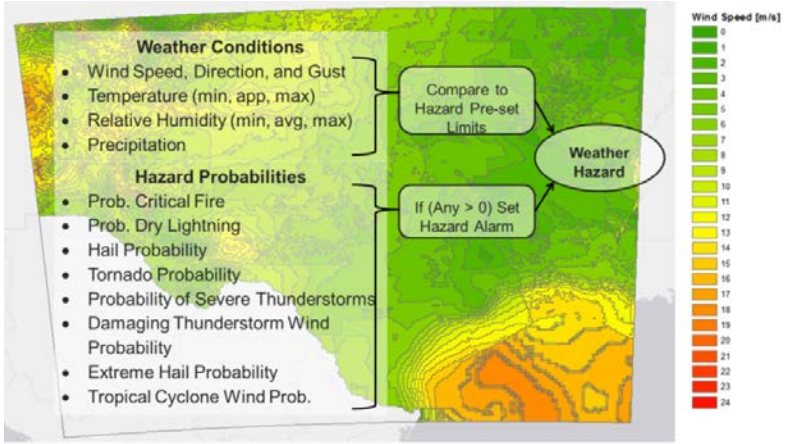


Figure 2. Land-based weather stations – processing of historical weather data

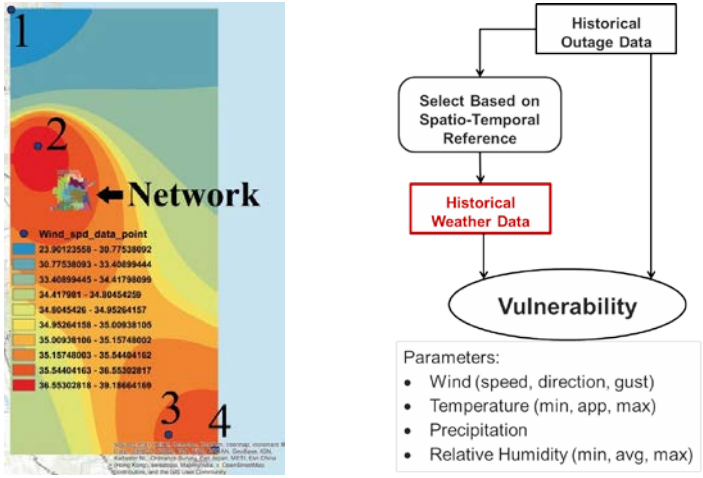


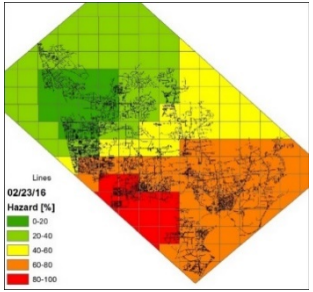
Figure 3. Weather forecast - data example and processing

Table II. Impact of wind on vegetation

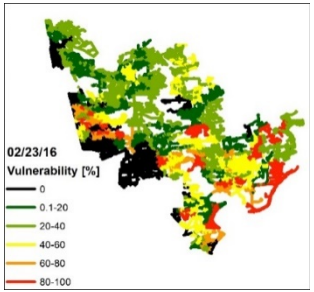
WS [m/s]	Effect on trees	Hazard	WS [m/s]	Effect on trees	Hazard
5.5-7.9	Small branches movement	0	17.2-20.7	Twigs broke from trees	2
8.0-10.7	Moderate size branches move	0	20.8-24.4	Large branches broke from trees	3
10.8-13.8	Large sized branches	1	24.5-28.4	Trees uprooted or broken	4
13.9-17.1	Whole trees in motion	1	>28.5	Severe vegetation damage	5

Risk Prediction

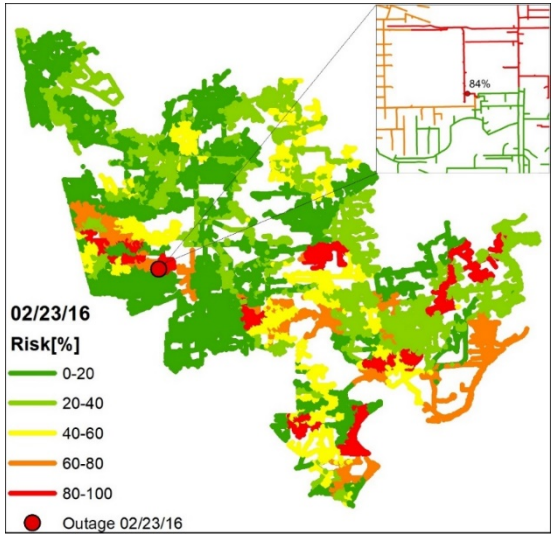
Weather Hazard



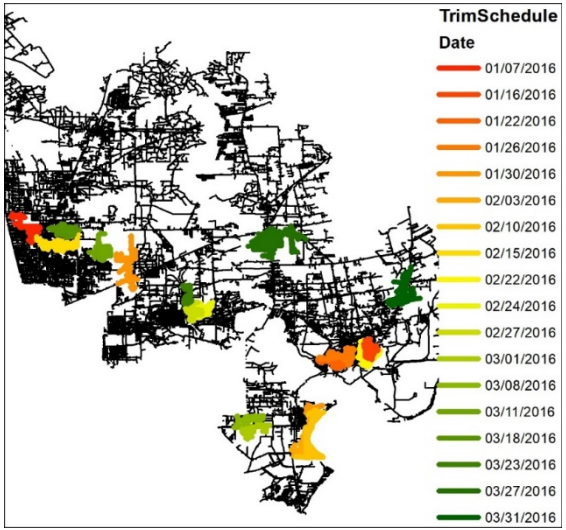
Network Vulnerability



Risk Map



Optimal Tree Trimming Schedule



Overall risk reduction 32.85%
Reactive tree trimming cost reduction 27.2%

Risk Management and Mitigation: Optimal Tree Trimming

For total of N feeder sections maximize the reduction in vegetation risk

$$max\left\{R = \sum_{t=1}^{T}\frac{1}{N}\sum_{n=1}^{N}\Delta R_{n,t}\cdot F_{n,t}\right\}$$

$$F_{n,t} = \begin{cases} 0, & \text{section not trimmed} \\ 1, & \text{section trimmed} \end{cases}$$

Difference in component risk before and after action:

$$\Delta R_{n,t} = R_{n,t}^{before} - R_{n,t}^{after}$$

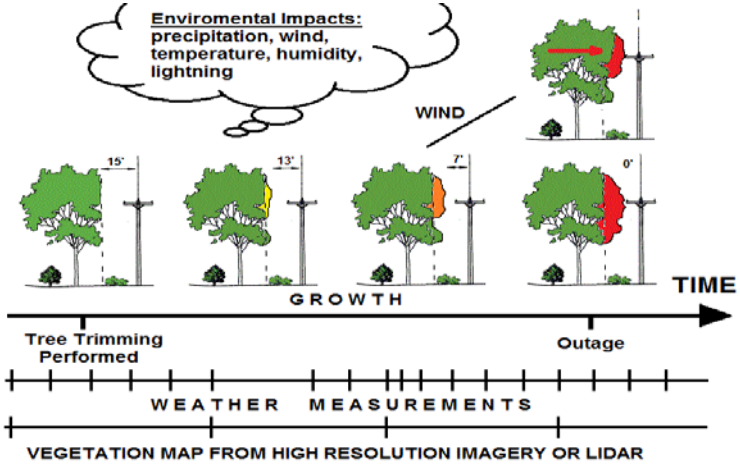
Constrains:

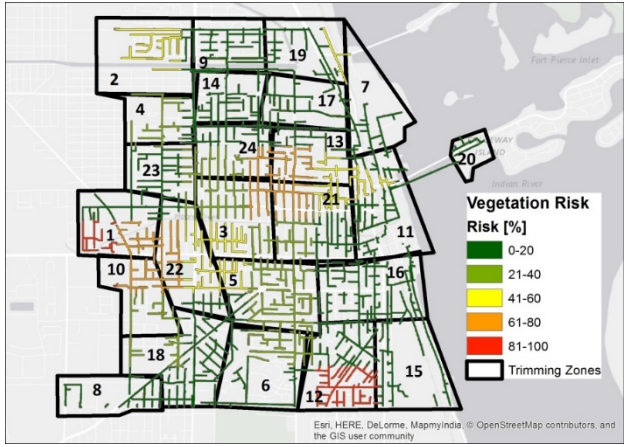
Total cost of tree trimming limit: $\sum_{t=1}^{T}\sum_{n=1}^{N} F_{n,t}\cdot PC_{n,t} \leq PA$

One section trimmed at the time: For t=1,…,T, $\sum_{n=1}^{N} F_{n,t} = 1$

n	feeder section
N	total number of feeder sections
t	time instance
T	number of time instances
$\Delta R_{n.t}$	reduction in risk after trimming
$PC_{n,t}$	cost of trimming on one section
PA	total allocated tree trimming budget

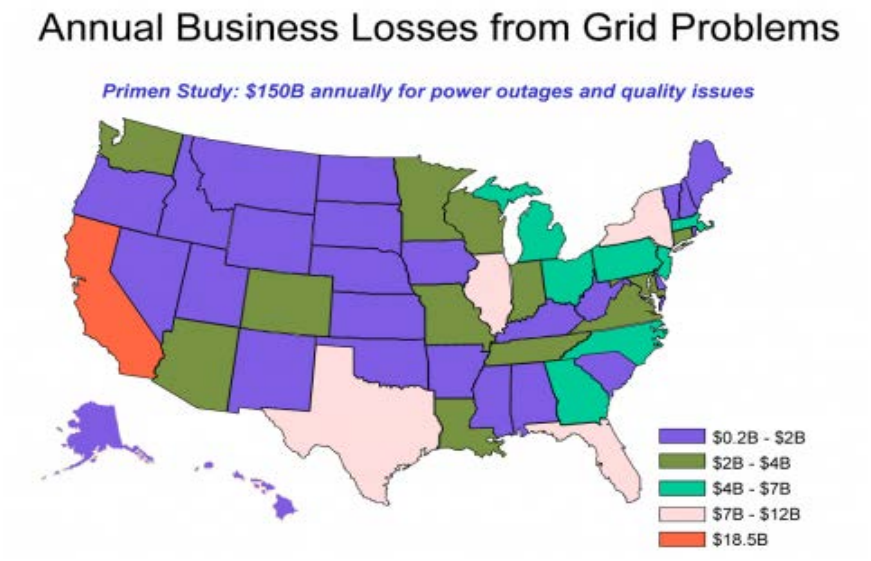
Risk Management and Mitigation

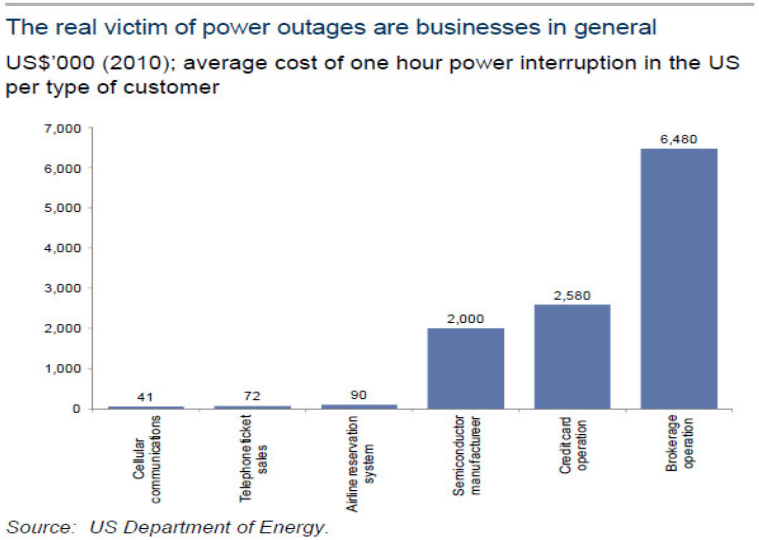




ID	Zone Order	Average Risk Reduction [%]	Economic Impact Reduction
1	12,1,21,22,13,24,2,3,10,19,11,5,6,18,4,23	32.18	0.39
2	12,1,13,24, 21,22,2,3,10,19,11,5,6,18,4,23	31.98	0.43
3	1,12,21,22,10,19,11,5,13,24,2,23,3,6,18,4	26.14	0.28
4	12,1,24,13, 2,3,10,21,11,5,6,18,4,22,19,23	23.84	0.25
5	1,12,21,22,24,13,3,10,2,19,6,4,11,5,23,18	20.89	0.26

Benefits of Outage Management





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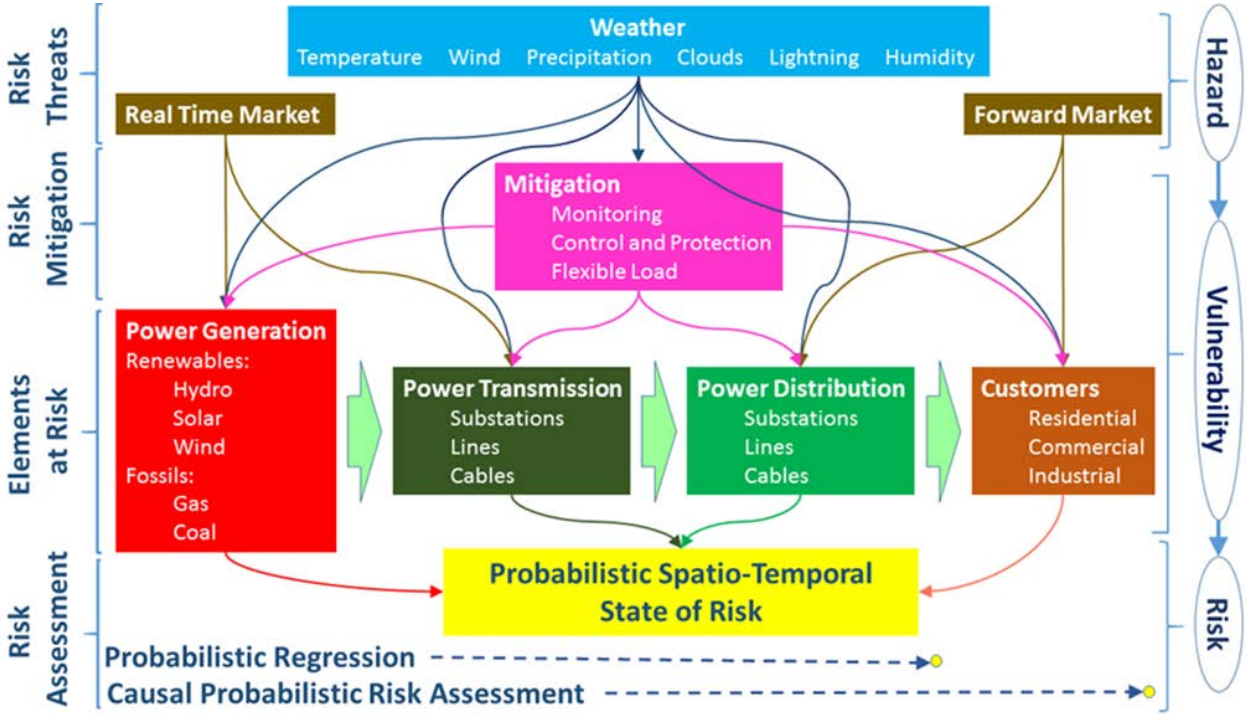

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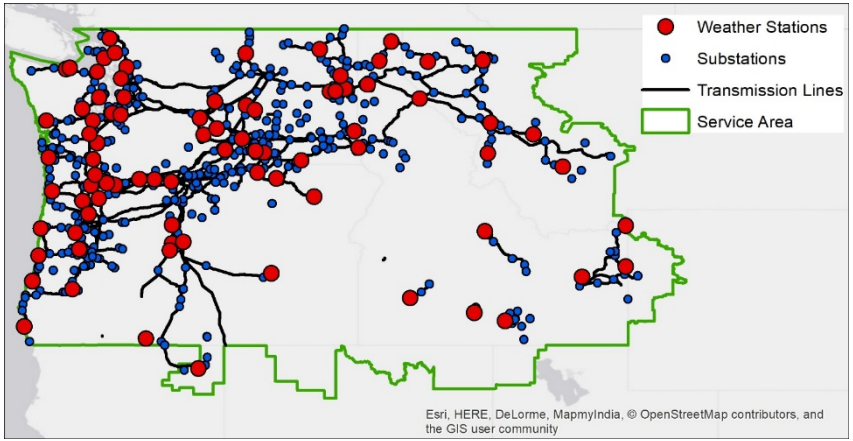
Transmission Outage Prediction

M. Kezunovic, T. Dokic, Z. Obradovic, M. Pavlovski, R. Said "Big Data Analytics for Predictive Lightning Outage Management Using Spatially Aware Logistic Regression Model", CIGRE General Session, Aug. 2020, Paris, France. (online)

Historical Weather Data

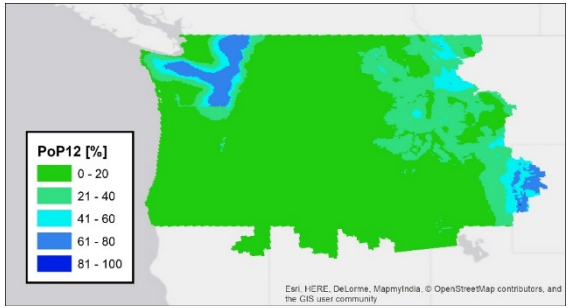


Fractions of missing data from ASOS observations

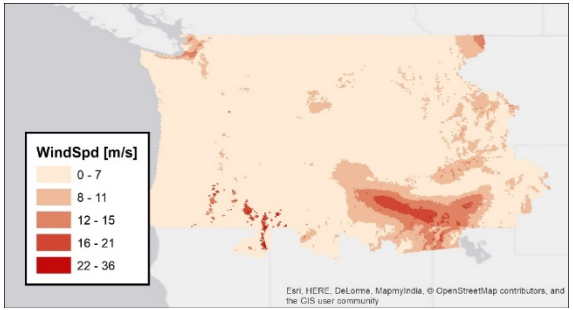
Temperature	Dew Point	Humidity	Wind Direction	Wind Speed	Precipitation	Pressure	Wind Gust	Weather Code
0.146	0.148	0.148	0.145	0.134	0.312	0.265	0.378	0.336

Weather Forecast

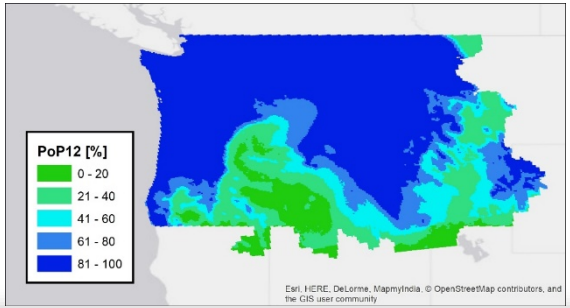
No Outage - Precipitation



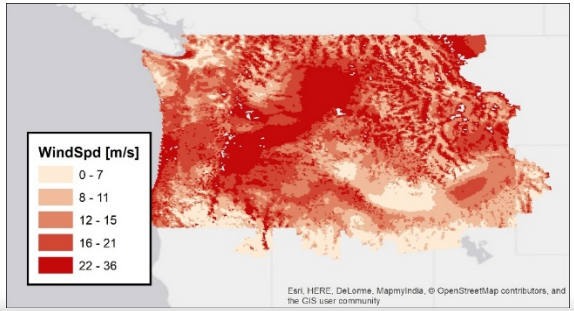
No Outage – Wind Speed



Outage - Precipitation

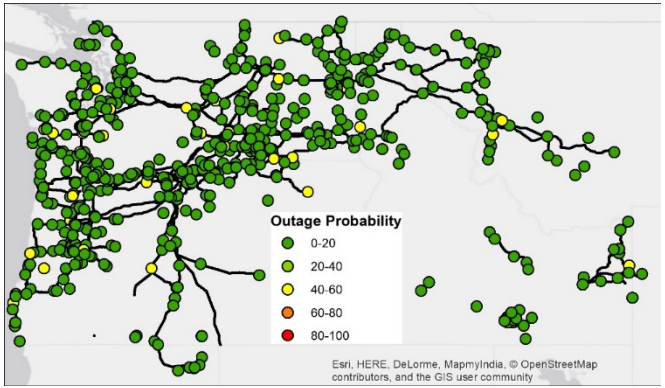


Outage – Wind Speed

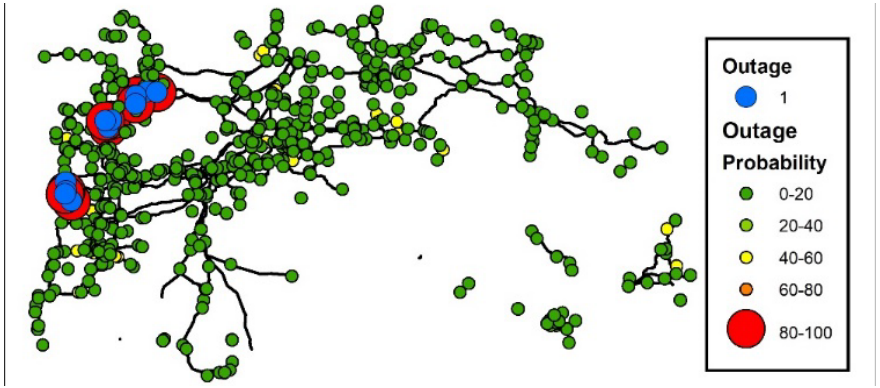


Risk Maps

No Outage



Multiple Lightning Outage



- **No outages occurred** ⇨ outage probabilities are **smaller than 60%** for all substations
- Outages occurred ⇨ the area around the outages has points with probability over 80%

Distribution Transformer Failure Prediction

E. Hui Ko, T. Dokic, M. Kezunovic, “Prediction Model for the Distribution Transformer Failure using Correlation of Weather Data,” CIGRE 5th International Colloquium Transformer Research and Asset Management, Opatija, Croatia, October 2019.

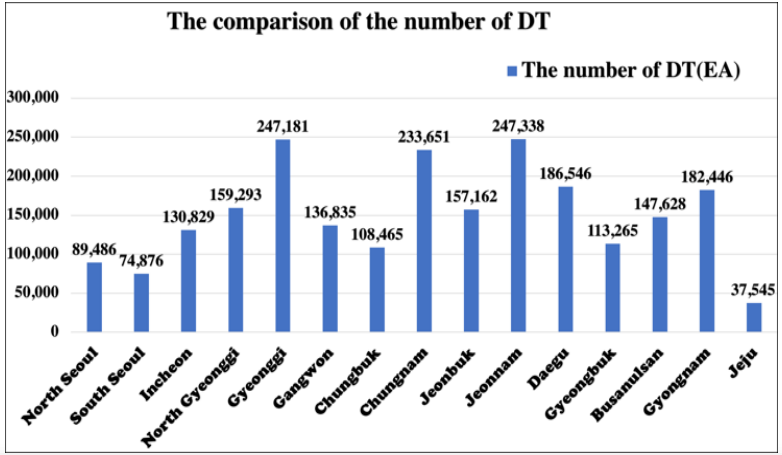
The System – South Korea

Distribution Facilities in JeonllaNam-do Area

	Transformer		Protective Devices		
Bank	Number	Capacity (kVA)	Breaker	Equipment	COS
104	243	9,252	12	1.4	72

JeonllaNam-do Area

The comparison of the number of DT in South Korea



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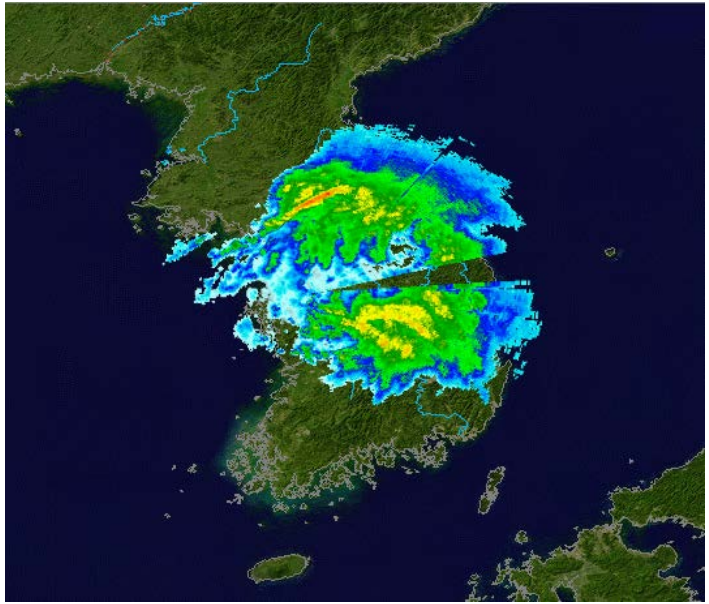
Weather Data



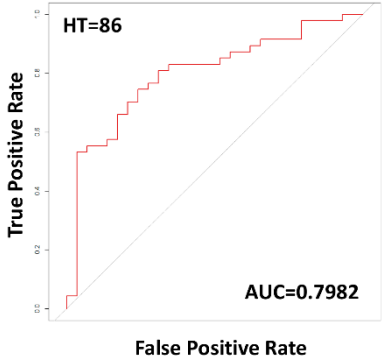
NOAA/U.S. Air Force, Blue Marble map
https://www.ncdc.noaa.gov/nexradinv/chooseday.jsp?id=rksg

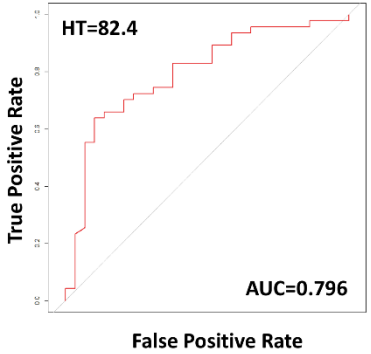
Historical Weather Measurements

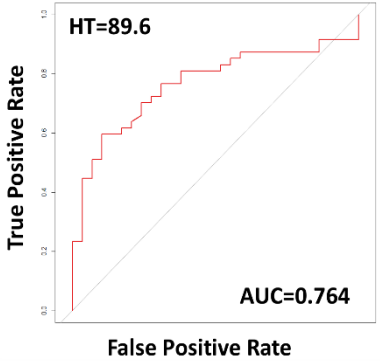
Lightning [0/1] (LI)	Average Temperature [˚F] (AT)	Highest Temperature [˚F] (HT)	Relative Humidity [%] (RH)	Maximum Wind Speed [m/s] (MWS)	Wind Gust [m/s] (WG)

Prediction Results

Receiver Operating Characteristics Curve (ROC)







Event vs. Prediction of Failure

Event	Failure (Y/N)	Prediction	
		Y=0	Y=1
HT 86°F or below	Y=0	113	47
	Y=1	35	190
HT 86°F - 89.6°F	Y=0	112	47
	Y=1	36	190
HT 89.6°F or above	Y=0	111	54
	Y=1	37	183

Conclusions

Big Data gives TRANSFORMATIONAL opportunities for risk assessment, management and mitigation

In the case of faults, we are able to PREDICT outages, which offers different opportunities for control, planning and protection mitigation actions

The outage PREDICTION can be at different spatiotemporal scales, minutes to hours, days and quarters, and as granular as a specific asset component

The time spent on DATA PREPARATION is the most consuming part of the overall development, and may take up to 80% of the development efforts

The TEST RESULTS are easy to confirm since the testing can be done using the data from the past when the outcomes of the events are already known

Thank you!

Questions?

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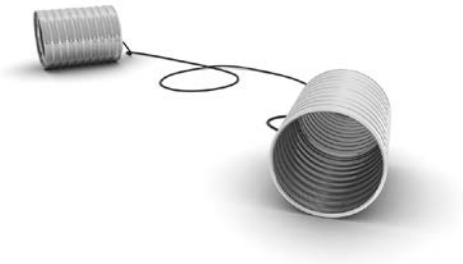

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