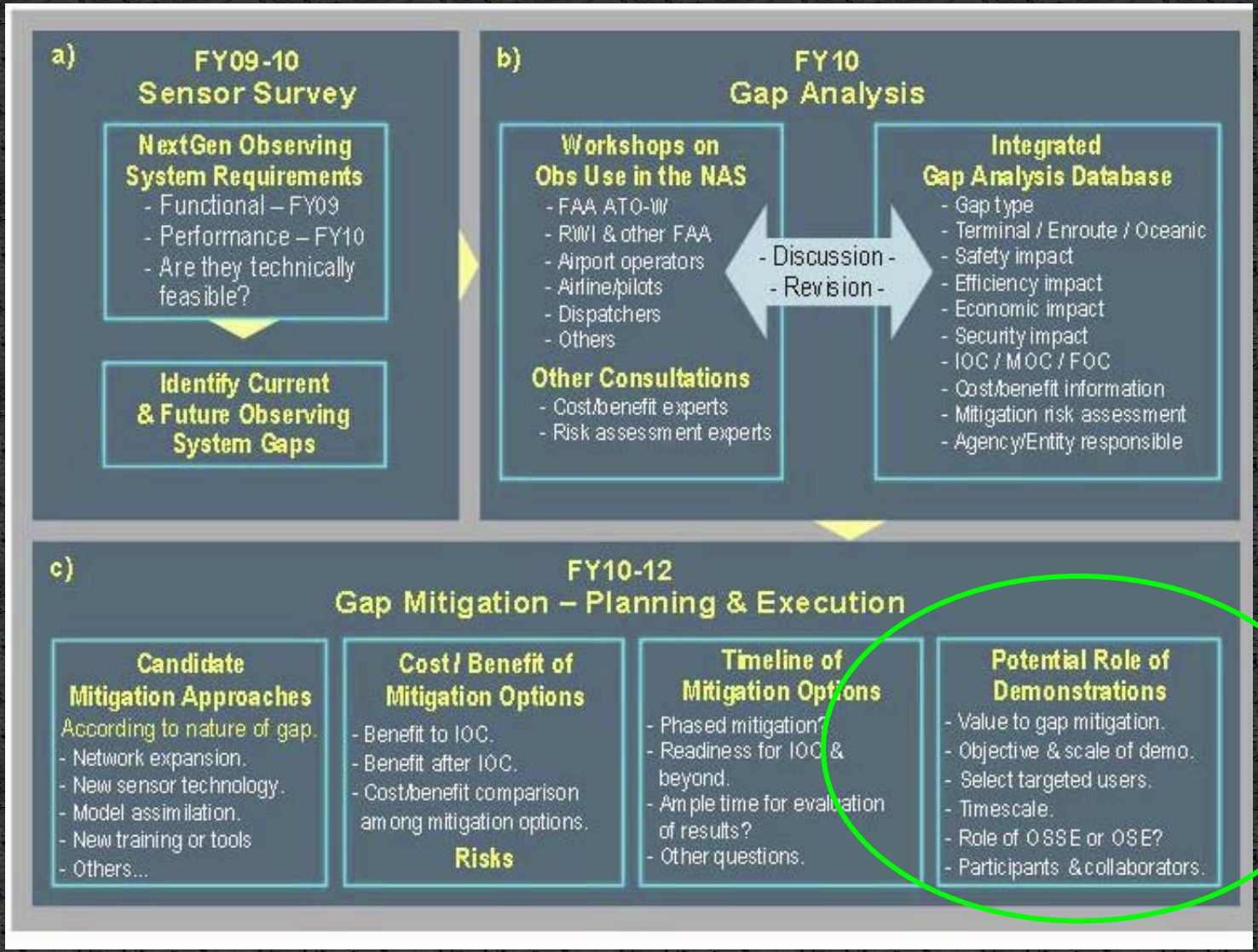
Right-Sizing: Demonstrations and Visualization

Advanced Data Management Applications & Demonstrations Sub-Team

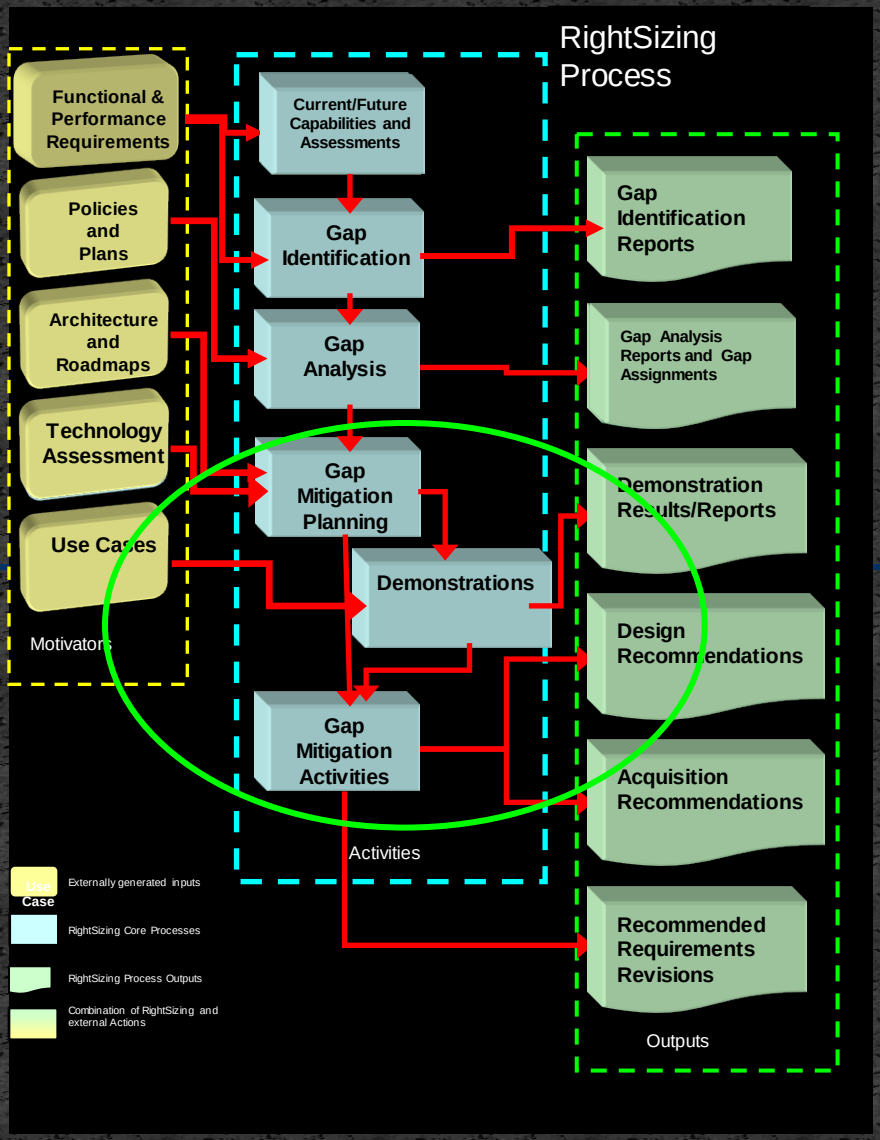
University of Oklahoma
Indiana University

March 23, 2010

Advanced Data Management Applications & Demonstrations



Gap Demonstrations & Mitigation Activities



Goal

- RWI Master Plan –

  "carry out analyses, modeling, and simulations to optimize weather observation capabilities by assessing sensor technology and network capabilities, and eliminating gaps, inaccuracies, and inconsistencies in aviation weather observations. "

Process

- Gap Analysis – Identified highest priority gaps
- Gap Mitigation Planning – Explore full-range of mitigation options; timelines; cost/benefit; risks
- Demonstrations – Quantify costs/benefits of mitigation options using OSSEs/OSEs/visualization
- Gap Mitigation Activities – Recommend sensor changes/additions based upon demonstrations

Responsibilities

- Conduct demonstrations for the mitigation of highest priority gaps
  - Best filled via data assimilation or new sensor deployment?
  - Impact of new sensors on analysis? Forecasts?
  - Apply OSSEs/OSEs to quantify relative value of observations

- Visualization
  - Visualization of existing sensors to demonstrate gaps
  - Visualization of proposed sensor solutions, new sensors

Tools for demonstrations:

- WRF – HRRR (High-Res Rapid-Refresh; 3km)
- ARPS – Advanced Regional Prediction System (1km)
  - Three-dimensional, non-hydrostatic, mesoscale NWP models
- ADAS – ARPS Data Analysis System
  - Assimilation package
  - Includes satellite, weather radar (NEXRAD, TDWR, gap fillers), mesonet, ACARS, NMQ, etc.
- LEAD – Linked Environments for Atmospheric Discovery
  - Service-oriented, NWP workflow environment

GRID COMPUTING

SERVICE-ORIENTED ENVIRONMENTS FOR DYNAMICALLY INTERACTING WITH MESOSCALE WEATHER

Within a decade after John von Neumann and colleagues conducted the first experimental weather forecast on the ENIAC computer in the late 1940s, numerical models of the atmosphere became the foundation of modern-day weather forecasting and one of the driving application areas in computer science. This article describes research that is enabling a major shift toward dynamically adaptive responses to rapidly changing environmental conditions.

Early part across the U.S. mesoscale weather events—flash floods, tornadoes, hail, strong winds, lightning, and localized winter storms—cause hundreds of deaths, routinely disrupt transportation and commerce, and lead to economic losses averaging more than US$13 billion.[1] Although mitigating the impact of such events requires a multifaceted approach involving technical hurdles, research funding in this goal is hindered by rigid IT frameworks that can't accommodate the real-time, on-demand, dynamically adaptive needs of mesoscale weather research. In response, high-volume data are archived now, or the tremendous computational demands of its models are beyond the capabilities of current IT.

In response to the increasingly urgent need for a comprehensive national cyberinfrastructure in mesoscale meteorology—particularly one that can interoperate with those being developed in other fields—the National Science Foundation (NSF) funded a large information technology research (ITR) grant in 2003 known as Linked Environments for Atmospheric Discovery (LEAD). A multidisciplinary effort involving nine institutions and more than 50 scientists, students, and technical staff in meteorology, computer science, and related disciplines, LEAD aims to address the fundamental research challenges needed to create an integrated, scalable framework for adaptive analysis and prediction during the atmospheric.

LEAD's foundation is a human workflow orchestration environment based on Grid and Web services. Time-capabilities provide for the use of analysis tools, forecast models, and data repositories,

KELVIN K. DROEGEMEIER, KEITH BROEWER, MING XUE, AND DAVID BOHNE
University of Oklahoma
DENNIS GANNON AND BETH PLALE
Indiana University
DANIEL REED AND LAURIA RAMAKRISHNAN
University of North Carolina
JOE ALAMEDA AND ROBERT WILHELMSON
U.S. National Center for Supercomputing Applications
TOM BAUER, BEN DOMENICO, DONALD MURRAY, MOHAN RAMAMURTHY, AND KEVIN WELSON
Unidata Corporation for Atmospheric Research
DAVID ANDERSON AND MARGARET TAYLOR
Millersville University
SAM CHANDLA, RAMIN RAMACHANDRAN, AND JOHN RUSHING
University of Alabama in Huntsville
STUART FRANKEL AND VERNON MORRIS
Hunter College

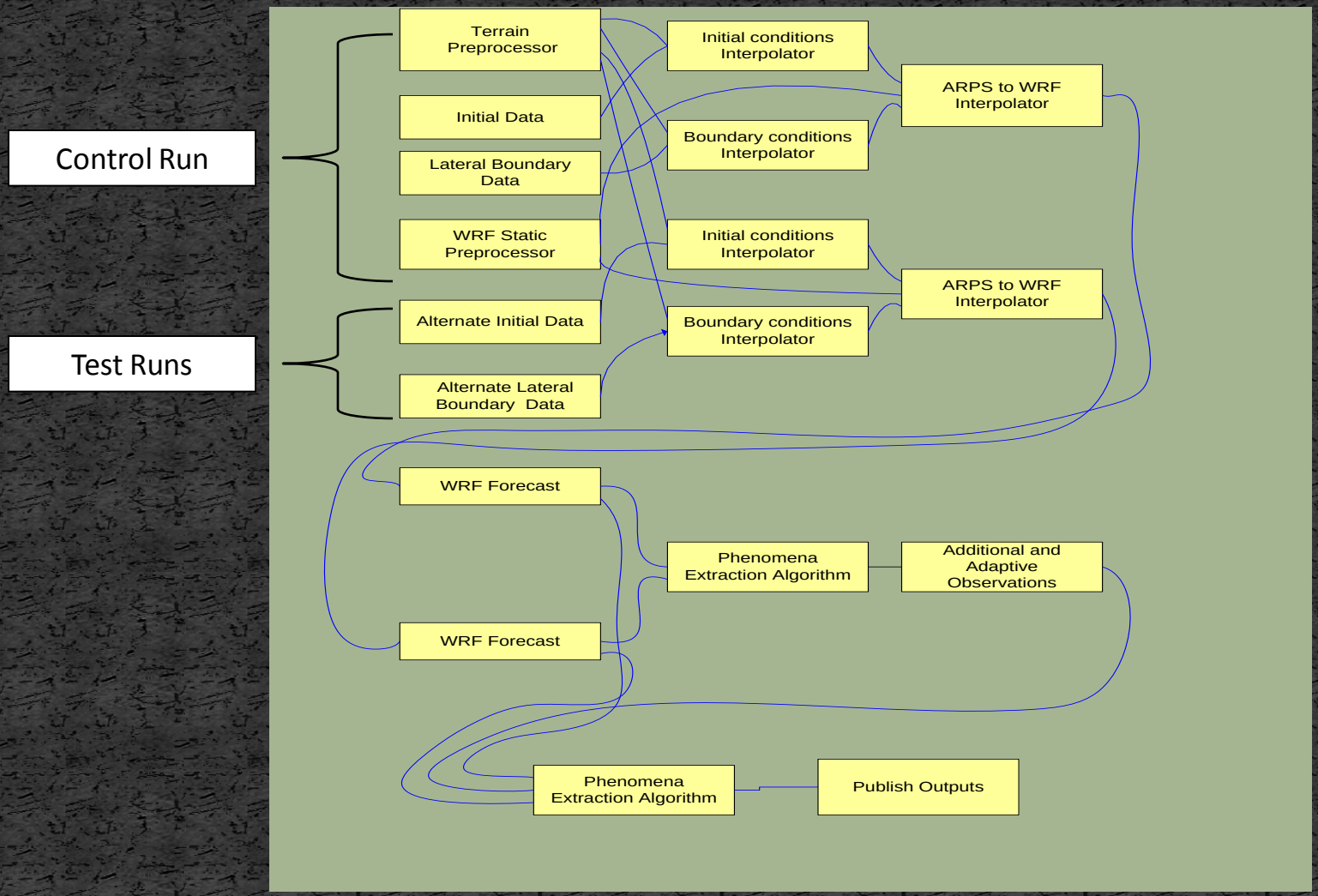
Planned demonstration: Denver airport OSSE: Observing System Simulation Experiment

- Utilize WRF/ARPS/ADAS/LEAD
- Determine impact of high priority gaps (spatial, temporal)
  - Long-term, quantitative impact studies
  - "Data denial" experiments (OSSEs)
- Optimize sensor placement, sampling
  - Test more rapid sampling; denser networks of existing sensors
  - Compare against data assimilation methods

Planned demonstration: Denver airport OSE: Observing System Experiment

- Assimilate current observations:
  - Radar: NEXRAD (KFTG), TDWR, CHILL (dual-pol)
  - LWAS (32), ASOS, AWOS
  - EnKF
- Determine value of existing sensors to analysis, forecasts
  - Long-term, quantitative impact studies
- Determine value of new, experimental sensors
  - Deployment of mobile, gap-filling radars
  - Temporary surface, airborne sensors

Planned demonstration: Denver airport OSEs/OSSEs



Typical workflow set-up design using LEAD.

Example: Sensitivity of observations to forecast error

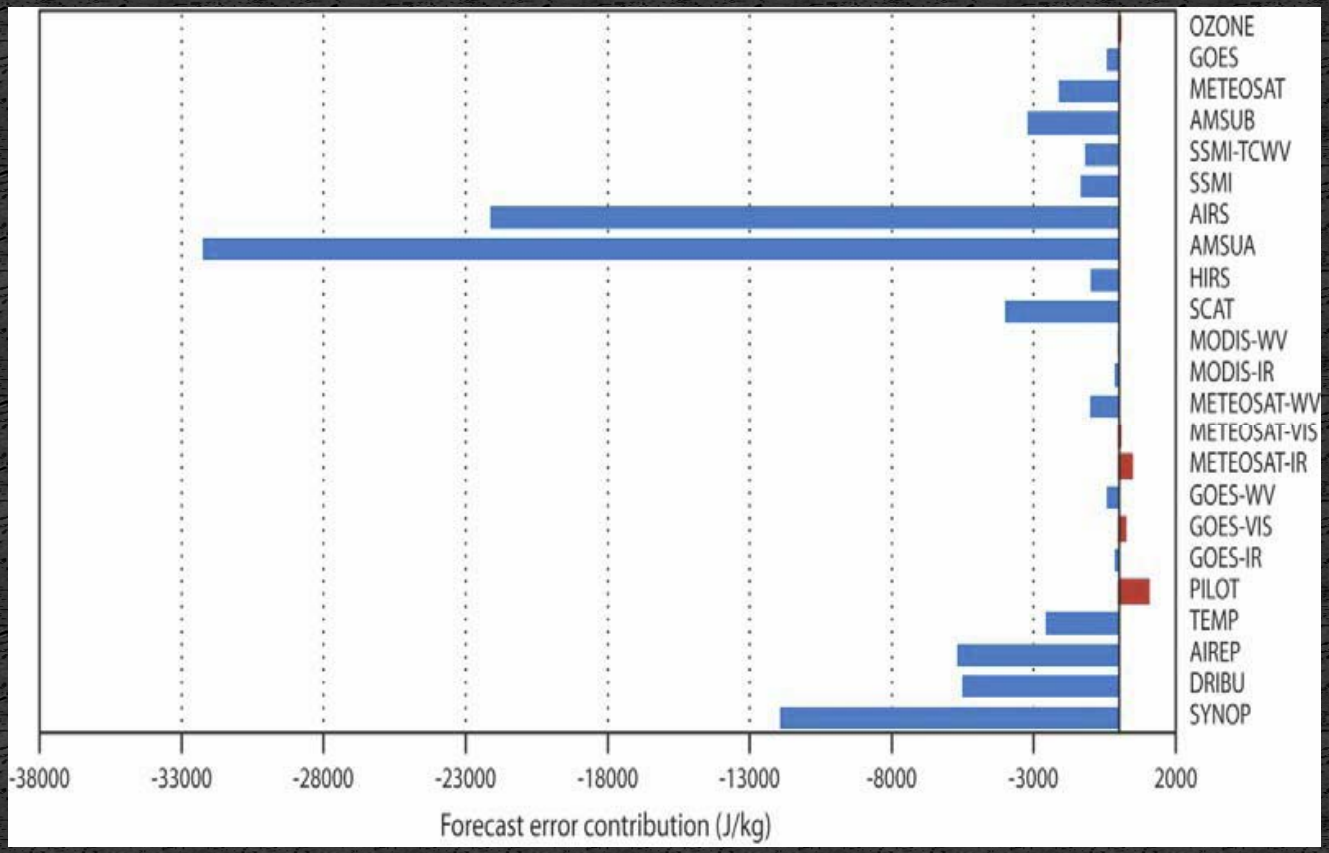
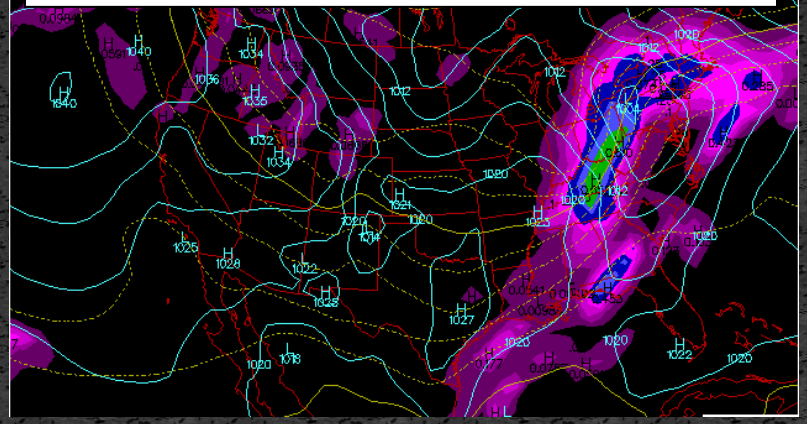


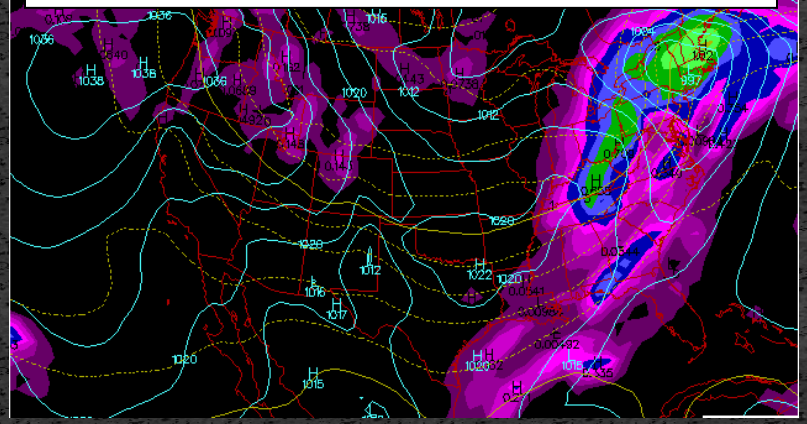
Figure 1: 24-hour forecast error contribution (third order sensitivity gradient) in J/kg of the components (types) of the observing system in summer 2006. Negative (positive) values correspond to a decrease (increase) in the energy norm of forecast error.
(ECMWF publication; C. Cardinali 2009)

Example: Sensitivity of observations to forecast error

Model Forecast Using Traditional Data Sources (ASOS, AWOS, soundings)

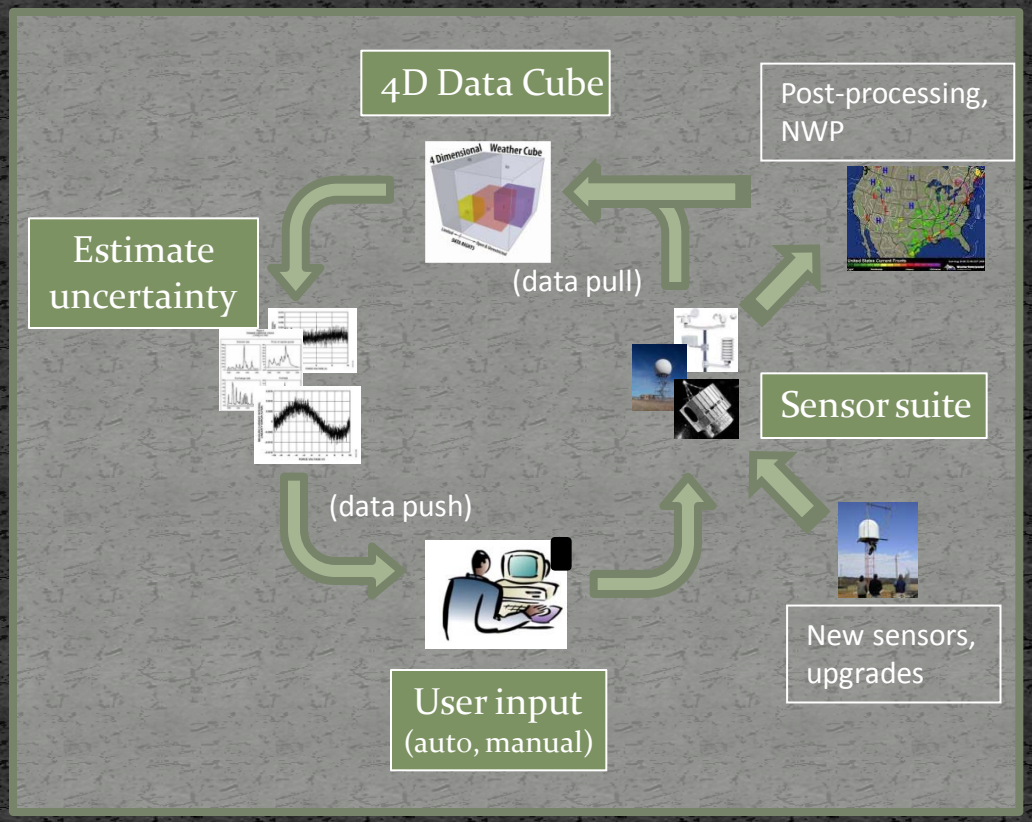


Model Forecast Utilizing Non-Traditional Data Sources (MADIS products – e.g., mesonets)



Differences between traditional and non-traditional initialized model forecasts

Planned demonstration: Denver airport
Value of dynamic, adaptive systems? (Long-term)



Dynamic Control System:

- Regulates the type and amount of data required to improve observation uncertainty.
- Regulates data flow as a function of temporal and spatial requirements.
- Regulates as a dynamic function of weather concerns and user needs.
- Operates in real-time
- New sensors added dynamically on an as-needed basis and as a function of operational requirements

Responsibilities

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- Visualization
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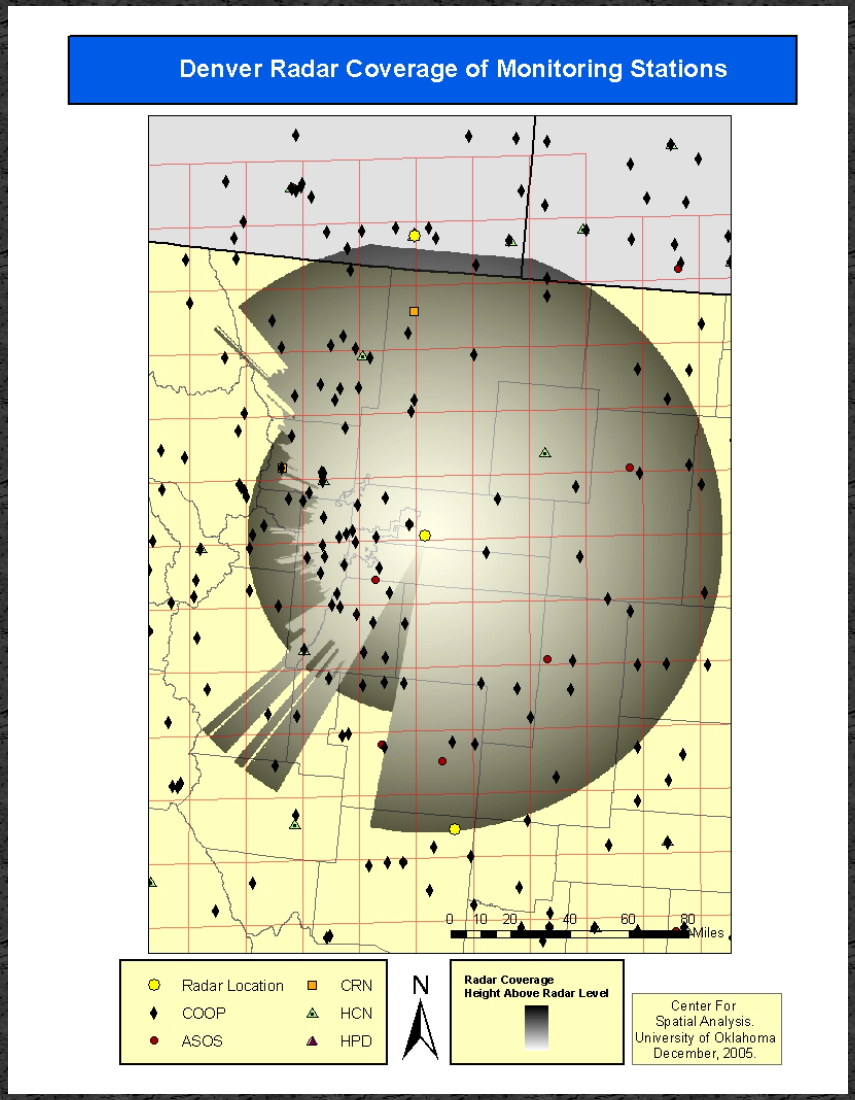
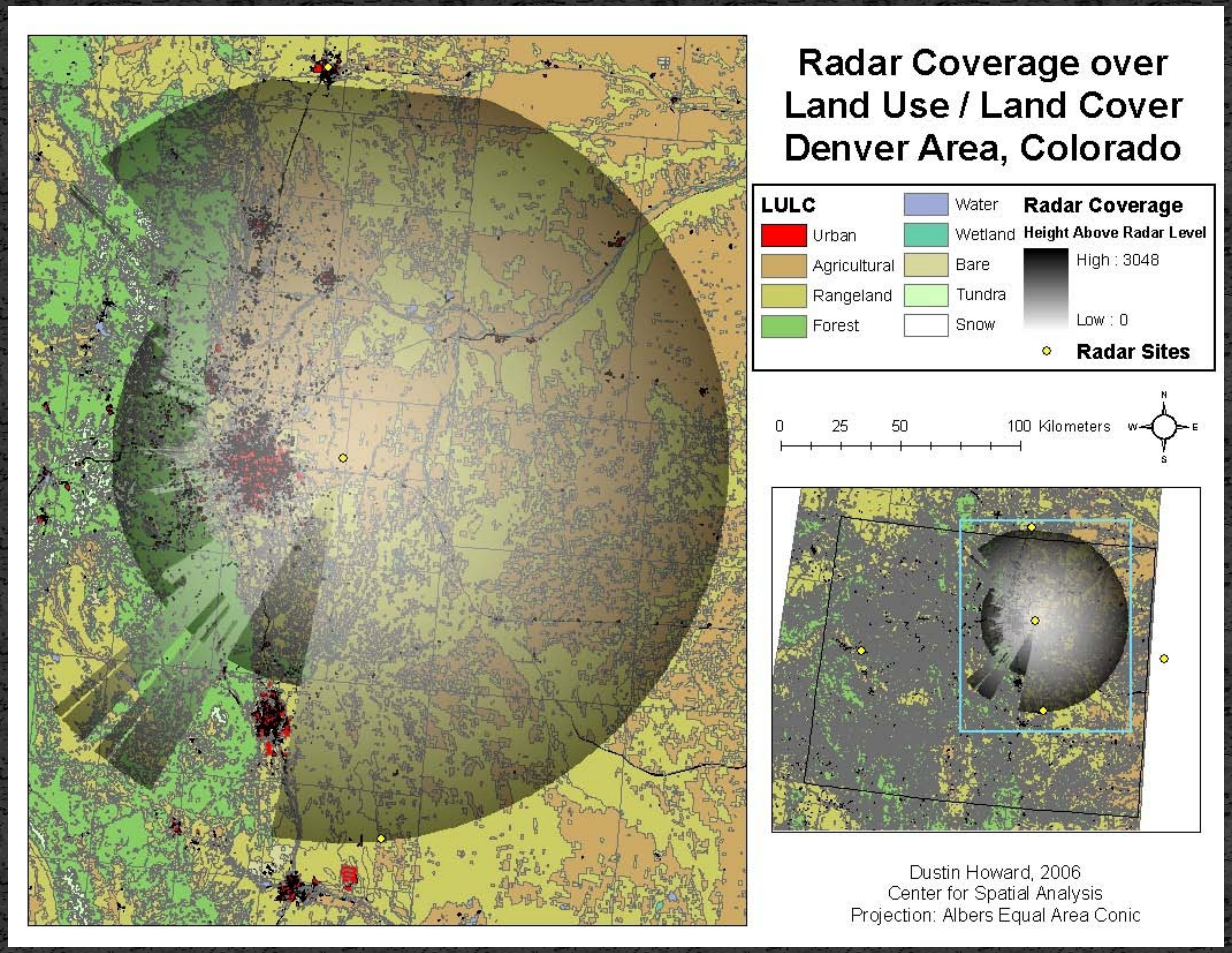
Visualization



- Surface sensors overlaid with radar coverage.

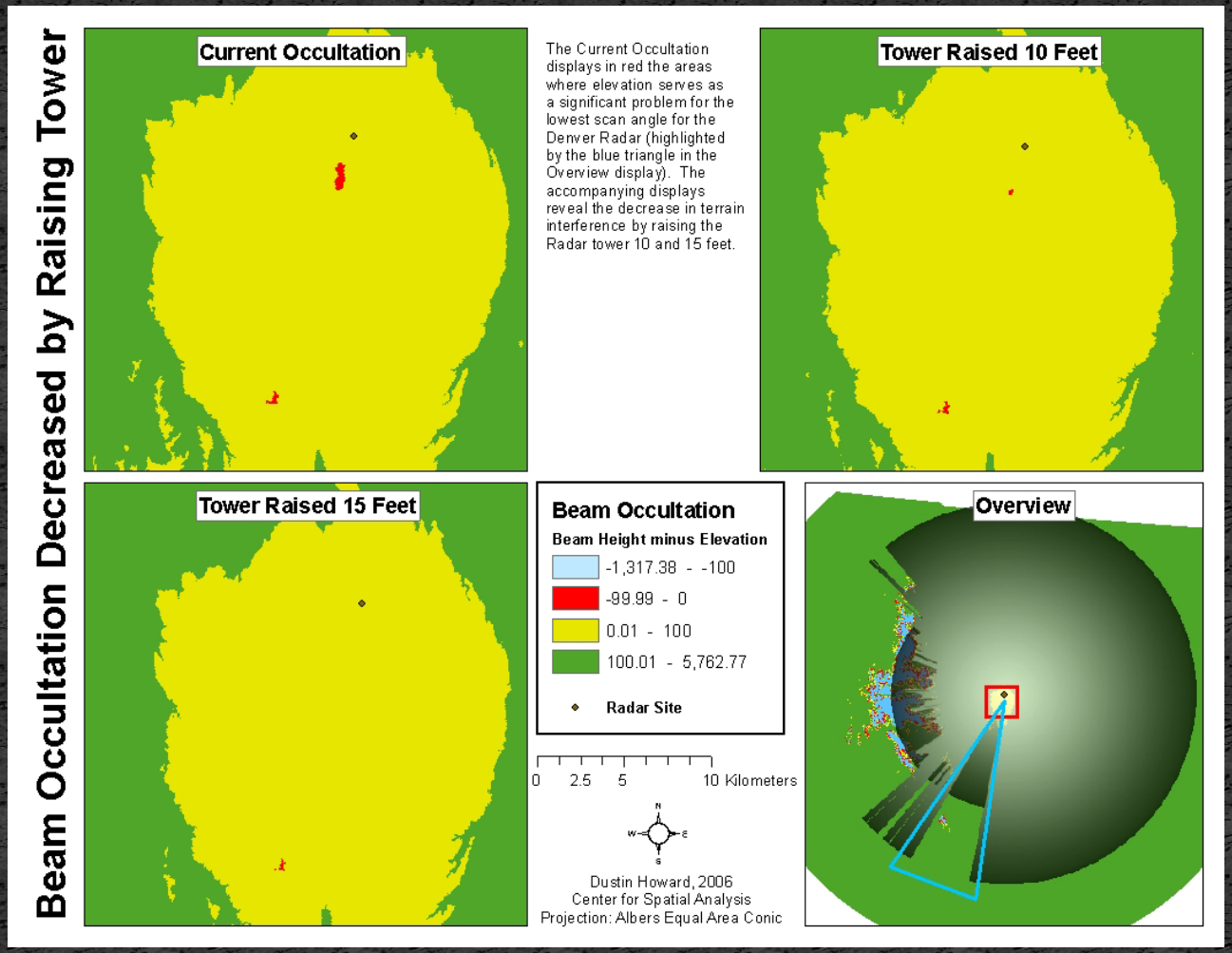
Visualization

- Radar Coverage of Urban/Populated areas



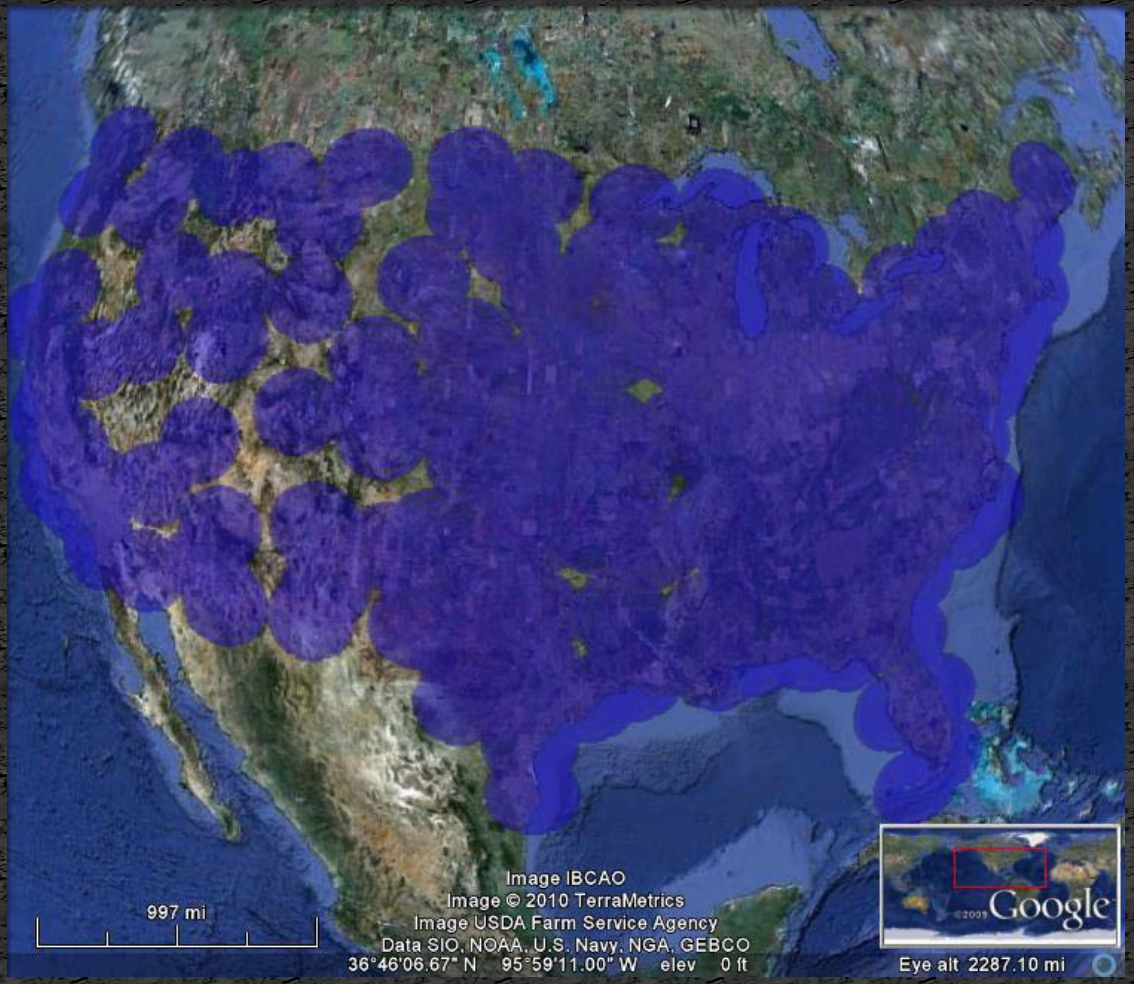
Visualization

- Potential benefits gained by increasing Radar tower height.

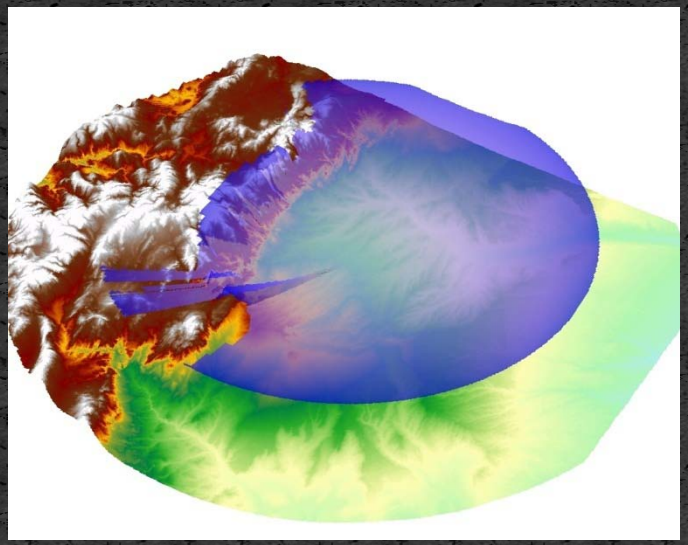


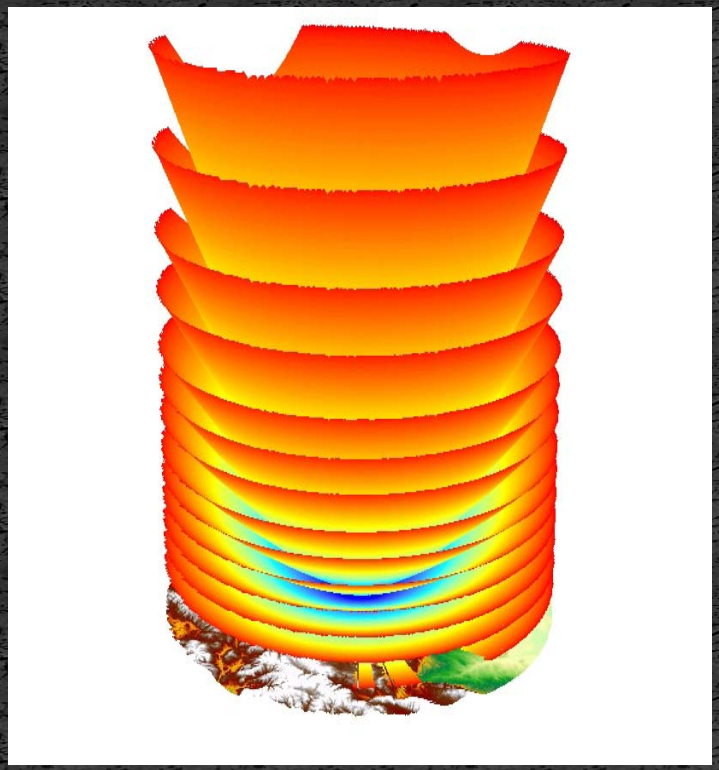
Visualization

- We may use Google Earth to display 2D spatial coverage.



Visualization

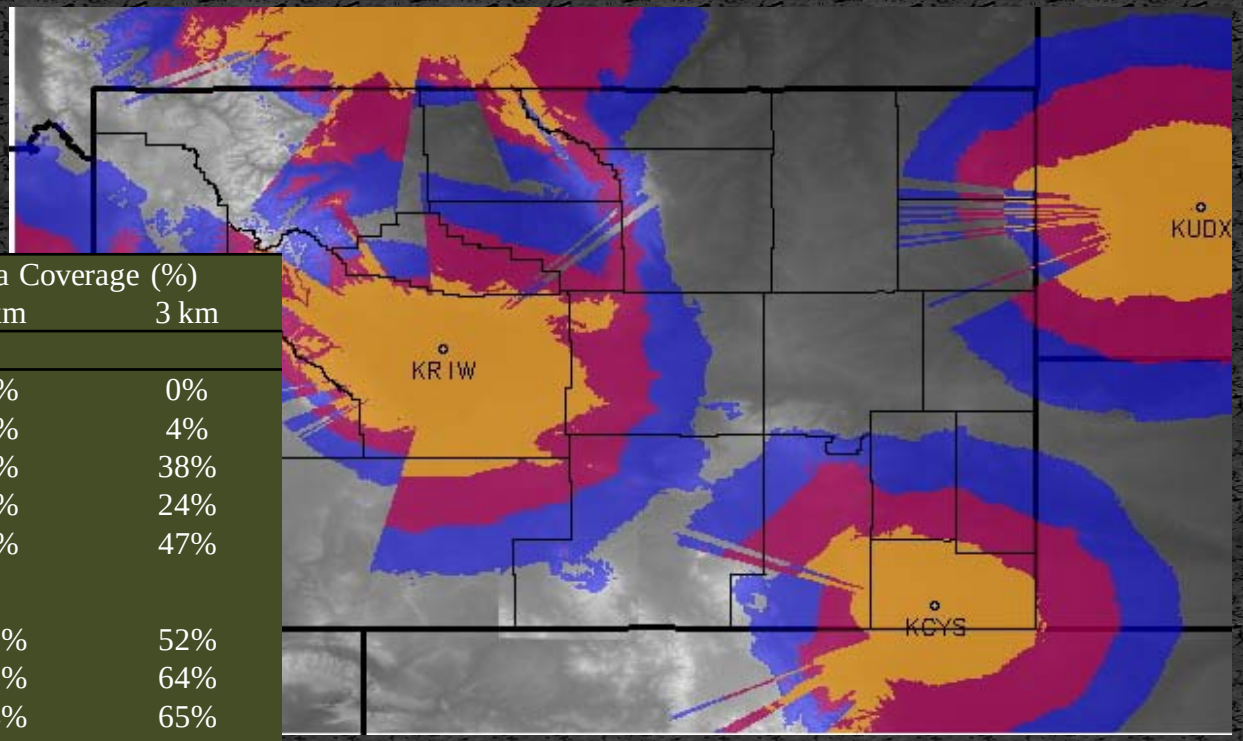




- 3 Dimensional modeling of Radar coverage
- By lowest band and all tilt angles

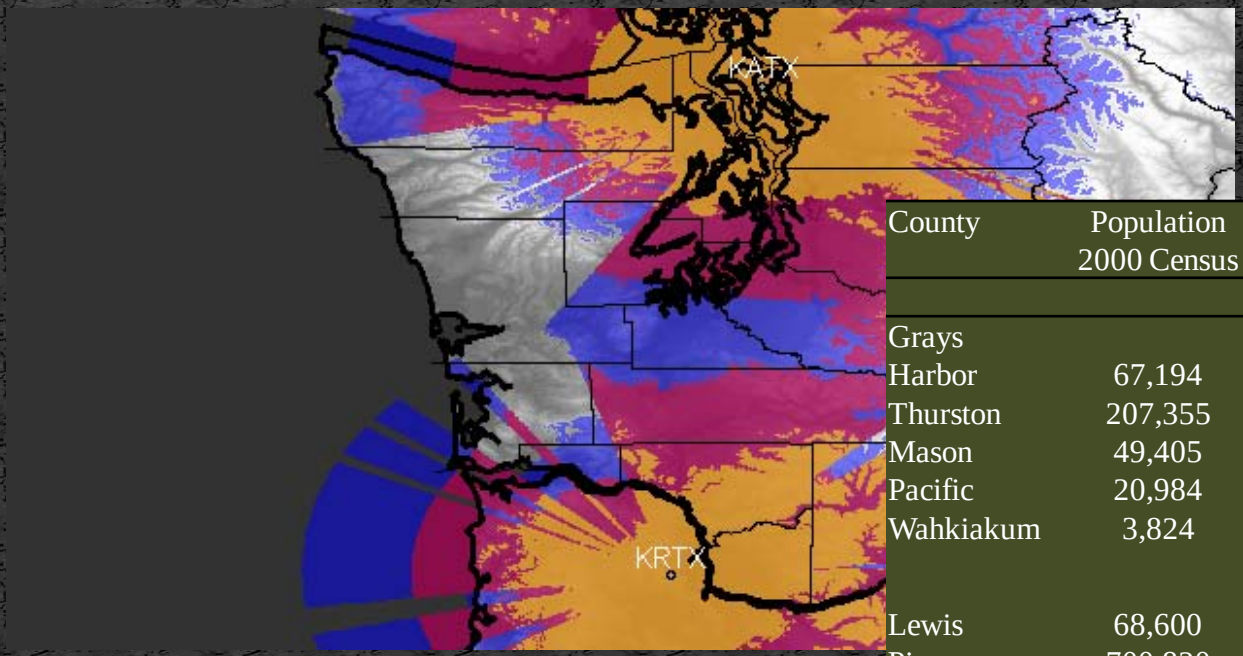
Visualization

Radar Gap Analysis (WY)



County	Population 2000 Census	WSR-88D Area Coverage (%) 1 km	2km	3 km
Campbell	33,698	0%	0%	0%
Converse	12,052	0%	0%	4%
Niobrara	2,407	0%	4%	38%
Johnson	7,075	0%	7%	24%
Carbon	15,639	0%	8%	47%
Uinta	19,742	0%	10%	52%
Teton	18,251	0%	17%	64%
Lincoln	14,573	0%	24%	65%
Washakie	8,289	0%	31%	93%
Park	25,786	2%	23%	48%
Goshen	12,538	2%	34%	78%
Crook	5,887	3%	30%	76%
Platte	8,807	3%	37%	81%
Weston	6,644	4%	11%	29%
Sublette	5,920	4%	17%	51%

Visualization



Radar Gap Analysis (WA)

County	Population 2000 Census	WSR-88D Area Coverage (%) 1 km	2km	3 km
Grays Harbor	67,194	0%	0%	15%
Thurston	207,355	0%	2%	100%
Mason	49,405	0%	48%	81%
Pacific	20,984	0%	7%	26%
Wahkiakum	3,824	1%	18%	85%
Lewis	68,600	2%	74%	95%
Pierce	700,820	3%	68%	100%
Clallam	64,525	26%	53%	84%
Jefferson	25,953	29%	46%	57%
Whatcom	166,814	29%	61%	88%
King	1,737,034	32%	91%	99%
Skagit	102,979	43%	75%	97%
Skamania	9,872	54%	93%	98%
Snohomish	606,024	57%	85%	100%
Kitsap	231,969	59%	100%	100%

Advanced Data Management Applications & Demonstrations Sub-Team

- Jerry Brotzge (OU Lead)
- Beth Plale (IU Lead)
- Keith Brewster (OU)
- Fred Carr (OU)
- Scott Jensen (IU)
- Andrew Reader (OU)
- Yunheng Wang (OU)
- May Yuan (OU)
- … And in close collaboration with the NCAR, MIT/LL and NSSL sub-teams.