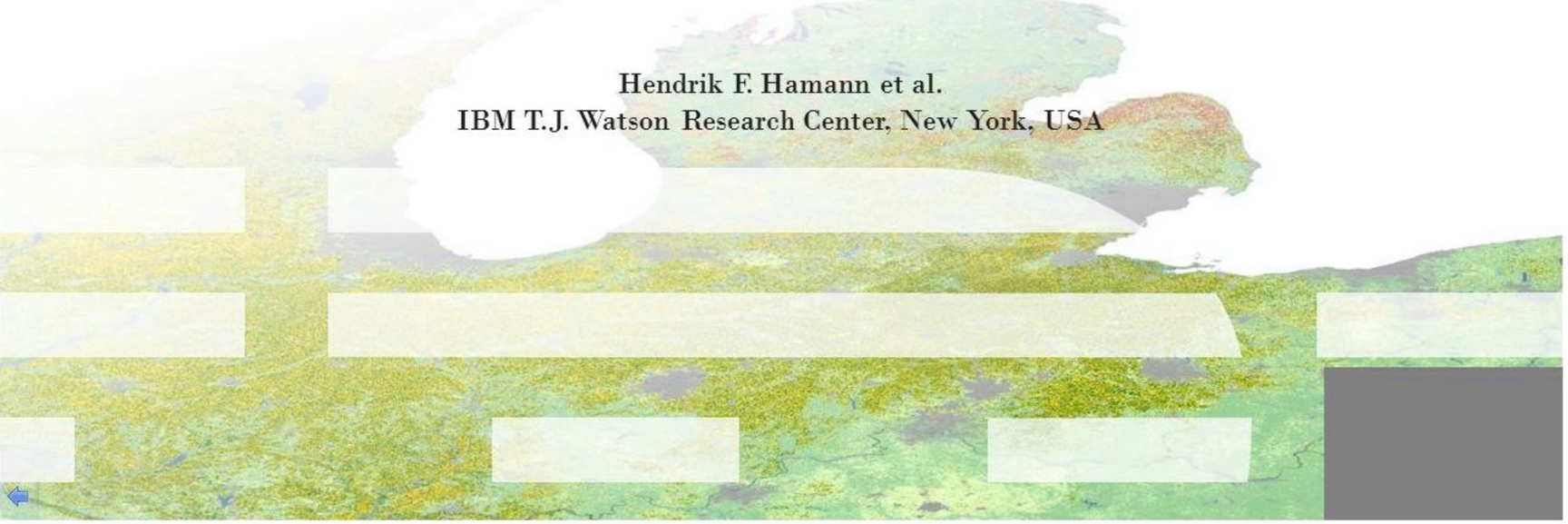
Making the invisible visible:

How to convert data from remote sensing systems and IoT devices to real information

Hendrik F. Hamann et al.
IBM T.J. Watson Research Center, New York, USA



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Can Wang	
Charles Ernst	
David McKay	
david pinkos	
Floyd Harris	
gerald hanlon	
Grace Harvey	
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Guest A11	
Guest A12	
Guest A15	
Guest A16	
Guest A17	
Guest A18	
Guest A19	

Participants 47 0

Materials

Event Materials

Insert...

AT&T Connect Materials: Ready to Use

Raise Hand | Send Note | Step Out | Whiteboard | Audio | Unmute

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Making the invisible visible:

How to convert data from remote sensing systems and IoT devices to real information

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Name	Comment
Guest A6	
Guest A7	
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Iman Morisset	
j f	
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Jenny Foley	
Jimmy Hsu	
Jody Schaeffer	
Man Peng	
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nishit pande	
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Priya Gopinath	
Rajat Kashyap	

Participants 60 0

Materials

Event Materials

Insert...

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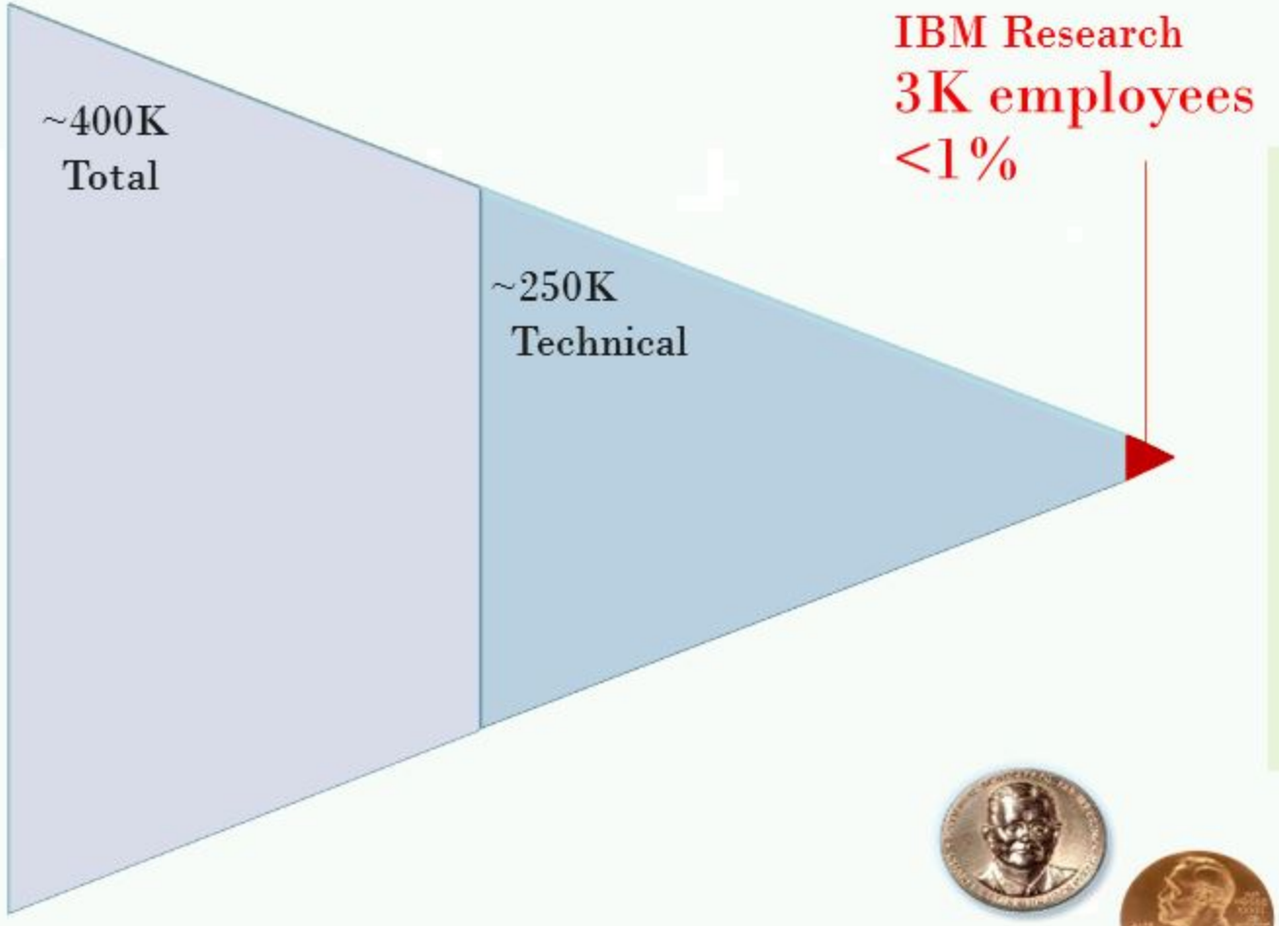
Outline

- IBM Research
- Technology Trends
- Physical Analytics
- Big data platform for spatio-temporal analytics
- Applications

Research is IBM's Innovation Engine

IBM Employee Population



Innovative

- 50% of external honors
- 46% of IBM Fellows
- 25% of all patents filed
- 26% of new academy members

Recognized

- 5 Nobel Laureates
- 13 National Medals
- 6 Turing Awards
- 80 Members, National Academies
- 11 Inductees, National Inventors Hall of Fame

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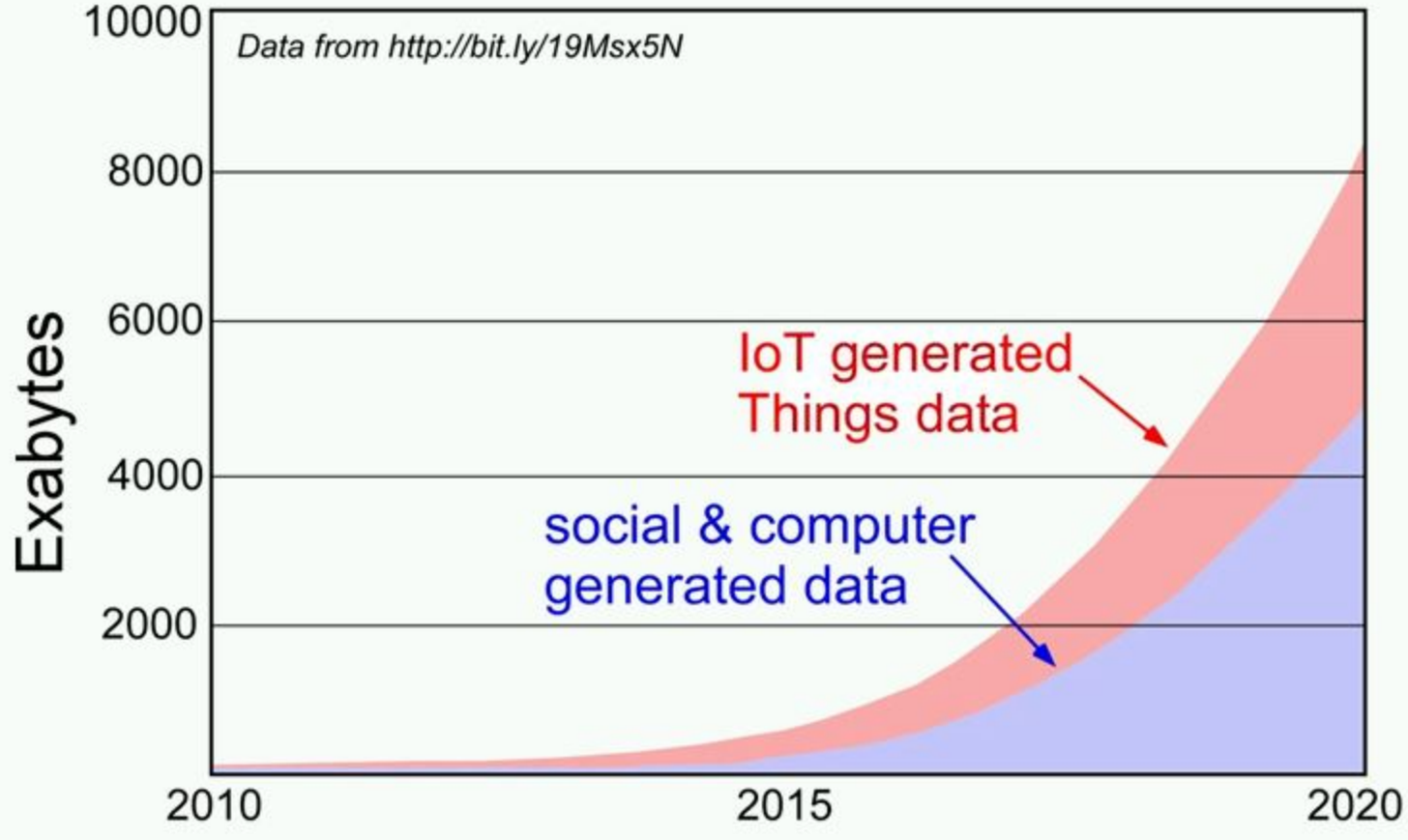
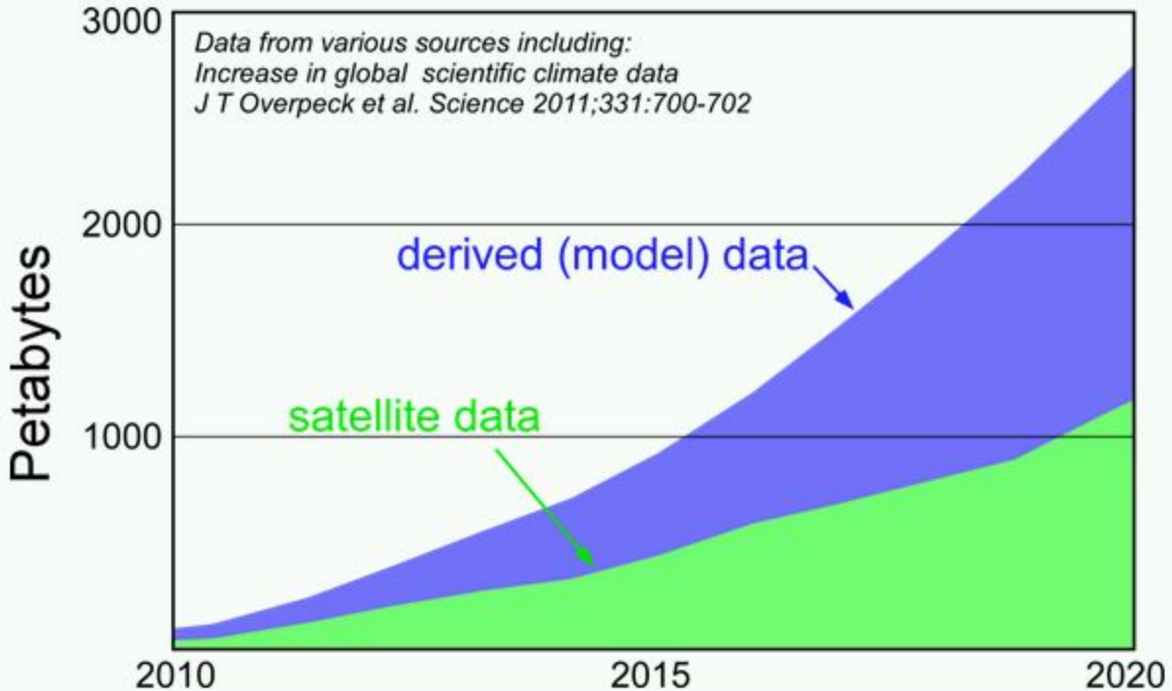
IBM Research is world-wide

"Internet-of-Things" generated data soon bigger than social and transactional data



~ 2x more data growth (currently @ 44EB/month) than social & computer generated da

Data from remote sensors is exploding



- **Number of satellite launches are growing exponentially**
  - Many countries have re-started major satellite programs (China, Europe, India etc.)
  - Cube satellites, Nano-satellites
- **Drones, cell phone with hyper-spectral cameras**

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The physical world is being digitized….

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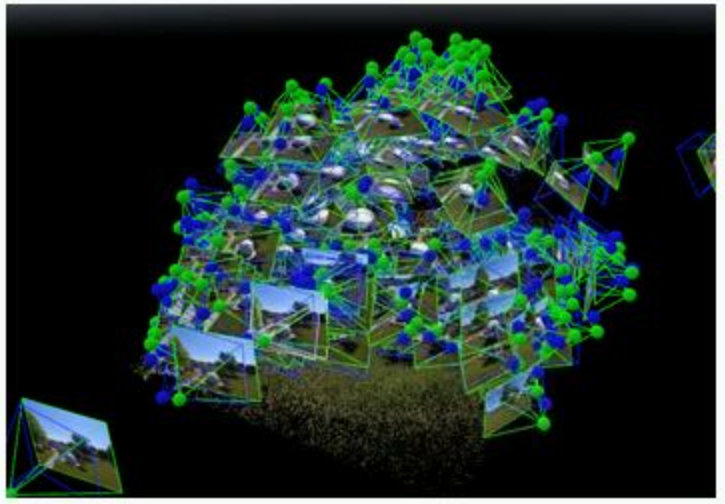
The physical world is being digitized….

Position of the camera and images used for reconstruction



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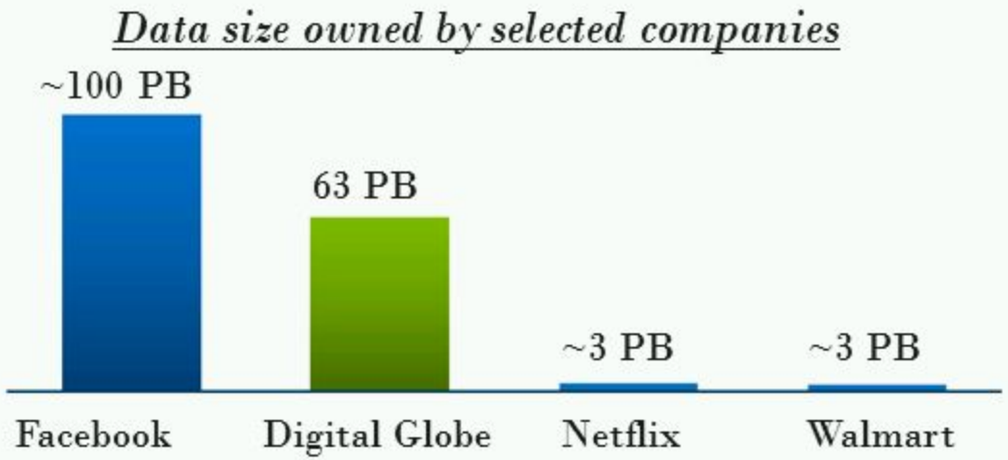
Traditional (physical) industries are being transformed by (IoT) data

Industry	Past – Selling a Product	Future - Service
Healthcare	Diabetes pumps	Diabetes care
Agriculture	Seeds	Crop yields
Consumer	Packaged goods	Nutrition
Automotive	Cars	Transportation
…	…	…
IT Industry	Computers	Computation

McKinsey, GE, IBM, Cisco et al. estimate **hundreds of billions dollar** savings/efficiency improvements in the next 10 years

Big data from the physical world is different than social or transactional data

- Data from the physical world is becoming soon **"mega" big.**
  - 44EByte / months corresponds to **~ 100M hard disks**
  - Processing 44 EByte with 100M servers **would still take more than one hour**
  - **Data throughput** (rather than processing) has become the limiting factor



Sources: Facebook IPO Propectus; Bloomberg May 2013; SAS 2012

- IoT data has more **noise** and is more prone to **error.**
- Data **security**, **verification** etc even more important.
- Data **not always cheap**.

Most analytics on big data is purely data-driven…

	Data-driven Models
Adaptability & deployability	Generic framework, easily adapted to new problems
Domain expertise reliance	Can provide useful results with little domain knowledge
Data availability reliance	Substantial amounts of data to train upon
Fidelity & robustness	Limited to the range of values from the training set and the complexity of the model
Interpretability	Limited
Computation	Big data technologies (high data throughput)

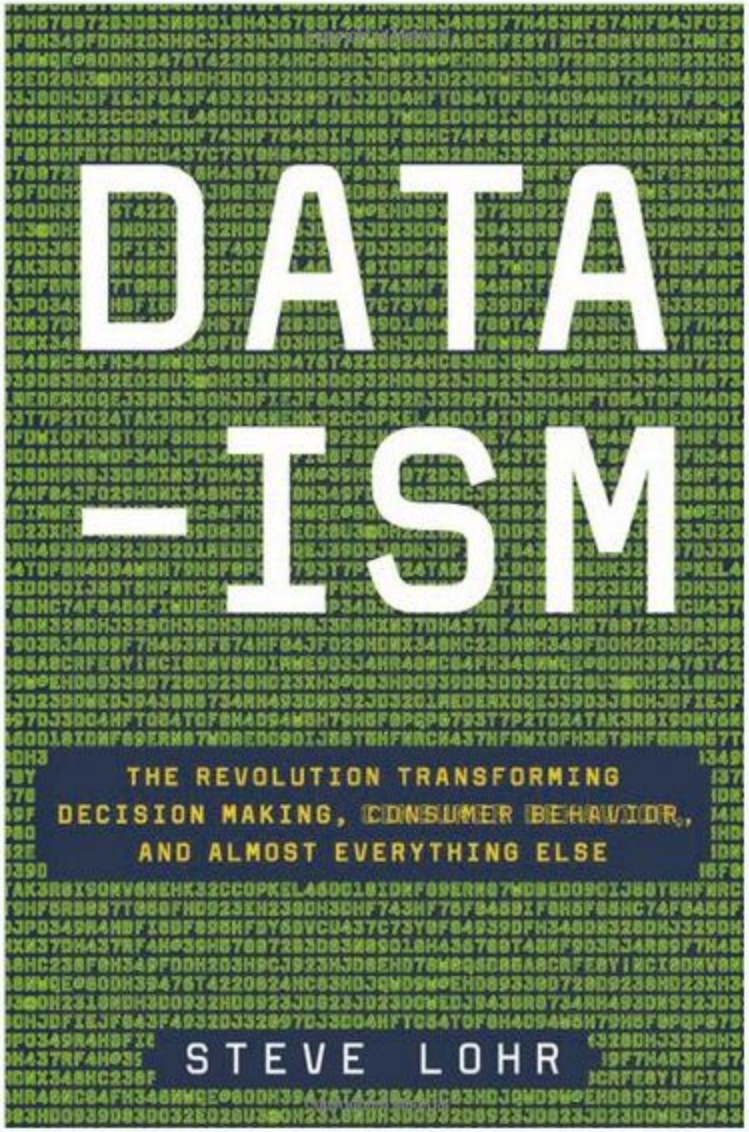
Most analytics on big data is purely data-driven. versus first-principle/domain based

	Data-driven Models	First-principle Models
Adaptability & deployability	Generic framework, easily adapted to new problems	Requires sometimes complex derivations
Domain expertise reliance	Can provide useful results with little domain knowledge	Reliance upon domain expertise
Data availability reliance	Substantial amounts of data to train upon	No / little data
Fidelity & robustness	Limited to the range of values from the training set and the complexity of the model	Universal links can handle highly non-linear and complex relations
Interpretability	Limited	Physically meaningful link between parameters
Computation	Big data technologies (high data throughput)	Traditional HPC (processing throughput)

Physical Analytics Ambition: Combining big da
data-driven and domain models

	Physical Analytics
Adaptability & deployability	Accounts for the relevant physics but still generic enough to easily and rapidly adapt
Domain expertise reliance	Provides useful results with some domain knowledge
Data availability reliance	Right data
Fidelity & robustness	Sufficient robustness and fidelities
Interpretability	Consistent to pinpoint to the relevant physics
Computation	Combination of big data technologies & traditional HPC (high processing & data throughput)

Physical Analytics: (Big) Data gets physical



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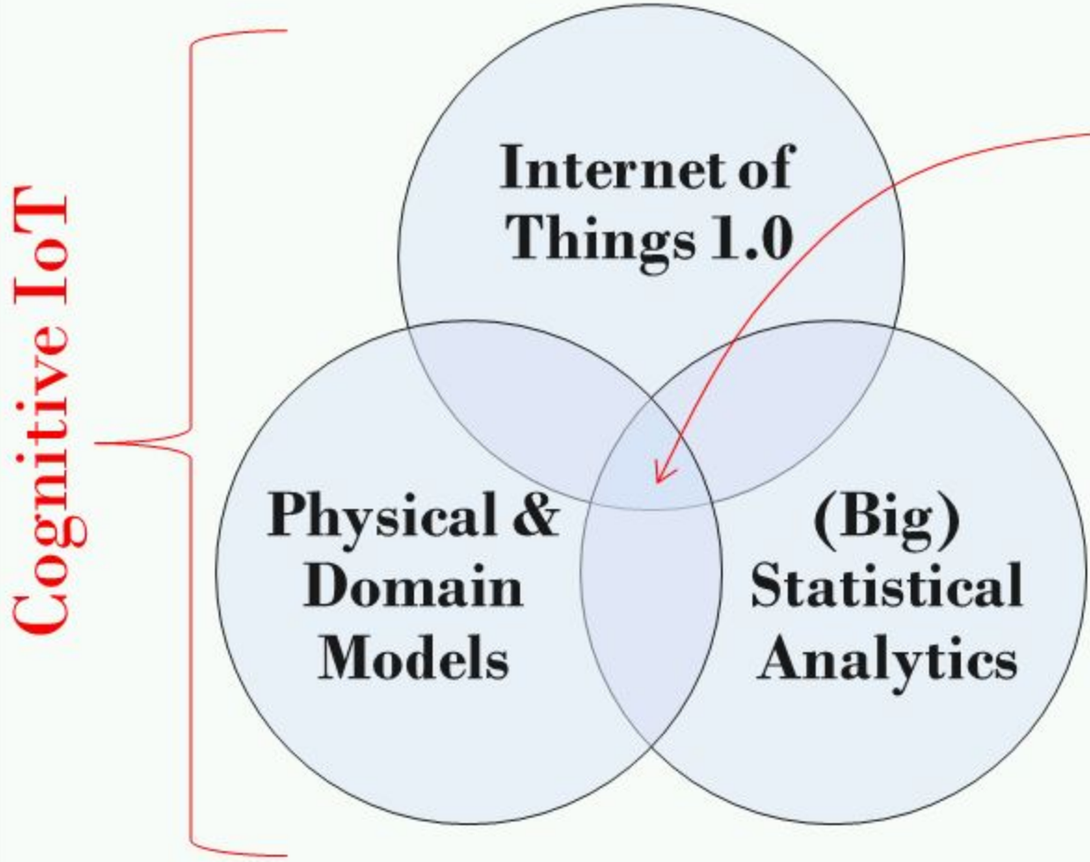
Physical Analytics lies between IoT 1.0, physics-based modeling and big data statistical analytics



Highly inter disciplinary with many interesting research topics

- Statistical learning under physical constraints
- Model complexity reduction
- Situation-dependent, machine-learnt multi-model blending
- Graph theory and statistical physics
- Parallelizing physical models for data-intensive computation
- …..

- Feed learning back to improve understanding of the underlying physics

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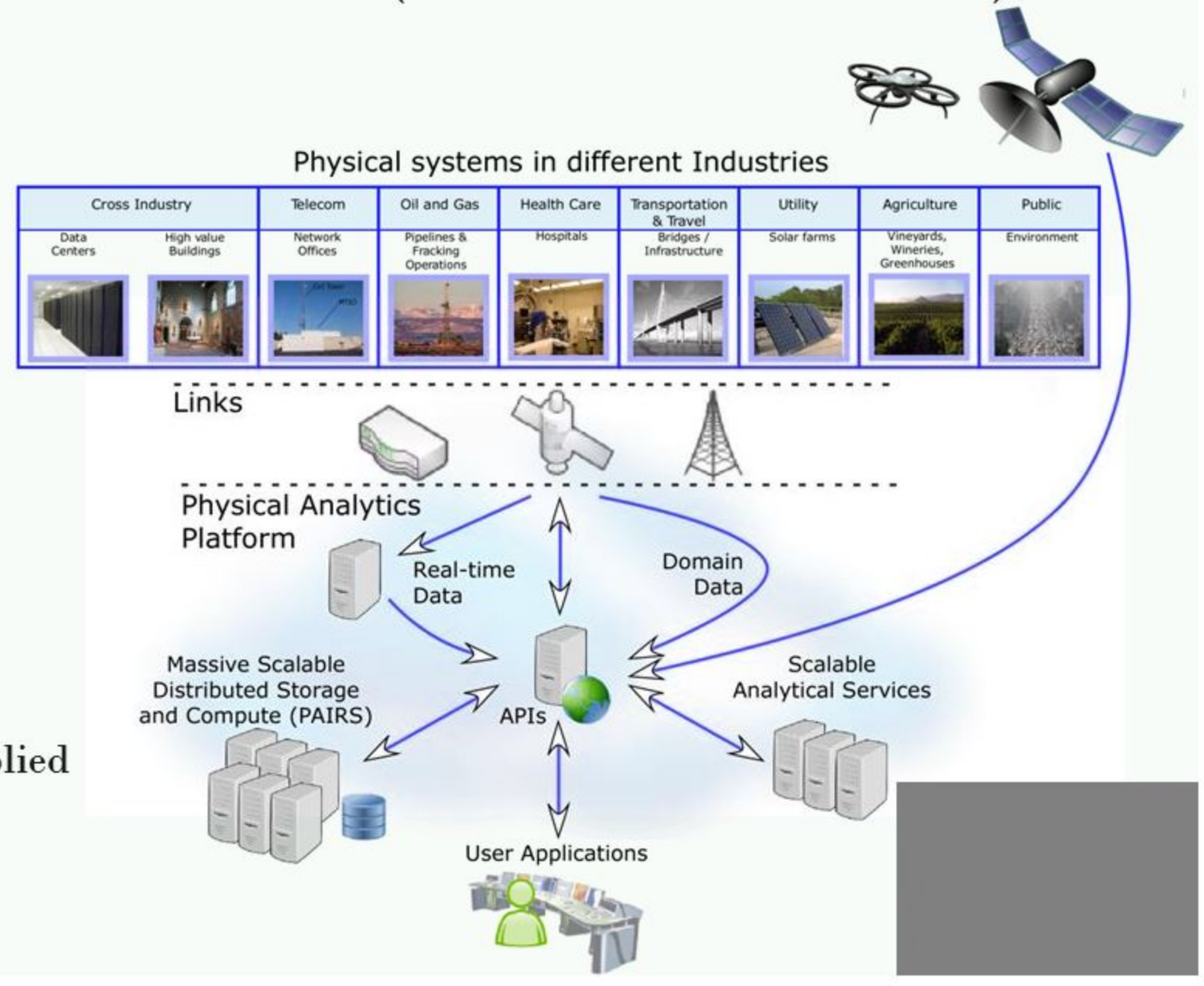
Physical Analytics Platform ("Research IoT")

- Sensor / Actuators
- Communication, Security
- Cloud-based IoT SW Platform
  - Server, Agents, Apps, Clients
- Physical analytics
  - Physical models
  - Reduction of Model Complexity
  - Machine-learnt, multi-model model blending
- (Big) data analytics platform
- Automation and Controls

- Platform has been successfully applied in various Industries



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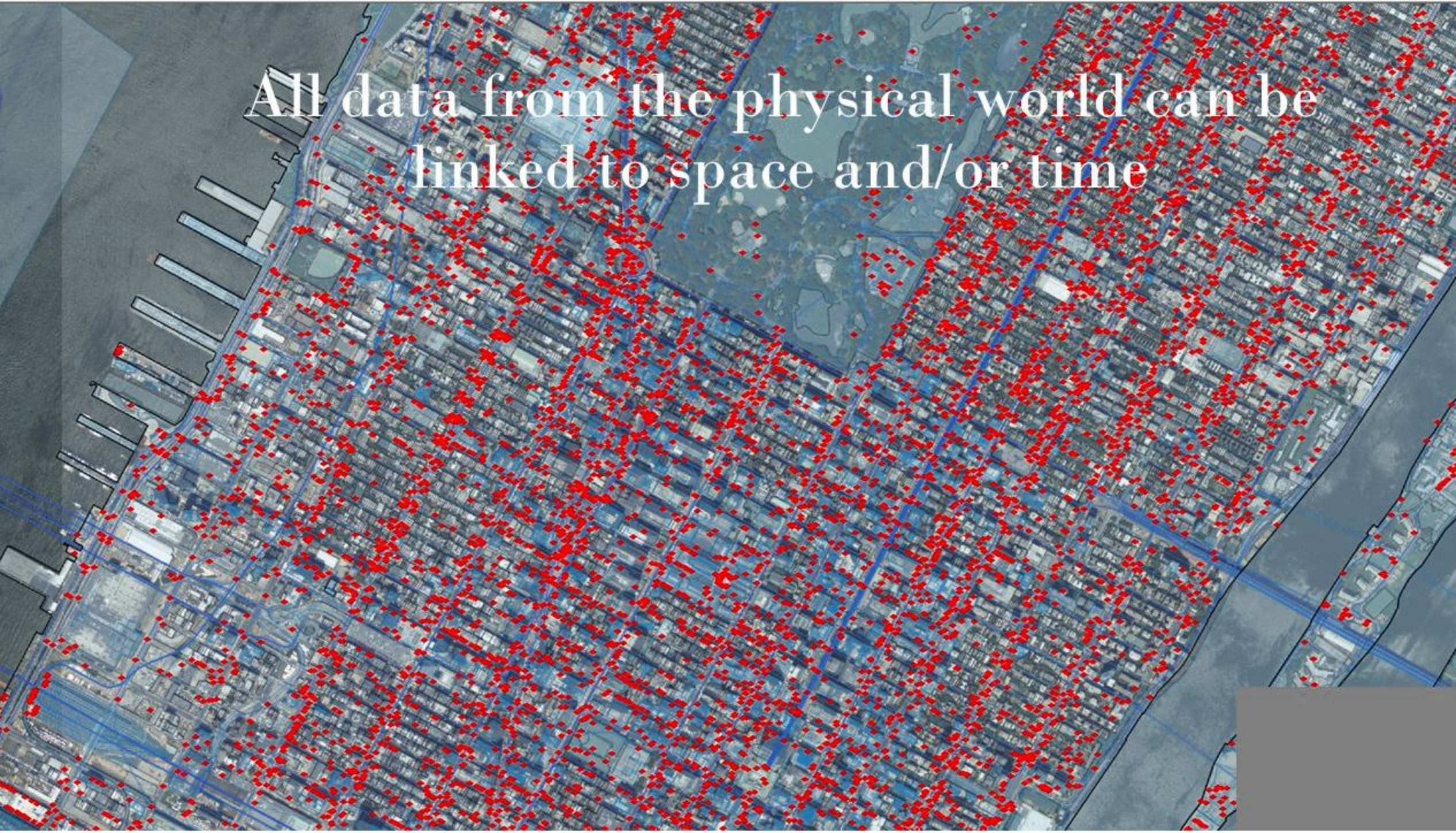
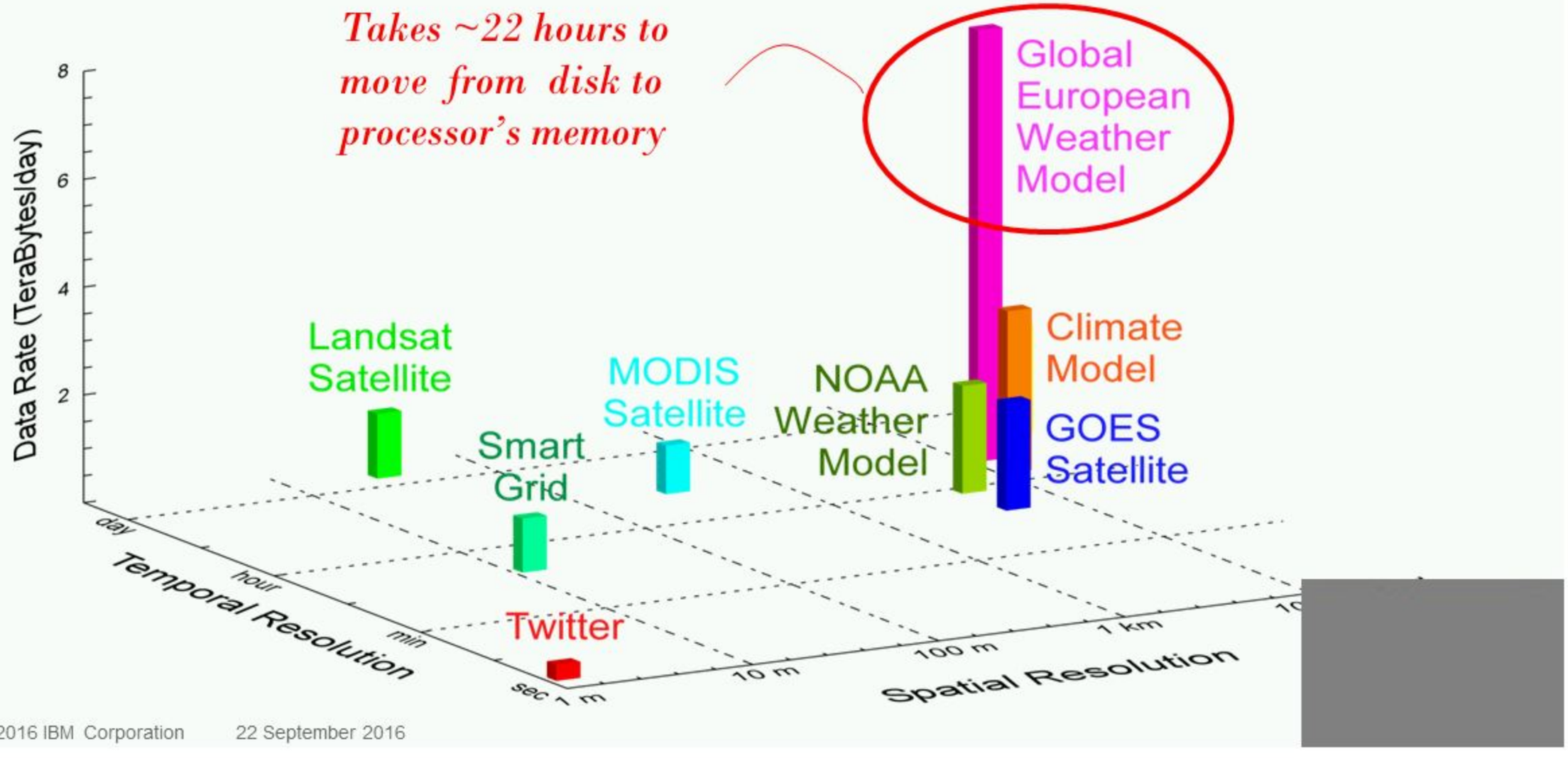

All data from the physical world can be
linked to space and/or time

Massive spatio-temporal data sets are generated every day



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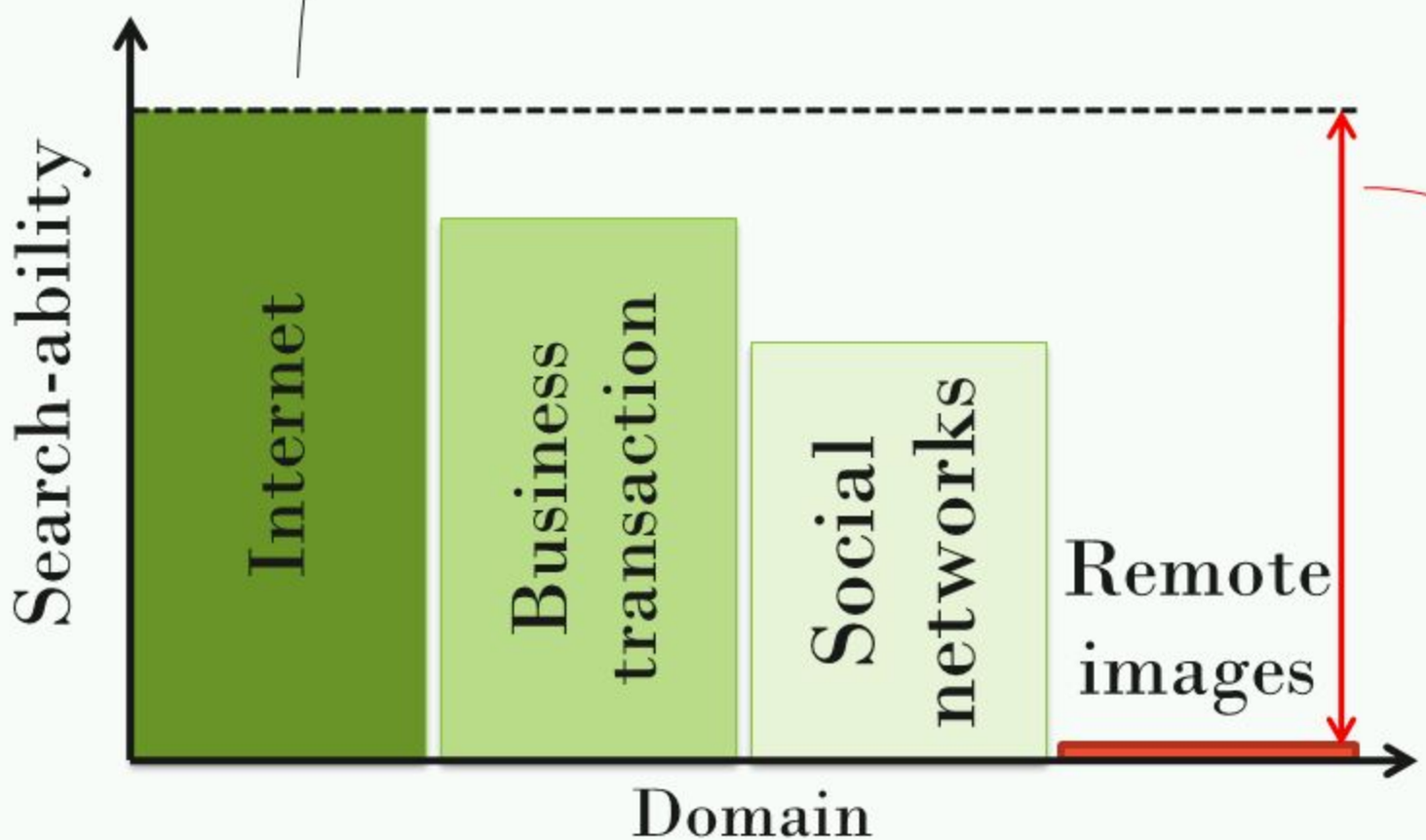
Spatio-temporal data is only coarsely indexed

45 billion web pages have been indexed allowing to search and discover them in ~ 0.5 second



One of the last frontiers for accelerating research and discover lies in the area of remote spatio-temporal images

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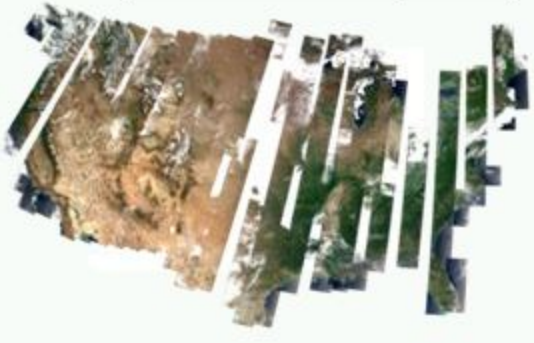
Today: Data is moved to the application

TODAY

- Each data set is kept at a different place in different formats, projections, units etc.
- Exabytes stored in billions of "individual scenes", or files typically on tape.
- Analysts has to "order" scenes from each source:
  - Download, assemble, re-sample, re-project, align, classify scenes, etc.....
- Data is moved to the application
- Time to value is limited by data curation (90%).

LandSat scenes/tiles from different satellite passes



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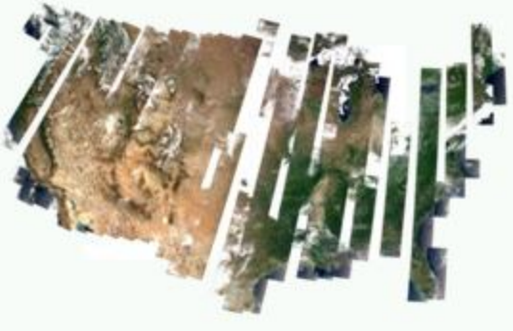
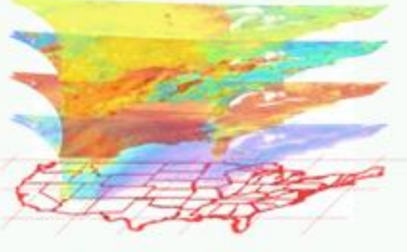
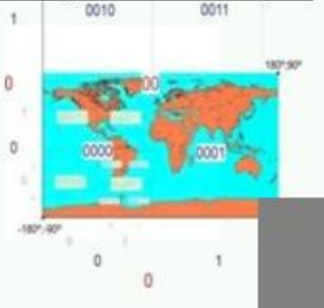
PAIRS: Analytics is moved to the data

TODAY	THIS WORK (PAIRS*)
• Each data set is kept at a different place in different formats, projections, units etc. • Exabytes stored in billions of "individual scenes", or files typically on tape. • Analysts has to "order" scenes from each source: – Download, assemble, re-sample, re-project, align, classify scenes, etc..... • Data is moved to the application • **Time to value is limited by data curation (90%).** *LandSat scenes/tiles from different satellite passes* 	• Large scale, pre-processed big data store with pre-aligned layers and data sets – Common formats and projections – Spatial & temporal joins – A global reference system • Accessible as a data service • Analyze without moving data • Access to new layers of analytics. • **Time to value reduced by orders of magnitudes.** *Pre-aligned data sets / layers*  *Global Mastergrid with matching resolution layers*  * Physical Analytics Integrated Repository and Services

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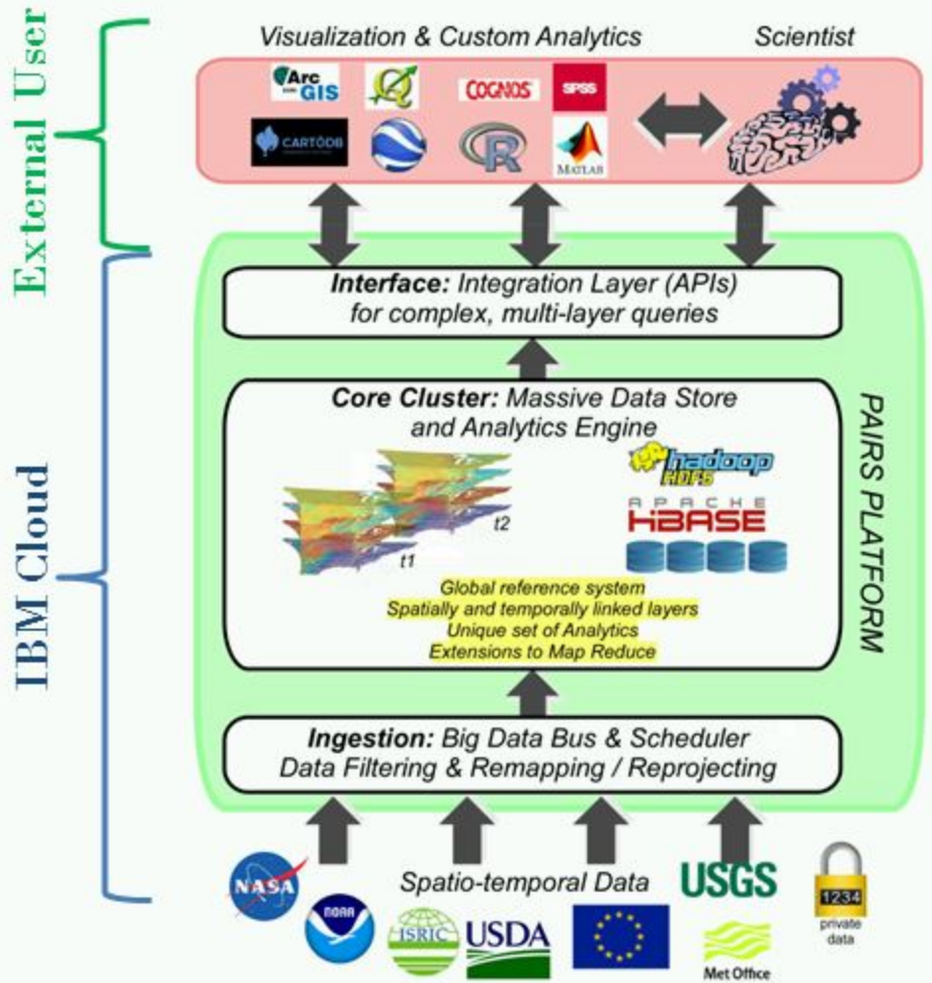
PAIRS: A big data platform for scalable spatio-temporal data and analytics



- Data bus feeds in (near) real-time open spatio-temporal data into PAIRS
- Full data curation process (filtering, classifying, aligning, resampling, reprojecting etc) at ingestion.
- Large-scale Hadoop / Hbase system for efficient distributed data store and processing
- System allows complex queries, e.g.
  - *Find all real estate in California with elevation gradient and high rain fall and certain soil type.*
- **Access to new layers of analytics**
  - Irrigation forecasts
  - Improved weather forecasts
- **Curated data and analytics** accessible **as a Service via** an integration layer
  - REST APIs to run queries
  - Basic web interface to run queries

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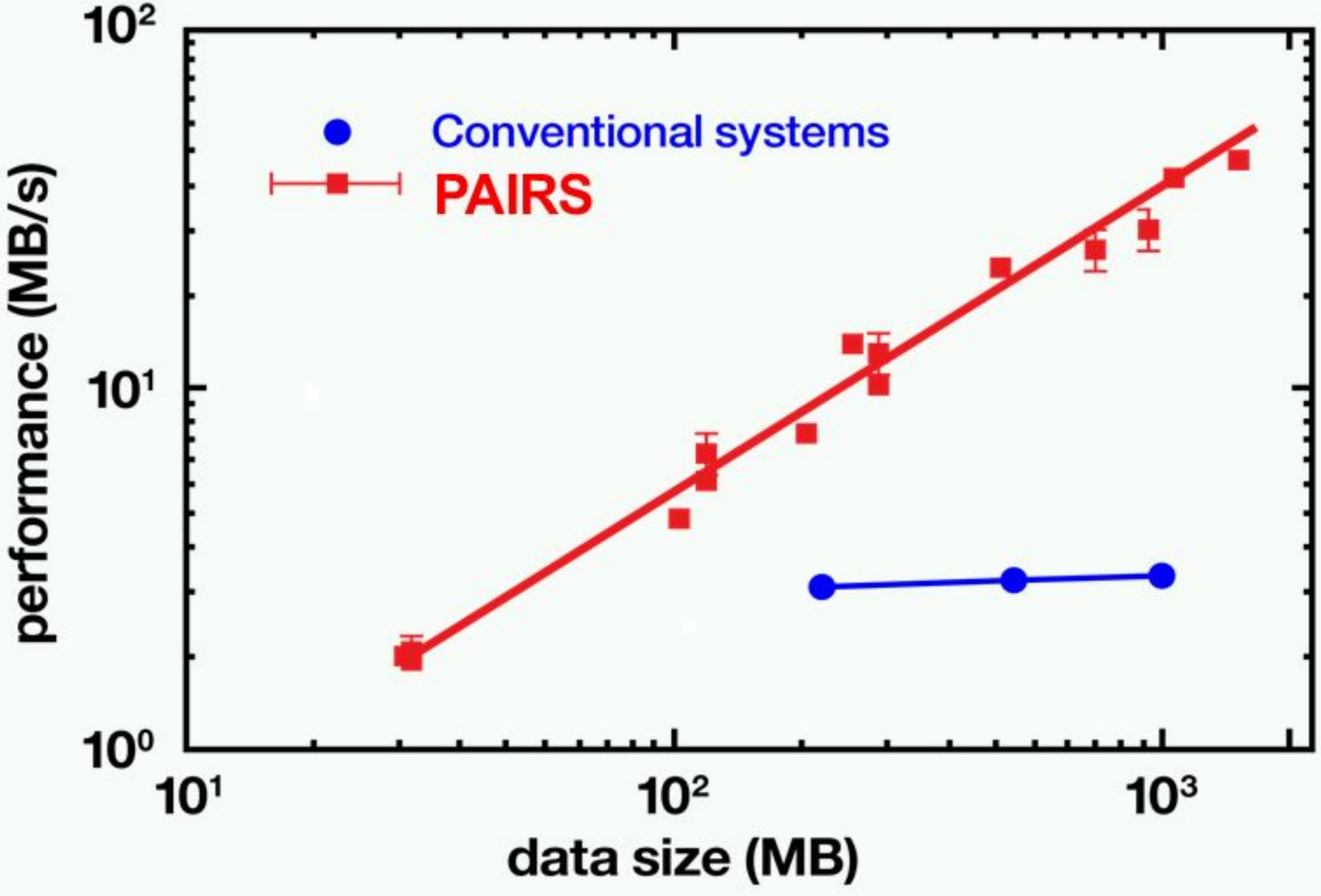
PAIRS "scales" to big data and complex analysis



- PAIRS queries (almost) independent of data size
- Conventional systems require more time of larger data sizes

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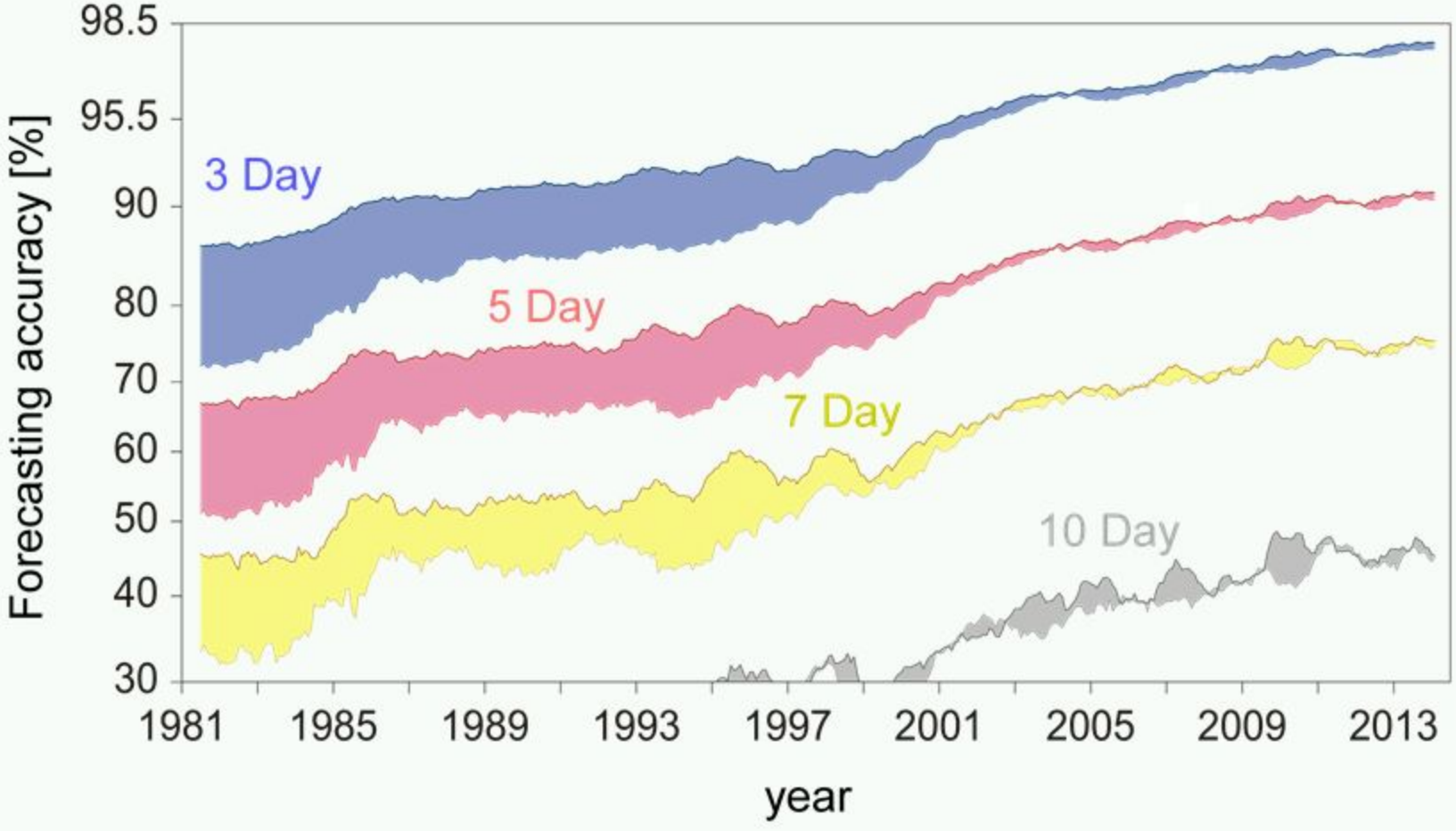
To summarize so far….

1. The world is being digitized at an accelerated rate transforming industries
2. A new form of physical analytics - combing statistical and physical models - are required to exploit the opportunity
3. All data from the physical world can be linked in space and time.
4. PAIRS technology allows scalable physical analytics on spatio-temproal data

Applications: Seasonal Weather Forecasting

Historically, NWP* model accuracy improvements have been (only) ~6% per** decade…How can we make a big impact?



* Numerical weather prediction
** Peter Bauer, Alan Thorpe & Gilbert Brunet doi:10.1038/nature14956

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Improved global **seasonal** forecasting via machine-learnt, situation-dependent model blending

PAIRS data layers:

- Multiple climate forecast models
- > 1600 weather station data, COSMIC GPS-RO sounding

Physical Analytics:

- Machine-learnt, situation dependent, multi-model blending using historical forecasts and weather data

New PAIRS layer(s):

- Improved climate forecasts

Hurricane Ike path forecasts from 8 different weather models*

Climate Models	NOAA CFS v2	ECMWF ENS Extended	ECMWF SEAS	EUROSIP	Beijing CC CGCM	Tokyo CC AGCM	....
Spatial Res & Coverage	0.5 Deg global	0.4 Deg global	0.75 Deg global	2.5 Deg global	2.5 deg global	2.5 deg global	
Temporal Resolution	6 Hourly	6 Hourly	6 Hourly	6 Hourly	Monthly	Weekly	
Forecasting Horizon	0 to 6 months	0 to 45 days	0 to 7 months	0 to 6 month	0 to 11 months	0 to 3 mont	
Ensemble Forecast	4 Members	51 Members	51 Members	41 Members	Ensemble Mean	Ensemble M	

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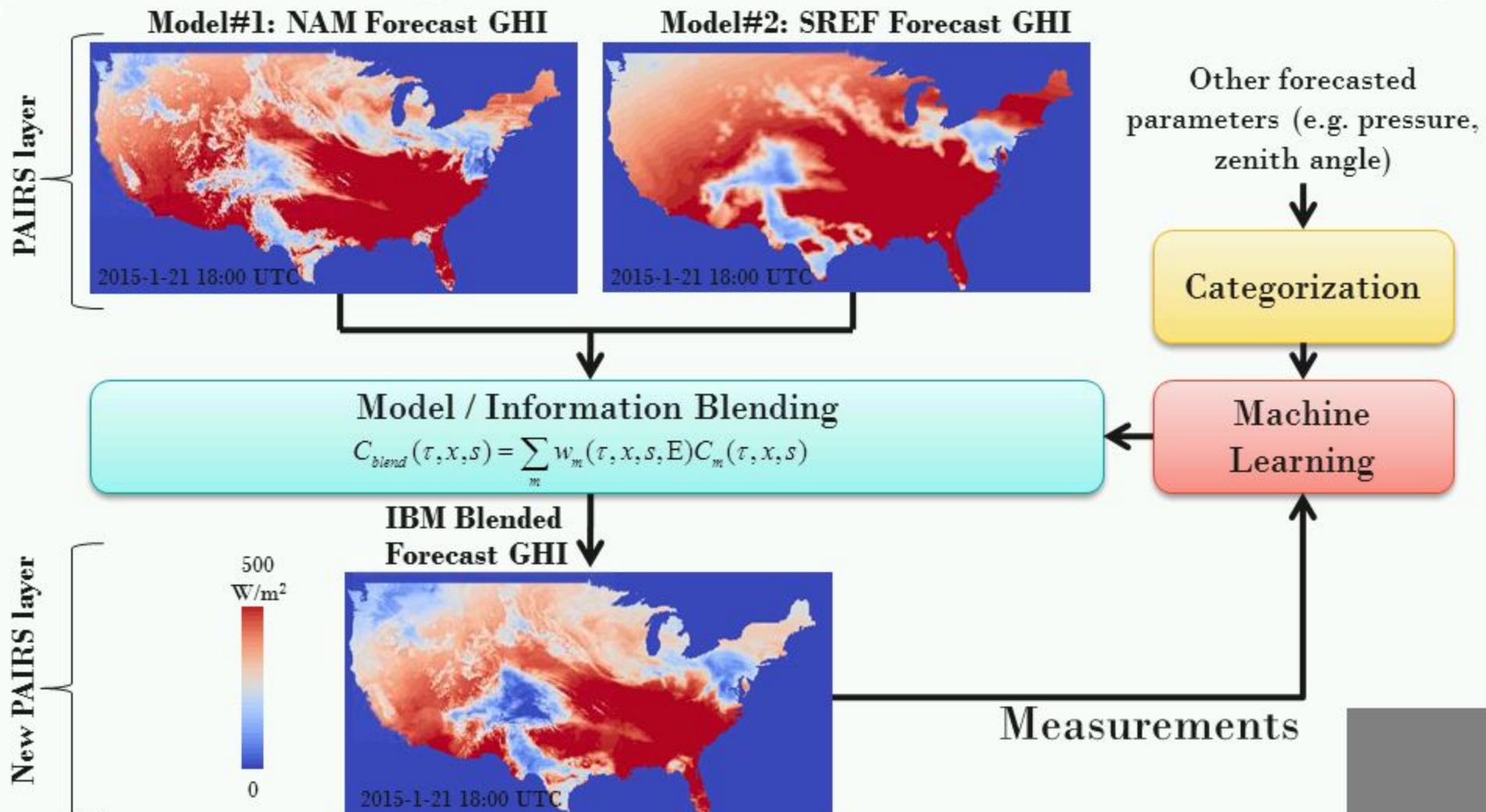
Creating a super forecast model via machine-learnt, situation dependent multi-model blending



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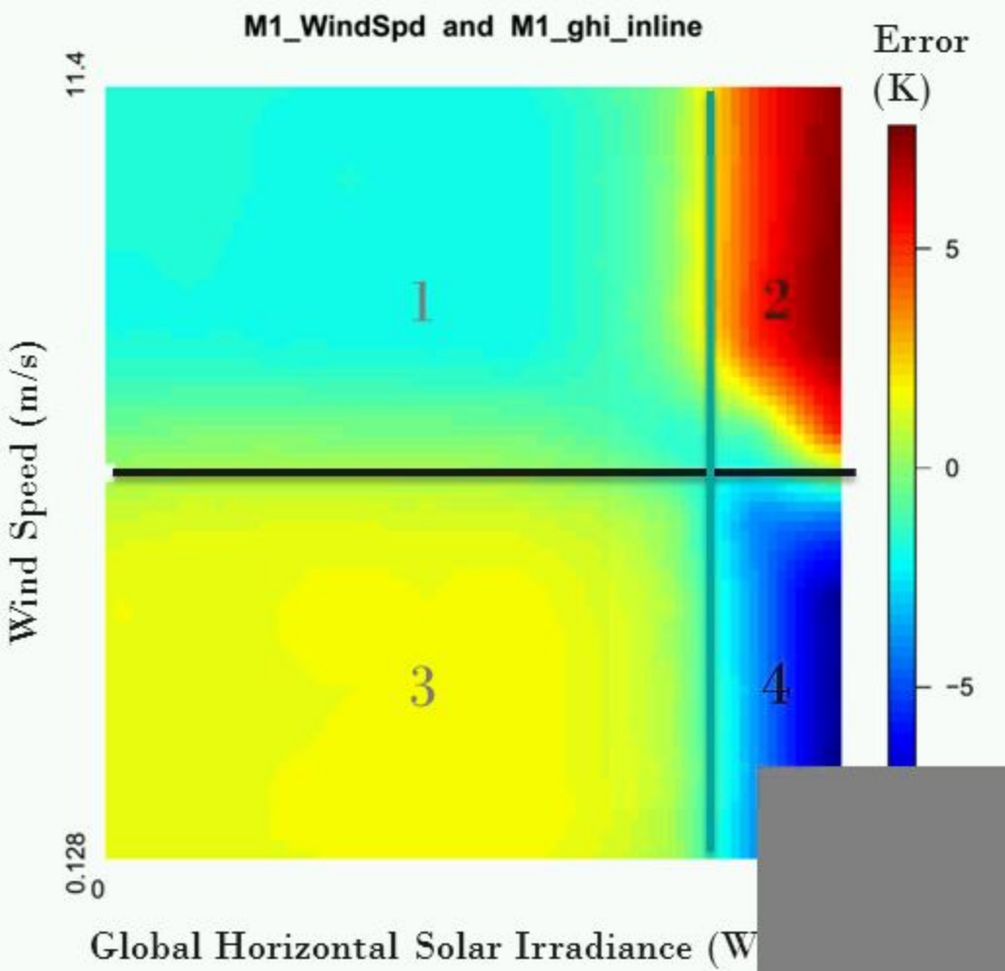
Situation-dependent model blending

Which model is more accurate, when, where, under what weather situation?

- Apply functional analysis of variance to understand 1st,2nd,3rd, ….order errors
- Model accuracy can depend strongly on **"weather situation"** category.
- "Weather situation" is determined using a set of parameters including forecasted ones on which model error depends on strongly.

2nd Order Error
NOAA CFSv2 Model 1, Temperature Forecast
30 days ahead, 6 hourly, Surfrad Stations BND



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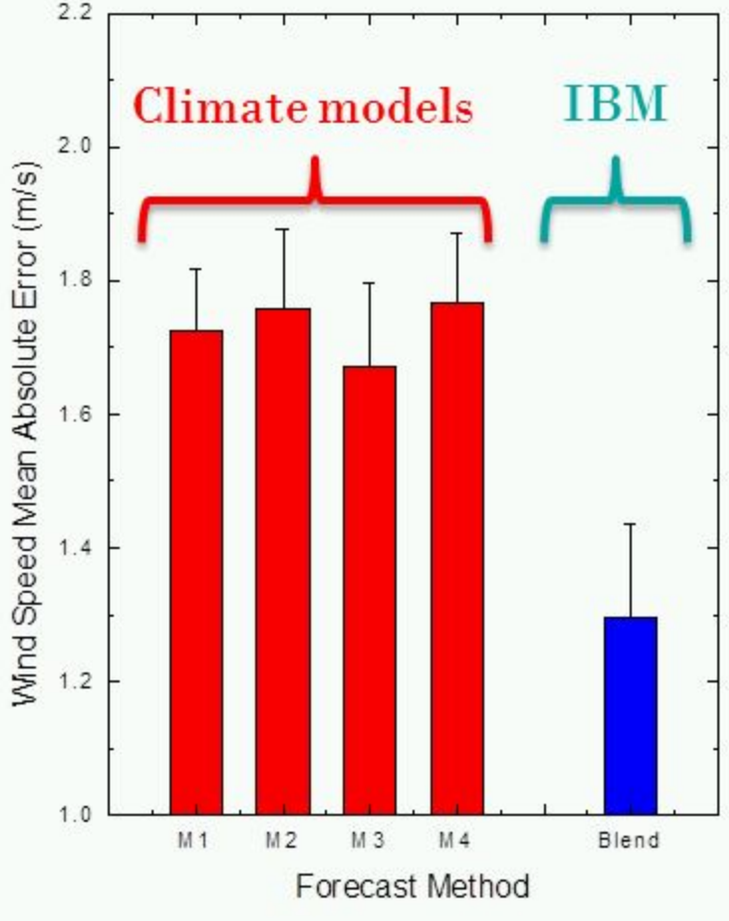
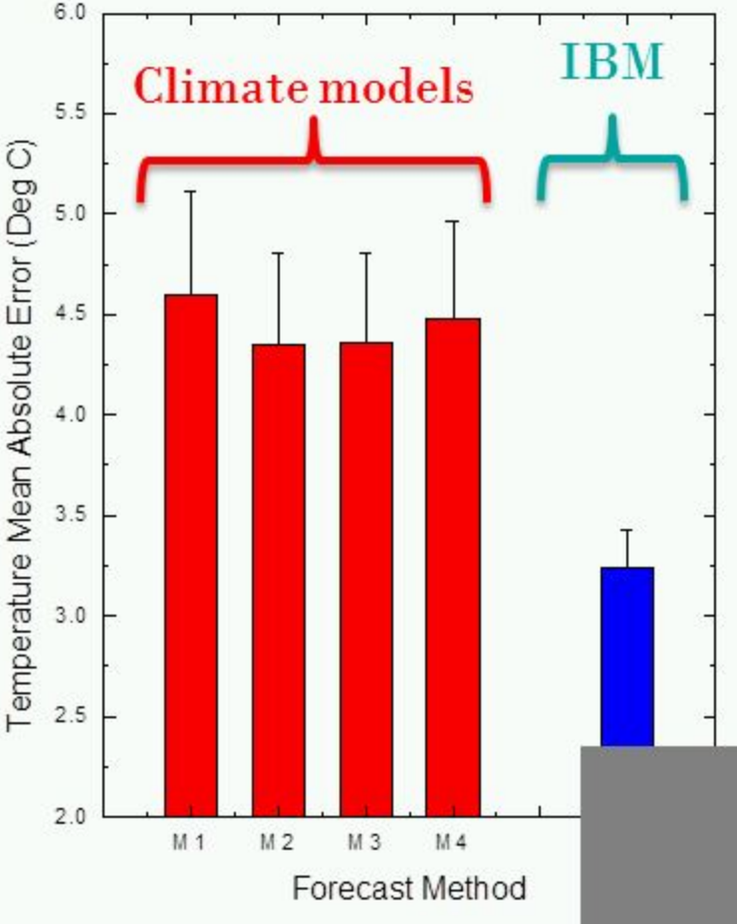
More than 30% error reduction for 30 day-ahead forecasting

10m Wind Speed, 30 Day-Ahead



2m Temperature, 30 Day-Ahead



7 Surfrad Stations
Validation
06/20/15 – 09/20/15

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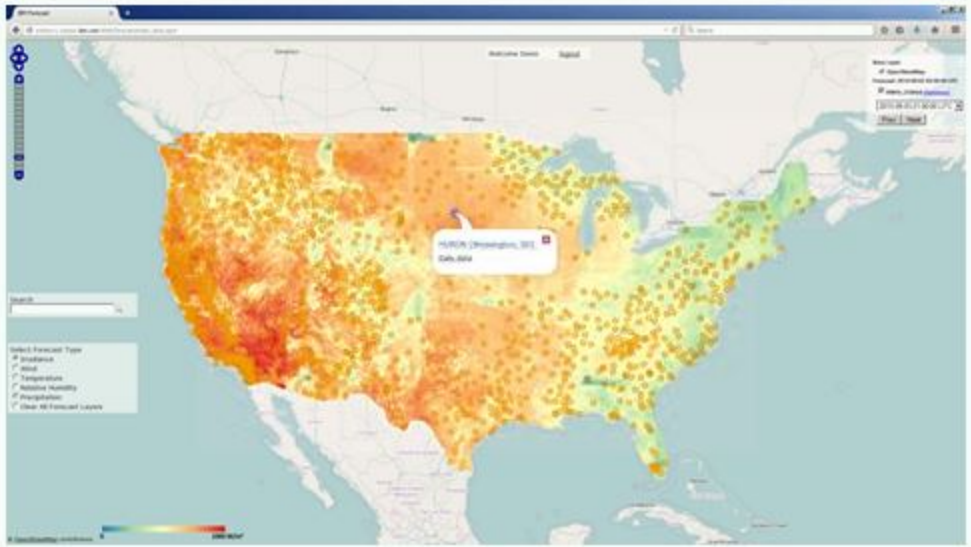
We scaled the technology to US continental wide forecasting and beyond



- > 35 % improved accuracy with respect to next best model at 1600 sites across the United States
- PAIRS provides gridded forecasts
- Continuously learns and improves

Performance Metrics

2015-05-10 to 2015-05-24

IBM Blended GHI 0-48hr Ahead

SiteSet	# of Sites	MAE* (W/m^2)	MAPE(%)	RMSE (W/m^2)	NRMSE (%)	MBE (W/m^2)	MaxAE (W/m^2)	KSIPer (%)	pcoe
RAWS_CONUS	1641	135.54	13.55	192.99	19.29	19.84	668.06	16.62	0.78

NOAA NAM GHI 0-48hr Ahead

SiteSet	# of Sites	MAE* (W/m^2)	MAPE(%)	RMSE (W/m^2)	NRMSE (%)	MBE (W/m^2)	MaxAE (W/m^2)	KSIPer (%)	pcoe
RAWS_CONUS	1641	179.06	17.91	253.60	25.37	118.94	814.81	22.27	0.75

NOAA SREF GHI 0-48hr Ahead

SiteSet	# of Sites	MAE* (W/m^2)	MAPE(%)	RMSE (W/m^2)	NRMSE (%)	MBE (W/m^2)	MaxAE (W/m^2)	KSIPer (%)	pcoe
RAWS_CONUS	1641	188.44	18.84	262.97	26.30	129.56	837.83	23.64	0.74

*Metrics Suites: Excluding night time values for solar. Hover mouse over the acronyms to see full definition.

IBM Blended GHI 0-48hr Ahead

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Applications: Crop Forecasting

Crop recognition

PAIRS data layers:

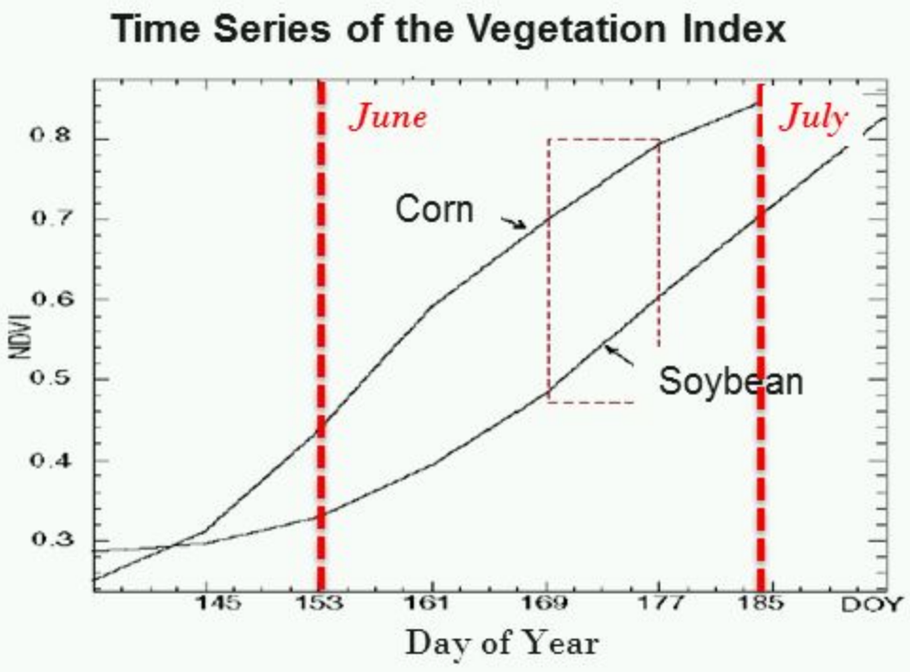
- Satellite data,
- Soil information
- Weather data
- Historical crop maps

Cognitive computing:

- Time-series analysis of NDVI evolution leveraging a 30 year record of satellite and survey data

New PAIRS layer(s):

- Crop maps early in the season



Vegetation Index Map

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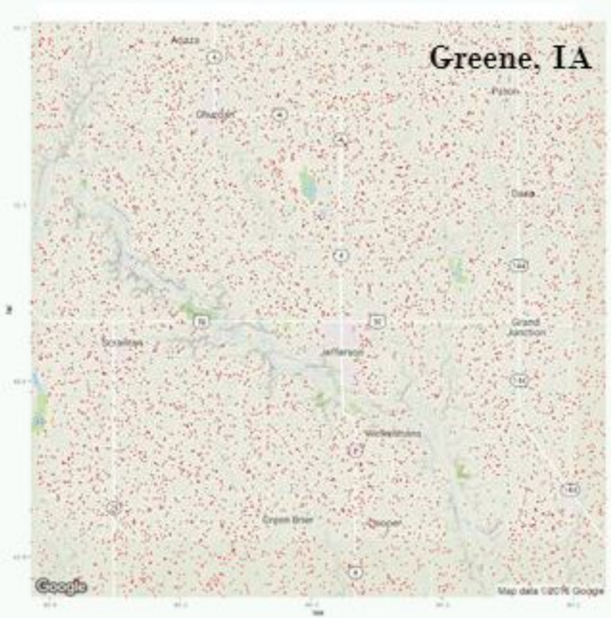
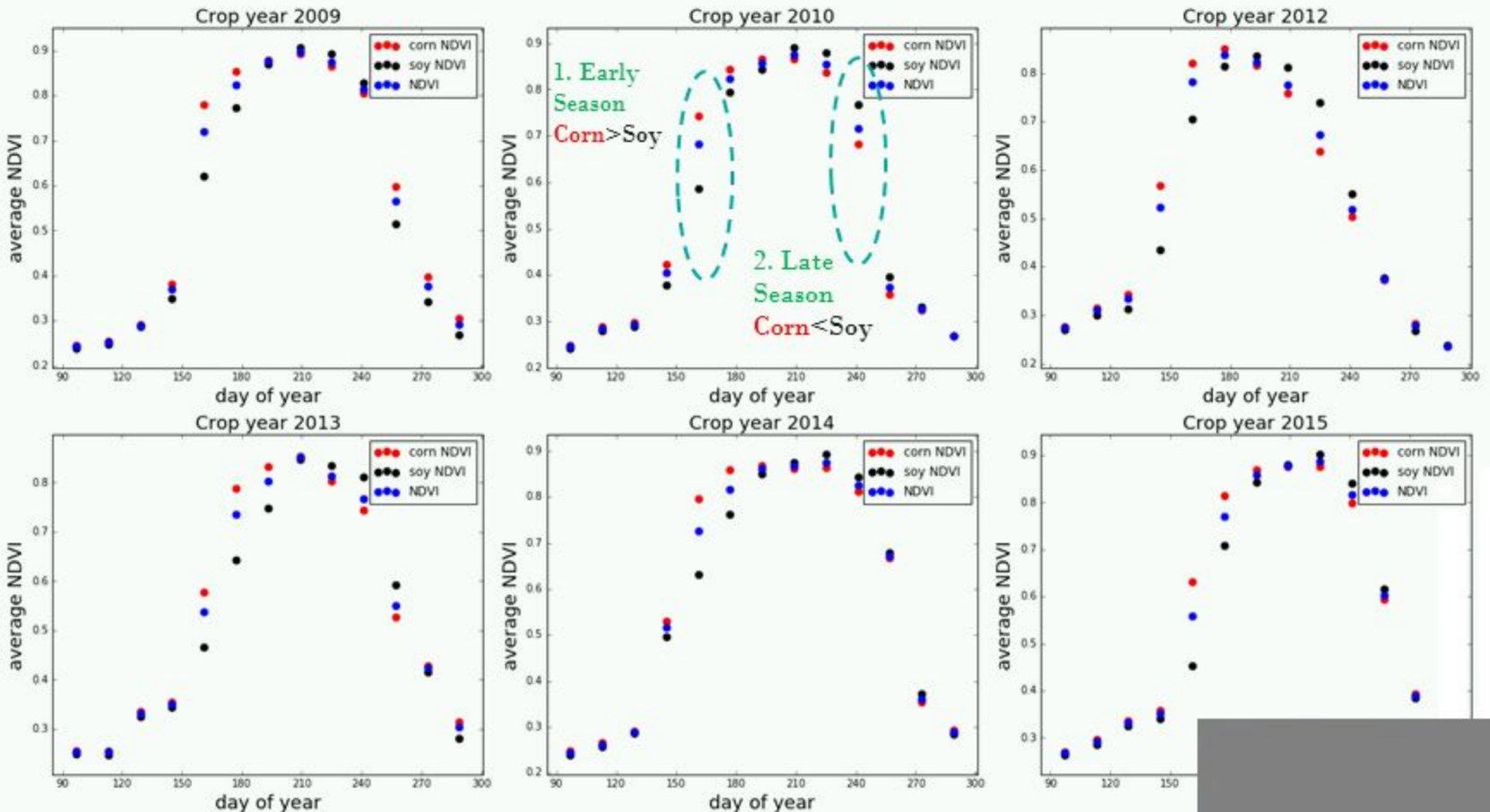
Acreage Prediction using Remote Sensing

Sampling good center-field locations (large enough for MODIS pixels) for Greene and Madison counties.



- Future work: field boundary detection using LANDSET. Enable sample points to better represent actual farm size.

Corn vs. Soy -- NDVI as a function of



- Corn NDVI rises faster than soy in spring. (NDVI 1, early season)
- Corn NDVI falls faster than soy in late summer / autumn. (NDVI 2, later

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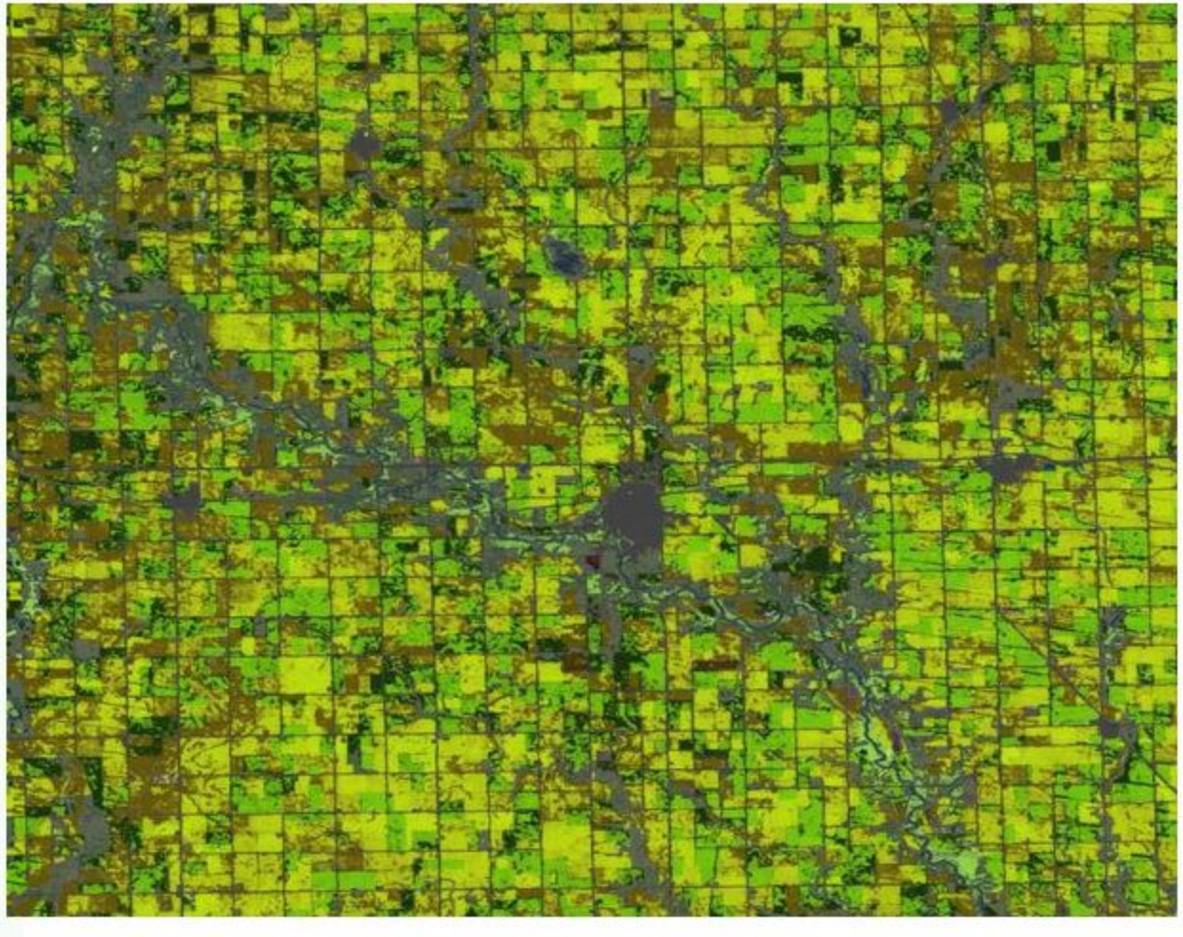
Early Crop Recognition
Greene County, IA - June 2013 Predictions



NDVI Prediction of early June 2012:

Percentage of Area in Greene County, IA

Corn:	51 %
Soybean:	29 %

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Early Crop Recognition
Greene County, IA - NASS Results

NDVI Prediction of early June 2012:

Percentage of Area in Greene County, IA

Corn:	51 %
Soybean:	29 %

NASS Results at Jan 2013:

Percentage of Area in Greene County, IA

Corn:	49 %
Soybean:	29 %

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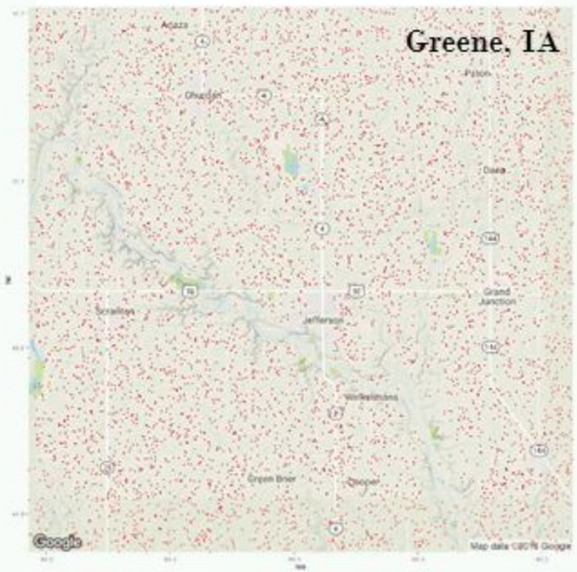
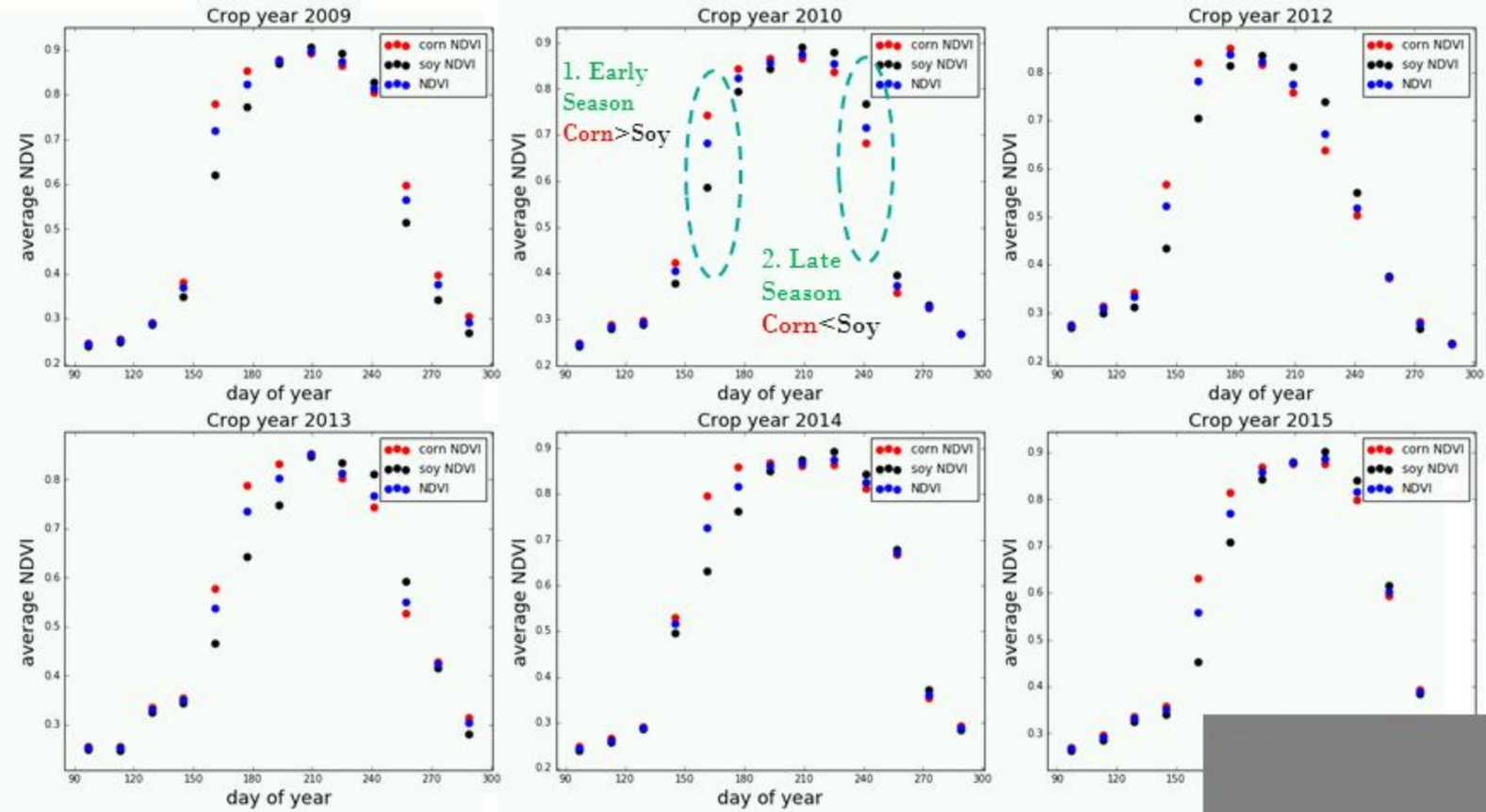
Acreage Prediction using Remote Sensing

Sampling good center-field locations (large enough for MODIS pixels) for Greene and Madison counties.



- Future work: field boundary detection using LANDSET. Enable sample points to better represent actual farm size.

Corn vs. Soy -- NDVI as a function of



- Corn NDVI rises faster than soy in spring. (NDVI 1, early season)
- Corn NDVI falls faster than soy in late summer / autumn. (NDVI 2, later

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