Big Data Uses in Smart Grids: Challenges and Opportunities

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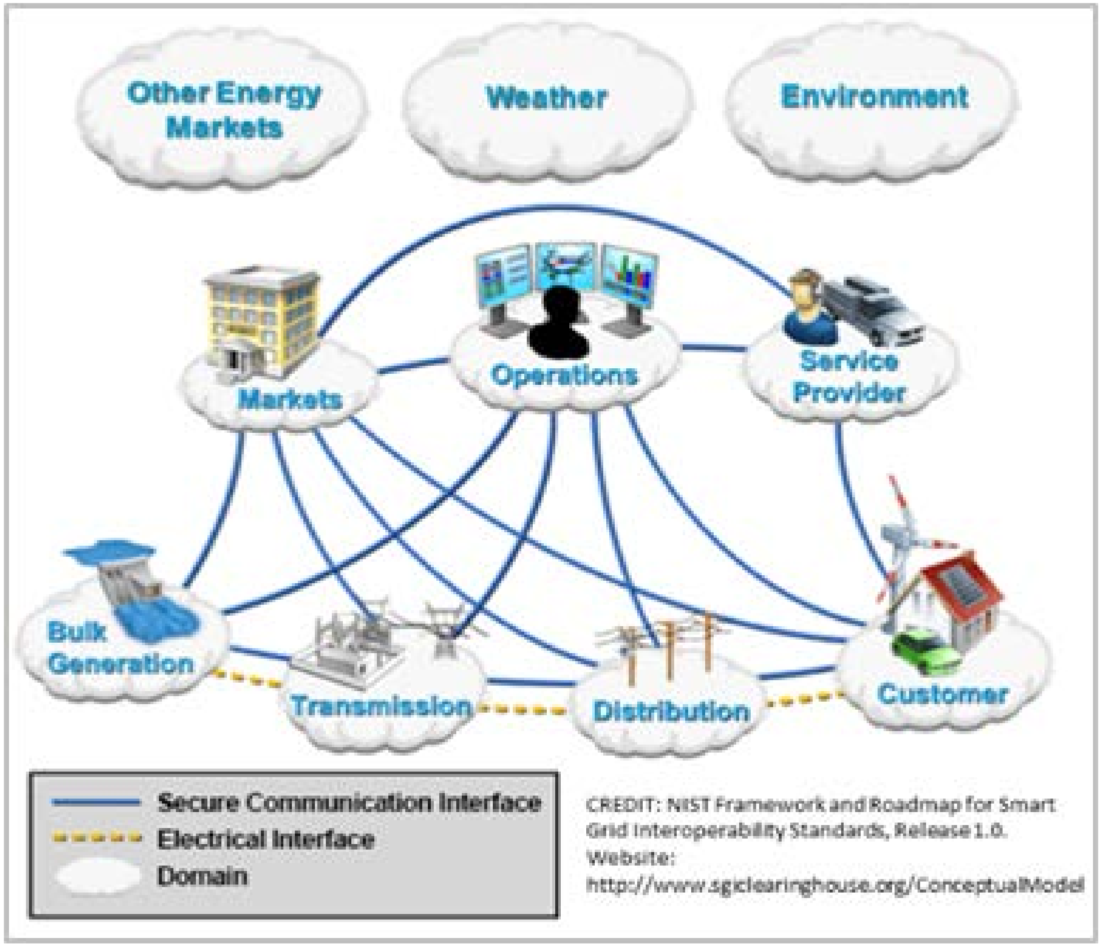
Outline

- Smart Grid Domains and Interactions
- Problems to Solve and Expectations
- Sources and Properties of Big Data
- Challenges and Opportunities
- Examples:
  - Asset Management
  - Outage Management
- Conclusions

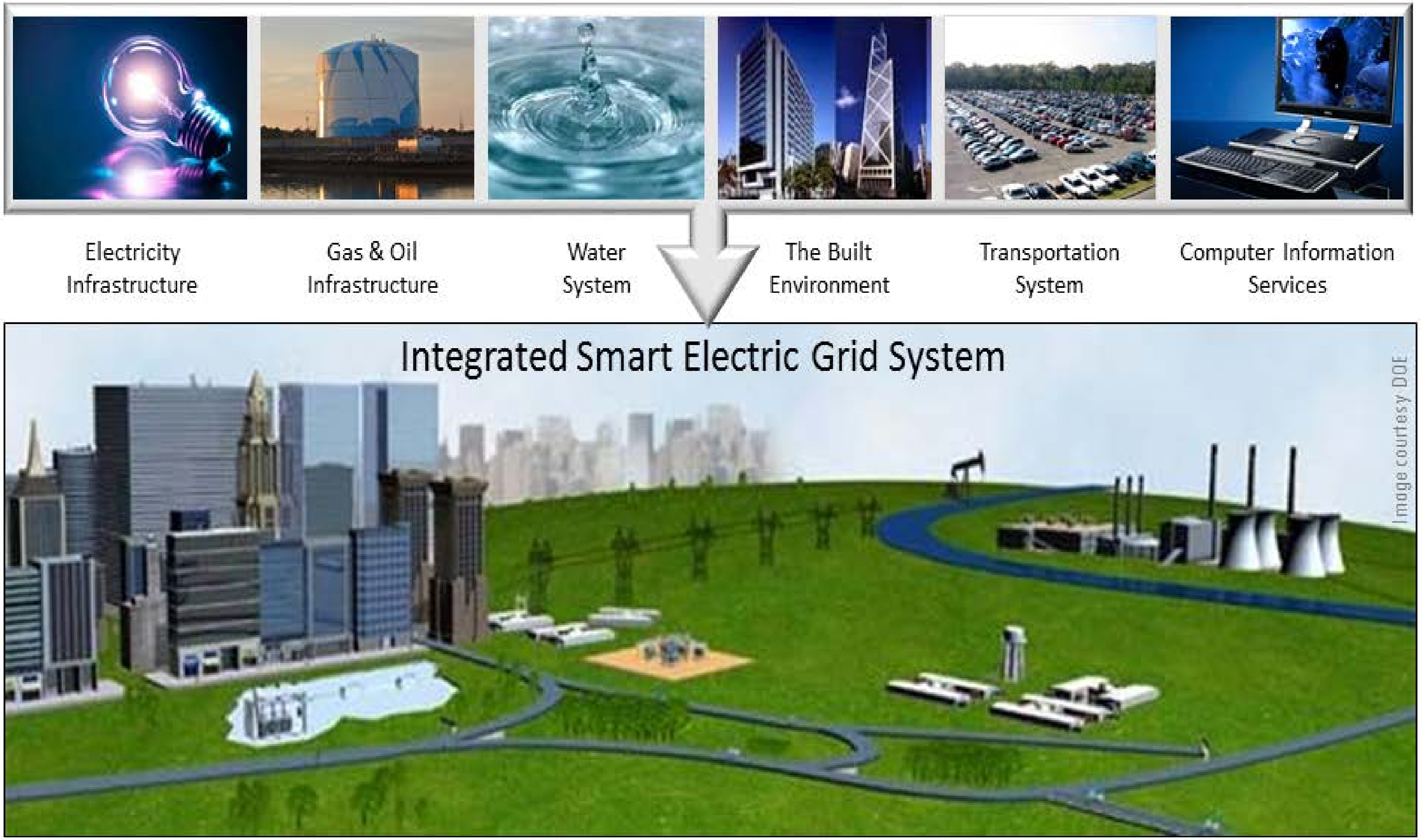
Smart Grid Domains



Domain evolution

- Original NIST domains, 2009
- Addition of other domains

Integrated Ecosystem



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Data Connectivity

The Internet of Things

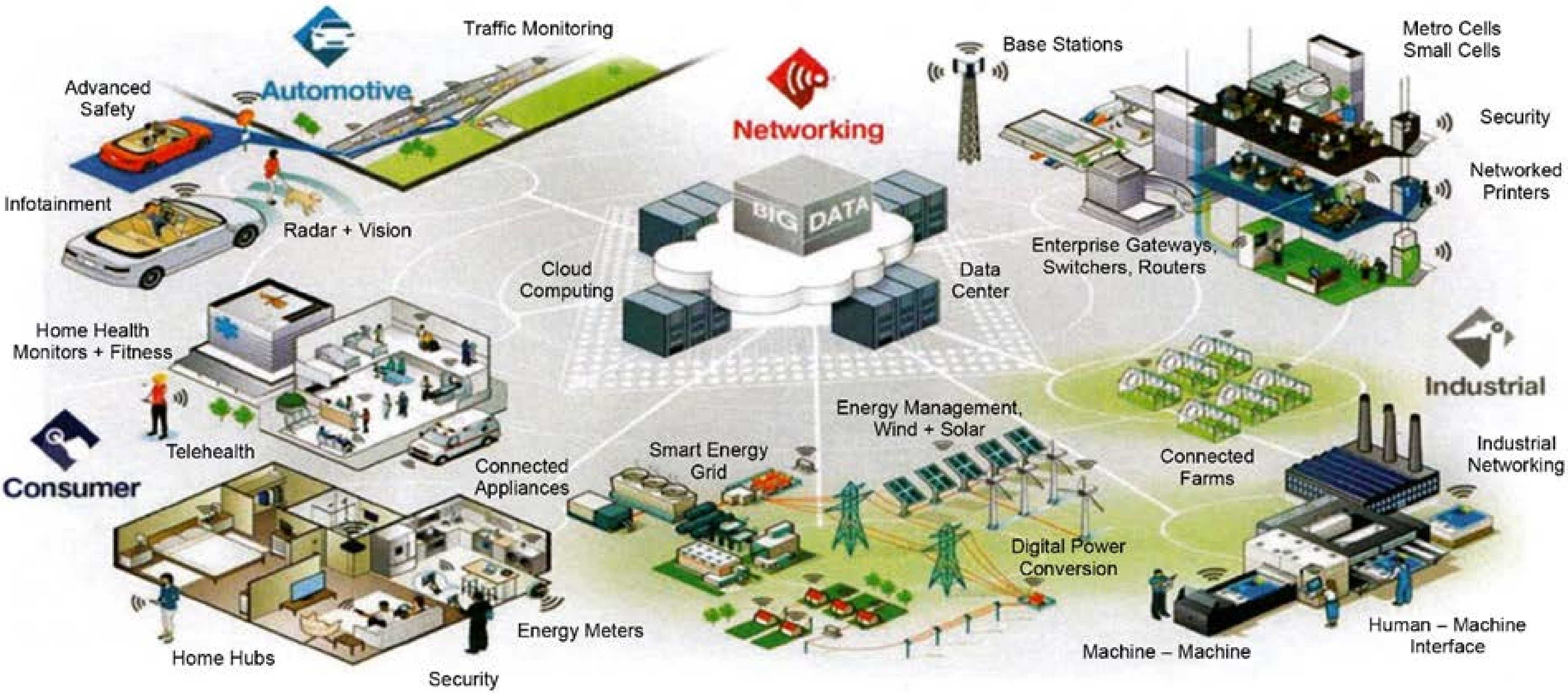

ILLUSTRATION CREDIT: The Register. Website: http://regmedia.co.uk/2014/05/06/freescale_internet_of_things_overview_1.jpg

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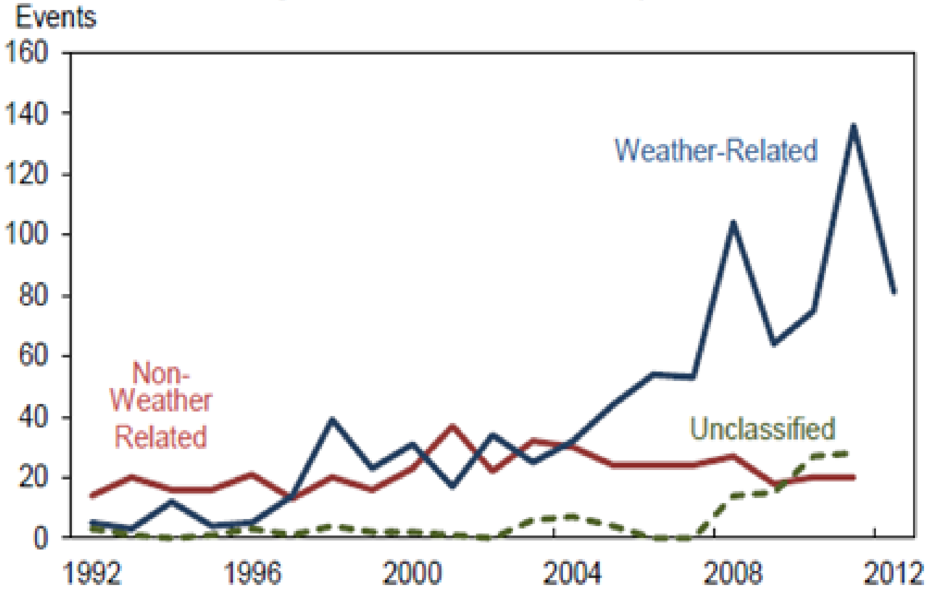
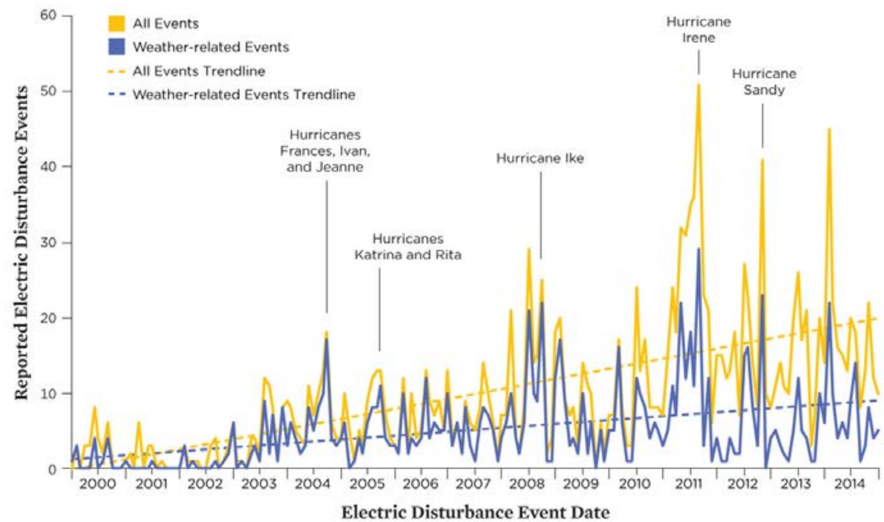
Problem to solve: Outages

Observed Outages to the Bulk Electric System, 1992-2012



Source: Energy Information Administration

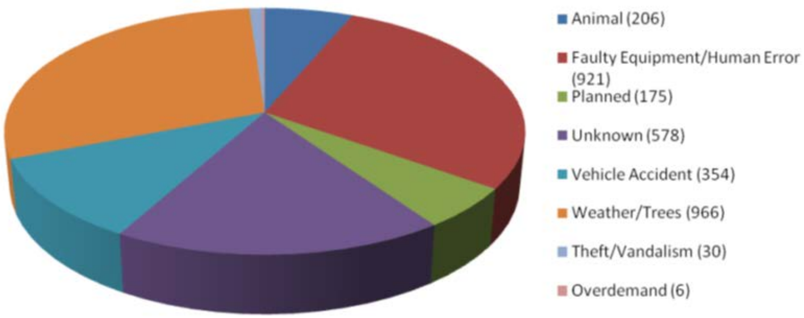
FIGURE 1. U.S. Electric Grid Disruptions



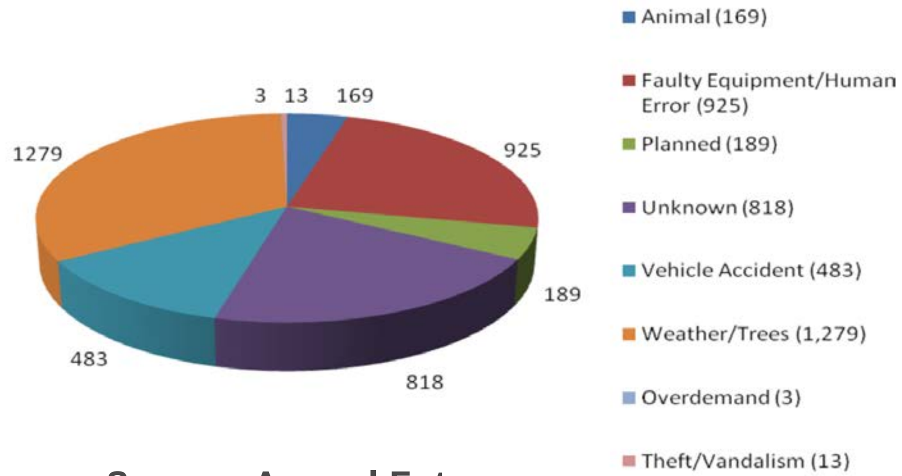
The Department of Energy tracks major electric disturbance events through Form OE-417. Utilities submit information about qualifying incidents, including when they occurred, where they occurred, what triggered them, and how many customers were affected. Notably, while the reported number of non-weather-related events is high, the vast majority of incidents resulting in customer outages occur because of weather.

SOURCE: UCS ANALYSIS, BASED ON OE N.D.

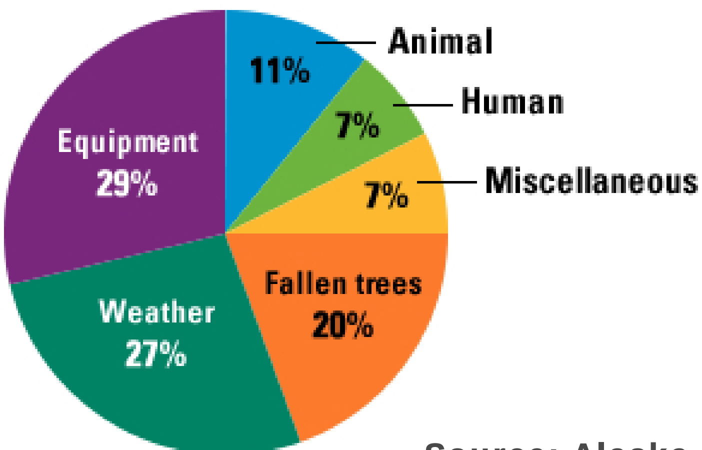
Major Outage Causes



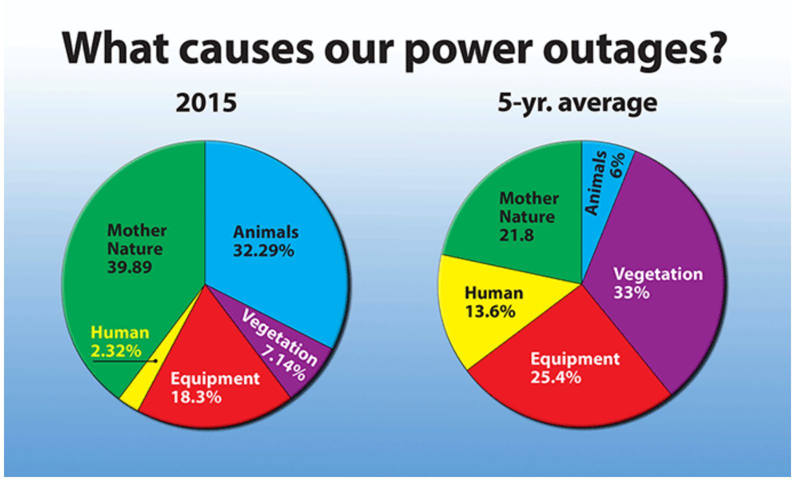
Source: Annual Eaton Investigation 2013



Source: Annual Eaton Investigation 2016



Source: Alaska Electric light and Power Company



Source: We Energies

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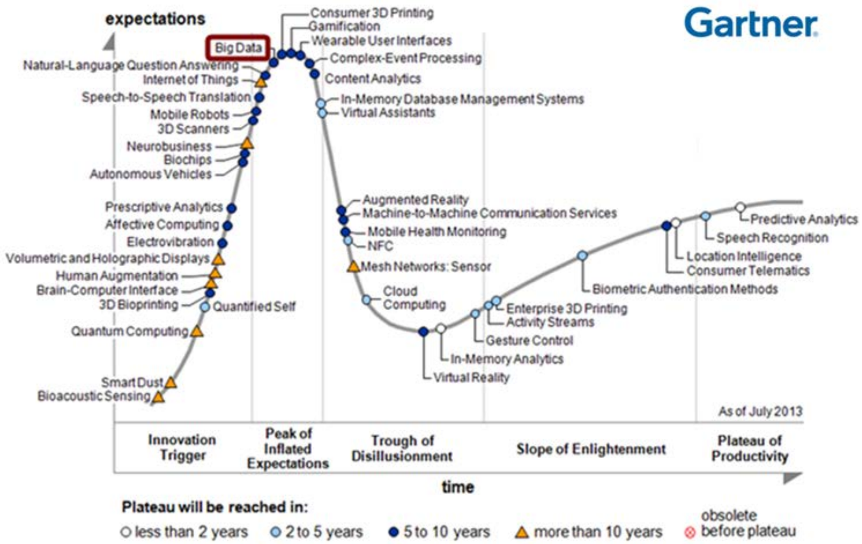
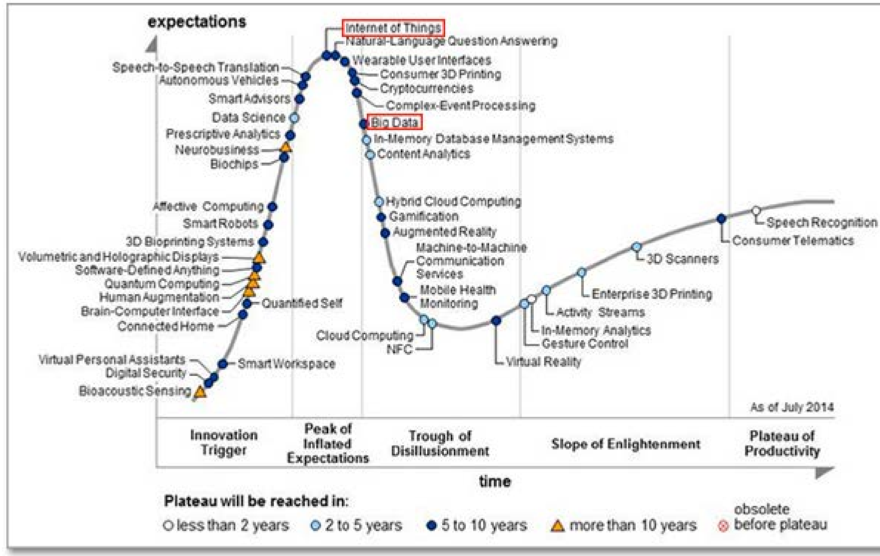
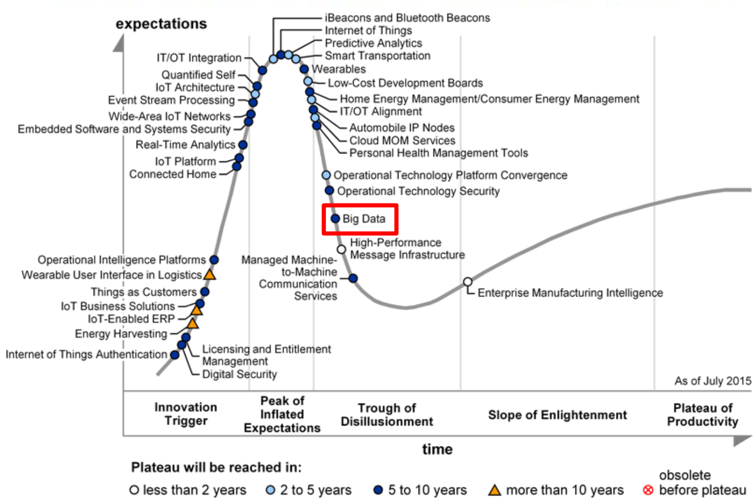
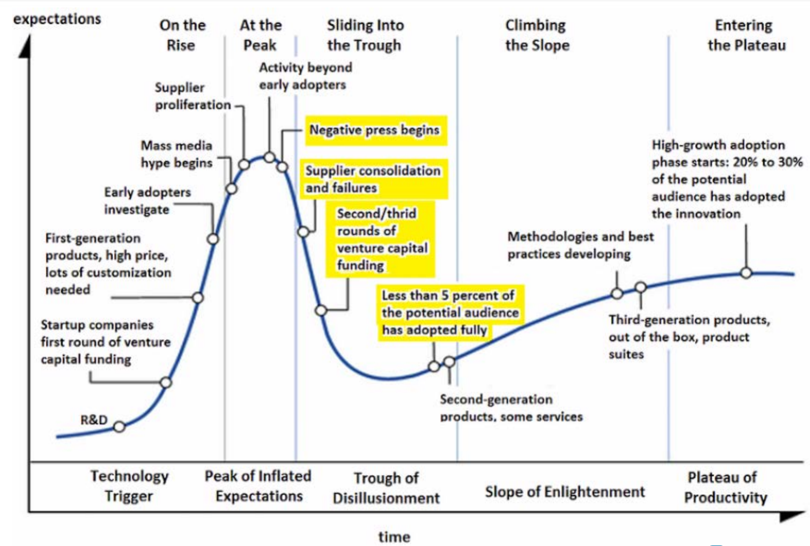
Expectations









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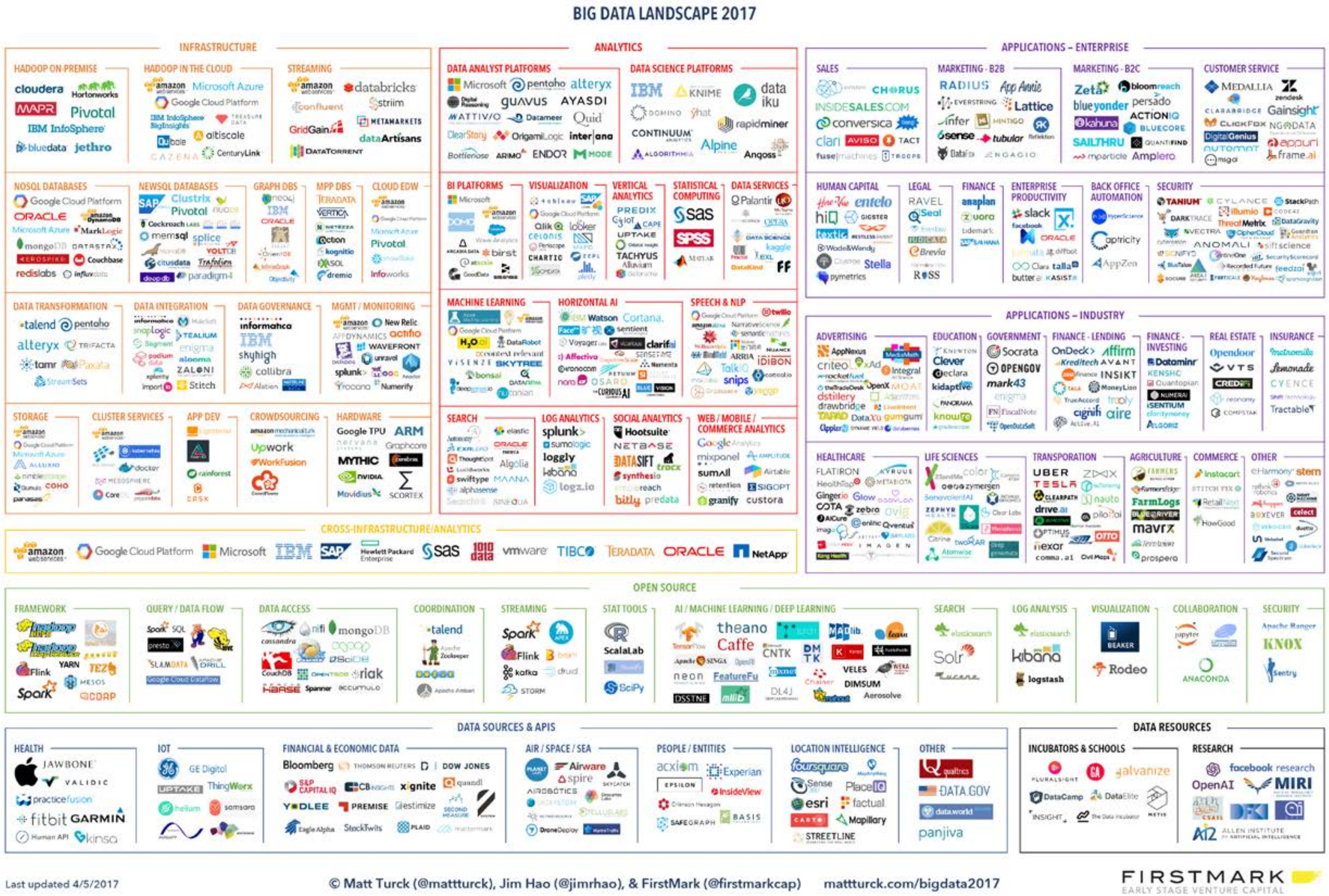
Products and Services



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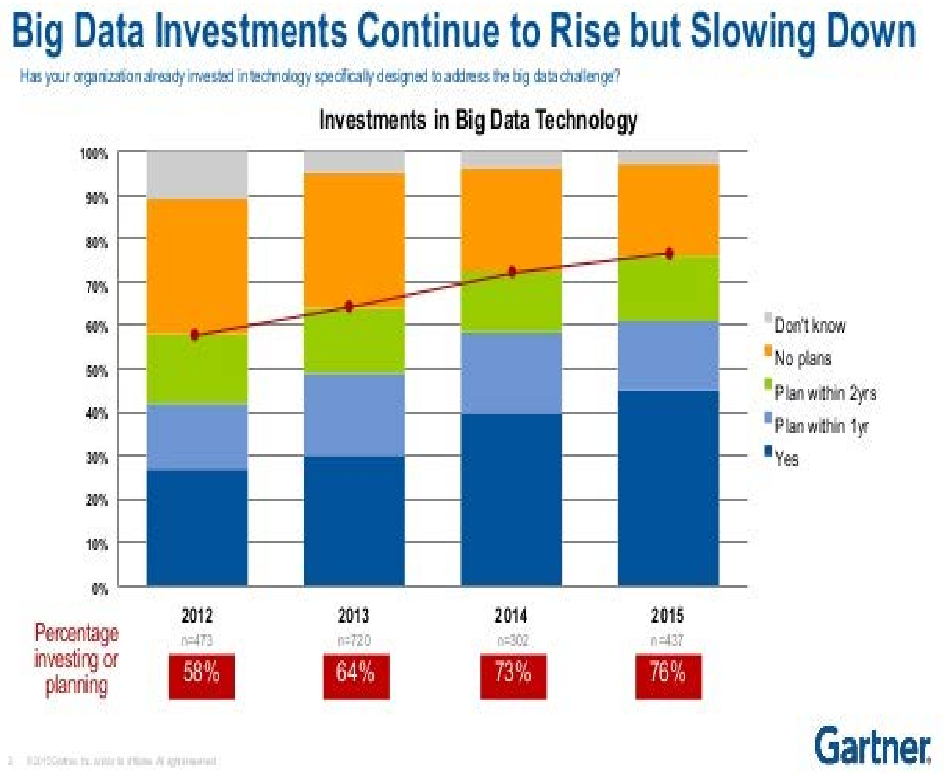
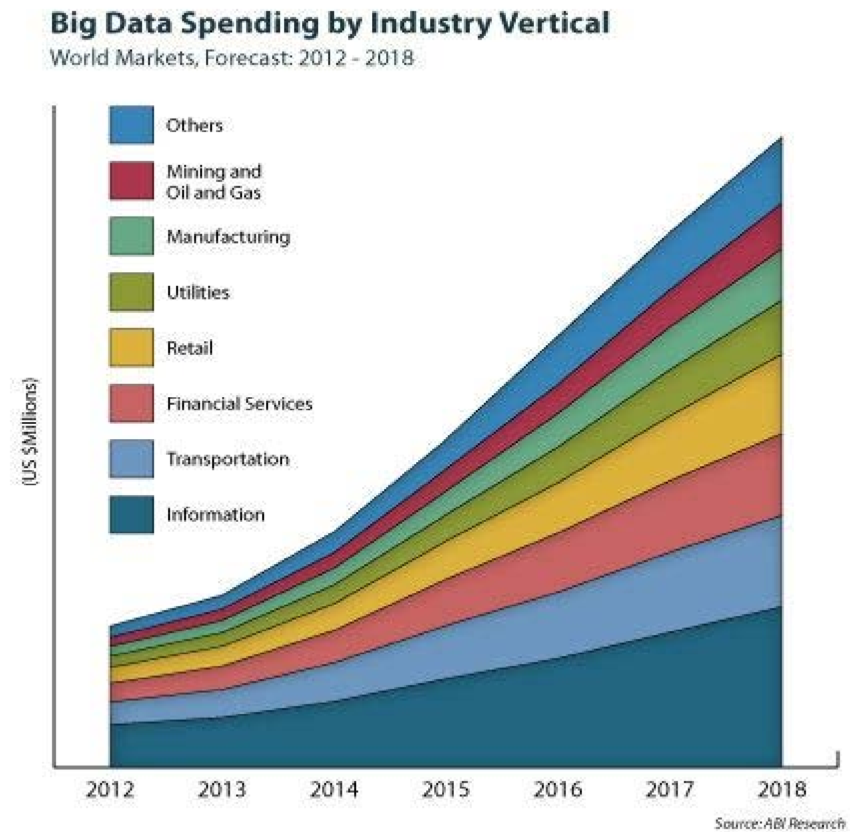
Investments





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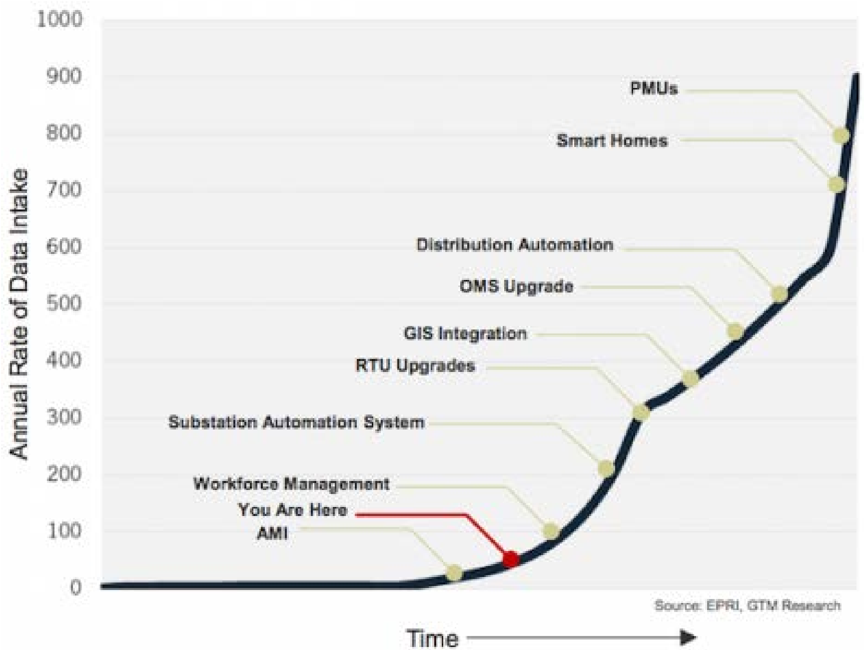
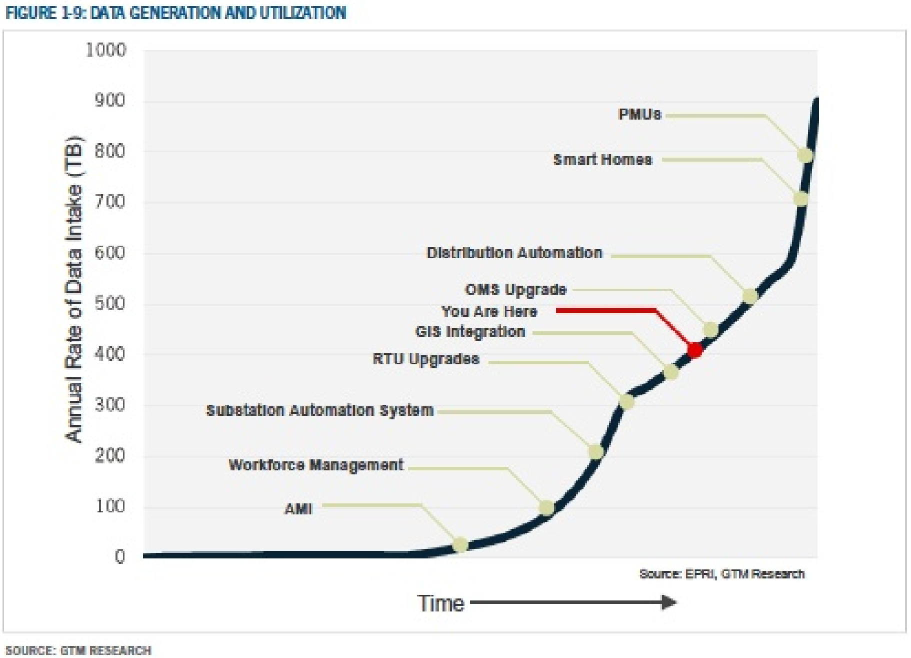
Smart Grid Data Growth





Source: EPRI, GMT Research 2013

Source: EPRI, GTM Research, 2014

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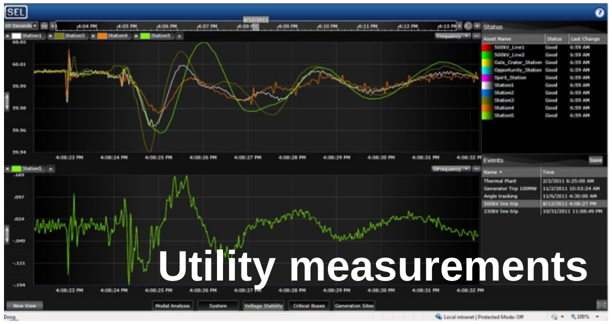
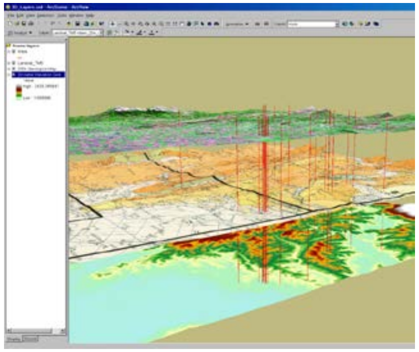
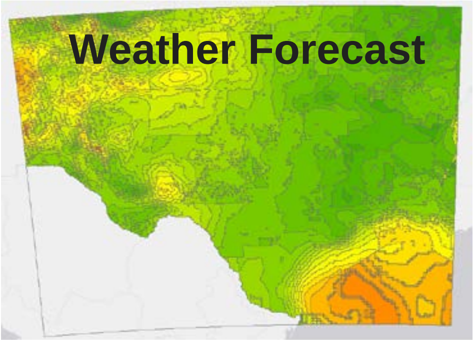
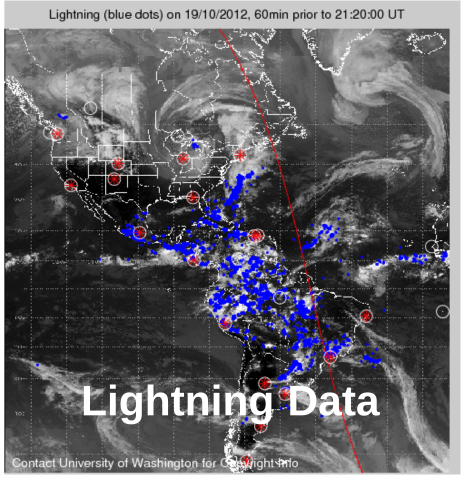
Sources of Big Data



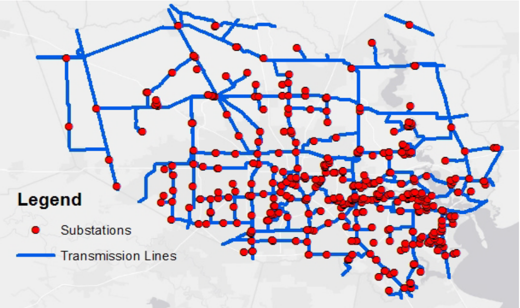
GIS



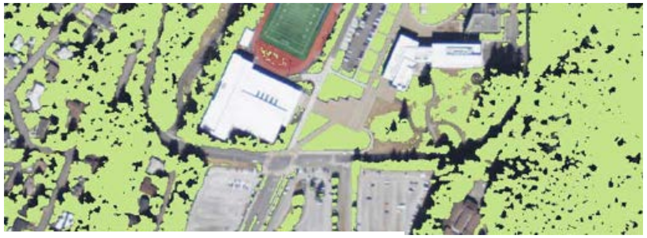




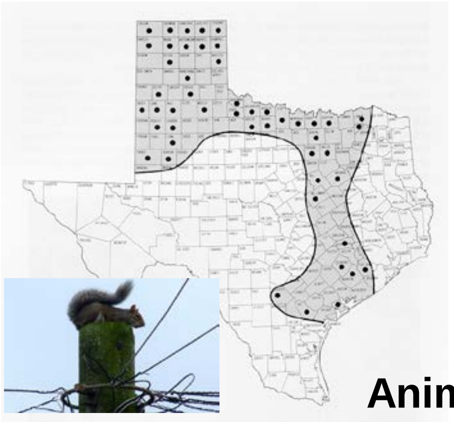
UAS



Vegetation Indices



Animals Data



Network Assets Data

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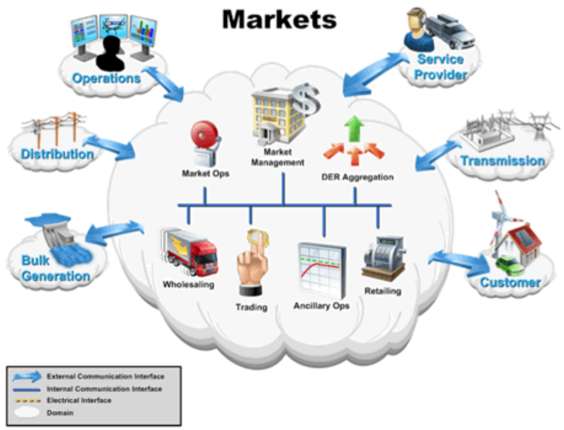
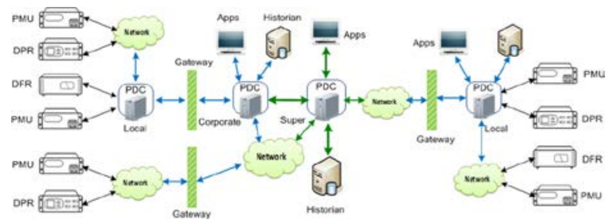
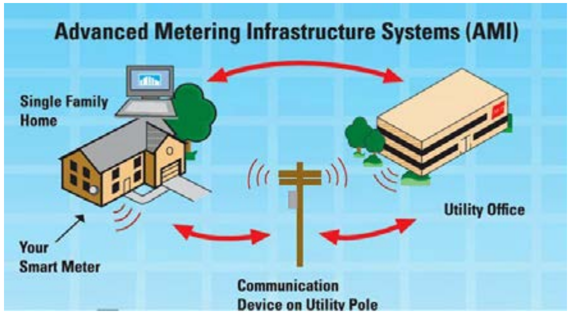
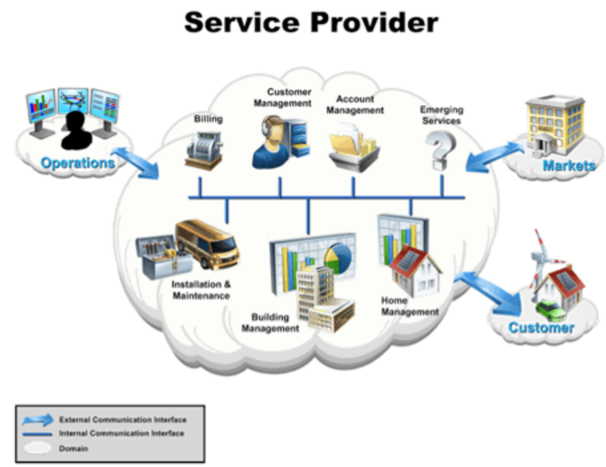
Utility measurements

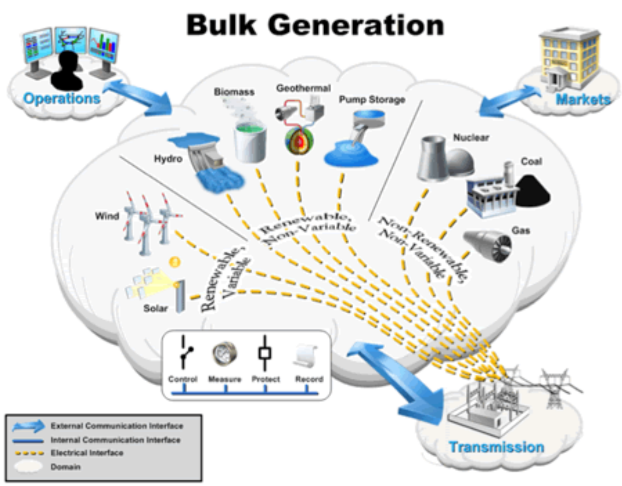


Synchrophasors

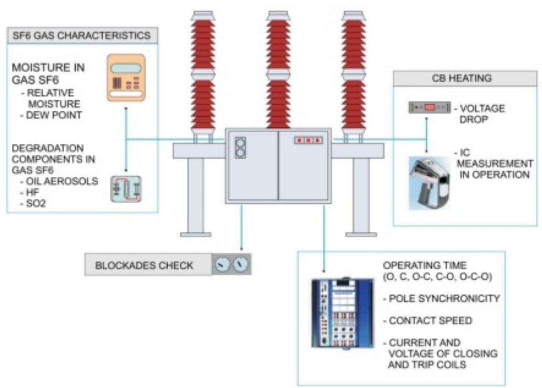


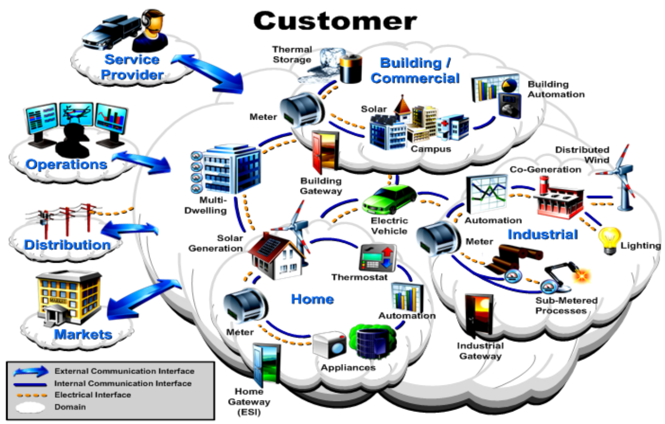






Assets





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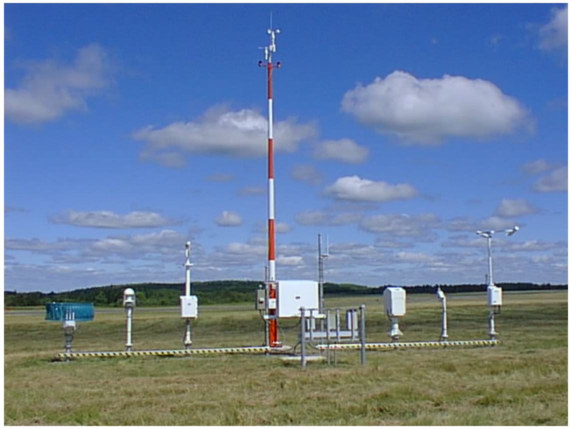
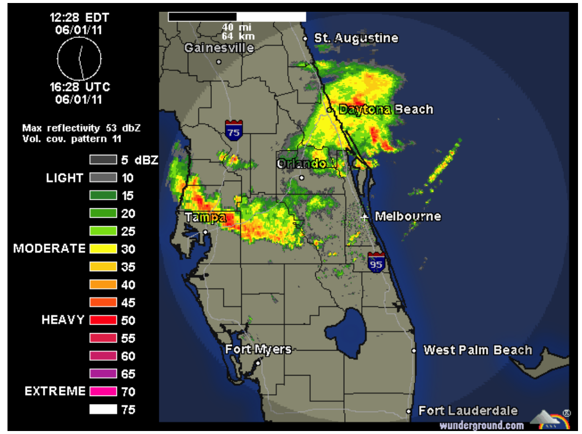
Weather Data

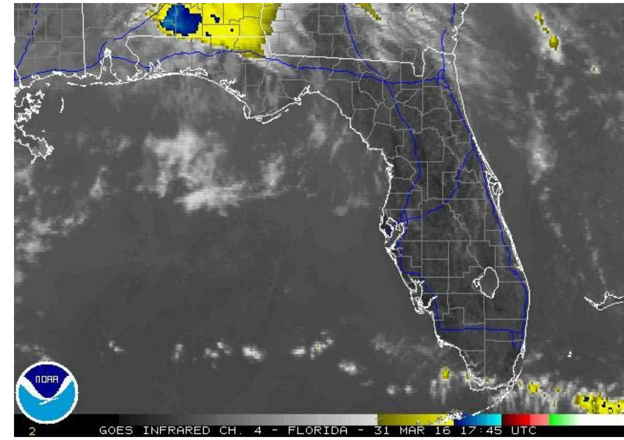
Weather Station



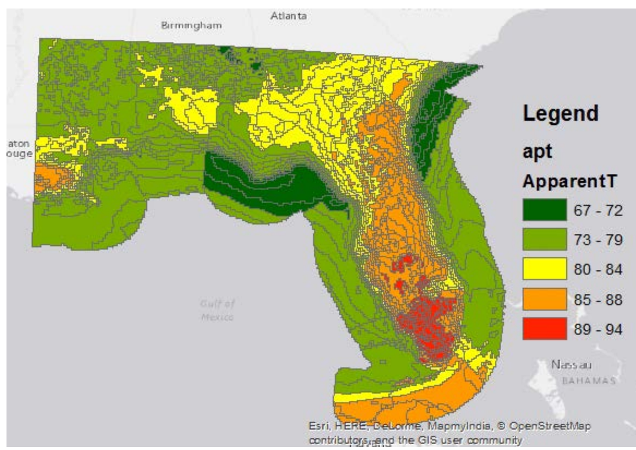
Radar



Satellite



National Digital
Forecast Database
(NDFD)



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

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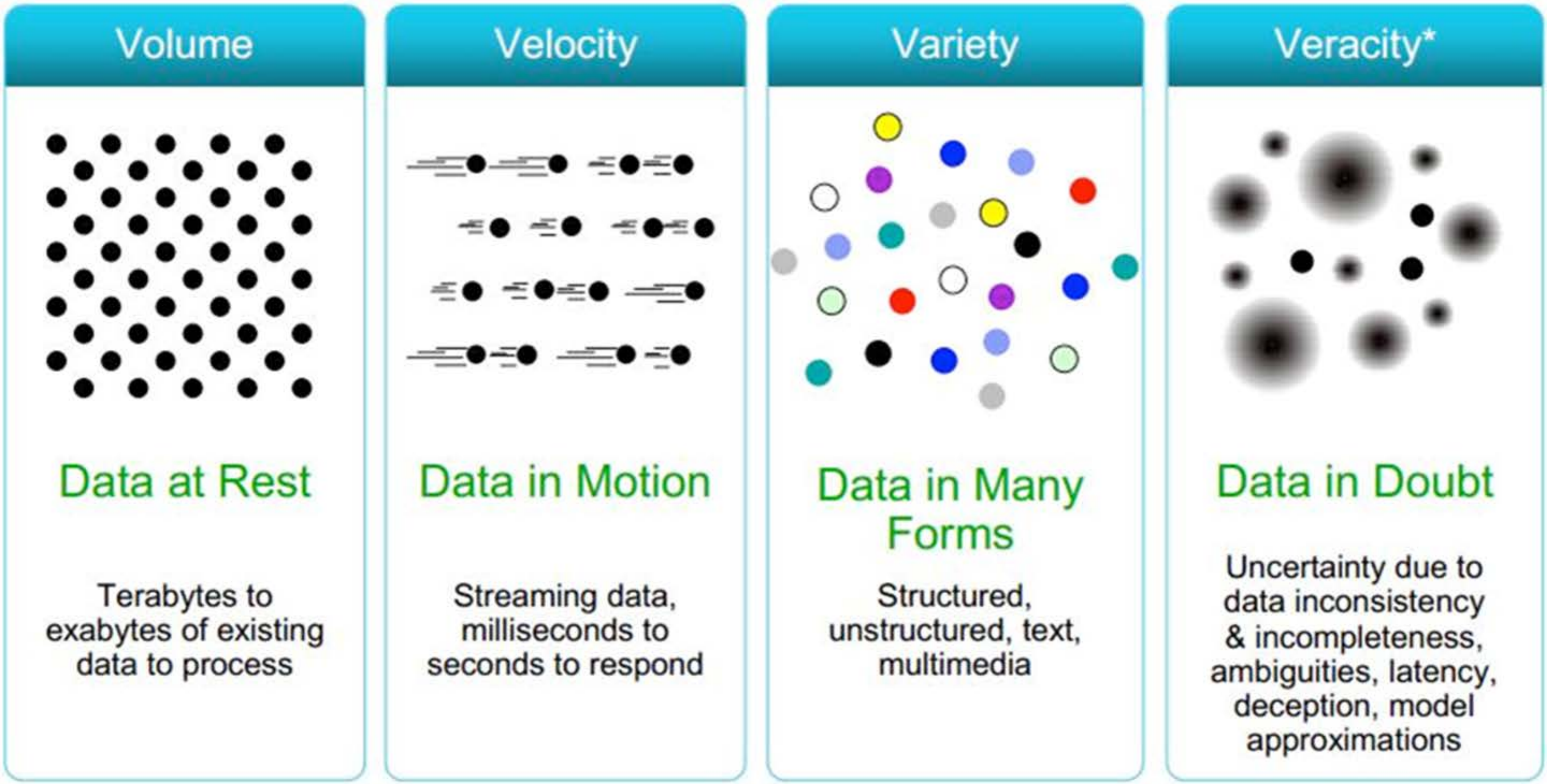
Big Data Properties: 4 Vs

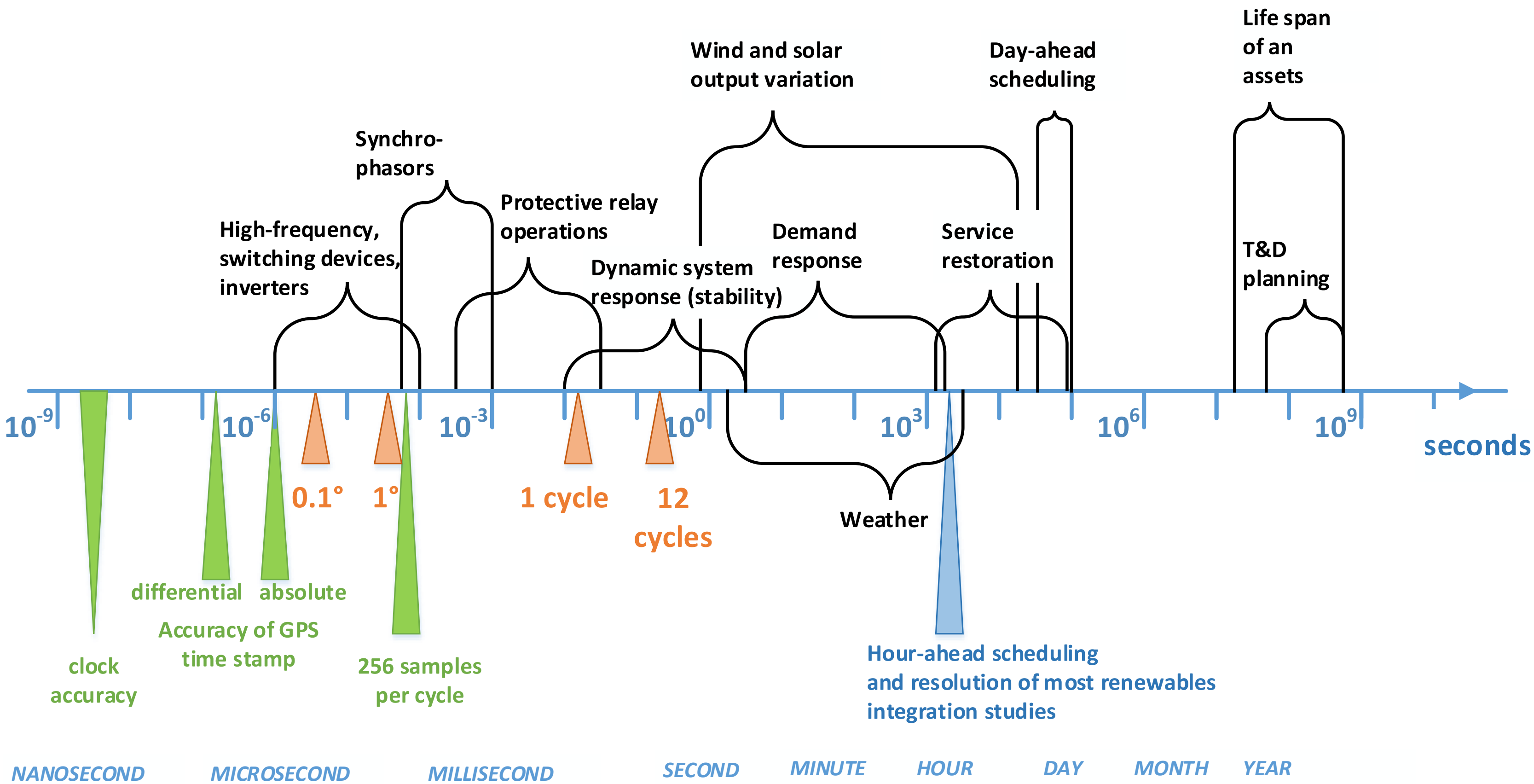


Big Data Properties: Examples

	Data Class	Data Source (Measurements)	VOLUME (Data file size)	VELOCITY (Rate of use)	VERACITY (Accuracy)
V A R I E T Y	Utility measurements	SM	120GB per day	Every 5-15 min	error <2.5%
		PMU	30GB per day	240 samples/sec	error <1%
		ICM	5GB per day	250 samples/sec	error <1%
		DFR	10MB per fault	1600 samples/sec	error <0.2%
	Weather data	Radar	612 MB/day per radar scan	Every 4-10 min	1-2 dB; $m\ s^{-1}$
		Satellite	At least 10 GB per day	Every 1-15 min	VIS<2%; IR<1-2K
		ASOS	10 MB/day per station	Every 1 min	T-1.8°F, P<1%, Wind speed - 5%, RR - 4%
		NLDN	40 MB/day	During lightning	SE < 200m, PCE <15%
		WFM	5-10 GB/day per model	15min - 12 hours	Varies by parameter
	Vegetation and Topography	TPWD EMST	2.7 GB for Texas	static	SE < 10 m
		TNRIS	300 GB for Texas	static	SE < 1 m
		LIDAR	7 GB for Harris Co.	static	HE < 1m, VE < 150 cm

SM – Smart Meter; PMU – Phasor Measurement Unit; ICM – Intelligent Condition Monitor (includes Intelligent Transformer Monitor – ITM, Circuit Breaker Condition Monitor – BCM, etc.); DFR – Digital Fault Recorder; Radar - Radio Detection and Ranging; Satellite - Geostationary and Polar-Orbiting Meteorological Spacecraft; ASOS - Automated Surface Observing System; NLDN – National Lightning Detection Network; WFM – Weather Forecast Model; TPWD EMST - Texas Parks & Wildlife Department - Ecological Mapping Systems of Texas; TNRIS - Texas Natural Resources Information System; LIDAR - Light Detection and Ranging.

Big Data Properties: Temporal



Modified from: A. von Meier, A. McEachern, "Micro-synchrophasors: a promising new measurement technology for the AC grid, " i4Energy Seminar, October 19, 2012.

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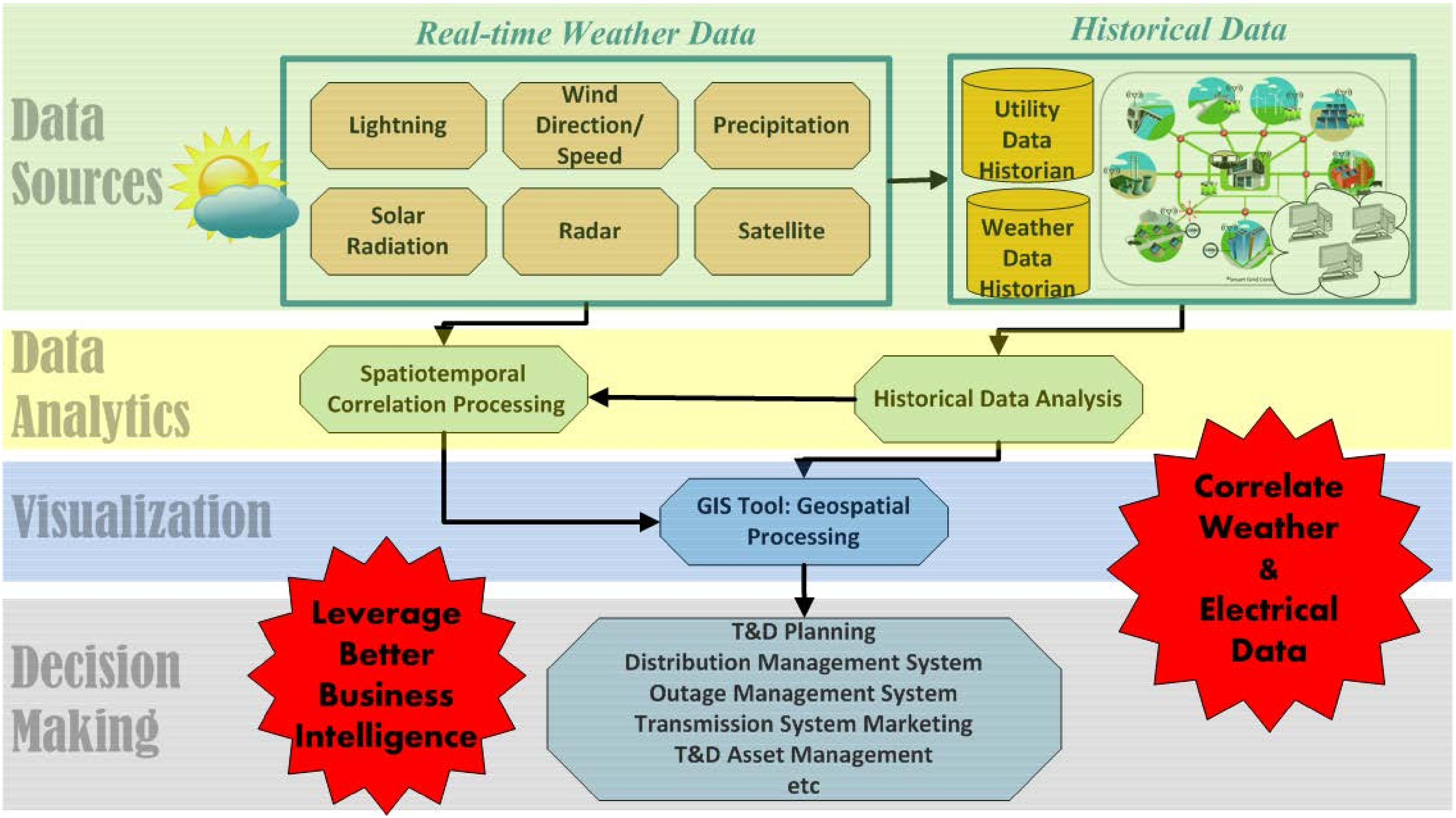
Challenges: Define Solutions



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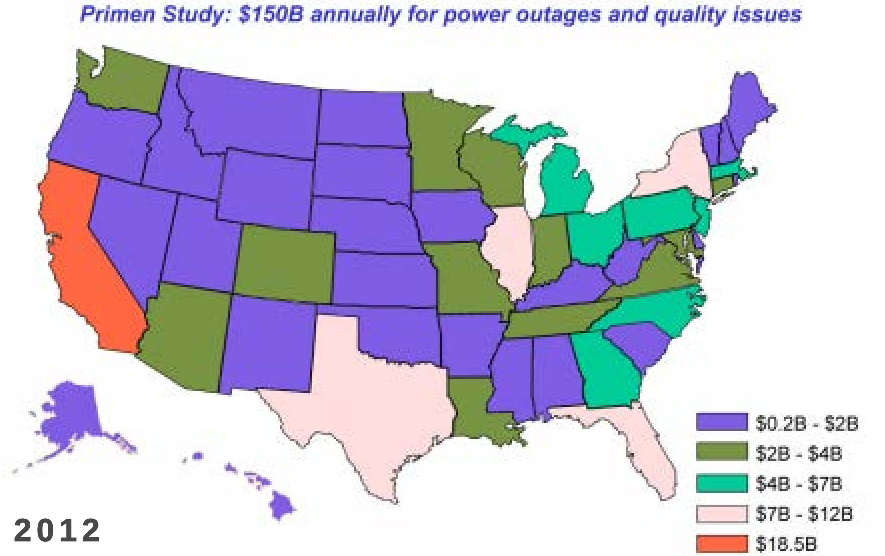
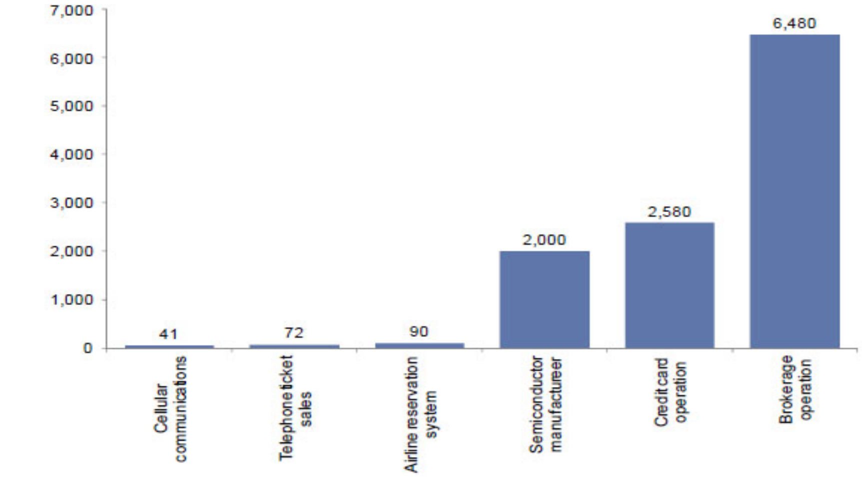
Challenges: Reduce Economic Loss

Annual Business Losses from Grid Problems

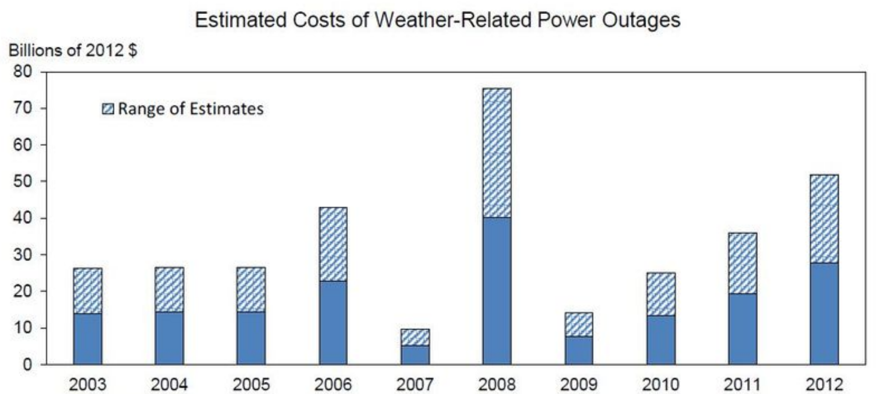


The real victim of power outages are businesses in general

US$'000 (2010); average cost of one hour power interruption in the US per type of customer



Source: US Department of Energy.



Source: CEA estimates using data from Census Bureau, Department of Energy , Energy I nformation Administration, Sullivan et al 2009.

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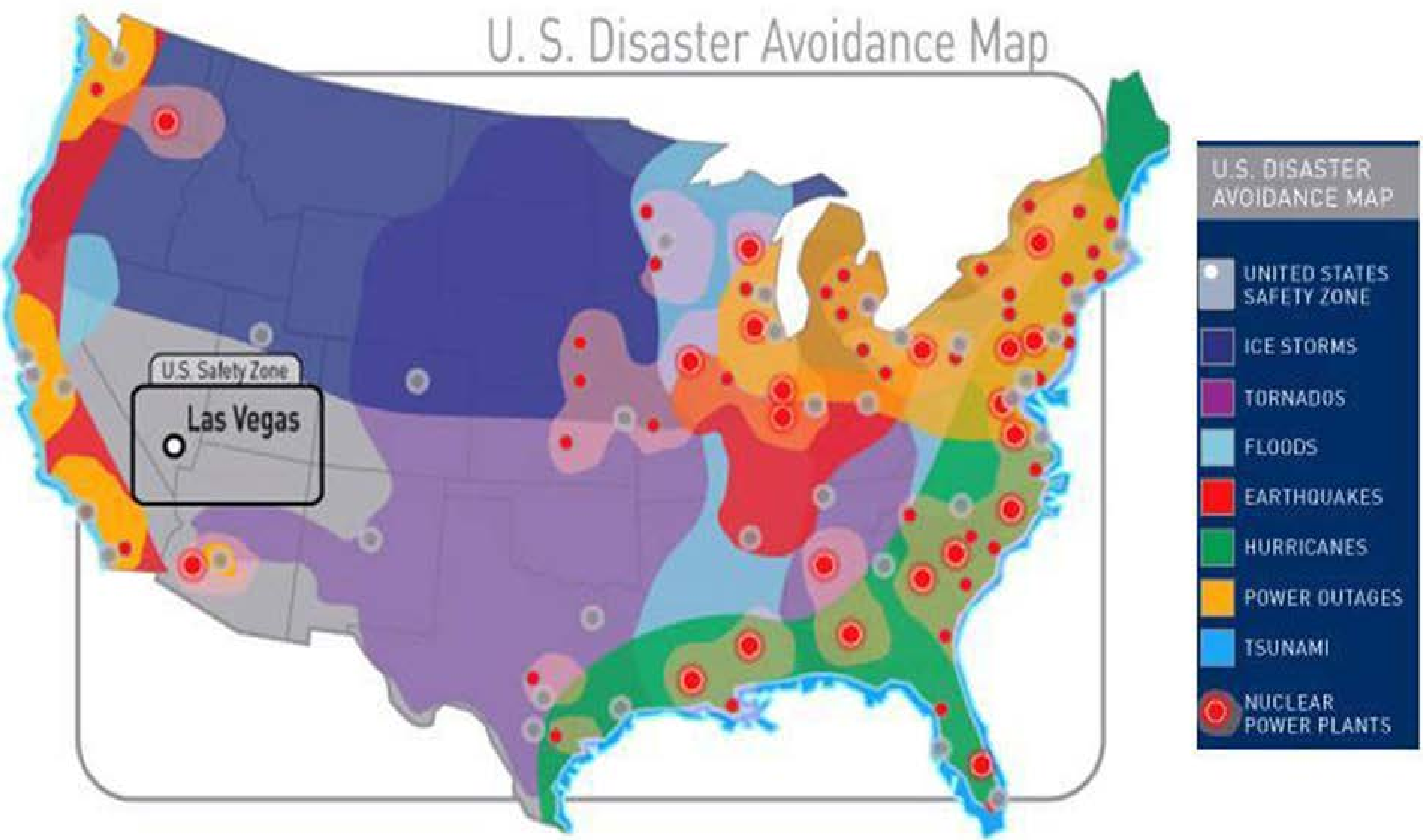
Challenges: Predict Risk



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Opportunities: Define Risk

Risk = Hazard x Vulnerability x Impacts

Intensity T – Threat Intensity

Hazard – Probability of a threat with intensity *T*

Vulnerability – Probability of a consequence *C* if threat with intensity *T* occurred

Impacts– Estimated economic and/or social impacts if consequence C has occurred

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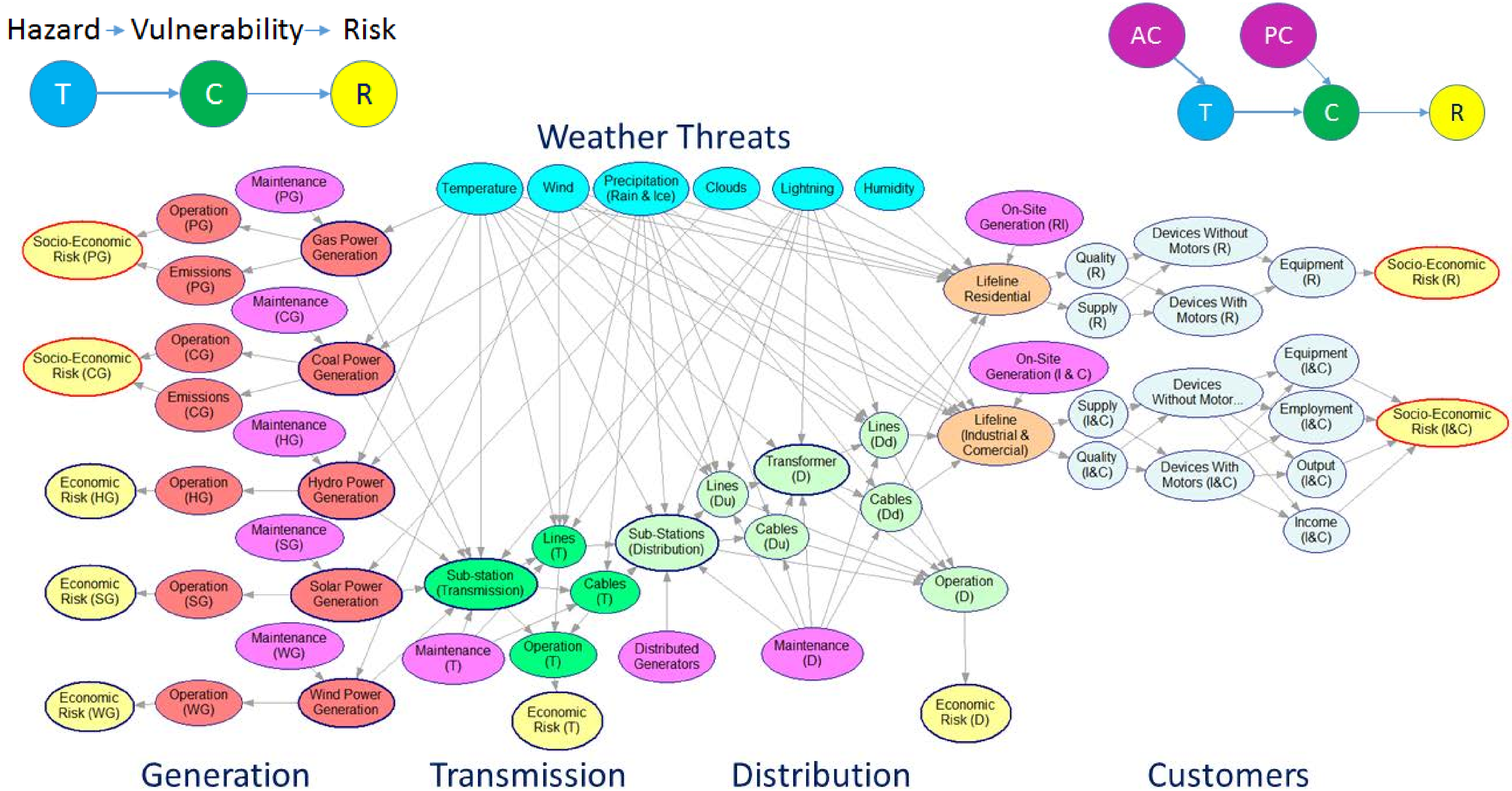
Opportunities: Weather Impact Risk



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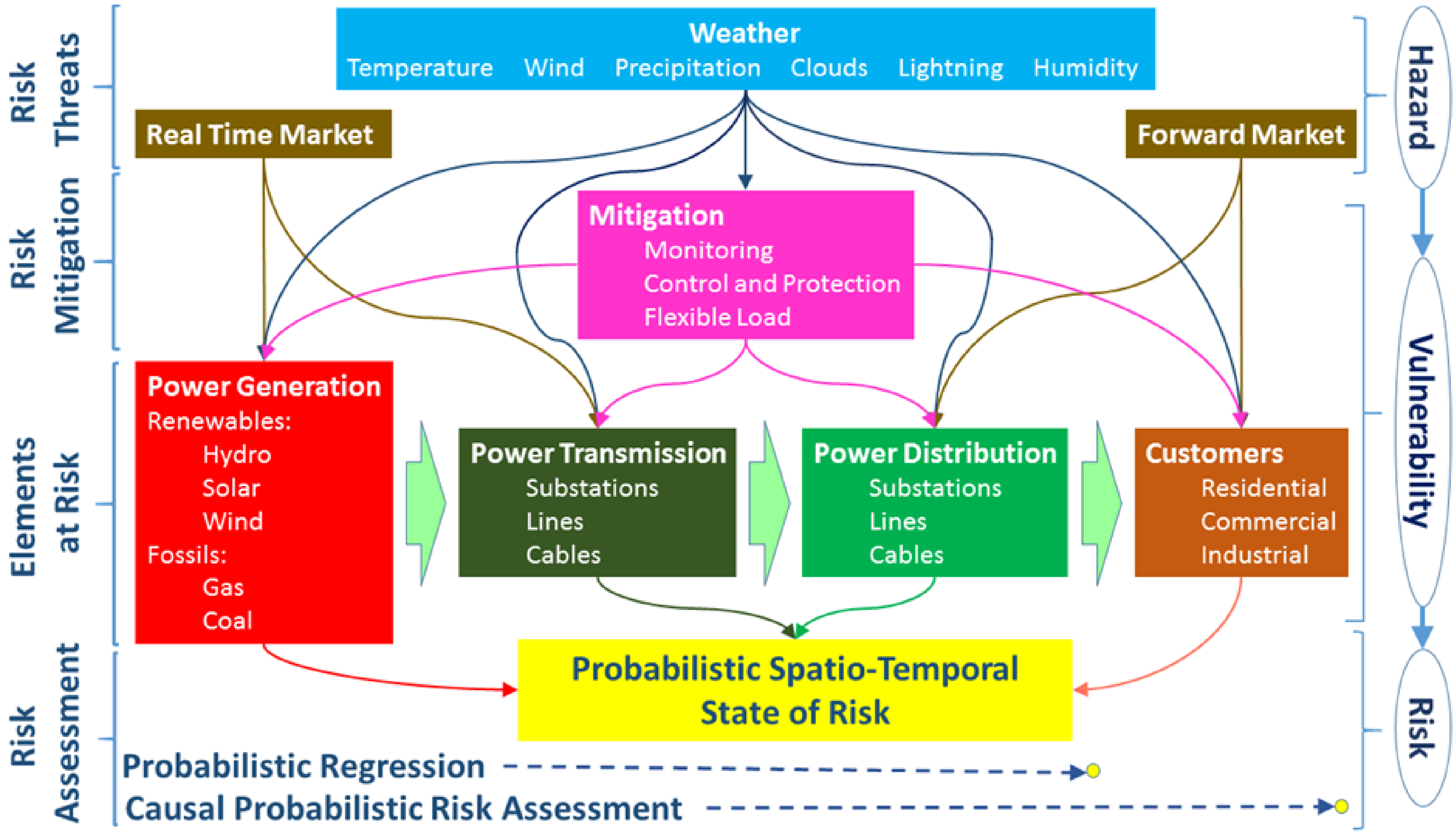
Opportunities: Risk Framework



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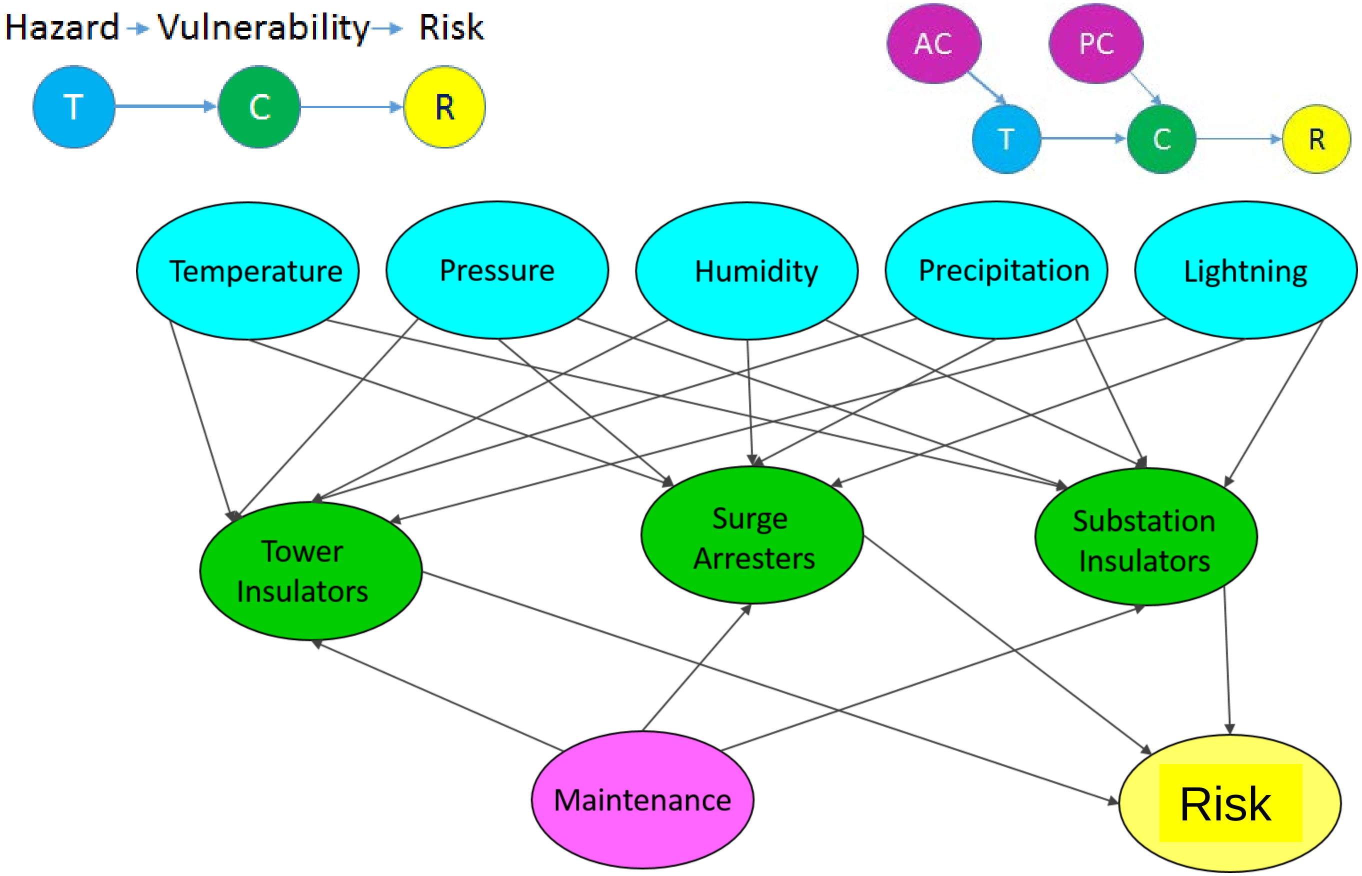
M. Kezunovic, Z. Obradovic, T. Dokic, B. Zhang, J. Stojanovic, P. Dehghanian, and P. -C. Chen, "Predicting Spatiotemporal Impacts of Weather on Power Systems Using Big Data Science," Studies in Big Data, Vol. 24, Witold Pedrycz and Shyi-Ming Chen (Eds), Springer Verlag, 2016

Example 1: Insulator Risk Model



M. Kezunovic, T. Djokic, P-C. Chen, "Big Data Uses for Risk Assessment in Predictive Outage and Asset Management," CIGRE Symposium, Ireland, May, 2017

M. Kezunovic, T. Djokic, "Predictive Asset Management Under Weather Impacts Using Big Data, Spatiotemporal Data Analytics and Risk Based Decision-Making, IREP, Portugal, August 2017

New Data Analytics

Risk = Hazard x Vulnerability x Economic Impact

$$\mathbf{R = P[T] \cdot P[C|T] \cdot u(C)}$$

Intensity T – Lightning peak current

Hazard – Probability of a lightning strike with intensity *T*

Vulnerability – Probability of a insulation breakdown for a given intensity of lightning strike

Economic Impact – Estimated losses in case of insulation breakdown (cost of maintenance and operation downtime)

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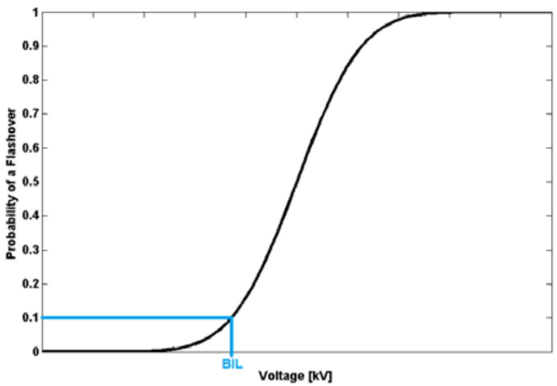
BD use in Modeling the Insulator BIL

Conventional method

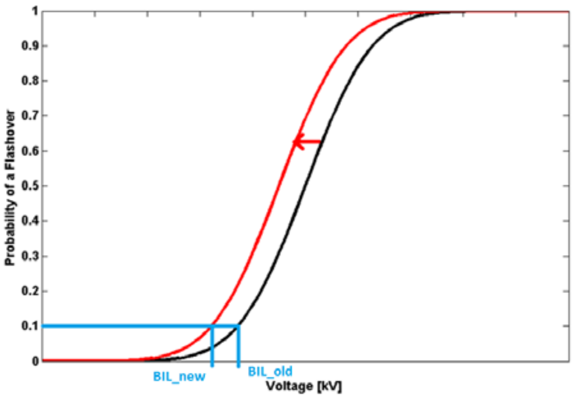
- BIL determined by insulator manufacturer.



- Insulator breakdown probability determined statistically.
- Economic impact not taken into account.

BD approach

- Manufacturers standard BIL used only as a initial value. Standard BIL changes during the insulator lifetime.



- Insulator breakdown probability determined based on spatio-temporally referenced historical data and real-time weather forecast using data mining.
- Risk model includes economic impact in case of insulator breakdown.

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Data Integration

TEMPORAL			SPATIAL	
Lightning Detection Network	**Weather**	**Traveling Wave Fault Locators**	**Insulation Coordination Studies**	**Geography**
Date and time of lightning strike	Temperature	Date and time when event was recorded	Surge impedances of towers	Location of substations
Location of a strike (latitude and longitude)	Atmospheric pressure	Distance to the fault from the line terminals	Surge impedances of ground wire	Geographical representation of the line
Peak current and lightning strike polarity	Relative humidity	Transient signals recorded at the line terminals	Footing resistance	Location of towers
Type of lightning strike (cloud to cloud or cloud to ground)	Precipitation	**Historical Outage Data**	Standard BIL	Location of surge arresters
	Lightning/Thunderstorm Probability (Forecast)	Insulator breakdown history	New BIL after accumulated lightning impact	Location of land-based weather stations

Black – Used in conventional insulation coordination

Red – Additional data used in BD method

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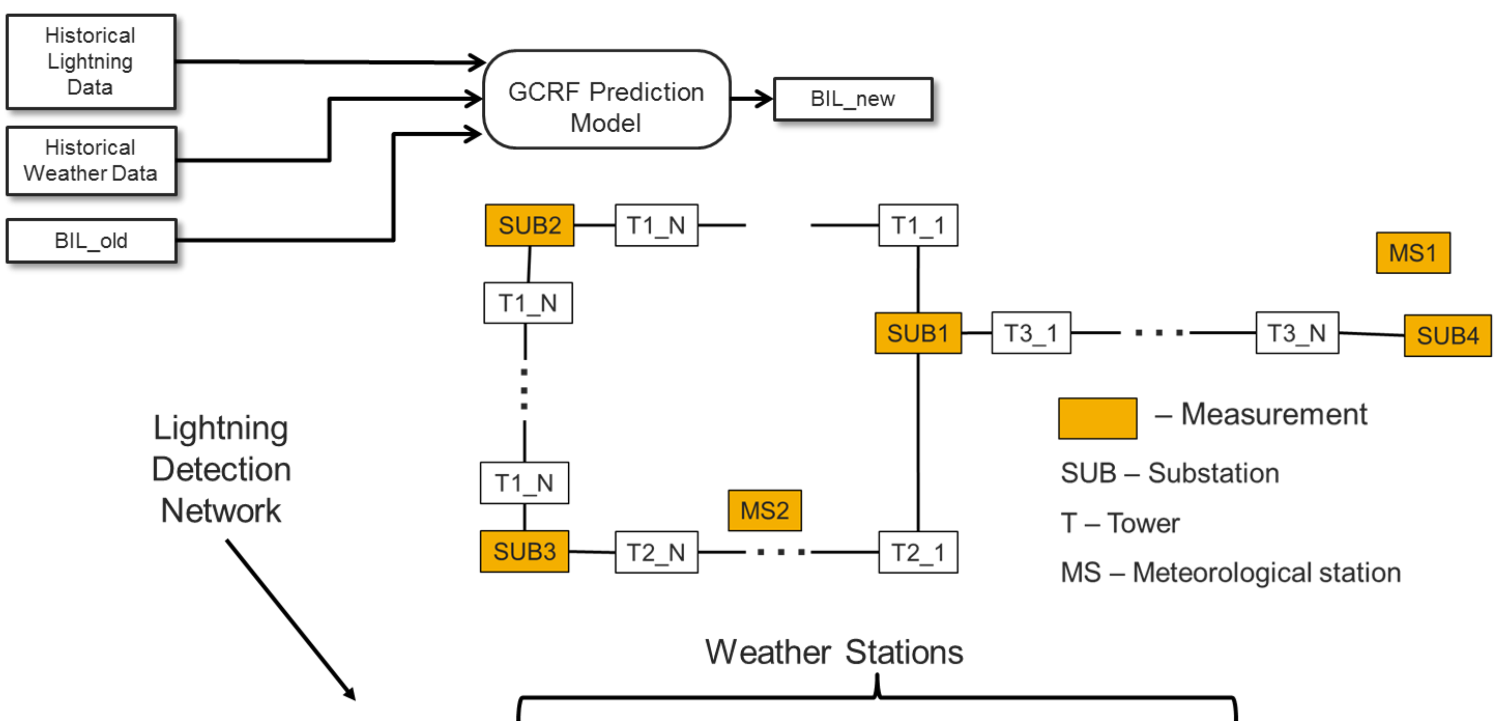
Prediction Model



Nodes: X = (Lightning Current, Temperature, Precipitation, Humidity, Pressure, BIL_old)

Y = (BIL_new)

Branches: Network Impedance Matrix

$$P(y|x) = \frac{1}{Z} exp\left(-\sum_{i=1}^{N}\sum_{k=1}^{K}\alpha_k\left(y_i - R_k(x)\right)^2 - \sum_{i,j}\sum_{l=1}^{L}\beta_l e_{ij}^{(l)} S_{ij}^{(l)}(x)\left(y_i - y_j\right)^2\right)$$

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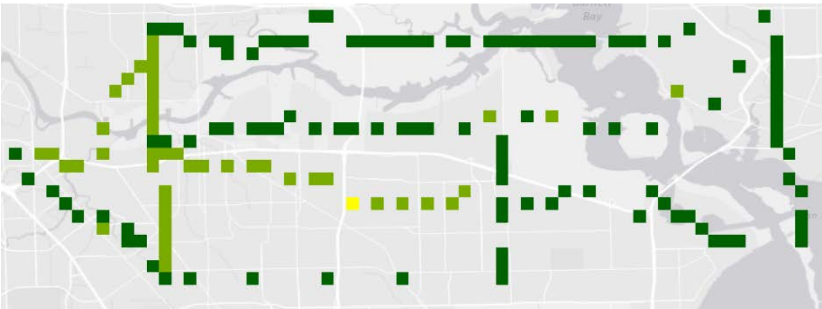
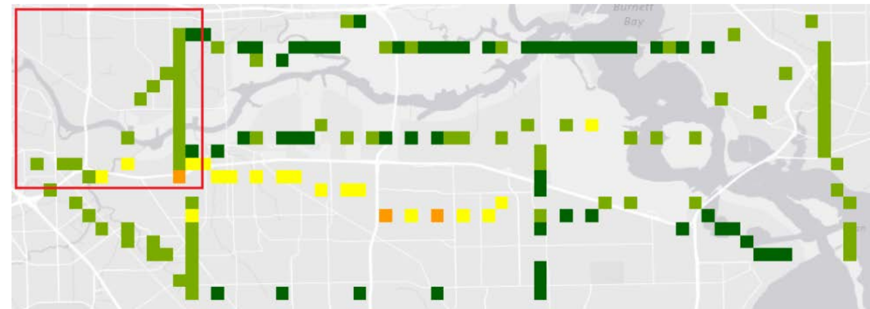
Result: Risk Map

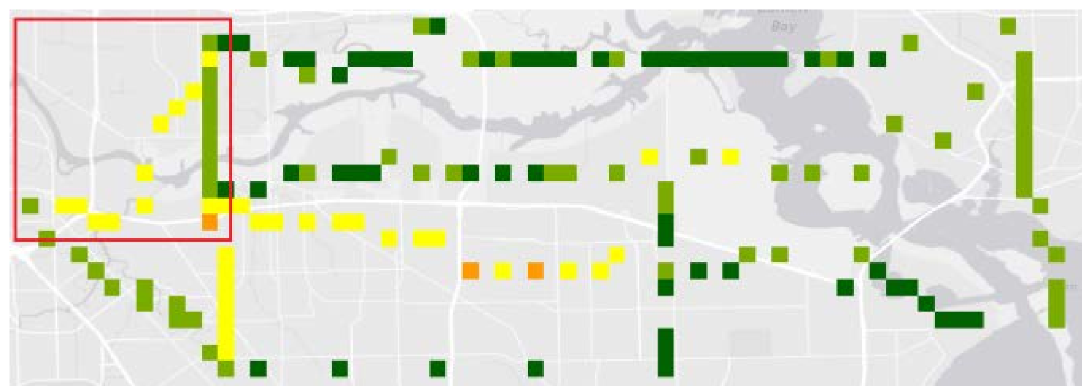
Risk on January 1st 2009



Risk on December 31st 2014



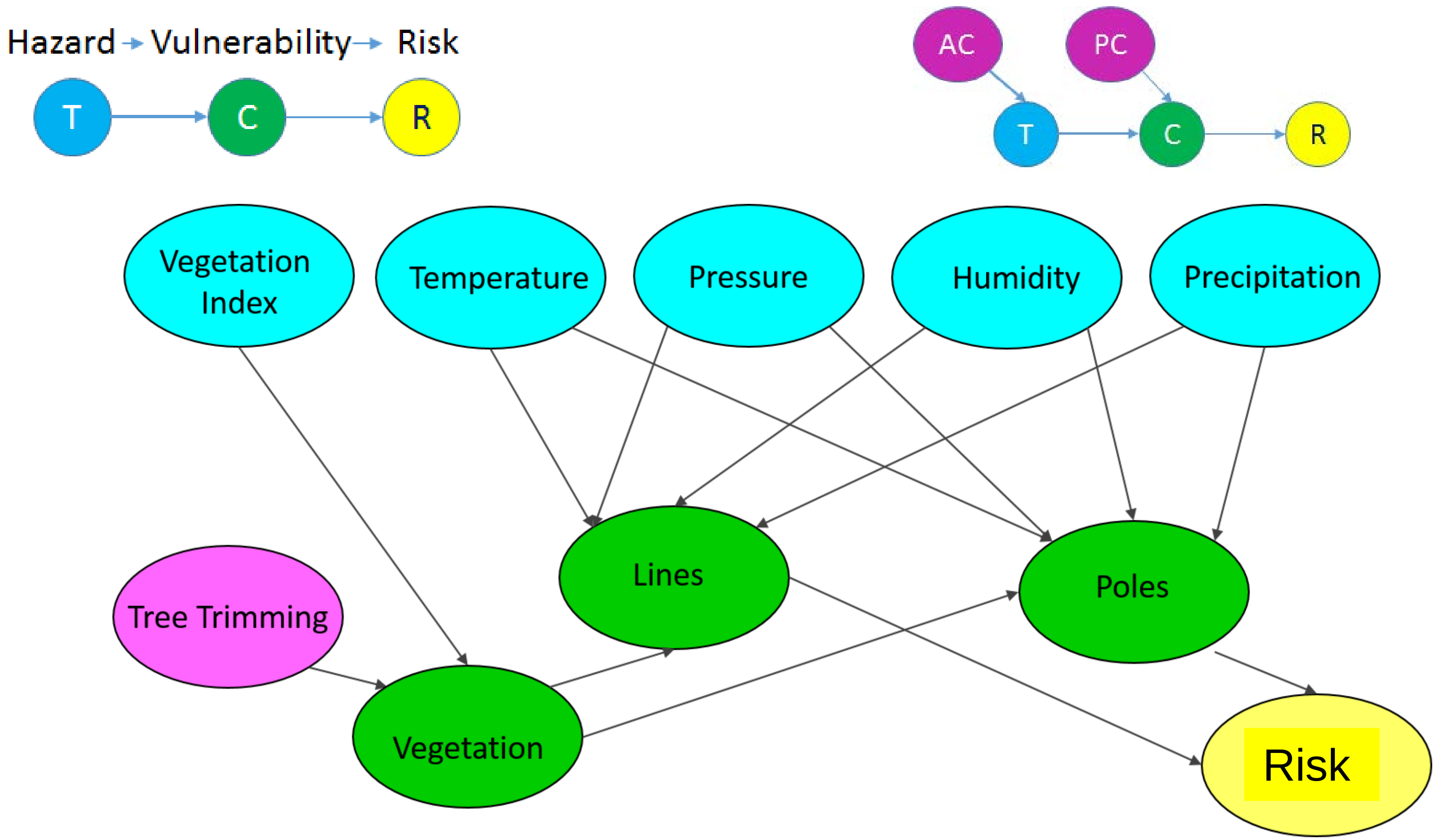
Risk on January 5th 2015 (Prediction)



RISK

- 0 - 20%
- 20 - 40%
- 40 - 60%
- 60- 80%
- 80- 100%

Example 2: Vegetation Risk Model



P. C. Chen and M. Kezunovic, "[Fuzzy Logic Approach to Predictive Risk Analysis in Distribution Outage Management]", *IEEE Transactions on Smart Grid*, vol. 7, no. 6, pp. 2827-2836, November 2016.

T. Dokic, P.-C. Chen, M. Kezunovic, "[Risk Analysis for Assessment of Vegetation Impact on Outages in Electric Power Systems]", CIGRE US National Committee 2016 Grid of the Future Symposium, Philadelphia, PA, October-November 2016.

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New Data Analytics

Risk = Hazard x Vulnerability x Economic Impact

$$\mathbf{R = P[T] \cdot P[C|T] \cdot u(C)}$$

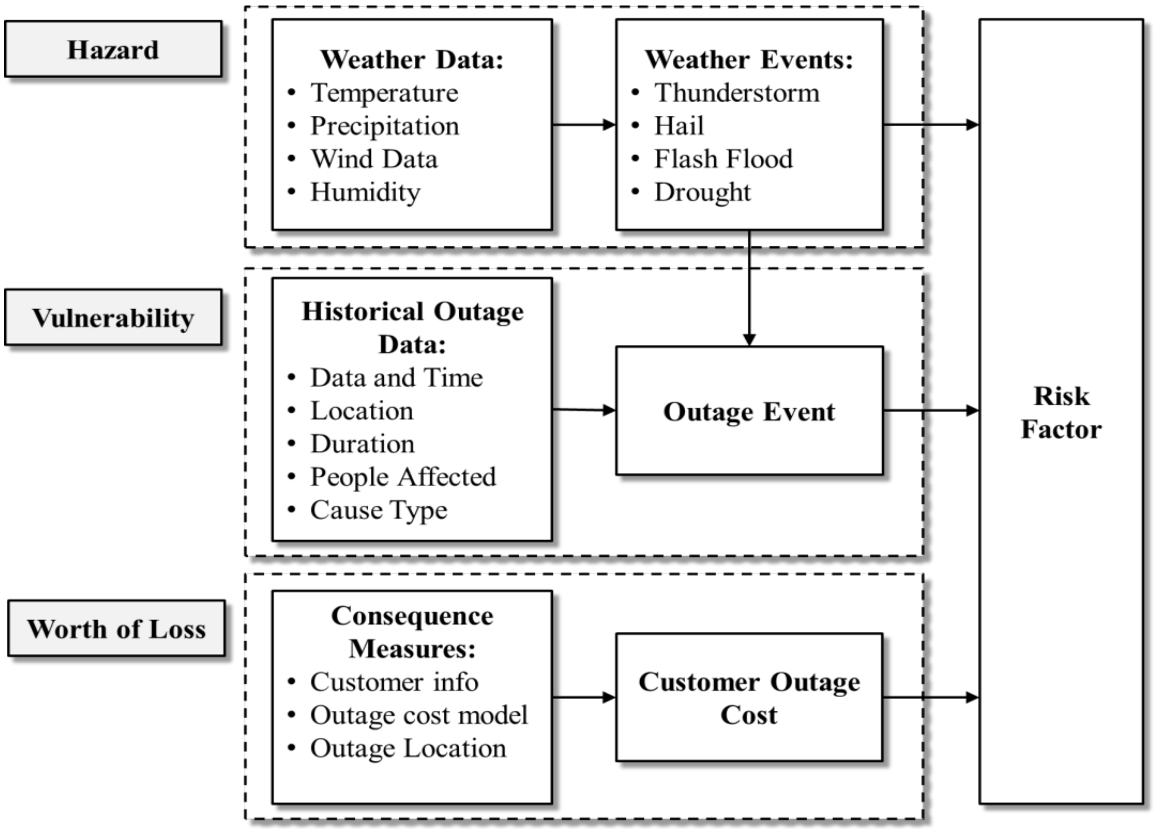
Intensity T – Wind Speed and Direction, Precipitation, Temperature

Hazard – Probability of a weather conditions with intensity *T*

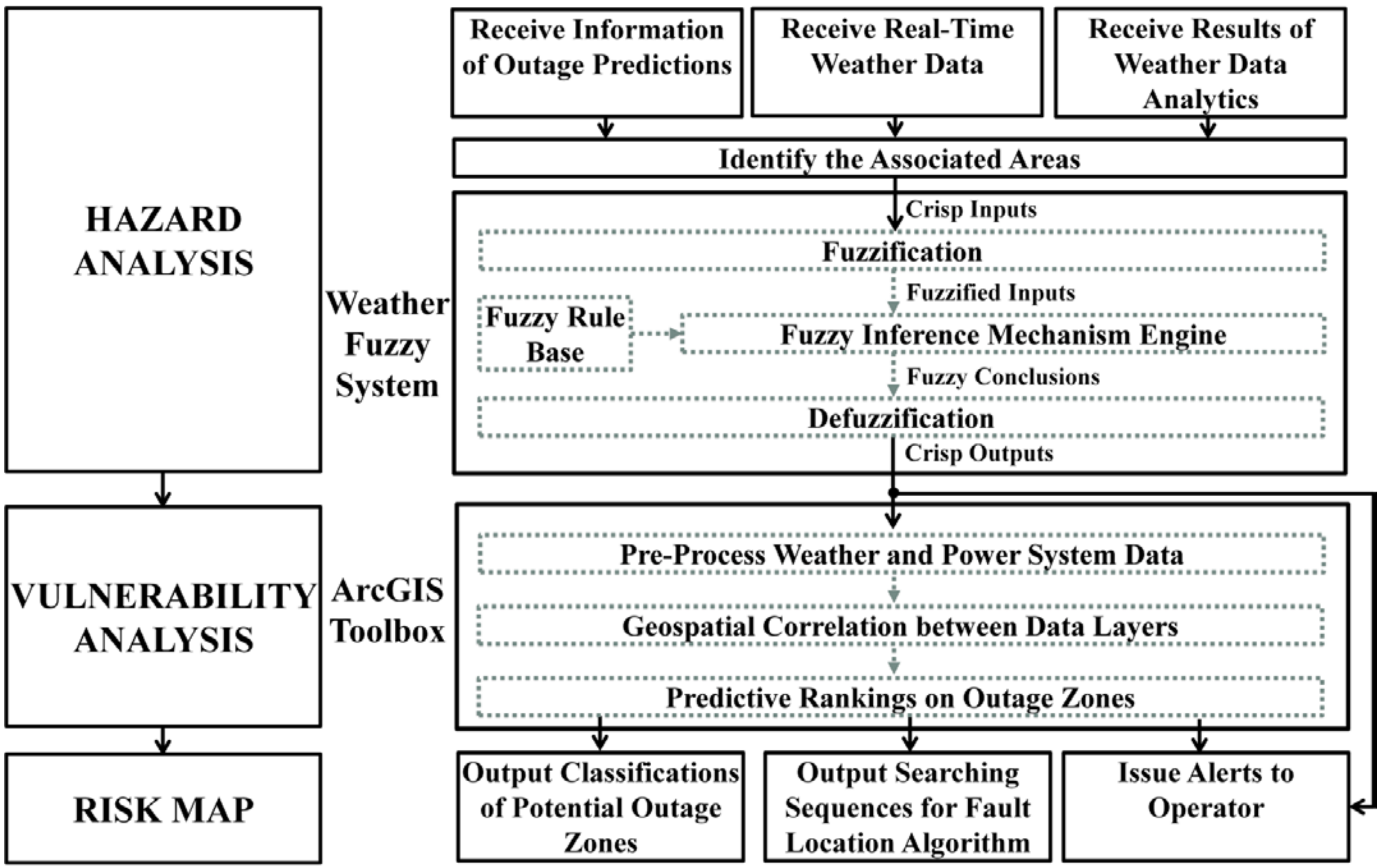
Vulnerability – Probability of a tree or a tree branch coming in contact with lines for a given weather hazard

Economic Impact – Estimated losses in case of an outage (cost of maintenance and operation downtime)

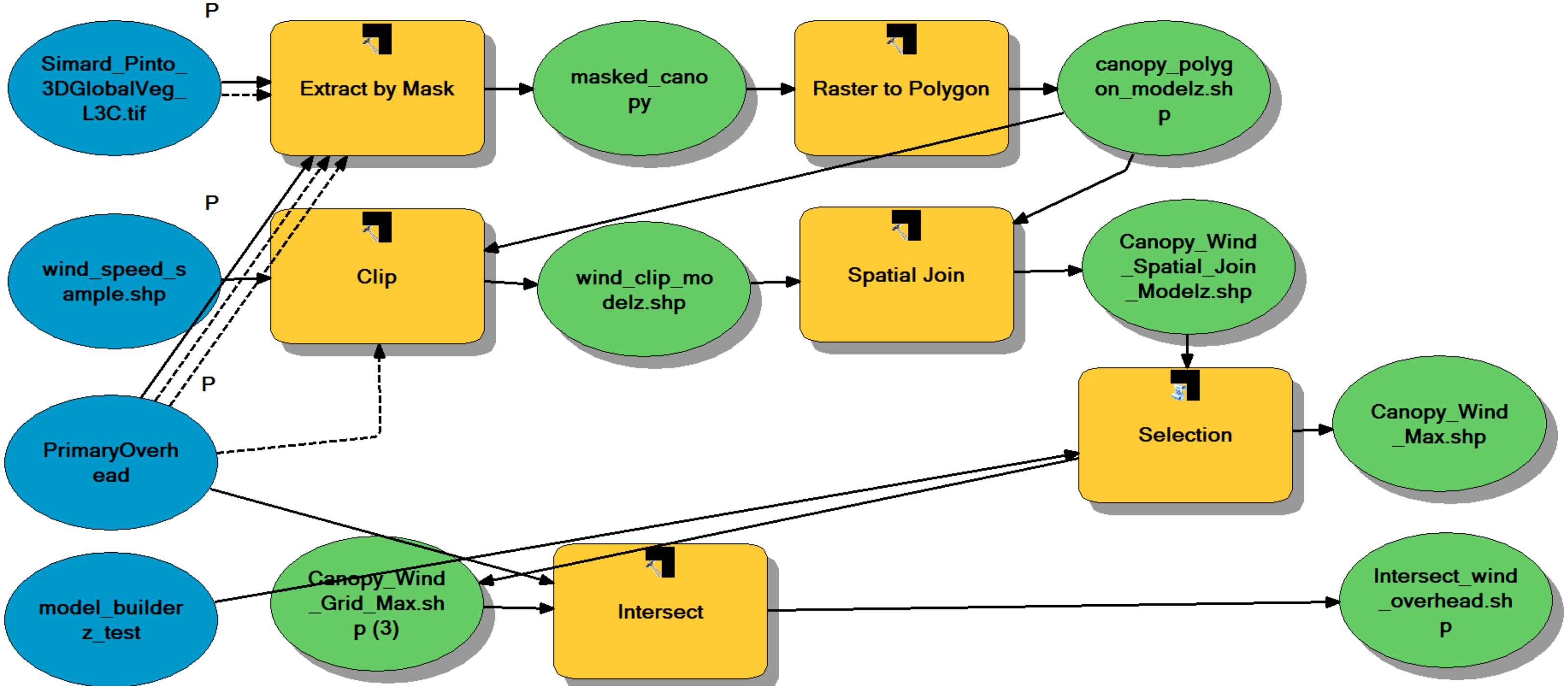
BD Use in modeling weather Impacts

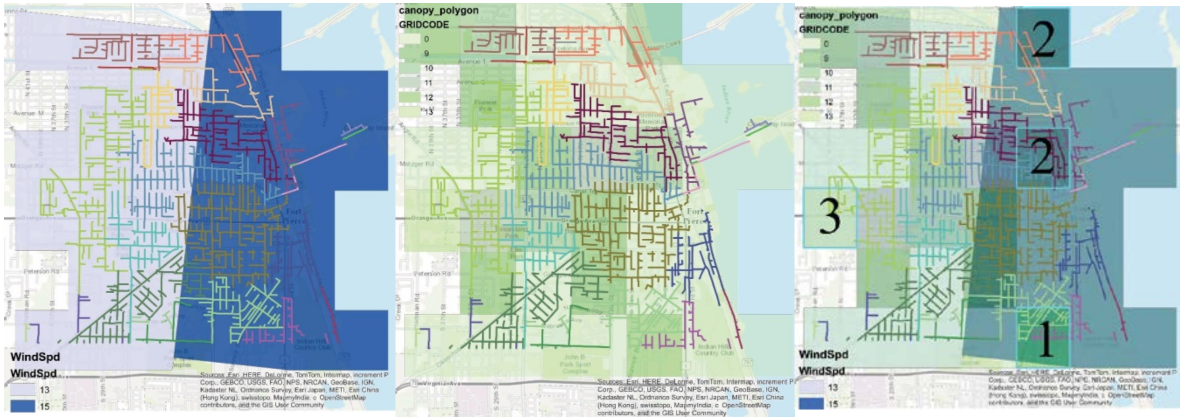


Data Integration



Spatial Correlation of Data





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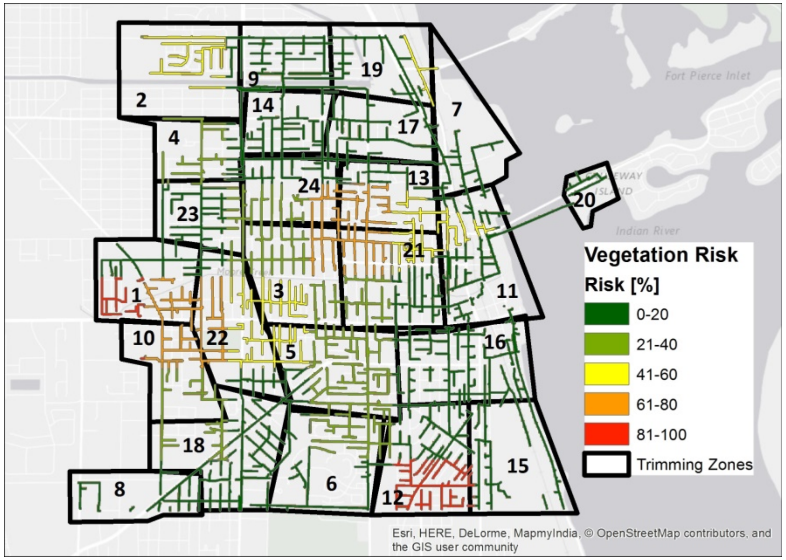
Result: Risk Maps



ID	Zone Order for Tree Trimming Schedule	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

Conclusions

- Big Data is abundant in smart grids
- It may be used to solve major problems
- More research on data analytics is required
- The solutions have to offer predictive capabilities associated with risks
- Managing assets and outages is a good candidate to gain from BD use
- Big Data created **big expectations**

QUESTIONS?

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