Results of the *Clarus* Demonstrations

Evaluation of Enhanced Road Weather Forecasting Enabled by *Clarus*

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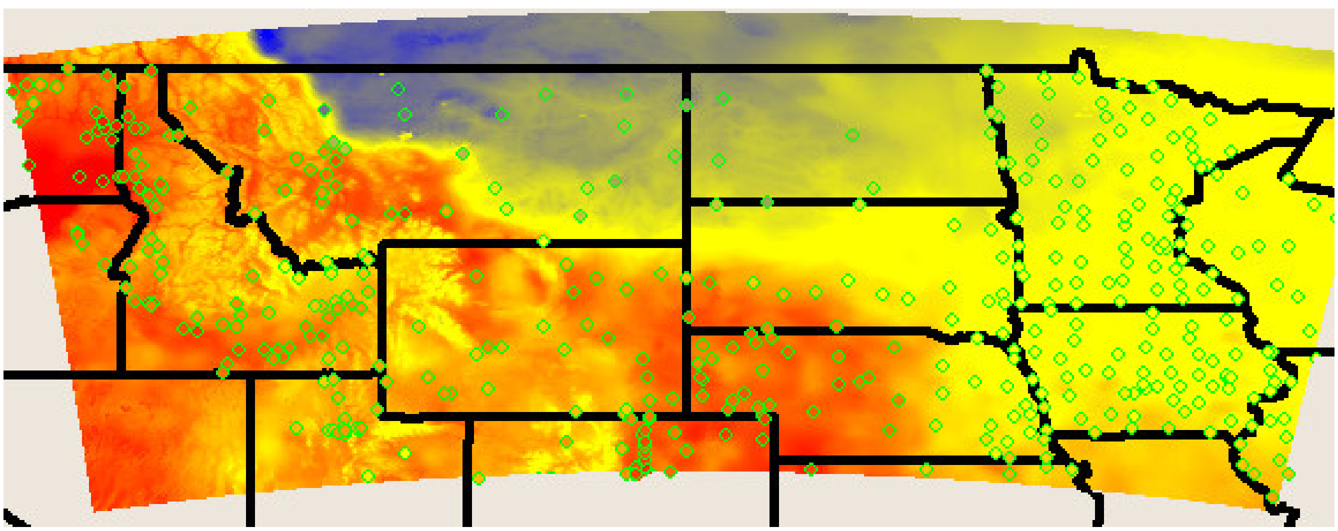

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16. Abstract

This document is the final report of an evaluation of Clarus-enabled enhanced road weather forecasting used in the Clarus Demonstrations. This report examines the use of Clarus data to enhance four types of weather models and forecasts:

- The Local Analysis and Predictions System (LAPS), used to estimate initial conditions for atmospheric weather forecast models.
- The Weather Research and Forecast (WRF) atmospheric weather forecast models.
- The Model of the Environment and Temperature of Roads (METRo) road weather forecast model.
- The Pavement Precipitation Accumulation Estimation System (PPAES) tool for enhancing radar-based precipitation estimates.

The results demonstrate the benefit of the Clarus System to enhance weather and road weather forecast and estimation systems. While the Clarus data did not appreciably improve the atmospheric forecasts, it did improve the estimates for the initialization data that fed those forecasts. The Clarus data did result in improved road temperature forecasts, particularly during the first 24 hours of the forecast. And, when used with the PPAES model, the Clarus data helped improve on estimates of the locations where precipitation was present, particularly in the winter months and at locations further removed from NexRad weather radar stations.

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Executive Summary

In 2004, the U.S. Department of Transportation (USDOT) established an initiative called *Clarus* with the objective to help public transportation agencies make better road management decisions by taking full advantage of investments in Road Weather Information Systems (RWIS). One element of the *Clarus* Initiative was the *Clarus* System, a functioning prototype data management system that collects, quality checks, and makes available public agency-sponsored surface transportation weather data from across most of North America. This system has been very successful at integrating state RWIS data, with a more than five-fold increase in states connected to *Clarus* between 2007 and 2010.

With this initial success and the population of the *Clarus* data cache with RWIS data from a significant number of stations, the *Clarus* Initiative launched a new stage in its process through two *Clarus* Regional Demonstrations intended to foster innovative use of *Clarus* data. These two demonstrations supported different combinations of five *Clarus*-enabled services:

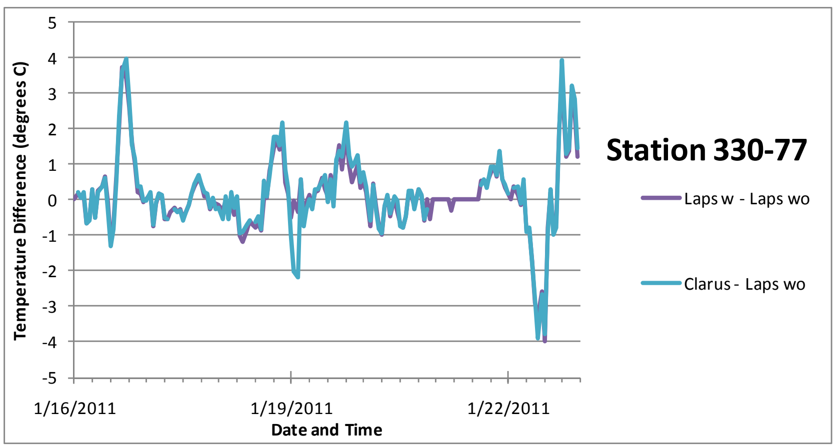
- Enhanced Road Weather Forecasting Enabled by Clarus. This service used Clarus-based environmental sensor stations (ESS) data to enhance atmospheric and pavement forecasts for surface transportation.
- Seasonal Weight Restriction Decision Support Tool. This tool estimated pavement sub-surface conditions in order to help determine whether spring thaw conditions warranted road closures to protect the roadway from damage.
- Non-winter Maintenance and Operations Decision Support Tool. This tool helped decision makers determine if weather conditions were likely to interfere with planned weather-dependent operations, such as pavement striping and vegetation management.
- Multi-State Control Strategy Tool. This tool provided consistent weather condition and forecast data to agencies from neighboring states to help coordinate road use restriction and closure decisions.
- Enhanced Road Weather Content for Traveler Advisories. This service provided weather-based road condition information to travelers.

USDOT also supported two evaluations of these demonstrations. One evaluation focused on the end user response to these five services (e.g., assessing whether the seasonal weight restriction decision support tool helped decision makers). The second evaluation focused on the impact of the Clarus data on the weather and road condition forecasting tools used to support these services. This report describes the results of this second evaluation. In particular, it reports on the impact of data obtained from the Clarus System on (1) an analysis tool used to initialize weather forecast models, (2) weather forecasting models, (3) road condition forecasting models, (4) and a precipitation estimation tool.

The Impact of Clarus Data on the Local Analysis and Prediction System (LAPS). LAPS is a tool that integrates data from many sources, including NexRad radar, satellite observations, and surface observations, to generate estimates of current weather conditions. These estimates are then used as the starting point for a weather forecast model. In particular, observations at Clarus stations impact weather forecast models through their impact on these initial conditions.

An assessment of the impact of the Clarus data on the LAPS estimates indicated that including the Clarus data in the LAPS estimation process did result in LAPS estimates that matched more closely with observations than LAPS estimates made without Clarus data. The inclusion of the Clarus data did not always impact the LAPS estimates – an impact was observed in only about 30 percent of the LAPS estimate for surface temperature. However, when it did impact the estimates, it usually improved them – about 65 percent of the time, the LAPS estimates made including Clarus data were closer to the observed values than those made without Clarus data. Similar results were found with other weather variables: when a difference was present, the LAPS estimates made with Clarus data more closely matched observations about 60 percent of the time for relative humidity, 55 percent of the time for wind speed, and about 50 percent of the time for dew point temperature and surface pressure. (A value of 50 percent in this metric indicates that the impact was about the same as if random changes were made to the data. A value greater than 50 percent indicates that an improvement occurred.)

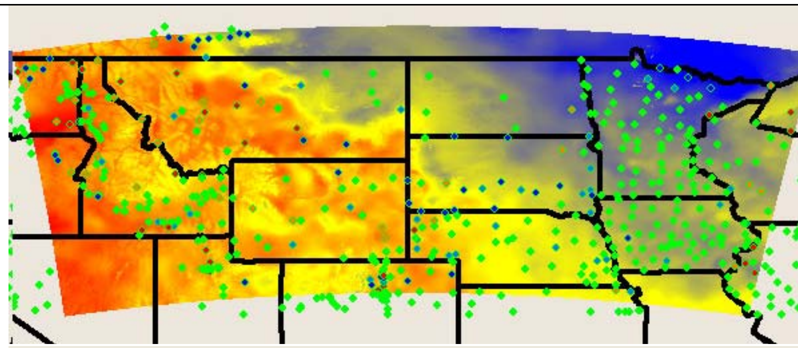
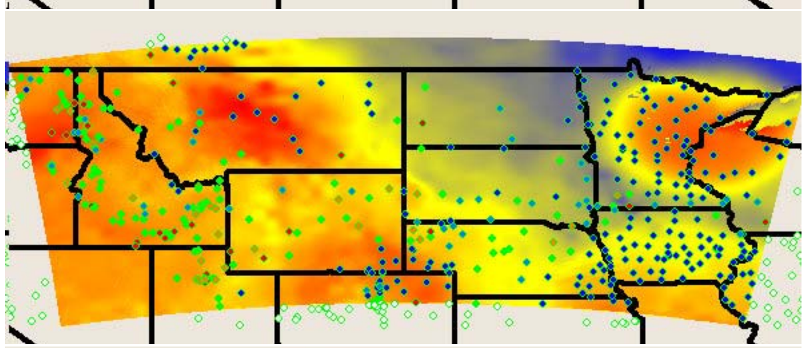
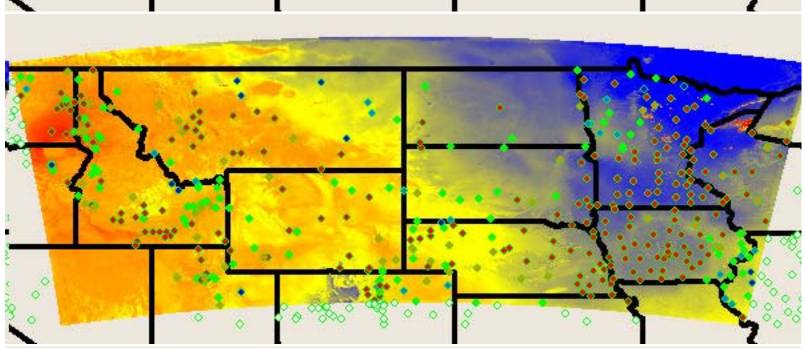
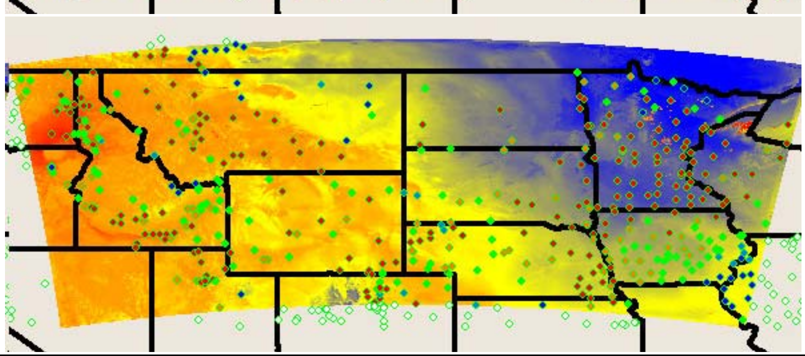
The type of improvement that resulted in the LAPS estimates is exemplified in the figure below, which shows the difference between the LAPS estimates made with and without Clarus data (purple line) and the difference between the Clarus observations and the LAPS estimates made without Clarus data.



These lines overlap when the LAPS estimate made with Clarus data completely corrected for the difference between the LAPS estimate made without Clarus data and the actual observations. This is clearly the case for most of the observations at this particular Clarus station, with the inclusion of Clarus data in the LAPS estimates correcting for differences of up to 4 degrees Celsius between LAPS estimates and observations.

The Impact of Clarus Data on the Atmospheric Weather Models. Atmospheric weather models take estimates for initial conditions produced by a tool like LAPS and step them forward in time by applying models of weather physics. An assessment was conducted to determine if the changes in the estimates in the initial conditions caused by the inclusion of Clarus data in the LAPS estimates carried over into differences in the forecasts produced by the weather models. The conclusion was that the inclusion of Clarus data in the WRF forecasts impacted the forecast results, but did not significantly improve or significantly degrade the agreement between the forecasts and Clarus observations.

This is exemplified by a series of maps depicting the LAPS temperature estimates for 1/16/2011 at 12:00 PM and a series of WRF forecasts for the following hours. In these maps, the areas are color-coded according to temperature, with blue indicating cooler temperatures, red indicating warmer temperatures, and yellow indicating temperatures intermediate between these. The dots on the map indicate the location of Clarus stations. The dots are color-coded to indicate the extent with which the temperature observations at the station agree with the LAPS estimates and WRF forecasts, with a green dot indicating good agreement, a blue dot indicating that the observation was below the model estimate, and a red dot indicating that the observation was above the model estimate.

LAPS temperature estimate for 1/16/2011 at 12:00 PM	
WRF 1/16/2011, 12:00 PM temperature forecast for 1/16/2011 at 12:00 PM (0 hr)	
WRF 1/16/2011, 12:00 PM temperature forecast for 1/16/2011 at 2:00 PM (2 hr)	
WRF 1/16/2011, 12:00 PM temperature forecast for 1/16/2011 at 3:00 PM (3 hr)	

Note the generally high level agreement in the first chart between the LAPS estimates and the Clarus observations – most of the dots are colored green. In the second map, there is much less agreement between the Clarus observations and the WRF forecasts. Comparing the second map with the third and fourth ones provides an indication of the source of this difference – the weather conditions in the first forecast seem flawed and do not seem to represent actual weather conditions. This is a well-known phenomenon in weather forecasting systems called spin-up.

The systems used to estimate initial weather conditions for weather forecasting models do not take into consideration the full complexity of the weather physics built into the forecasting models. The result is that the weather forecasting models often make large changes to those initial conditions during the first forecasts hours, generating results that are not accurate weather forecasts and often wash away small differences in the initial conditions. This appeared to be the case with the impact of the Clarus data on the WRF forecasts introduced through changes in the LAPS estimates – the changes in the LAPS estimates were washed out while the forecast model spun-up.

This was verified by examining similar metrics to those that were used for the LAPS estimates. When differences existed in the WRF temperature forecasts, the difference more closely matched observations about 50 percent of the time – the same percentage that would be expected from random changes to the forecasts. Similar results held for WRF forecasts for atmospheric pressure. Thus, although the Clarus data did improve the LAPS estimates, this improvement did not carry over into the WRF forecasts.

The Impact of Clarus Data on the Road Condition Models. On the other hand, including Clarus data in the site-specific air and road temperature forecasts did improve agreement between the forecasts and the Clarus observations. During the early hours of the forecast, the inclusion of Clarus data in the road temperature models resulted in an improvement of almost 2 degrees Celsius in the level of agreement between the model forecasts and observed values. The model forecasts made including Clarus data continued to show better agreement with observations throughout the first 24 hours. After that period, there was little difference between the road temperature forecasts made with and without Clarus data.

The Impact of Clarus Data on a Precipitation Estimation Tool. The Clarus data was also used in a Pavement Precipitation Accumulation Estimation System (PPAES) to attempt to improve on radar-based estimates of whether precipitation was present. The results of this evaluation indicated that the use of Clarus data and the PPAES analysis does enhance real-time precipitation estimates, but only under some circumstances, and actually degrades the estimates in other situations. In particular, the PPAES analysis with Clarus data was more effective than radar alone at estimating when and where precipitation occurred during winter months, particularly at higher latitudes and for locations relatively far from the nearest NexRad weather radar station. However, the PPAES analysis with Clarus data was more likely to indicate that precipitation occurred where it did not (i.e., generate false alarms) than to indicate that precipitation did not occur where it did.

These results are consistent with known limitations of radar precipitation measurements, such as overshoot (where radar observations miss precipitation forming at lower elevations) and low reflectivity of snow particles to radar signals (causing radar to underestimate wintertime precipitation). Thus, it appeared that using the PPAES model with Clarus data helped improve precipitation estimates in the circumstances where radar observations are weakest.

Taken together, these results demonstrate the benefit of the Clarus System and the surface observations in it to enhance weather and road weather forecasting and estimation systems. While the Clarus data did not appreciably improve the atmospheric forecasts, it did improve the estimates for the initialization data that fed those forecasts. The Clarus data did result in improved road temperature forecasts, particularly during the first 24 hours of the forecast. And, when used with the PPAES model, the Clarus data helped improve on estimates of the locations where precipitation was present, particularly in the winter months and at locations further removed from NexRad weather radar stations.

And, one must keep in mind that these improvements were supplemental to the direct benefits brought about by the surface observations produced by those stations. RWIS stations are usually deployed because agencies have an interest in the weather conditions at the deployment location – at locations subject to freezing conditions, for example. The Clarus System already helps states achieve these benefits by providing them with consolidated access to this data from sensor stations they and other states deploy and by performing quality checks on that data. The additional benefits observed during this study, particularly in the form of improved ability to forecast road conditions and estimate the locations where precipitation is present, provide benefits over and above those that originally motivated the states to deploy environmental sensor stations in the first place.

1 Introduction

This document is the draft Evaluation Report for the independent evaluation of the *Clarus* Multi-State Regional Demonstrations Use Case 1.

Introduction to *Clarus* and the *Clarus* Regional Demonstrations

In 2004, the U.S. Department of Transportation (USDOT) established an initiative called *Clarus*. A primary objective of the *Clarus* Initiative is to help public transportation agencies make better road management decisions by taking full advantage of investments in Road Weather Information Systems (RWIS). The *Clarus* System is the physical (hardware and software) portion of the initiative and is currently a functioning prototype data management system that collects, quality checks, and makes available public agency-sponsored surface transportation weather data from across most of North America. The goal is to have all public transportation agencies provide their atmospheric and pavement data and metadata to *Clarus,* which would benefit both the transportation and weather communities. Table 1 demonstrates the success of *Clarus* in obtaining state participation, with a more than five-fold increase in states connected to *Clarus* between 2007 and 2010.

Table 1. Number of States Participating in Clarus, by Participation Level

Participation Level	Number of States			
	2007	2008	2009	2010
Connected to Clarus	6	18	33	**38**
Partially Connected to Clarus	0	1	1	**0**
Pending	8	15	4	**3**
Considering Connecting	11	10	6	**4**
TOTAL	25	44	44	**45**

With this initial success and the population of the *Clarus* data cache with RWIS data from a significant number of stations, the *Clarus* Initiative has launched a new stage in its process through two *Clarus* Regional Demonstrations intended to foster innovative use of *Clarus* data. These two demonstrations support different combinations of the following five Clarus-enabled services:

- Service #1 – Enhanced Road Weather Forecasting Enabled by Clarus. This service will use Clarus-based environmental sensor stations (ESS) data to enhance atmospheric and pavement forecasts for surface transportation.
- Service #2 – Seasonal Weight Restriction Decision Support Tool. This tool will couple a pavement/subsurface temperature prediction model with a long-range atmospheric model to forecast

2-meter thermal profiles of subsurface conditions 10 days into the future and incorporate restriction decision policies to provide decision support to any Department of Transportation (DOT) personnel.

- Service #3 – Non-winter Maintenance and Operations Decision Support Tool. This tool will leverage components of the winter maintenance decision support system to provide decision support to DOT personnel regarding pavement striping, pavement preservation (e.g., crack sealing, pothole repairs, and pavement overlays), vegetation management, and mowing operations, both intra- and interstate.
- Service #4 – Multi-State Control Strategy Tool. This tool will incorporate restriction or closure decisions of neighboring agencies, provide guidance on implementing particular restrictions or closures in a state, push alerts to agencies in neighboring states, and provide guidance on when advisories should be disseminated to travelers.
- Service #5 – Enhanced Road Weather Content for Traveler Advisories. This service will include an intuitive, effective method of visualizing ESS data through a web interface; provide a web-based mechanism to warehouse current and forecast road weather information; and allow travelers to establish user profiles, access information for desired routes, and request notification of changing conditions. This service will be provided to State DOTs and/or their 511 service providers.

One demonstration, labeled the University of North Dakota (UND) Demonstration in this document, is developing systems for Services #1, #2, and #5 for State DOTs in Idaho, Montana, North Dakota, South Dakota, and Minnesota. The other demonstration, labeled the National Center for Atmospheric Research (NCAR) Demonstration, is developing systems for Services #1, #3, and #4 for State DOTs in Iowa, Illinois, and Indiana. The following two sections briefly describe these two demonstrations.

1.1.1 Introduction to the Meridian Demonstration

Meridian Environmental Technologies, Inc., led one team, which included as partners Iteris and the UND Surface Transportation Weather Research Center. This team developed systems for Services #1, #2, and #5 for State DOTs in Idaho, Montana, North Dakota, South Dakota, and Minnesota. These services are depicted in Figure 1.

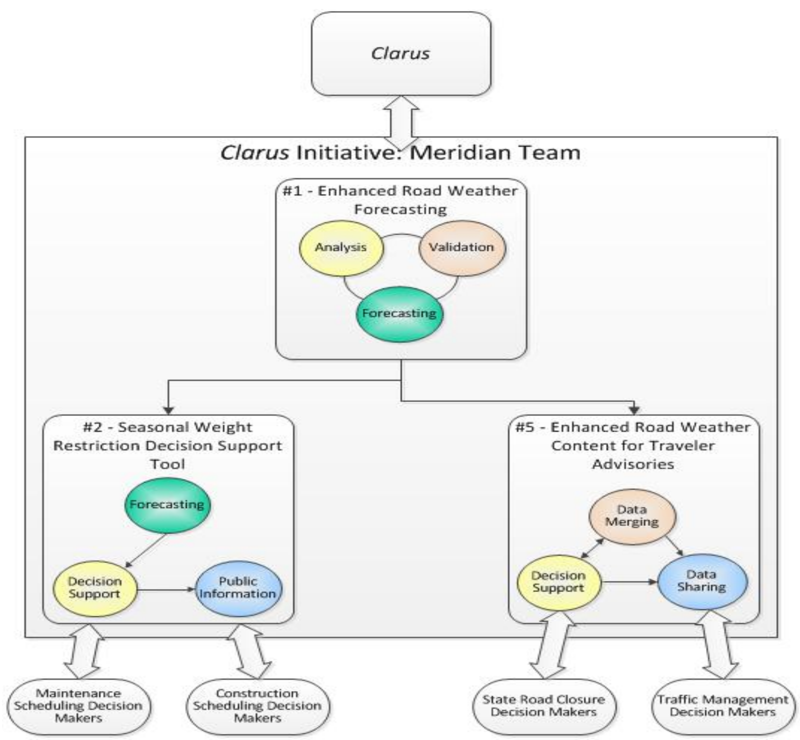


Figure 1. Overview of the Meridian Demonstration

The system supporting Service #1 started with mesoscale weather prediction models, which took advantage of *Clarus* data to provide better surface analyses near roadways. The model estimates were refined along roadways by subjective adjustments made by professional weather forecasters and forward error correction algorithms that used *Clarus* data to identify and correct for bias in the model forecasts. These atmospheric weather model estimates were correlated with road locations to provide road-specific forecasts of atmospheric conditions along roads.

The atmospheric model forecasts served as the basis for two additional models. First was a blowing snow forecast model, which estimated the potential for blowing snow to augment atmospheric precipitation along a roadway. Second was a pavement condition model, which estimated the condition of the pavement surface (e.g., pavement temperature, presence of ice or snow).

The last part of Service #1 was a system for estimating data quality for the estimates the Service #1 models produced, as well as for ESS data obtained from *Clarus*.

The data that Service #1 produced was fed to a system to support Service #2, a Seasonal Weight Restriction Decision Support Tool. The key input to this tool was the subpavement temperature predictions that the pavement condition model produced. This data was combined with information about State weight restriction policies to provide support for weight restriction decision making. A public Web site was established to disseminate information about seasonal weight restrictions in participating States.

The Service #1 data was also used to feed weather forecast data to a system to support Service #5, Enhanced Road Weather for Traveler Advisories. This system analyzed road-specific weather data and forecasts, combined with information about winter road maintenance activities, to estimate current and future road conditions. When warranted, the system associated travel advisories with roads, pushed these travel advisories to State 511 systems, and provided travel advisories to travelers through a public Web site.

1.1.2 Introduction to the Mixon-Hill Demonstration

Mixon-Hill, Inc., led the second team, which included as partners NCAR, Nortel Government Solutions, KMJ Consulting, and Anthey Creek Consultants. This team developed systems for Services #1, #3, and #4 for State DOTs in Iowa, Illinois, and Indiana. These services are depicted in Figure 2. As with the Meridian team, the Mixon-Hill team integrated *Clarus* data into weather prediction models to provide improved estimates for current and forecast atmospheric weather conditions. They also modified planetary boundary layer models to provide better estimates for

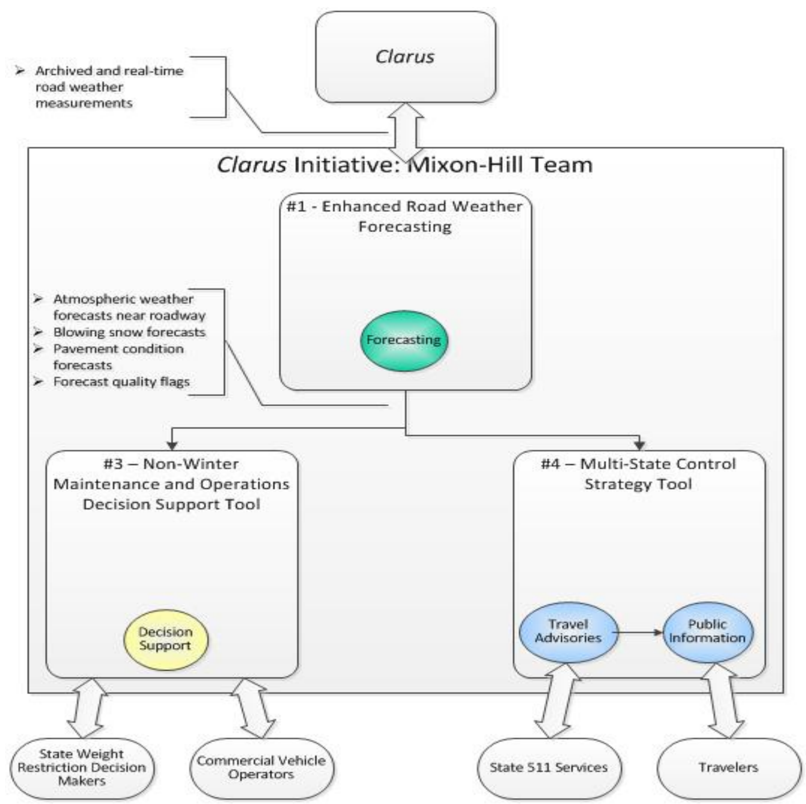


Figure 2. Overview of the Mixon-Hill Demonstration

atmospheric weather elements that directly affect transportation systems, such as precipitation type and wind gusts, and develop new algorithms to estimate pavement conditions.

The improved atmospheric and pavement weather estimates were used to support Service #3, Nonwinter Maintenance and Operations Decision Support Tool. Many maintenance activities, such as mowing and striping, are affected by inclement weather conditions. Many construction activities, such as paving and curing, can be performed only under appropriate weather conditions. A decision support tool was developed that helped decision makers schedule maintenance to reduce interruptions by inclement weather. A different tool helped ensure that construction activities were scheduled to be performed only when appropriate weather conditions existed and that alerts were generated if weather conditions suggested halting scheduled construction activities.

The Service #1 weather data also was used to support Service #4, a Multi-state Control Strategy Tool. This tool combined road weather data from *Clarus* with data from other to-be-determined sources to provide a consolidated source of road condition and other information that was shared across multiple States. Decision support tools were developed to take advantage of this combined data to support transportation decision making, such as recommending tire chains during winter storms, closing flooded roads, and closing bridges during high winds. Information about road closures was one piece of data included in the system, and decision support tools were developed to “push” information about road closures across jurisdictional boundaries to improve cross-jurisdictional coordination when road closures occur.

Introduction to the Evaluation

The objective of this evaluation, as stated in the statement of work (SOW), was to:

> *Conduct an independent evaluation of the innovations that will be delivered from the Clarus Regional Demonstration Use Case 1 development activities. This is to be a scientific evaluation which spans metrics associated with both the atmosphere as well as the pavement (or subsurface). The intent is to work with both development teams to perform analyses that quantify changes to surface transportation meteorology forecast skill.*

Further discussion with the Federal Highway Administration (FHWA) indicated that the primary objective of this evaluation was to assess the impact of the *Clarus* data on the forecasts of atmospheric and pavement conditions through comparison of model results generated with and without inclusion of *Clarus* data.

Overview of This Document

This document presents the results from evaluating the impact of *Clarus* data on the weather forecasts used during the two *Clarus* Multi-State Regional Demonstrations:

- Section 2 provides more information on the two regional demonstrations on the approach used to conduct the evaluation of these demonstrations.
- Section 3 describes the impacts of Clarus data on the atmospheric weather model.
- Section 4 describes the impacts of Clarus data on the Pavement Precipitation Accumulation Estimation System (PPAES) model.

- Section 5 describes the impacts of Clarus data on the pavement condition model.
- Section 6 summaries the evaluation results and presents conclusions.

2 The Evaluation Approach

This section of the report describes two Use Case 1 Regional Demonstrations and the plans for the evaluations.

The Meridian Use Case 1 Regional Demonstration

Use Case 1 of the Meridian Regional Demonstration consisted of four separate weather forecasting activities:

- One set of forecasts used the Weather Research and Forecast (WRF) atmospheric weather models initialized using the Local Analysis and Predictions System (LAPS) to produce atmospheric weather forecasts for a region that includes Montana, North Dakota, and South Dakota. These were run with and without Clarus data, and the impact of inclusion of the Clarus data was studied during this evaluation. These models were run in real time from March through August 2010 and from December 2010 through April 2011.
- A second set of forecasts used a PPAES to produce estimates for the amount and type of precipitation that occurs, as well as its location, time of onset, and end time. This system was run for a grid that covers that continental United States and was run withholding subsets of observational data that was used for mode validation. The impact of inclusion of the Clarus data was studied during this evaluation. These models were run from March through August 2010.
- A third set of forecasts used the Seasonal Weight Restriction (SWR) model developed at the UND Surface Transportation Weather Research Center (STWRC) to forecast subsurface temperature trends within pavement subgrade. With and without Clarus data versions of this model were not run. Therefore, these forecasts were outside the scope of this evaluation.
- A road weather forecast system developed by Meridian was used to estimate road weather along roadways. This system applied forward error correction to the atmospheric forecasts (with Clarus data only) and applied a Roadway Environment Blowing Snow (REBS) prediction system to estimate blowing snow intensities along roadways. Meteorologists then reviewed and edited the data before it was used to produce road weather forecasts. With and without Clarus data versions of this model were not run. Therefore, these forecasts were outside the scope of this evaluation

The following two sections provide a more detailed description of the two weather forecasting activities that were studied during this evaluation and the plans for evaluating these activities.

2.1.1 Evaluation of the Meridian Atmospheric Weather Model

The Meridian weather models produced an ensemble of weather forecasts for a region of the United States that includes Montana, North Dakota, and South Dakota. The basic approach applied with the Meridian weather models was to use the LAPS to “hot start” the WRF model to produce regional atmospheric weather forecasts on a 4-km horizontal grid. The “hot start” helps reduce the “spin up” time during which weather forecasts produce unstable results. This resulted in 245,000 surface grid elements that covered the study region. This compares to the 612 Clarus stations that are located in the study area for which data was available during the study period. So, Clarus data was available for only about 0.25 percent of the surface grid elements.

Initially, the model produced a 12-hour and was rerun (cycled) every 6 hours. Later during the project, 18-hour forecasts were produced. LAPS "hot start" input included data from global weather models and direct atmospheric state variables, including Clarus data, as well as the data produced from the previous model run (i.e., the cycling data). This forecast provided the three-dimensional initialization data for the WRF model. These forecasts, which overlapped in time, were combined into an ensemble of forecast data, which was the source of weather data for downstream systems that relied on weather data, including forward error corrections. This general approach for the operational system is depicted in Figure 3.

Two versions of this operational system were run continuously throughout the operational period of the

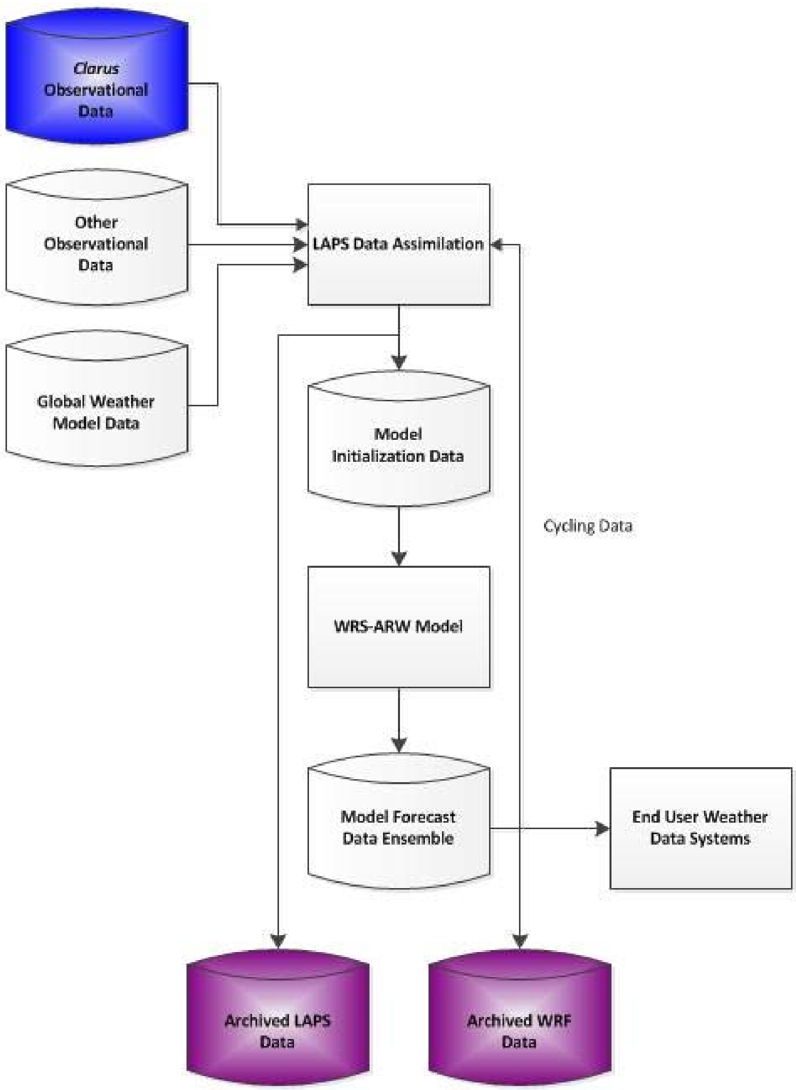


Figure 3. The Meridian Weather Forecast System

regional demonstration, with one version including the Clarus data as a source of initialization data and the other version excluding the Clarus data. For each version, surface values from both the LAPS and WRF data were made available to the evaluators. The evaluation focused on the following impacts of the Clarus data on this data:

- Whether the Clarus data affected the weather forecasts:
  - Assess differences between the LAPS estimates made with and without Clarus data. The Clarus data affects the weather forecasts through the LAPS initialization data, so this data is the most direct measure of the Clarus data on the forecasts.
  - Assess differences between the WRF forecasts made with and without Clarus data. The weather forecasts are used to support weather-based decision making. Impacts on the WRF forecasts could directly affect weather-based decisions.
- Whether the Clarus data improved the weather forecasts:
  - Assess whether the WRF forecasts made with Clarus data more closely matched observation data than forecasts made without Clarus data. This analysis will help determine whether the impact of Clarus data on forecasts was negative or positive.

Assessing the impact of Clarus data on weather forecasts is complicated by a number of factors:

- The impacts are not expected to be large. The Clarus data is only one of many sources of data used to initialize the weather models and only represents a small percentage of the overall initialization data.
- The impacts tend to be localized. The Clarus observations provided data at about 600 points points within a grid of more than 240,000 points. The impact of the Clarus observations is expected to be localized around these points.
- The impacts are expected to be present only part of the time. The Clarus data is expected to affect the weather forecasts only when the Clarus observations differ from the other data used to initialize the forecasts.
- The impacts could differ with forecast time. It is possible that the impact of the Clarus data on the LAPS initialization data could be damped over time as the impact of the physics built into the weather model takes precedence over the initialization data. Alternately, small perturbations introduced in the LAPS data could be magnified by the weather models.

For these reasons, the analysis of the impact on the weather models will begin with qualitative analyses meant to provide some insights into whether any impacts existed, the general size of those impacts, and whether the impacts were localized.

2.1.2 Evaluation of the Meridian Pavement Precipitation Accumulation Estimation System

The PPAES (Askelson, 2008) uses surface, radar, satellite, and model/analysis data to estimate observed wintertime precipitation occurrence and accumulation along roadways. PPAES is a precipitation data integration and analysis system, not a forecast system. PPAES provides estimates for the amount and type of precipitation that occurred, as well as its location, time of onset, and end time. The PPAES data flows are depicted in Figure 4.

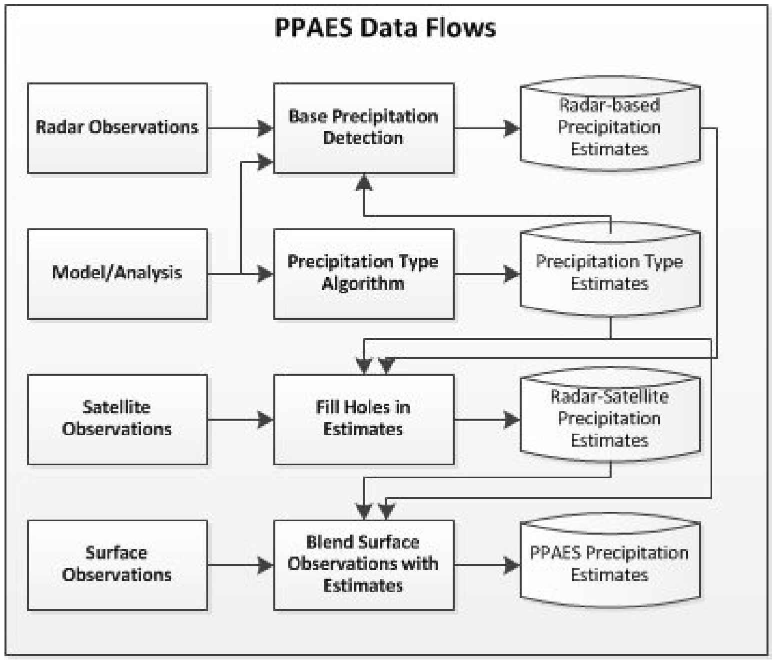


Figure 4. PPAES Data Flows

The PPAES process begins by combining radar and model/analysis results to produce initial estimates of current precipitation rates and type. Satellite observations are used to fill in gaps in the radar coverage, primarily by associating analysis points with surface observing stations based on similarity in cloud cover fields. The precipitation observations at these observing stations then are used to refine the precipitation estimation at the location of interest.

For this demonstration, the PPAES analysis was accomplished hourly to produce enhanced precipitation estimates on a national grid. To support the evaluation of the impact of Clarus data on the PPAES results, three sets of precipitation estimates were made, one based on surface observations, one using only radar data, and the third using PPAES with Clarus data. (In the third set of estimates, a subset of Clarus data was excluded as a control group and results are presented for this control group. The control group varied from run to run.) The evaluation team was provided with the results for these control stations: whether observations indicated precipitation at each control station, whether the radar data indicated precipitation at each control station, and whether PPAES with data from Clarus stations indicated precipitation at each control station, as well as summary statistics based on these values.

The evaluation focused on whether the inclusion of the Clarus data in the PPAES process improved the ability to estimate whether precipitation was observed at the control stations. The assessment examined the usual statistics used for such binary estimates, such as the Probability of Detection (POD), False Alarm Ratio (FAR), and BIAS for entire control group. The assessment also charted these statistics against metrics related to the proximity of other Clarus stations.

The Mixon-Hill Use Case 1 Regional Demonstration

Use Case 1 of the Meridian Regional Demonstration consisted of two separate weather forecasting activities:

- One set of forecasts used the WRF model to produce atmospheric weather forecasts for a region that includes Iowa, Illinois, and Indiana. These models were run with and without Clarus data, and the impact of inclusion of the Clarus data was studied during this evaluation.

  - Another set of forecasts used NCAR's Road Weather Forecasting System (RWFS) to forecast pavement conditions at Clarus sites. This model was run both with and without Clarus data, and the impact of inclusion of the Clarus data was studied during this evaluation.

These systems were run during five historical test cases that were selected to highlight the impact of Clarus data during times when weather conditions were changing rapidly in the study region (see Table 1).

Table 2. Mixon-Hill Test Cases

Test Case	Date Range	Description
Test 1 – Heavy Rains	6/6/2008 – 6/7/2008	A storm front with heavy precipitation moves across the study region.
Test 2 – Hurricane Ike	9/12/2008 – 9/15/2008	The remnants of Hurricane Ike pass through the study region.
Test 3 – Squall Lines	5/14/2009 – 5/16/2009	Two separate squall lines along two different fronts form in the study region.
Test 4 – Cold	6/15/2009	A cold, dry Arctic air mass moves into the study region.
Test 5 – Warm	7/20/2008	A warm, moist air mass moves into the study region.

The first test case involved a strong storm system that passed through the study region between June 6 and 7, 2008, bringing heavy precipitation. Figure 5 depicts precipitation maps for these 2 days.

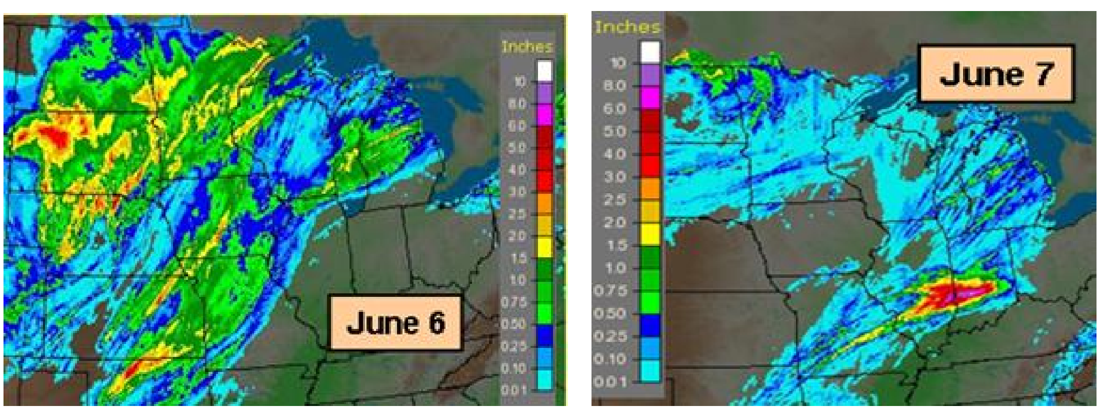


Figure 5. Liquid Precipitation Map for Test Case 1

The second test case involved the remnants of Hurricane Ike, which passed through the study region between September 12 and 15, 2008. This system brought high winds to the region (see Figure 6) and winds that varied dramatically in speed and direction across the region.

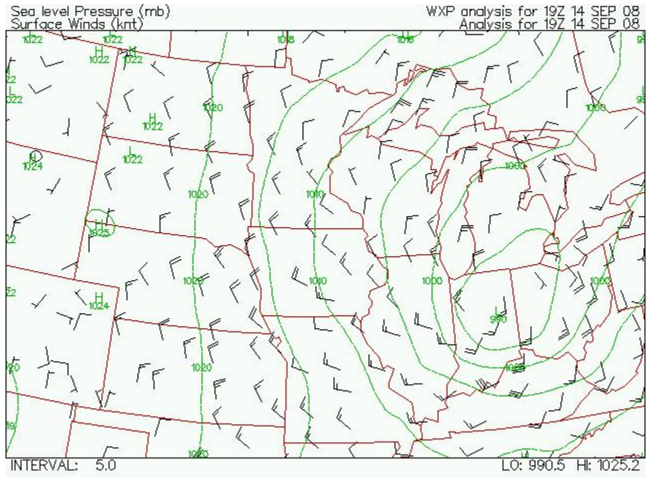


Figure 6. Surface Winds Map for Test Case 2

The third test case involved two separate squall lines that formed in the region between May 14 and 16, 2009. This occurrence resulted in strong differences in temperature and wind direction through the study region, as shown in Figure 7.

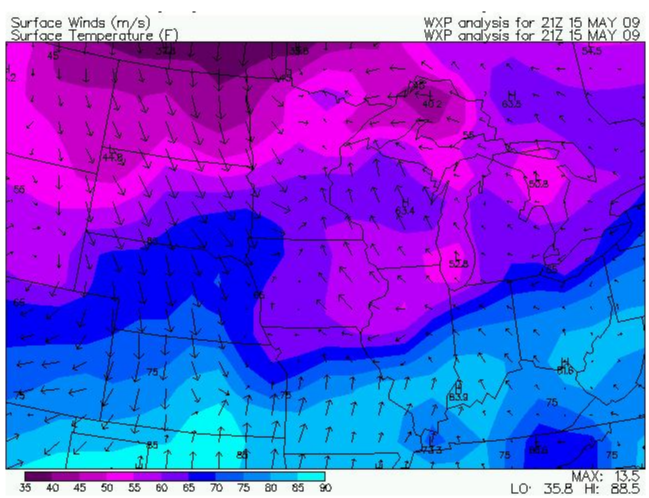


Figure 7. Surface Wind and Temperature Map for Test Case 3

The fourth test case involved the movement of a strong cold dry Arctic air mass into the region on January 15, 2009, as depicted in Figure 8.

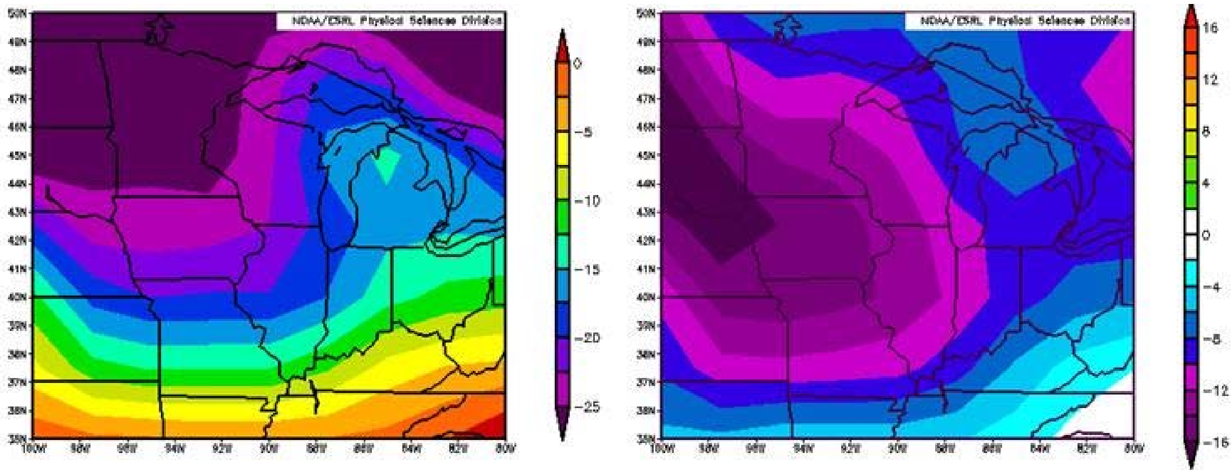


Figure 8. Temperature Maps for Test Case 4

The fifth test case involved movement of a strong warm moist air mass into the region on July 20, 2008. A surface dew point temperature map of this test case is depicted in Figure 9.

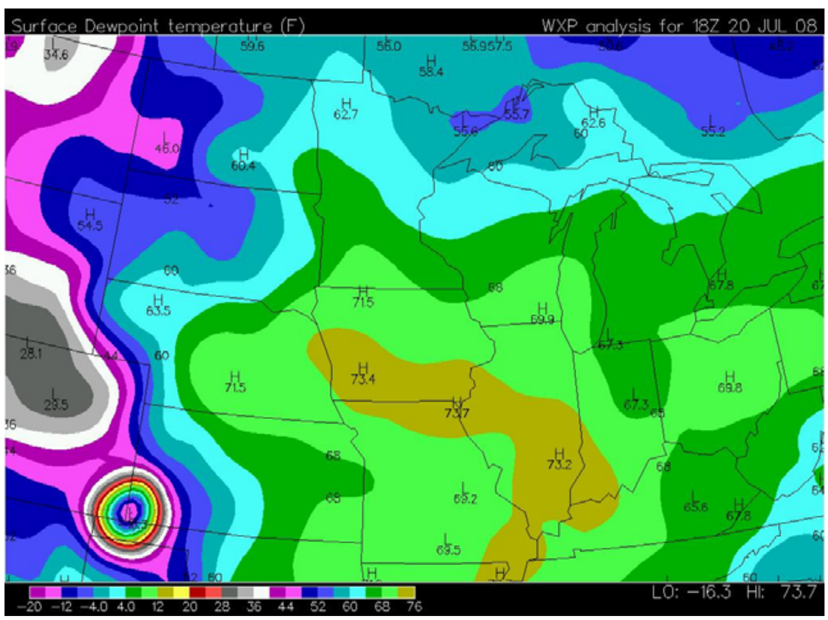


Figure 9. Surface Dewpoint Temperature Map for Test Case 5

The following two sections provide a more detailed description of the evaluation of the two weather forecasting activities that occurred for these five test cases.

2.1.3 Evaluation of the Mixon-Hill Atmospheric Weather Model

The Mixon-Hill team used the Advanced Research Weather Research and Forecasting (ARW) atmospheric weather model to produce the atmospheric weather forecasts for this regional demonstration. Figure 10 depicts the main components and general data flow for this model.

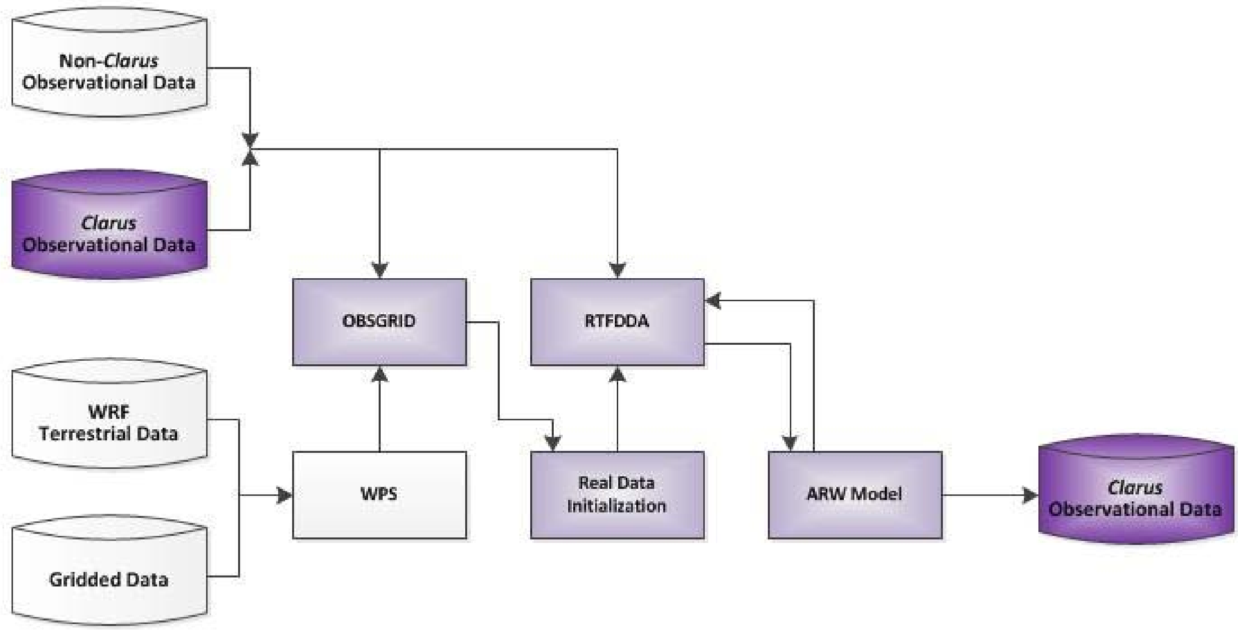


Figure 10. The Mixon-Hill Atmospheric Weather Model

The Weather Research and Forecast Preprocessing System (WPS) combined information about the study region terrain (i.e., Weather Research and Forecast (WRF) Terrestrial Data) with gridded weather data (e.g., from global forecasts) to produce estimates of the initial weather conditions on the grid defined for the study region. The OBSGRID program combined this data with observational data to create a refined set of initial weather conditions. The RTFDDA process performed data assimilation, combining observational and forecast data to produce improved initialization data ARW model time-steps. The ARW Model applied the model dynamics and physics to the initialization data to produce forecasts of future weather conditions.

The Clarus data was used, with many other sources of data, in the initialization data for the model and as part of the data that is assimilated during forecast cycles. The entire model process was run twice for each of the five test cases: once per test case including the Clarus data and once excluding that data. The evaluation process for these weather forecasts was similar to that used for the Meridian atmospheric weather model, as described in Section 2.1.1.

2.1.4 The Mixon-Hill Pavement Condition Model

The Mixon-Hill pavement condition model used information about the road composition and estimates of the initial road temperature profile at specific points on a road, with forecasts of future weather conditions at that point, to produce estimates of future road conditions. A simplified representation of this process is depicted in Figure 11.

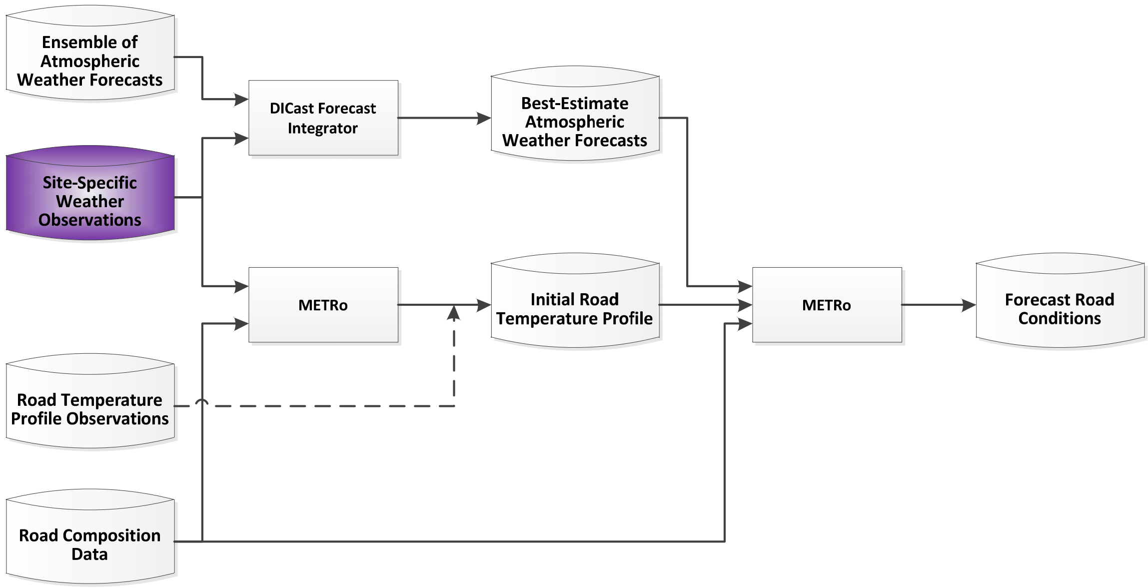


Figure 11. The Mixon-Hill Pavement Condition Model

In this process, the DICast Forecast Integrator compared historical forecasts to historical observations to produce a weighted average of the forecasts that provided an improved estimate for the forecast atmospheric conditions at the site. The model also required an estimate for the initial road temperature profile. Because observational data on the road temperature profile was not available, the Mixon-Hill approach assumed a temperature profile for some specified time and uses the METRo[1] model with observed weather conditions to estimate the road temperature profile at the start of the forecast period. The METRo model then was applied to the estimate of the initial road temperature profile and the forecast weather conditions to estimate future road conditions. As with the atmospheric weather models, this process was applied twice per test case: once including and once excluding the Clarus data.

In this process, the Clarus data affected the road condition forecasts in two ways:

1. The Clarus data was used for the initial road temperature profile before starting a road condition forecast run. When Clarus data was available, these observations were used to estimate the initial road temperature profile. Without these site-specific observations, historical atmospheric forecasts were used for estimating the initial temperature profile.
2. The Clarus data was used to produce improved atmospheric weather forecasts that were used during the road condition forecast run. When Clarus data was available, site-specific weights were developed by comparing the site-specific historical observations to historical forecasts. Without the Clarus data, site-specific weights could not be developed, and generic weights were used.

The evaluation focused on comparing the pavement surface temperature observations with the pavement surface temperatures forecast by the pavement condition model.

[1] See http://home.gna.org/metro/. (Access tested on 3/1/2010.)

3 The Impact of *Clarus* Data on the LAPS Estimates

Producing an atmospheric weather forecast starts with estimating initial conditions for the area covered by the forecast model. With the WRF model used by Meridian Team, the initialization data was produced using LAPS. This section describes the results of evaluating the impact of Clarus data on initialization data produced by LAPS. It begins by describing how the Clarus data impacts the LAPS estimation process (section 0). Section 0 provides a detailed description of the impacts observed during the week of January 16, 2011, with a particular focus on the LAPS estimates at the locations of seven specific Clarus stations. The intent is to demonstrate the types of impacts observed and provide a basis for the metrics that will be used to assess these impacts over the entire study region through the entire study period. Section 0 defines metrics for assessing the impact of Clarus data on the LAPS estimates and presents the results of assessing these performance metrics as they apply to different weather variables across the study region and throughout the study period. Summary and conclusions drawn from those assessments are provided in Section 0.

How *Clarus* Data Impacts LAPS

The Clarus data is only one of many data sources used to initialize the weather models for the Clarus Use Case #1 Regional Demonstrations. Other initialization data include NexRad radar, satellite observations, global weather models, previous cycles of the Regional Demonstration weather models, and other surface observations. To get some perspective on the amount of Clarus data relative to the amount of initialization data, consider the Meridian demonstration. For this demonstration, a 350 by 700 grid was used to cover the study region, resulting in 245,000 surface grid points in the weather model. In addition, the weather model included 64 vertical layers, so the atmospheric weather conditions were represented by meteorological values at more than 15 million grid elements. In this region, there were about 800 Clarus stations, though not all stations were active throughout the study period. So, the observations at these stations provided weather observations no more than 800 of these 15 million grid elements. In this context, the impact of the Clarus observations would be expected to be small.

On the other hand, Clarus stations make up an important fraction of the total available surface observations. A review of stations for which data is available in Meteorological Assimilation Data Ingest System (MADIS), a common source of surface observation data, identified just over 14,000 observation stations. The Clarus network includes over 2,200 stations, many of which are also included in MADIS. Thus, while the number of surface observations is small relative to the number of grid elements in the weather models, the Clarus observations make up an important fraction (about 16 percent) of total surface observations.

Another factor that could influence the impact of the Clarus data is the method used to integrate this data into the model initialization data. The forecast models used for the Regional Demonstrations each use techniques that approximate physically realistic approaches to integrating surface observations into the initialization data. This affects the impact of the Clarus data in two ways. First, the presence of other data sources could dilute the impact of a Clarus surface observation on the initialization data at the point where the observation was measured. Second, any impact that did occur could spread across a number of nearby grid elements, rather than being isolated at a single point.

For example, suppose a Clarus surface temperature was 5 degrees higher than the surface temperature estimates from other sources. Then, the initial estimate for the surface temperature of the grid element where the observation occurred would likely be higher for the model run with Clarus data than the model run without it, but might be less than 5 degrees higher. In order to raise the surface temperature at that grid element in a physically realistic way, the temperature of other nearby elements would also need to increase. And, this temperature increase could impact other weather parameters of these grid points.

Impacts of *Clarus* Data on LAPS Estimates during the Week of January 16, 2011

During the week of January 16, 2011, a low pressure system moved through the study region, resulting in higher than normal temperatures and lower than usual atmospheric pressures on January 17, as shown in Figure 12.

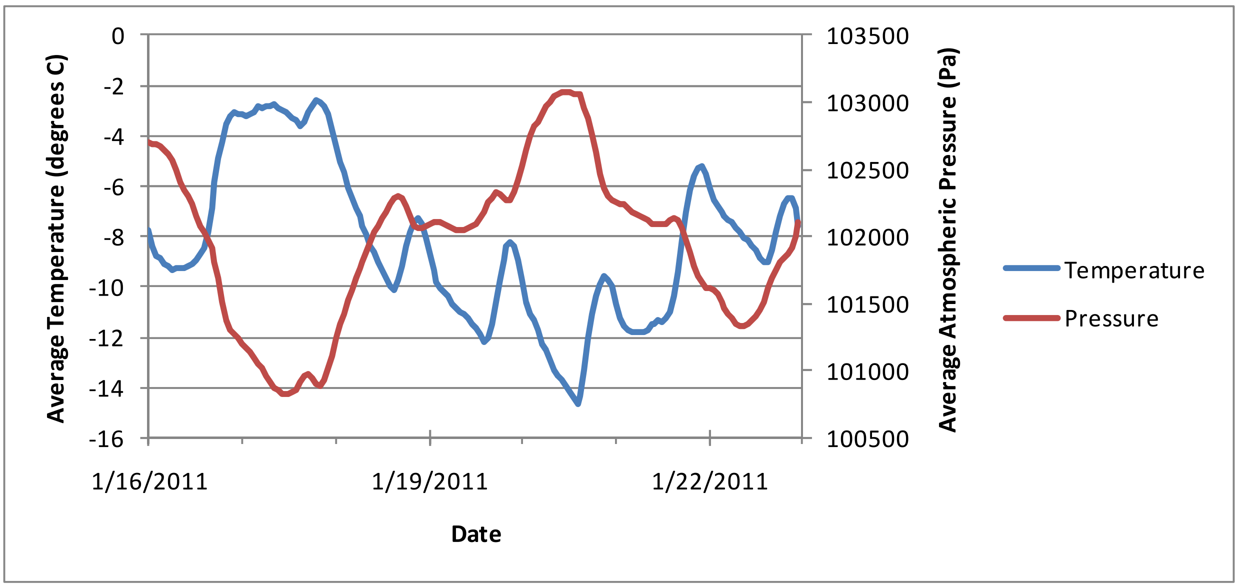


Figure 12. LAPS Average Temperate (degrees C) and Pressure (Pa), 1/16/2011 to 1/23/2011

This also brought in an increase in precipitation in the region, as shown in Figure 13. (No precipitation data is shown for most of the period from January 20 to January 22 because no WRF archives were available for that period.)

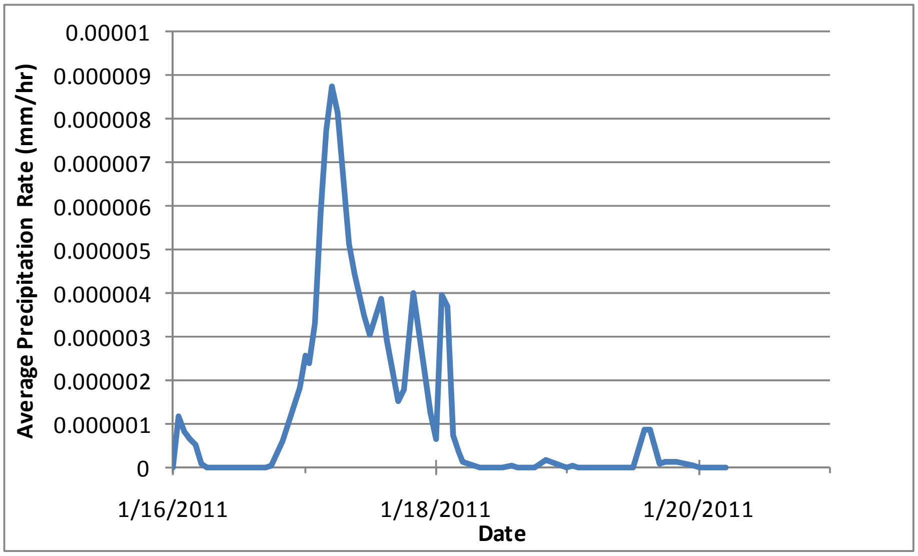


Figure 13. WRF Average Precipitation Rates (mm/hr), 1/16/2011 to 1/21/2011

This assessment begins by focusing on the impact of the Clarus data on the LAPS initialization data during the period where this front was moving into the region, from noon January 16, 2011 to noon January 17, 2011.

3.1.1.1 LAPS Temperature Estimates for January 16, 2011 at 12:00 PM

Figure 14 shows the temperature distribution produced by the LAPS data assimilation step used by Meridian that excluded Clarus data for January 16, 2011 at 12:00 PM, overlaid with dots representing Clarus stations that produced temperature observations. The map areas are color coded according to the LAPS temperature estimates, with blue used for temperatures below -30 degrees C, red for temperatures above 10 degrees C, yellow for temperatures around -10 degrees C, and shadings between these colors for other values. The Clarus stations were color coded to indicate whether the observed temperature was different from the LAPS value for the corresponding location – blue if the Clarus observation was more than one degree below the corresponding LAPS value, red if the Clarus observation was more than one degree above the corresponding LAPS value, and green if the Clarus observation and the corresponding LAPS value were about equal.

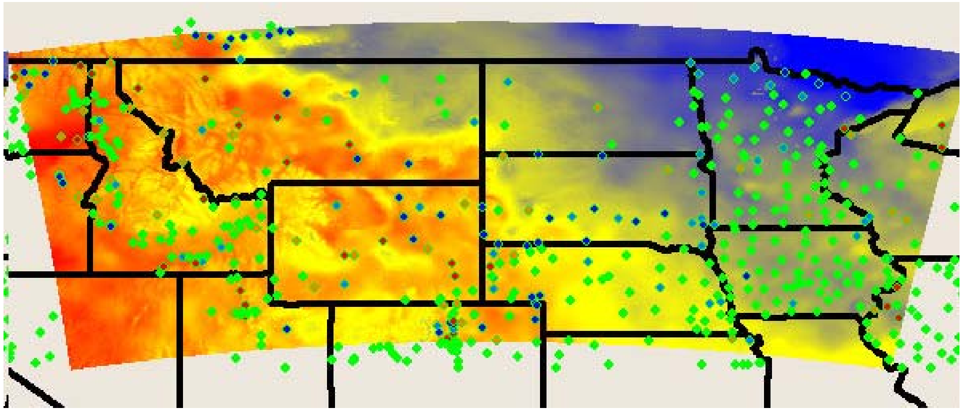


Figure 14. LAPS Temperatures (degree C), without *Clarus*, for 1/16/2011 12:00 PM

Figure 15 is a similar temperature distribution map, but for the LAPS analysis performed including the Clarus data.

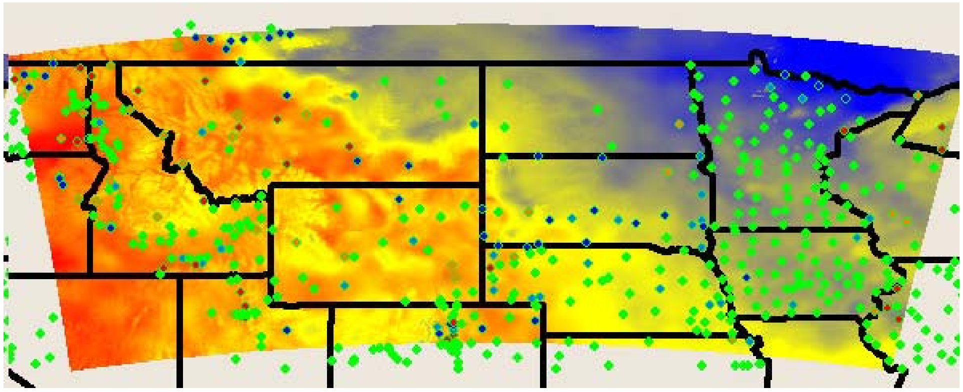


Figure 15. LAPS Temperatures (degree C), with *Clarus*, for 1/16/2011 12:00 PM

One would expect to see fewer Clarus observations that differ from the LAPS values in the second chart because inclusion of the Clarus data would "pull" the LAPS estimates closer to the observed values. This is exactly what is observed in some areas:

- In Wyoming, a number of Clarus observations that were higher than the LAPS estimates made without Clarus data are closer to the LAPS estimates made with Clarus data.
- In northern Minnesota, a cluster of observations that were below the LAPS estimates made without Clarus data are closer to the LAPS estimates made with Clarus data.
- At the intersection of Colorado and Nebraska, a cluster of Clarus values were below the LAPS estimates (without Clarus), but were much closer to the LAPS estimates made with Clarus data.
- In North Dakota, there were several isolated Clarus stations whose observations more closely matched the LAPS estimates made with Clarus data than without.

But, there were also a number of locations where differences between the observed values did not appear to be closer to the LAPS estimates made using Clarus data:

- In Canada, just north of the Montana border, there were a cluster of stations with observed temperatures lower than the LAPS estimates. In fact, there was no apparent difference to the LAPS analysis with these stations included in the analysis.
- In Idaho, there were a few stations with observed temperatures different from the LAPS estimates. However, these stations were mixed in with a much larger number of stations whose observations closely matched the LAPS estimates.
- In northern Colorado, a cluster of stations existed with temperatures that differed from the LAPS estimates, some higher and some lower. These stations were mixed in with a large number of stations whose temperatures closely matched the LAPS estimates.

Figure 16, a map that shows the difference between the LAPS temperature estimates made with and without Clarus data, shows the final impact on the LAPS estimates.

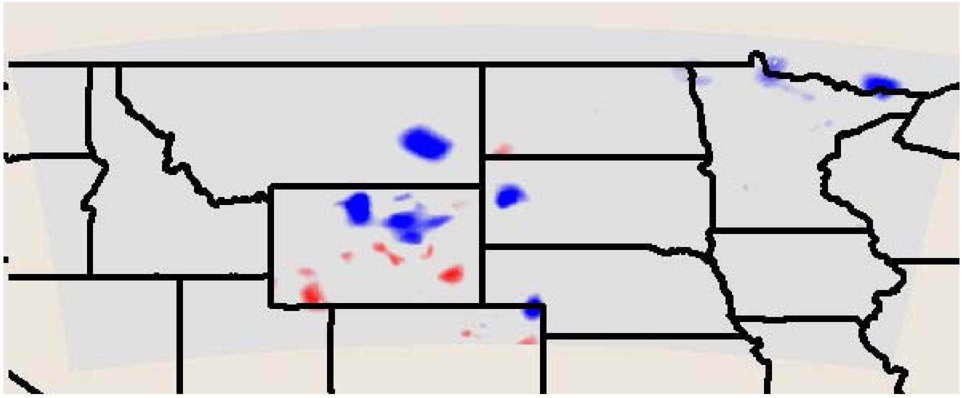


Figure 16. LAPS Temperature Difference (degree C), with *Clarus* Minus without *Clarus*, for 1/16/2011 12:00 PM

Note the cluster of higher values in southern Wyoming corresponding to a cluster of Clarus stations with higher temperatures than the LAPS estimates made without Clarus data and the clusters of lower values at the Colorado and Nebraska border and in northern Minnesota corresponding to the Clarus stations there with lower-than-LAPS temperature values. This does suggest that the Clarus observations directly impacted the LAPS results in meaningful way. In areas where Clarus observations were below LAPS estimates made without using Clarus data, including Clarus data could decrease the LAPS estimates, with analogous changes occurring in areas where Clarus observation were above LAPS estimates.

But, there were locations were Clarus observations appeared to have little impact on the LAPS estimates. In Idaho and northern Colorado, the presence of many stations with observations consistent with the LAPS estimates seemed to prevent the few stations with inconsistent observations from affecting the LAPS estimates. It was not clear why the cluster of Clarus stations in central Montana with temperature observations higher than the LAPS estimates and the cluster of stations in central South Dakota with observations lower than LAPS estimates did not seem to impact the LAPS estimates made including the Clarus data.

The impact of the Clarus data on the LAPS temperature estimates is summarized in Figure 17, which identifies different temperature ranges and depicts the percent of grid elements for which the difference in LAPS temperature estimates made with and without Clarus data is within each range.

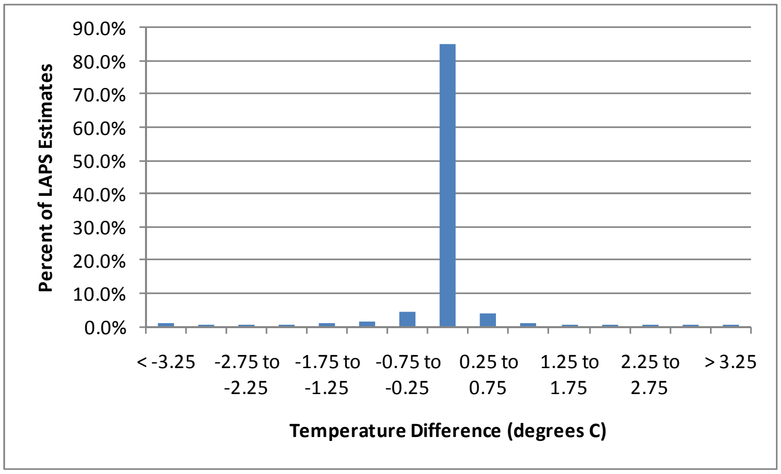


Figure 17. Summary of LAPS Temperature Difference (degree C), with *Clarus* Minus without *Clarus*, for 1/16/2011 12:00 PM

Note that for about 85 percent of the grid elements, the LAPS estimates made with and without Clarus data differed by less than 0.25 degrees Celsius. The two estimates differed by at most 1 degree Celsius for about 95 percent of the grid elements.

In summary, these figures and charts indicate that, for the LAPS estimate made on January 16, 2011 at 12:00 PM, the LAPS estimates made without Clarus data agreed closely with the Clarus observations for most stations. In these cases, including the Clarus data in the LAPS estimation process would not be expected to impact the LAPS estimates. When there was a difference between the LAPS estimates made without Clarus data and the Clarus data, including the Clarus data in the LAPS estimates only sometimes impacted the estimates.

3.1.1.2 LAPS Temperature Estimates for Eight Specific Clarus Locations

Additional insights come from examining individually the eight Clarus stations shown in Figure 18.

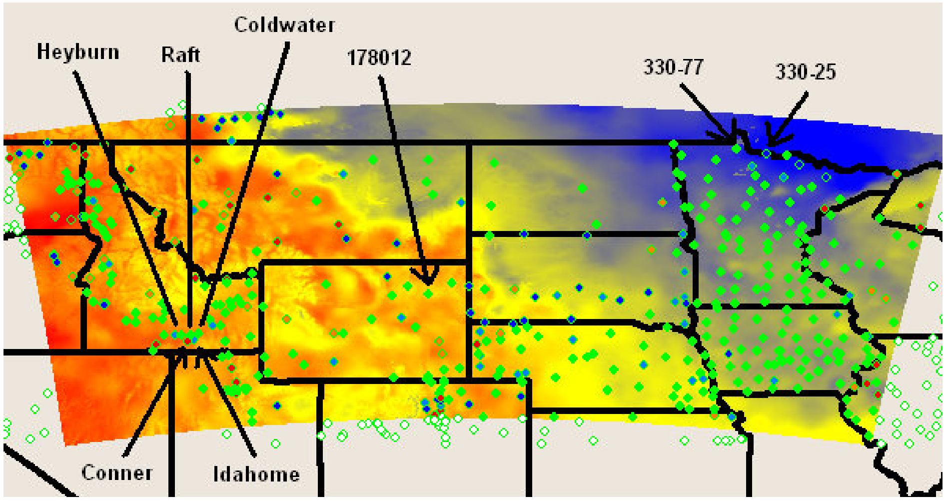


Figure 18. LAPS Temperatures for 1/16/2011 at 12:00 PM, with Eight Marked *Clarus* Stations

These stations were selected because of the following reasons:

- The 330-77 and 178012 stations were selected as examples of stations for which including Clarus data in the LAPS process improved the estimate.
- The 330-25 station was selected because it was close to the 330-77 station, but the LAPS estimate with Clarus data did not closely match the Clarus observation.
- Conner and Idahome stations were selected because the Clarus observations differed from the LAPS estimate, with the difference being positive for Conner station and negative for Idahome.
- The Heyburn, Raft, and Coldwater stations were selected because they were nearby the Conner and Idahome stations.

Figure 19 depicts the LAPS temperature estimates and Clarus observations for station 330-24 for the period from 1/16/2011 to 1/23/2011, showing the close correlation between these values.

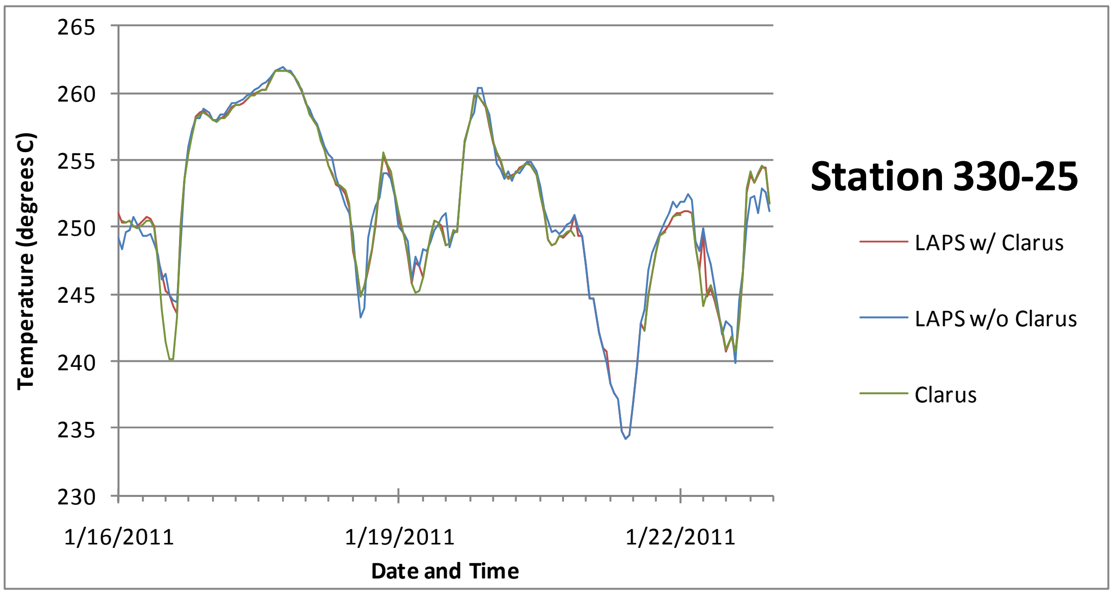


Figure 19. LAPS and *Clarus* Temperature Values (degrees C) for Station 330-25, 1/16/2011 to 1/23/2011

The main thing to note from this chart is that the LAPS estimates closely track with the observations, whether or not the Clarus data is used in the LAPS estimation process. When differences did exist (e.g., around noon on 1/22/2011), the LAPS estimates made using Clarus data tracked more closely to the observations than the LAPS estimates made without suing Clarus data.

The next chart, Figure 20, focuses on the extent to which including Clarus data in the LAPS estimation process improved the correlation of the LAPS estimates with the Clarus observations by plotting (a) the difference between the LAPS estimates made with Clarus data and the LAPS estimates made without Clarus data and (b) the difference between the Clarus observations and the LAPS estimates made without Clarus data. This chart shows:

- If the Clarus line is close to zero, it indicates that the LAPS estimates made without Clarus data matched the observations, so little improvement in the LAPS estimates would be expected by including the Clarus data.
- If the LAPS line is close to zero, it indicates that including the Clarus data in the LAPS estimates had little impact on the LAPS estimation process.
- If the LAPS line and the Clarus line are close together and away from zero, then including the Clarus data in the LAPS estimation process did a good job at correcting for differences in the LAPS estimates made without Clarus data and the Clarus observations.

At this location, there were often differences between the LAPS estimates made without Clarus data and the Clarus observations. When these differences existed, including the Clarus data in the LAPS estimates did a very good job of correcting for these differences. It is also interesting to note that, during the period when no Clarus data was available on January 21, 2011 there was little difference in the LAPS estimates, indicating that it was the Clarus observations that were causing the difference in the LAPS estimates. This is expected as introducing new observed data should refine the LAPS estimates.

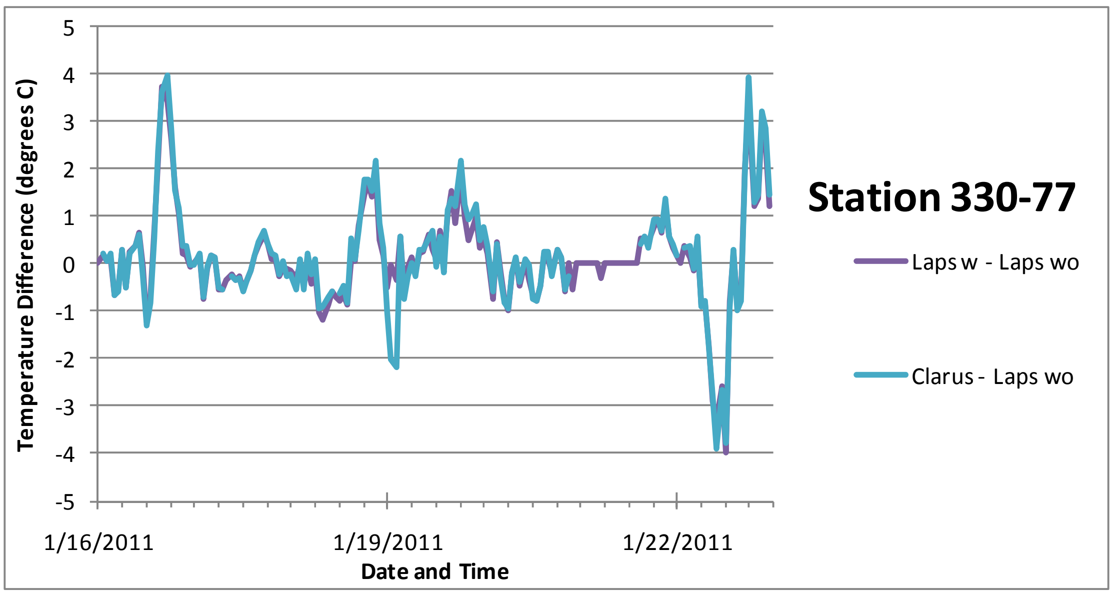


Figure 20. LAPS w *Clarus* and *Clarus* Temperature Difference (degrees C) for station 330-77, 1/16/2011 to 1/23/2011

Figure 21 depicts similar charts for the four other Clarus stations mentioned previously. Note that for Station 178012 and Station 330-25, the LAPS estimates made with Clarus data closely match the Clarus observations. However, for the Conner and Idahome stations, including Clarus data in the LAPS estimation process had little impact on the LAPS estimates, even when there were differences between these estimates and the observations.

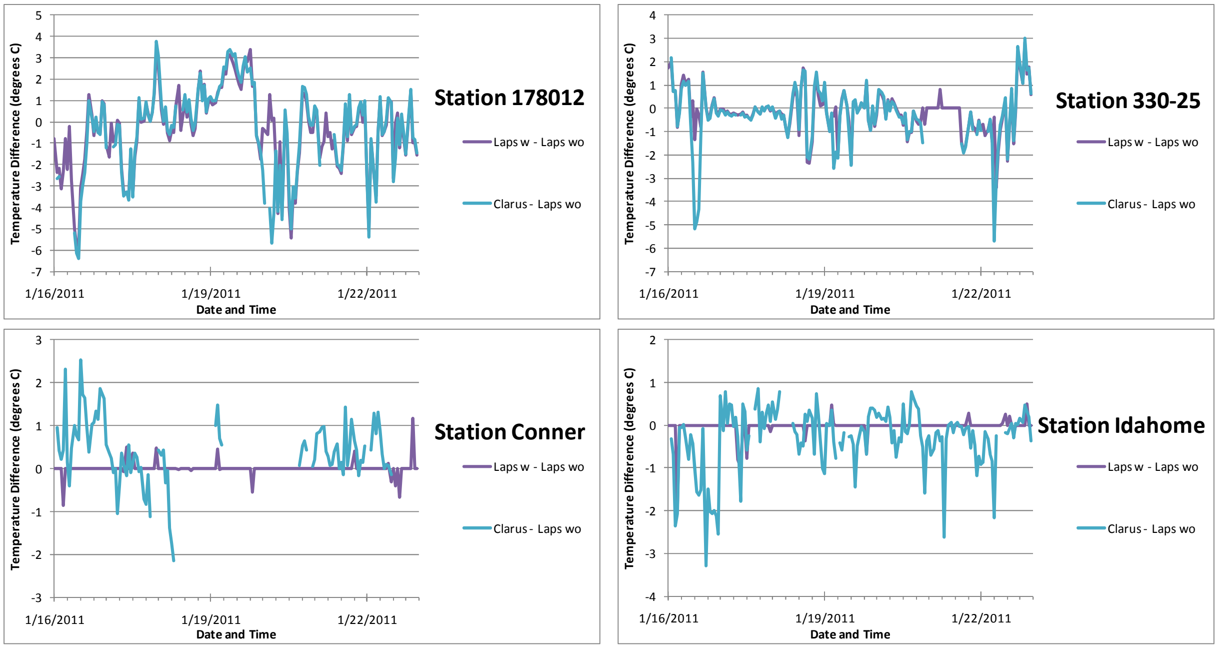


Figure 21. LAPS w *Clarus* and *Clarus* Temperature Difference (degrees C) for four stations, 1/16/2011 to 1/23/2011

So, for some stations and at some times, the inclusion of Clarus data in the LAPS estimation process resulted in the LAPS estimates closely matching the Clarus observations. At other times, the inclusion of Clarus data had little impact. This can be summarized in numerical form by computing the percentage of LAPS estimates during this one week period for which the LAPS estimate made using Clarus data was closer to the Clarus observation than the LAPS estimate made without Clarus data. The results of this calculation are listed in Table 3.

Table 3. Percent of Time *Clarus* Impacted the LAPS Estimates for Temperatures from 1/16/2011 to 1/23/2011

Clarus Station	Is Equal	Is Closer	Is Improved	Is Equal and Different	Is Closer and Different	Is Improved and Different
330-25	1%	95%	96%	1%	97%	98%
330-77	1%	92%	93%	1%	98%	99%
178012	1%	90%	91%	1%	97%	98%
Conner	91%	3%	33%	94%	3%	50%
Idahome	91%	5%	57%	91%	7%	78%
Heyburn	92%	6%	71%	90%	8%	80%
Raft	91%	4%	47%	93%	5%	71%
Coldwater	92%	4%	46%	93%	5%	67%

These metrics were selected to help answer the following questions related to the types of impacts that the Clarus observations had on the LAPS estimates.

Did the Clarus observations often impact the LAPS estimates? The “Is Equal” metric addresses this question. The “Is Equal” column indicates the percent of the LAPS estimates made with and without Clarus observations that were nearly equal (i.e., within 0.01 degrees C). When “Is Equal” is small, the Clarus observation often impacted the LAPS estimates. When “Is Equal” is large, the Clarus observation often had little impact on the LAPS estimates.

Did the Clarus observations improve the LAPS estimates? The “Is Closer” metric, which indicates the percent of LAPS estimates for which the LAPS estimates made with the Clarus data were different from those made without Clarus data and were closer to the Clarus observations, partially addresses this question. If the “Is Closer” metric is large, then including the Clarus observations in the LAPS process tended to make the LAPS estimates closer to the observed values.

This metric can be difficult to interpret. For example, if 90 percent of the LAPS estimates are about the same when made with and without Clarus data (i.e., “Is Equal” is 90 percent), then the “Is Closer” metric can be no larger than 10 percent. If the Clarus data had an entirely random impact, then the “Is Closer” metric would be about half of this maximum value – 5 percent. When the “Is Closer” metric is bigger than the value expected from an entirely random impact, then inclusion of the Clarus observations can be said to have improved the LAPS estimates by making them agree more closely with the observations.

However, the cutoff value for an entirely random impact depends on the value of the “Is Equal” metrics. For example, if the “Is Equal” metric is only 10 percent, then a value of about 45 percent for “Is Closer” (i.e., half of 100 percent minus the 10 percent that are about equal) would indicate that the Clarus data had an entirely random impact. This makes the “Is Closer” metrics difficult to interpret.

The “Is Improved” metric, which equals the “Is Closer” metrics divided by one minus the “Is Equal” metric, corrects for this by rescaling the “Is Closer” to always take a value between 0 and 1, with a value of 50 percent indicating an entirely random impact. When “Is Improved” is larger than 50 percent, then the LAPS estimates made with the Clarus observations were closer to the observed values than the LAPS estimates made without the Clarus observations.

Did the Clarus observations improve the LAPS estimates when the LAPS estimates made without Clarus observations differed from the Clarus observations? If the LAPS estimates made without the Clarus observations agreed with the Clarus observations, then including the Clarus observations in the LAPS estimation process would not be expected to impact the LAPS estimates. Including these cases in the metrics described above dilutes the ability of these metrics to measure the impact of the Clarus observations on the LAPS estimates. For example, if the LAPS estimates made with Clarus observations agreed with the Clarus observations 90 percent of the time, then “Is Equal” would be at least 90 percent, even if including the Clarus observations in the LAPS estimation process improved the estimates every time the observations differed from the LAPS estimates. The “and Different” metrics correct for this by excluding from the computation of the metrics all cases where the LAPS estimate made without Clarus data are within 0.2 degrees Celsius of the Clarus observations. For example, the “Is Equal and Different” metric indicates the percent of cases for which the LAPS estimates made with and without Clarus observations were about equal, despite the fact that Clarus observations differed from the LAPS estimates.

For these eight stations, the “Is Equal” columns shows that the inclusion of Clarus data in the LAPS estimation process often impacted the estimates for the three stations at the top of the table, but seldom impacted the estimates for the five stations at the bottom of the table. The “Is Improved” metric indicates that, when the Clarus observations impacted the LAPS estimates, the LAPS estimates matched more closely to the observations. This is clarified further by looking at the “and Different” metrics. When a difference existed between the LAPS estimates made without Clarus observations and the Clarus observations at these eight stations, including the Clarus observations in the LAPS estimation process consistently resulted in LAPS estimates that were closer to the Clarus observations.

In other words, these metrics indicate that for three of the stations, the inclusion of the Clarus data often impacted the LAPS estimates and, when it did impact the estimates, usually improved them. For the other five stations, the Clarus data seldom impacted the LAPS estimates and, when it did impact the estimates, did not consistently improve them. A later section of this report will apply these same metrics to all the Clarus stations in the study region.

Impacts of *Clarus* Data on LAPS Estimates throughout the Study Period

The previous section demonstrated the types of impacts that the Clarus data had on the LAPS temperature estimates and provided examples of metrics that could be used to assess and summarize these impacts. This section will extend those results by considering those metrics across the entire region and throughout the entire study period. The following performance metrics will be considered:

No Change. This metric is the percent of LAPS grid elements for which the estimates made with and without Clarus data were within a specified range of each other. For example, in the previous section it was observed that the LAPS temperature estimates made with and without Clarus data were within 0.25 degrees Celsius of each other 85 percent of the time. In order to refer to this concisely in the text and charts below, this will be written as “NoChange(0.25) = 85%”. If this metric is close to 1, then the impact of the Clarus data seldom exceeded the specified range. If this metric is close to 0, then it almost always exceeded the specified range. (Note that this metric captures in a numeric way the information presented in Figure 16 on page 23 by indicating the percentage of the map that would be colored gray.)

Is Equal. This metric indicates the percent of the LAPS estimates for locations with Clarus stations for which the estimates made with and without Clarus observations were nearly equal (i.e., within 0.01 degrees C). In other words, the Is Equal metric is the same as the No Change metric, but restricted to the grid elements where Clarus observations were available.

Is Improved. The Is Improved metric takes values between 0 and 1, with a value of 100 percent indicating that including the Clarus data in the LAPS estimates always improved the LAPS estimates when a difference existed, a values of 0 percent indicating that including the Clarus data never improved the LAPS estimates, and a value of 50 percent indicating an entirely random impact.

3.1.2 Impacts of *Clarus* Data on LAPS Temperature Estimates

The LAPS performance metrics introduced in Section 3.1.1.2 and applied to individual stations can, when applied to all the Clarus stations in the study area, provide a mechanism for assessing the overall impact of the

Clarus data on the LAPS estimates. Figure 22 depict the Is Equal and Is Improved metrics computed across all Clarus stations for each week for which data was available.

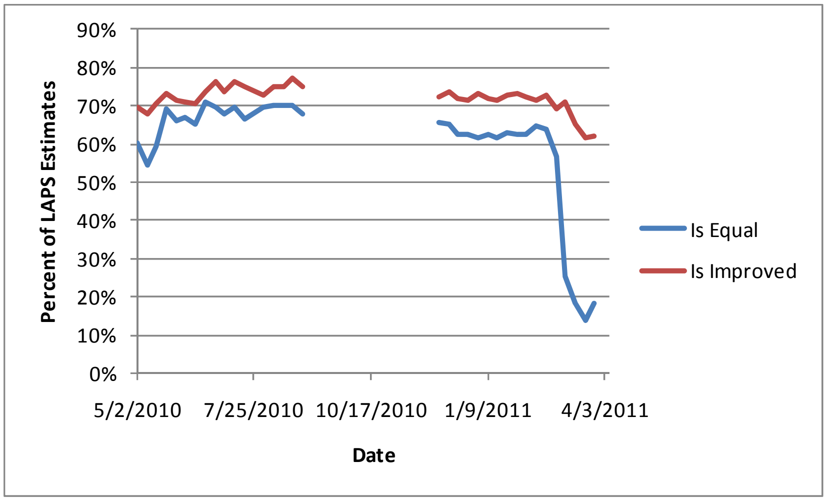


Figure 22. The Is Equal and Is Improve Performance Metrics for LAPS Temperature Estimates

These charts reinforce the conclusions drawn in the previous sections. Recall, it is desirable that the Clarus data have an impact on the LAPS estimates and improve those estimates in the sense of making the estimates agree more closely with the observations. The Is Equal metric (blue line) indicates whether the Clarus data impacted the LAPS estimates, with a lower value indicating that an impact did exist. (It's like playing golf – lower score is best.) Prior to March 2011, the Clarus data had little or no impact on the LAPS estimates between 60 and 70 percent of the time. Starting in March 2011, the Clarus data had no impact about 15 percent of the time.

The Is Improved metrics (red line) indicates whether the inclusion of Clarus data in the LAPS estimation process resulted in estimates that were closer to the observed value. When the Clarus data did impact the LAPS estimates, it improved the estimates more than 70 percent of the time for much of the study period. This percentage dropped to about 60 percent in March 2011. (Since random changes to the LAPS estimates would be closer to the Clarus observations about 50 percent of the time, a value above 50 percent indicates that the impact of the Clarus observations is better than would have been achieved by chance alone.) Thus, the changes in March 2011 increased the frequency with which the Clarus observations impacted the LAPS estimates, but the changes induced by the Clarus data were less likely to make the LAPS estimates more consistent with the observations.

Figure 23 shows the No Change metric for the LAPS temperature estimates.

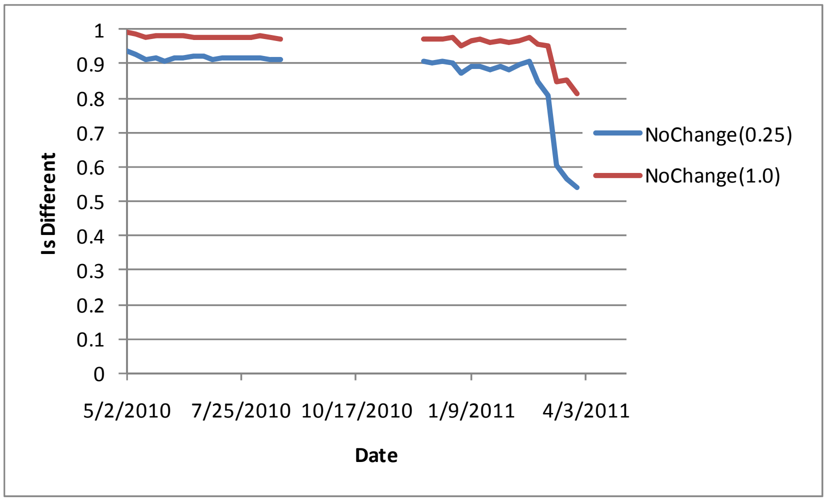


Figure 23. The No Change Performance Metrics for LAPS Temperature Estimates

Throughout most of the study period, the inclusion of Clarus data in the LAPS estimates resulted in a difference of less than 1 degree Celsius about 95 percent of the time. It is interesting to note that, even though Clarus stations existed in less than 0.01 percent of the LAPS grid elements, including Clarus data in the LAPS estimates impacted the estimates for about 5 percent of those elements. In other words, including the Clarus data in the LAPS estimates impacted not just the grid elements at which the Clarus stations were located – it impacted the estimates for many nearby grid elements.

This is further demonstrated in Figure 24, which shows the absolute value of the temperature difference between the LAPS estimates made with and without Clarus data, averaged over each month during the study period. The maps in this figure show the absolute value of the difference in LAPS estimates, averaged over each month from April to August 2010 and from December 2010 to March 2011, arranged chronologically from left to right, then top to bottom. Values of 0 degree Celsius were colored gray, values of 1 degree Celsius were colored yellow, and values above 2 degrees Celsius colored red. Values between these values were shaded with colors intermediate to those listed.

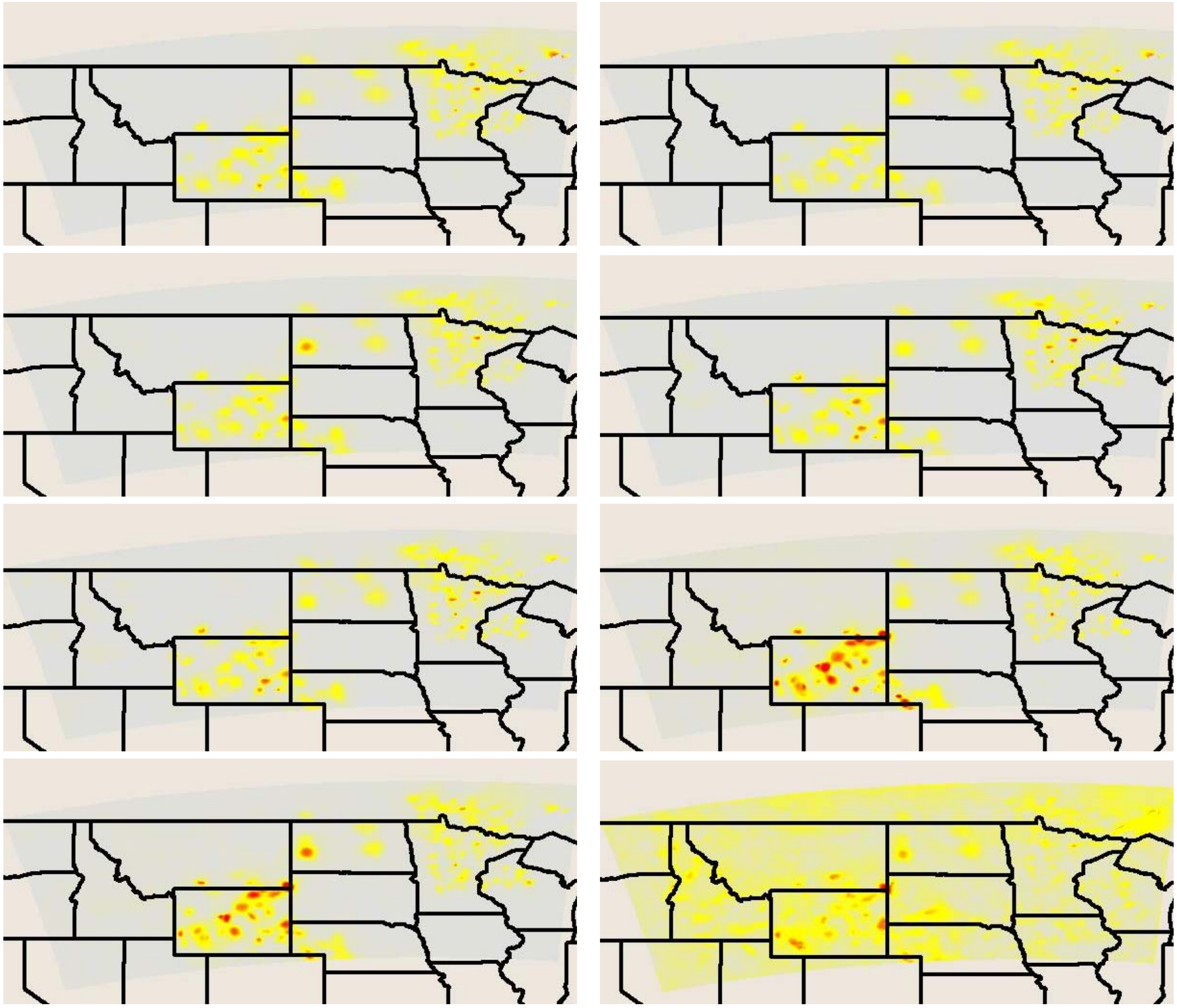


Figure 24. Maps of Monthly Average Difference in LAPS Temperature Estimates, April 2010 through March 2011

As indicated by the No Change metric, the inclusion of Clarus data impacted the LAPS estimates at only a small percentage of the map location throughout most of the study period. Prior to March 2011, most locations had no difference with the differences that occurred being concentrated in Wyoming, Minnesota, North Dakota, and Nebraska. After March 2011, the differences were spread more evenly throughout the country.

3.1.3 Impacts of *Clarus* Data on LAPS Dew Point Temperature Estimates

Similar results to those described in the previous sections were observed when other weather variables were examined. The charts below present results for the dew point temperature. The first chart, Figure 25, shows the LAPS estimate for January 16, 2011, along with the Clarus stations color-coded according to the extent the Clarus observations match the LAPS estimate. For the purpose of this section, the most important characteristic of this chart is that it indicates the Clarus stations for which dew point temperature observations are available.

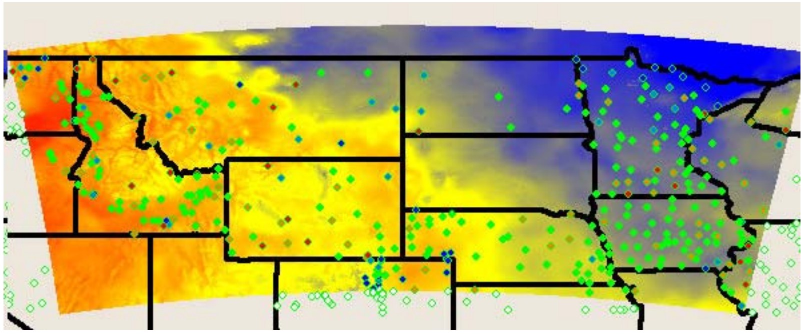


Figure 25. LAPS Dew Point Temperature Estimates with *Clarus* Stations, January 16, 2011

Figure 26 depicts the difference in the LAPS dew point estimates made with and without Clarus data. As with the LAPS temperature estimates examined previously, there was a marked change in the LAPS estimation process in March 2011.

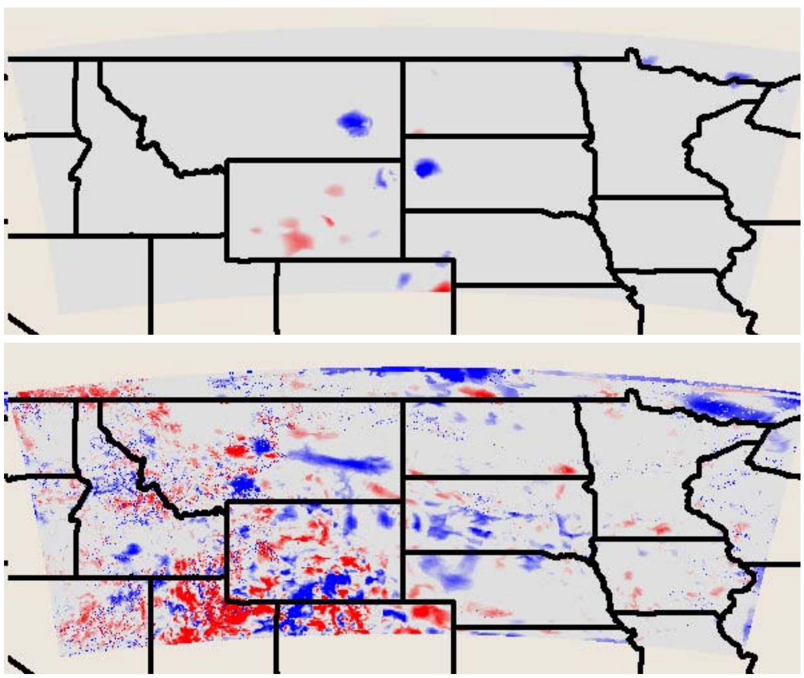


Figure 26. LAPS Dew Point Temperature Differences, With *Clarus* minus Without Clarus, 1/16/2011 at 12:00 PM (top) and 3/21/2011 at 12:00 PM (bottom)

The impact of this change is reflected in the LAPS performance metrics shown in Figure 27. Note that the Is Improved metric is less than 50 percent – significantly less than the 70 percent value for LAPS temperature estimates – indicating that inclusion of Clarus data in the LAPS estimate did not improve agreement between the LAPS estimates and the Clarus observations.

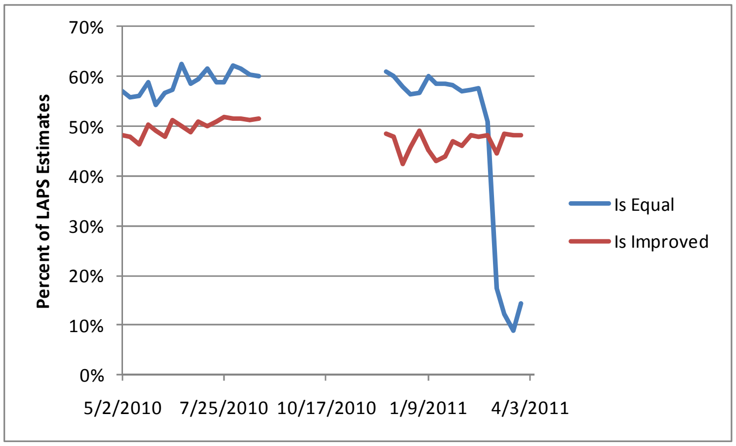


Figure 27. LAPS Is Equal and Is Improved Performance Metrics for Dew Point Temperature

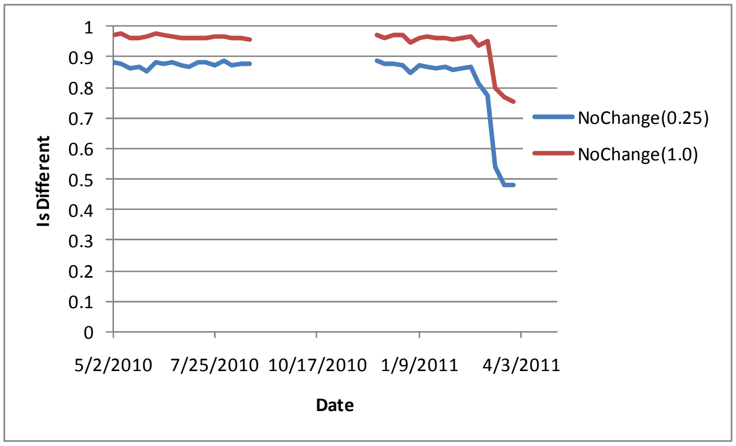


Figure 28. LAPS No Change Performance Metric for Dew Point Temperature

As with the temperature data, including the Clarus data in the LAPS estimates often had no impact on the estimates – an impact was observed at about 40 percent of grid elements where Clarus stations existed and about 5 percent of grid elements overall. Unlike the temperature data, the Clarus data did not tend to improve the dew point temperature estimates – the Is Improved metric is close to, but below, 50 percent.

3.1.4 Impacts of *Clarus* Data on LAPS Relative Humidity Estimates

The LAPS estimates for relative humidity on January 16, 2011 at 12:00 PM, along with the Clarus stations for which relative humidity observations were available, is shown in Figure 29. The difference between the LAPS relative humidity estimates made with and without Clarus data is shown in Figure 30.

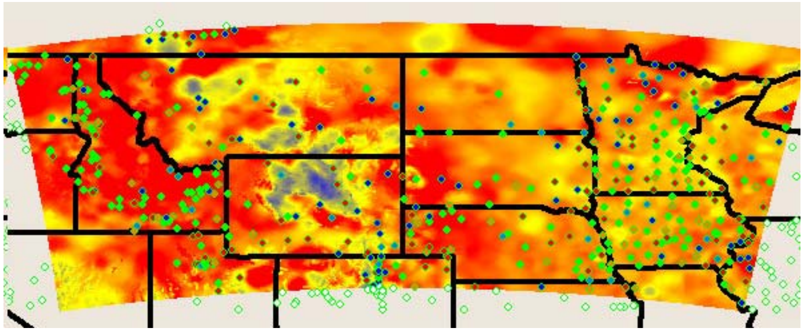


Figure 29. LAPS Relative Humidity Estimates with *Clarus* Stations, January 16, 2011

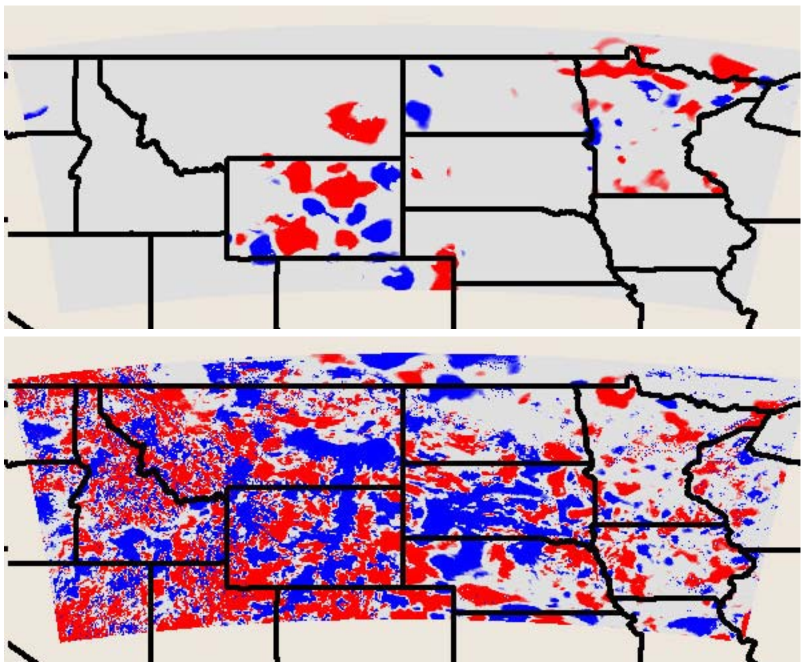


Figure 30. LAPS Relative Humidity Differences, With Clarus minus Without Clarus, 1/16/2011 at 12:00 PM (top) and 3/21/2011 at 12:00 PM (bottom)

The Is Equal and Is Improved performance metrics for the LAPS relative humidity estimates are shown in Figure 31. In this case, including Clarus data in the LAPS estimation process did improve the agreement between the Clarus observations and the LAPS estimates.

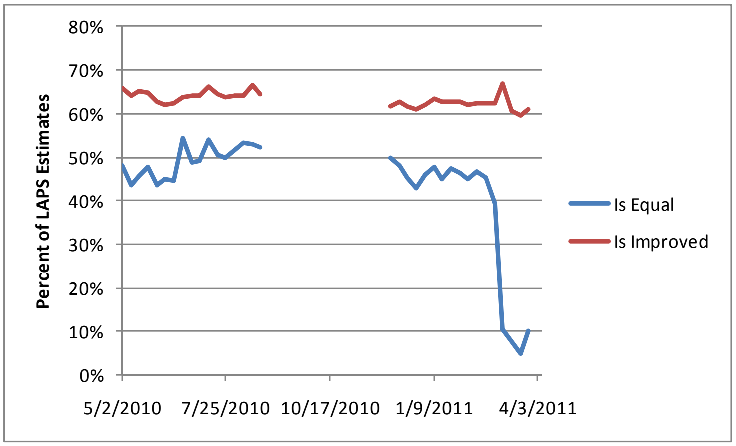


Figure 31. LAPS Is Equal and Is Improved Performance Metrics for Relative Humidity

This chart indicates that the Clarus data only impacted the LAPS relative humidity estimates at locations with stations present about 50 percent of the time throughout most of the study period. And, as with the temperature estimates, including the Clarus data tended to increase the agreement between the LAPS estimates and the Clarus observations.

Figure 32 depicts the No Change performance metric for relative humidity, indicating that including the Clarus data in the LAPS estimation process resulted in a change in of at least 5 percent relative humidity about 5 percent of the time.

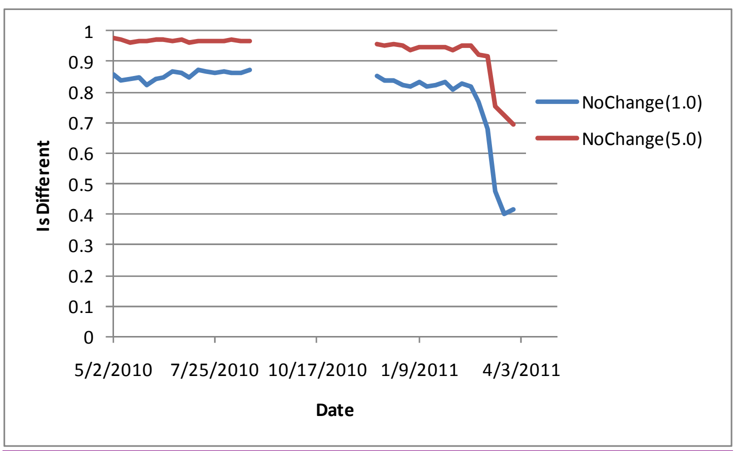


Figure 32. LAPS No Change Performance Metric for Relative Humidity

3.1.5 Impacts of *Clarus* Data on LAPS Wind Speed and Surface Pressure Estimates

Similar results held for wind speed, as shown in Figure 33, which depicts the Is Equal and Is Improved performance metrics for LAPS wind speed estimates. The Clarus data did not often impact the wind speed estimates (Is Equal between 20 and 40 percent). When it did impact the estimates, it tended to improve them (Is Improved around 57 percent).

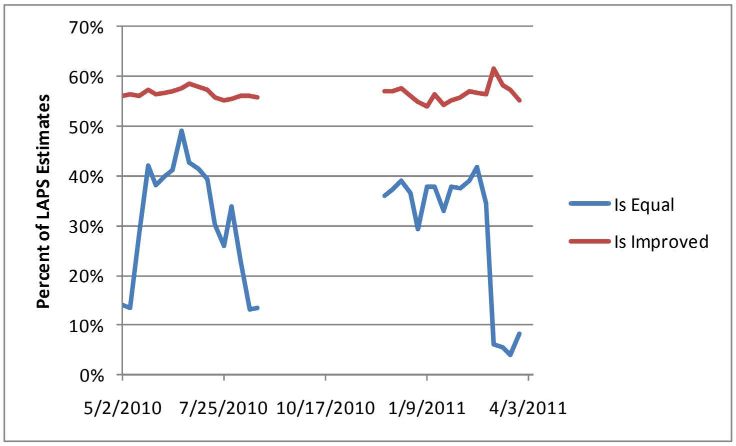


Figure 33. Performance Metrics for LAPS Wind Speed Estimates

Figure 34 (which depicts these performance metrics for LAPS surface pressure estimates) indicates that the Clarus data seldom impacted LAPS surface pressures estimates (i.e., the Is Equal metric is close to 100 percent).

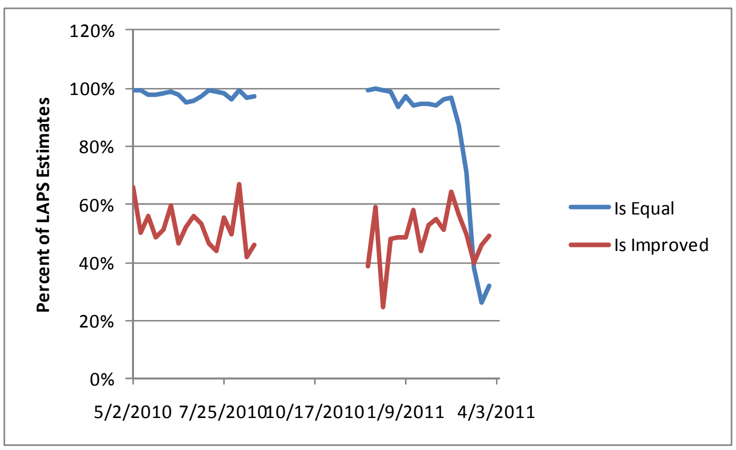


Figure 34. Performance Metrics for LAPS Surface Pressure Estimates

LAPS Temperature Estimates for March 21, 2011 at 12:00 PM

In March 2011, the Meridian team made some significant changes to their LAPS analysis process, greatly increasing the responsiveness of the LAPS estimates to the Clarus values. In particular, the Is Equal value averaged across all Clarus stations dropped from about 60 percent on March 4, 2011 to 30 percent on March 6, then dropped even further on March 16. In other words, prior to March 4, 2011, the LAPS temperature estimates made with and without Clarus data were essentially the same about 60 percent of the time. After March 16, 2011, these estimates were the same only about 15 percent of the time. This is demonstrated in Figure 35, which shows the difference in the LAPS temperature estimates made with and without Clarus data for January 16, 2011 at 12:00 PM (on the left) and for March 21, 2011 at 12:00 PM (on the right).

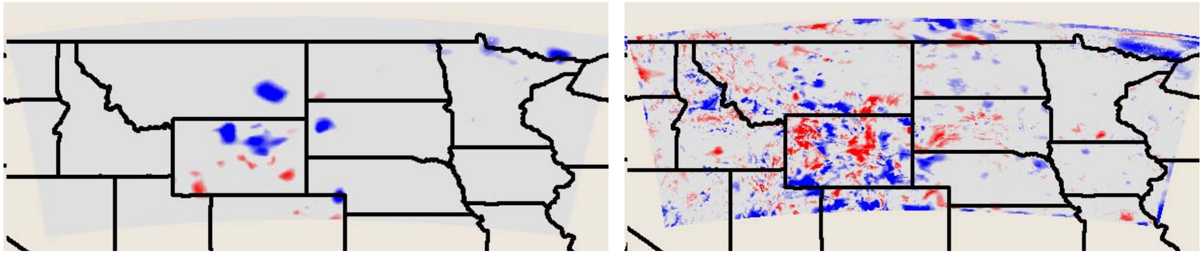


Figure 35. LAPS Temperature Difference (with *Clarus* minus without *Clarus*), 3/21/2011 at 12:00 PM

Figure 36 depicts the LAPS temperature estimate distribution with the Clarus stations for the estimates made with and without Clarus data.

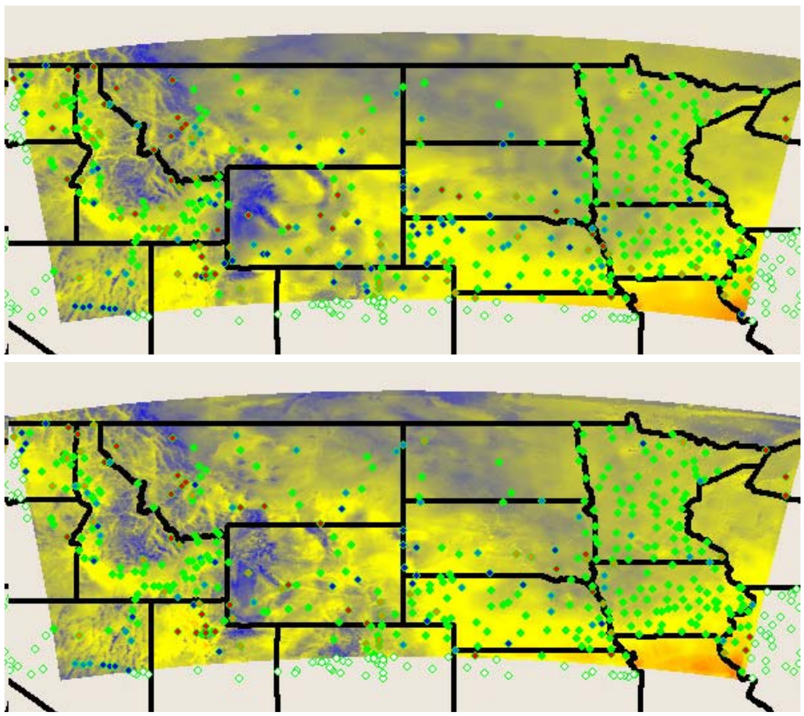


Figure 36. LAPS Temperature Estimates, without (top) and with (bottom) *Clarus*, 3/21/2011 at 12:00 PM

Table 4 lists the performance metrics for the eight stations previously considered.

Table 4. Improvement in LAPS Estimates with Inclusion of *Clarus* Data, March 21, 2011

Clarus Station	Is Equal	Is Closer	Is Improved	Is Equal and Different	Is Closer and Different	Is Improved and Different
330-25	4%	91%	94%	2%	91%	93%
330-77	3%	71%	73%	1%	78%	79%
178012	0%	72%	72%	0%	84%	84%
Conner	10%	43%	48%	11%	50%	56%
Idahome	10%	59%	66%	11%	72%	81%
Heyburn	12%	52%	59%	13%	60%	69%
Raft	10%	59%	66%	10%	71%	79%
Coldwater	7%	65%	69%	8%	75%	82%

This table also exemplifies the changes that occurred with the changes to the LAPS estimation process, with the Is Equal metric indicating that the LAPS estimates made with Clarus data seldom equaled the estimates without Clarus data.

Summary and Conclusions

The inclusion of Clarus data in the LAPS initialization did result in LAPS estimates that more closely matched observations for many types of surface observations. During most of the study period, including Clarus data in the LAPS estimation process impacted observations at about half the locations where observation stations were present. When the Clarus data did impact the LAPS estimate, the estimates more closely matched observations about 70 percent of the time for surface temperature, more than 60 percent of the time for relative humidity, and about 55 percent of the time for wind speed. For dew point temperature and surface pressure, including Clarus data in the LAPS estimation process improved the estimates about half the time, which is no better than would have been achieved by random changes to those estimates.

During the last month of the study period, the LAPS estimation process was modified and the Clarus data was much more likely to impact the LAPS estimates. For surface temperatures, the LAPS estimates were impacted more than 80 percent of the time during the last month, as opposed to less than 40 percent of the time during the earlier months of the study. However, these changes also decreased the frequency with which the Clarus data improved the LAPS estimates.

These results suggest that including Clarus observations in weather forecasts has the potential to improve forecasts – if the improvements in the initialization data carry forward into the forecasts themselves. (That is the subject of the next section of this report.)

4 The Impact of *Clarus* Data on the Atmospheric Weather Models

The previous section described the impacts of Clarus data on the LAPS estimates used to initialize the Meridian atmospheric weather models. This section describes the impact of the Clarus data on the weather model forecasts.

How *Clarus* Data Impacts the Models

The Clarus data impacts the atmospheric weather models through its impact on the model initialization data – the weather model that included Clarus data would have a different starting point then the weather model that excluded that data because of the impact of the Clarus data on the model initialization data. The amount of difference in the starting point data should give an indication of the amount of difference the Clarus data makes in the weather models. A large difference between the with- and without-Clarus initialization data would suggest a large difference in the weather models is likely. As the weather model evolves forward from this starting point, it is possible that the differences introduced by the Clarus data could dissipate, or the differences could grow.

However, there is another factor that could prevent the changes in the initialization data from carrying forward into the model forecasts. Most atmospheric weather models have what is called a "spin-up" period during which the model forecasts are not stable. The origin of "spin up" is that the initialization data can be inconsistent with the full complexity of the weather physics built into the weather models. For example, increasing the temperature estimate for a grid point decreases the density of the air at that grid point, which would encourage local rising air currents drawing in air from nearby (cooler) areas. (This is the origin of sea breezes – the sea heats more slowly than nearby land after sunrise, creating a temperature difference that induces the sea breeze. Cool, sea air at ground level flows into the space created by rising warm over the land. The rising warm air circulates out to sea at higher elevations to replace the air being drawn into land at lower elevations. The result, viewed from the side, is a circular circulation pattern.)

During this spin-up period, the weather models can introduce large changes in the initialization data in order to force the forecasts to be more consistent with the physics of weather. These large changes during the spin-up period can washout small differences in initialization data.

Impacts of *Clarus* Data on Weather Forecasts during the Week of January 16, 2011

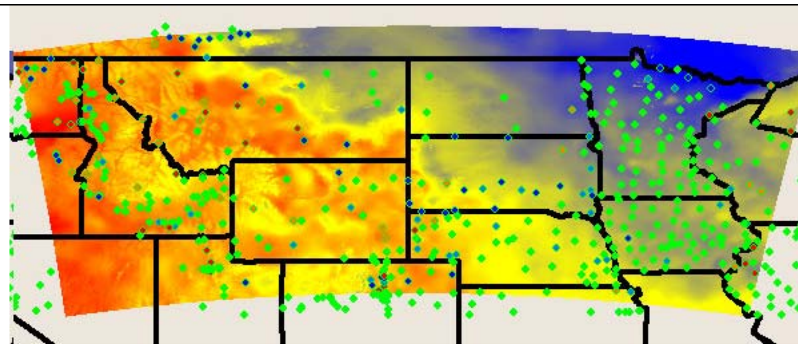
This section uses similar methods to those used in the LAPS assessment to evaluate the impact these changes in the LAPS estimates have on the WRF forecasts. The differences in the LAPS estimates and WRF forecasts do require some changes in approach. First, the WRF forecasts cover a period of time after the forecast initialization and results could change over time. For example, the weather forecasts made using Clarus data could more closely match the observations early in the forecasts (when the impact of the initialization data would be strongest) and grow smaller at later times. So, most of the results of this section will be presented as time series based on the forecast hour so these changes can be identified.

The second change has to do with the fact that, over time, weather tends to move and the effect of the Clarus observations observed in the previous section tended to be local in nature. Thus, a change in LAPS estimates that might be caused by a Clarus observation will mostly affect an area around the Clarus station and will, over time, migrate away from that station. If there is a second Clarus station “downstream” of the first, then the impact of the LAPS changes will be seen when comparing observations at this second Clarus station to the WRF forecasts. If not, the impact will not be seen in any performance metrics based on surface observations. For this reason, this section will include evaluation of additional metrics meant to correct for this weakness in the LAPS performance metrics when applied to the WRF forecasts.

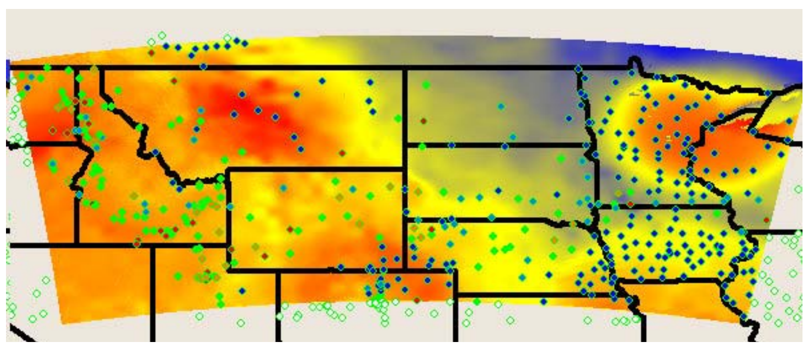
4.1.1 WRF Temperature Forecasts during the Week of January 16, 2011

Figure 37 depicts the LAPS estimate for January 16, 2011 at 12:00 PM and a time-series of the forecasts produced from the January 16, 2011, 12:00 PM forecast run.

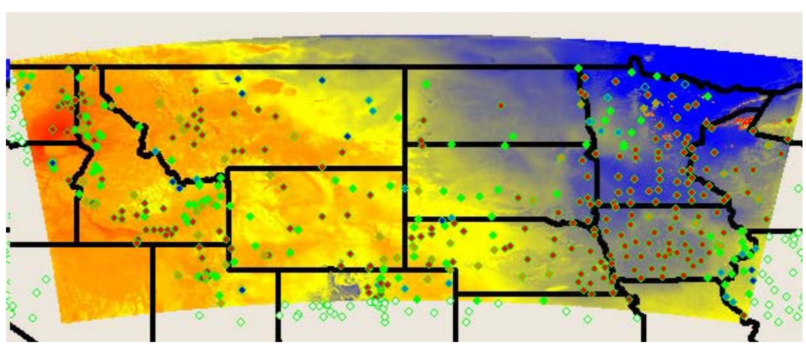
LAPS temperature estimate for 1/16/2011 at 12:00 PM



WRF 1/16/2011, 12:00 PM temperature forecast for 1/16/2011 at 12:00 PM (0 hr)



WRF 1/16/2011, 12:00 PM temperature forecast for 1/16/2011 at 2:00 PM (2 hr)



WRF 1/16/2011, 12:00 PM temperature forecast for 1/16/2011 at 3:00 PM (3 hr)

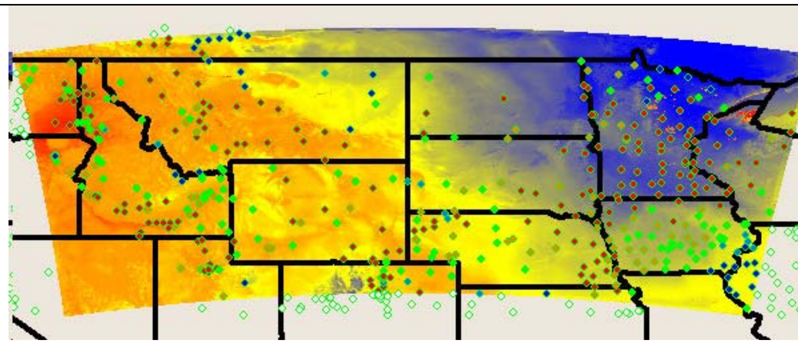
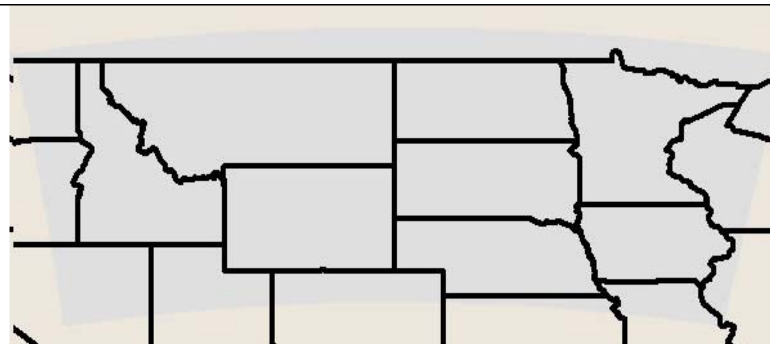


Figure 37. A Series of WRF Temperature Forecasts on 1/16/2011

Note that the first forecast included an anomalous area of high temperatures near the border of Minnesota and Michigan. This is a remnant of the “spin up” process, indicating that the weather model was not yet producing stable weather forecasts. Note also that much of the detail present in the initialization data was lost during this spin-up process, do that the small changes introduced into the LAPS initialization data were washed out by the large changes that occurred during spin-up.

This is further reinforced by the maps in Figure 38, which shows the difference between the WRF forecasts made with and without Clarus data for the first forecast hour (the 0 hr forecast at the top) and the next hour (the 1 hr forecast at the bottom) for which forecasts were available. Note that the top map shows essentially no difference between the two forecasts existed for the surface temperatures for the first forecast, but that small differences did exist for the next forecast. Thus, despite the fact that the Clarus data did introduce differences in the initialization data for this forecast (see Figure 16 on page 23), these differences are not apparent in the initial forecast produced by the weather model.

Difference in WRF 1/16/2011, 12:00 PM temperature forecasts with and without *Clarus* data for 1/16/2011 at 12:00 PM (0 hr)



Difference in WRF 1/16/2011, 12:00 PM temperature forecasts with and without *Clarus* data for 1/16/2011 at 2:00 PM (1 hr)

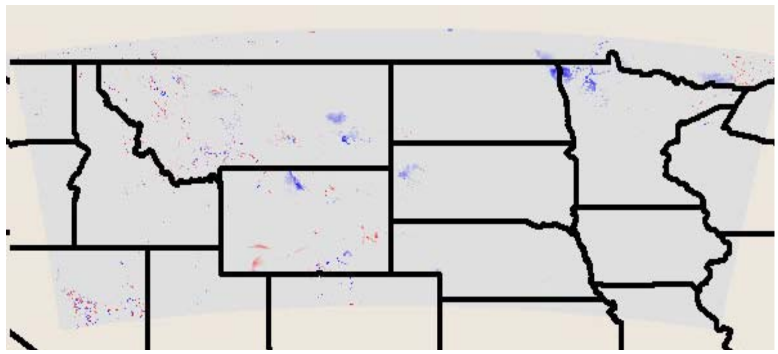


Figure 38. Difference in Temperature Forecasts With and Without *Clarus* Data on 1/22/2011

These results were also typical of those observed by examining forecasts made throughout the study period – the Clarus data introduced differences in the LAPS estimates used to initialize the weather models, but these differences did not appear in the initial model forecasts and these initial forecasts often included anomalies that suggest the part of the impact of the initialization data was being washed out as model spin-up occurred. Additional examples of this are shown in Figure 39, Figure 40, and Figure 41.

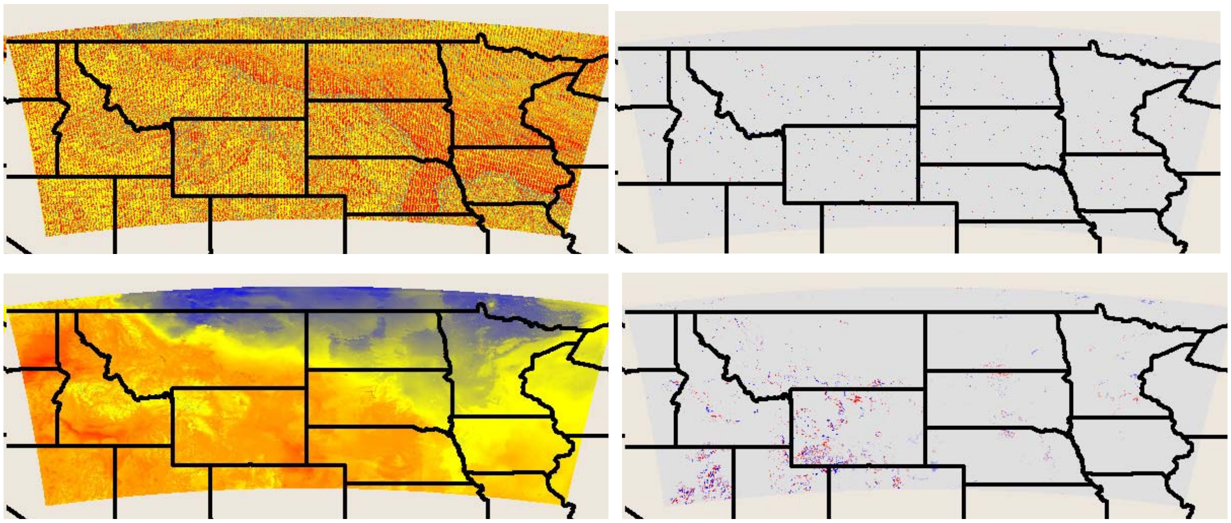


Figure 39. WRF 1/17/2011, 12:00 PM temperature 0 hr and 1 hr forecasts (left) and Difference in Forecasts With and Without *Clarus* Data (right)

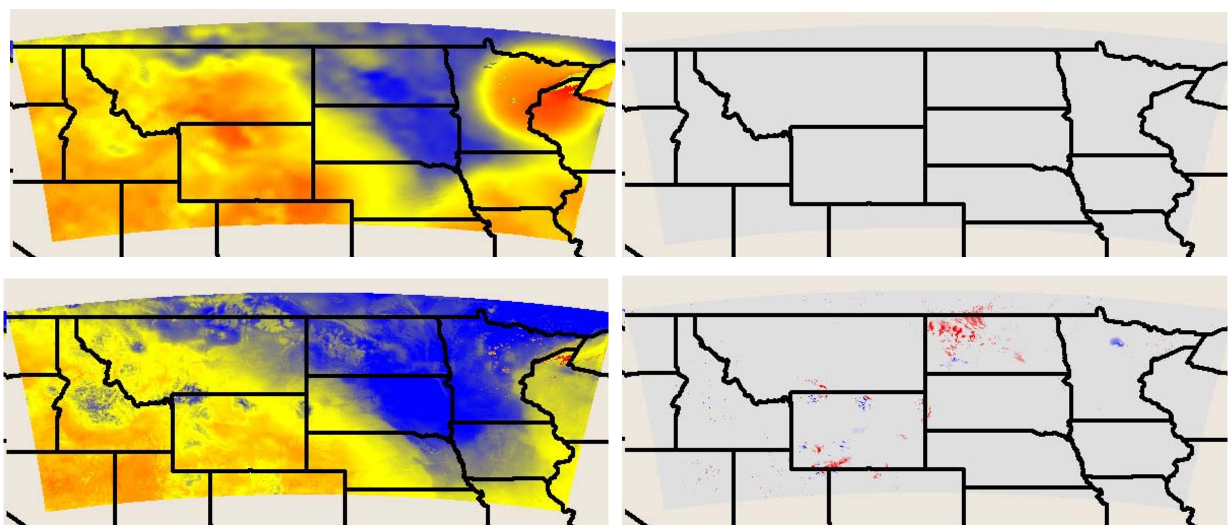


Figure 40. WRF 1/19/2011, 12:00 PM temperature 0 hr and 1 hr forecasts (left) and Difference in Forecasts With and Without *Clarus* Data (right)

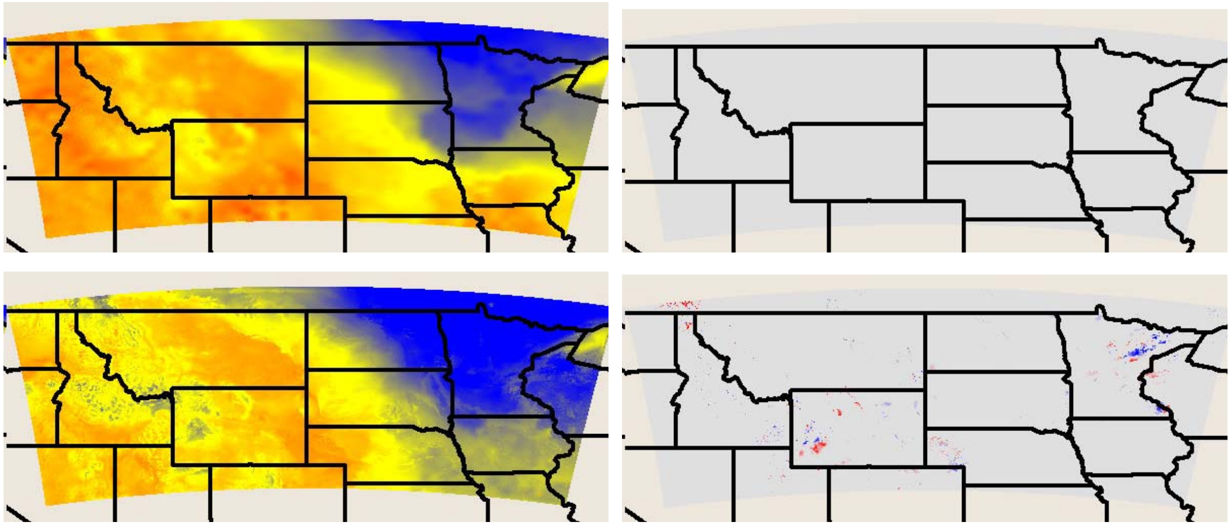


Figure 41. WRF 1/22/2011, 12:00 PM temperature 0 hr and 1 hr forecasts (left) and Difference in Forecasts With and Without *Clarus* Data (right)

Note that, in each of these examples, the 0 hr WRF forecast showed anomalies, ranging from the pixilated data apparent in Figure 39 to the lack of detail in Figure 41, and little or no difference existed in the WRF temperature 0 hr forecasts with and without Clarus data. However, the 1 hr forecasts did not include such anomalies and differences existed in the WRF temperature forecasts with and without Clarus data. The evaluators reviewed many WRF forecasts throughout the study period, and these results were typical of these forecasts.

4.1.2 WRF Temperature Estimates for Eight Specific *Clarus* Locations

The WRF forecasts at the eight Clarus stations previously considered provide further demonstration of this behavior. Figure 42 depicts the WRF forecasts, with and without Clarus data, and the Clarus observations at the two stations in northern Minnesota.

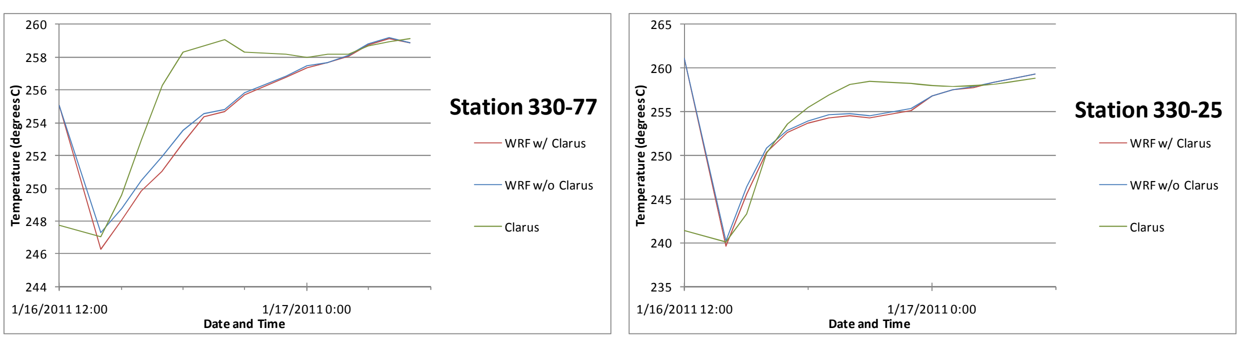


Figure 42. WRF Temperature 1/16/2011 12:00 PM Forecasts With and Without *Clarus* Data at Stations 330-77 and 330-25

Referring back to Figure 37, this is an area of the study region where the WRF forecasts showed anomalously high temperatures during the initial forecast. This same pattern appears in the data at these two stations –

temperature forecasts that were much higher than observations during the initial forecast hour, but more closely approximated the observed values at later forecast times, with little difference between the forecasts made with and without Clarus data.

At Station 178012, located in northeastern Wyoming, and the five stations in southern Idaho (Heyburn, Raft, Coldwater, Conner, and Idahome), the situation was different. In these regions, the WRF forecasts showed less detail during the initial forecast period than in later periods, but did not show a general pattern of temperatures consistently above or below nearby observations. The charts in Figure 43 show WRF forecasts at each of these stations, along with the Clarus observations. Note that there is little difference between the WRF forecasts made with and without Clarus data.

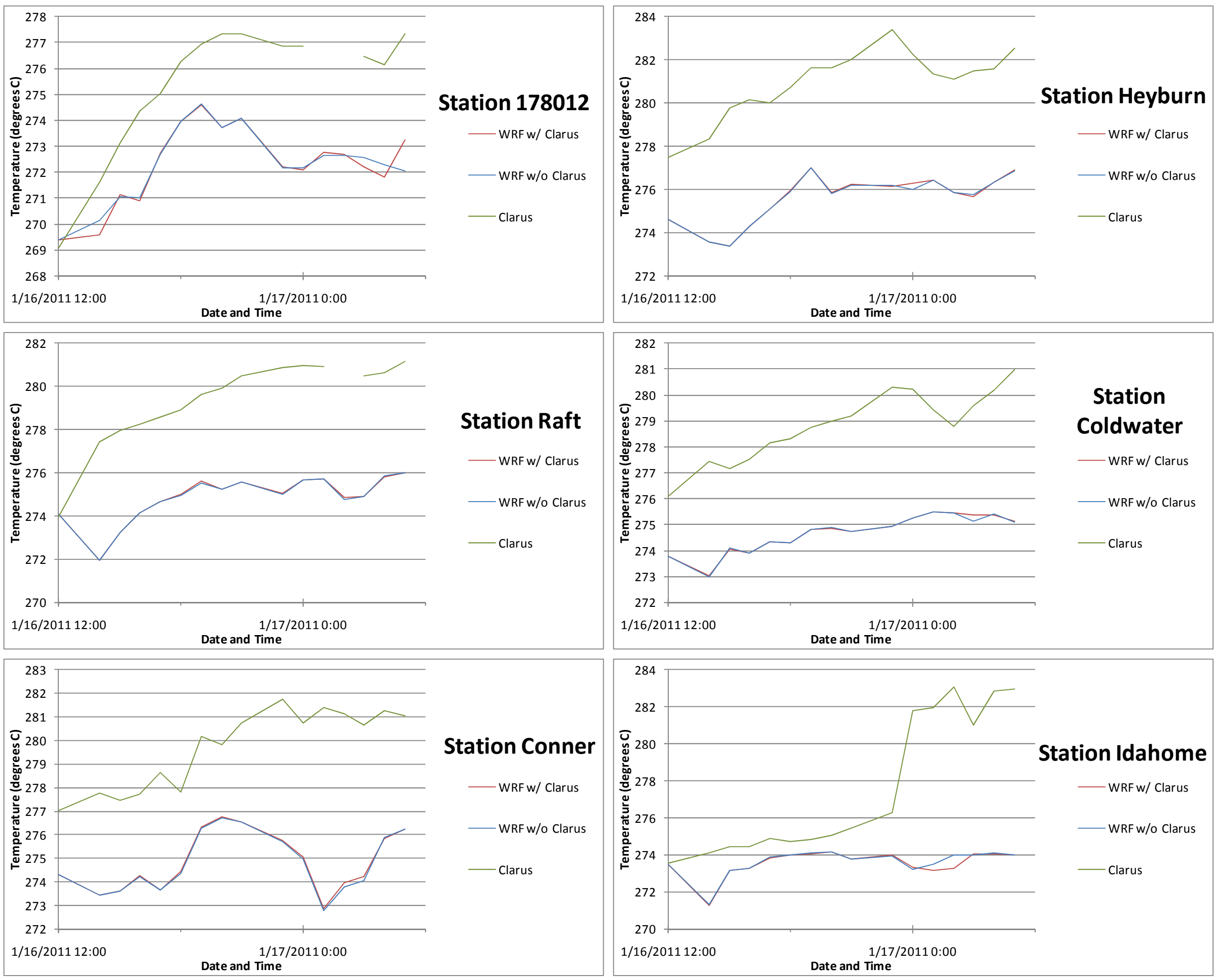


Figure 43. WRF Temperature 1/16/2011 12:00 PM Forecasts With and Without *Clarus* Data at Six *Clarus* Stations

Table 5 summarizes these results by listing the Clarus observations, LAPS estimates, and WRF forecasts for 1/16/2011 12:00 PM.

Table 5. WRF Temperature 1/16/2011 12:00 PM Forecasts With and Without *Clarus* Data at Eight Stations

Clarus Station	Clarus Observation	LAPS		WRF	
		w/o Clarus	w/ Clarus	w/o Clarus	w/ Clarus
330-25	241.4	246.6	245.2	261.1	261.1
330-77	247.7	249.1	247.8	255.1	255.1
178012	269.1	272.8	269.7	269.4	269.4
Conner	277.0	274.5	274.5	274.3	274.3
Idahome	273.5	274.6	274.6	273.5	273.5
Heyburn	277.5	277.2	277.2	274.6	274.6
Raft	274.0	275.0	275.0	274.1	274.1
Coldwater	276.1	275.1	275.1	273.8	273.8

Note that the LAPS estimates with Clarus data were often closer to the observations than those without, but that this difference does not carry over to the WRF forecasts.

Impacts of *Clarus* Data on WRF Forecasts throughout the Study Period

The impacts of the Clarus data on the WRF forecasts throughout the study period were summarized using the same Is Equal and Is Improved metrics as used for the LAPS data and defined in Section 0, as applied to WRF temperature and atmospheric pressure forecasts. When computing these metrics, forecasts that contained evidence of anomalies were excluded. Two filters were used to identify such forecasts. The first filter searched for pixilated data, like that in Figure 39, by excluding forecasts that included a large fraction of nearest neighbors with large differences in the temperature forecasts for these nearest neighbors. The second filter searched for anomalous regions like that in Figure 40 by excluding forecasts where large differences existed over a large fraction of the grid elements between a forecast and the forecast for the preceding or following hour.

Figure 44 depicts the performance metrics for WRF temperature forecasts, averaged over each all forecasts made during each week of the study period. Note that the inclusion of Clarus data in the forecast often impacted the forecast results (since the Is Equal metric is much smaller than 100 percent), but that the impact of the data did not result in either a consistent beneficial or detrimental impact (since the Is Improved metric was about 50 percent, the inclusion of the Clarus data on the WRF forecasts was equally likely to results in forecasts that better matched observations as forecasts that matched observations less well).

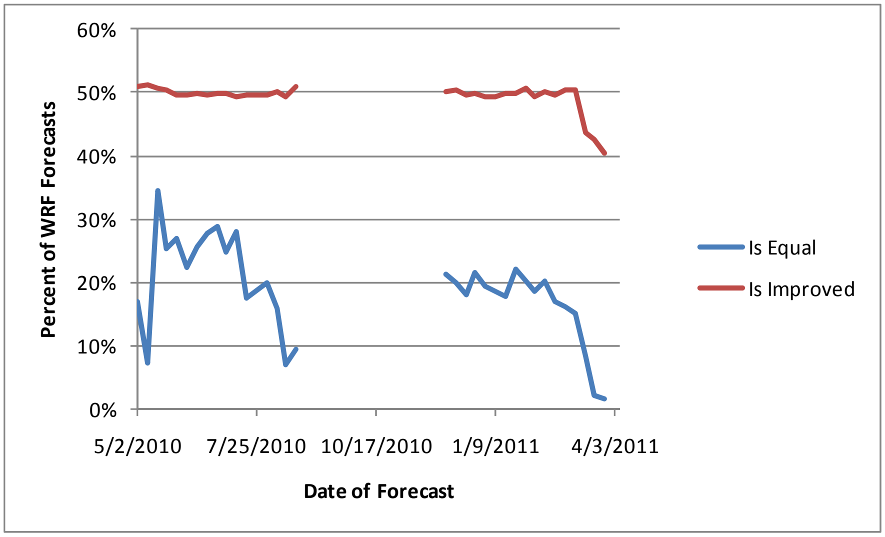


Figure 44. Performance Metrics for WRF Temperature Forecasts by Forecast Date

After the changes were made in March 2011, the Clarus data impacted the forecasts much more frequently (Is Equal decreases from about 20 percent to less than 4 percent), but the impact was more frequently negative than positive (Is Improved is below 50 percent).

The chart below depicts the performance metrics for WRF temperature forecasts by forecast hour for the period before March 2011.

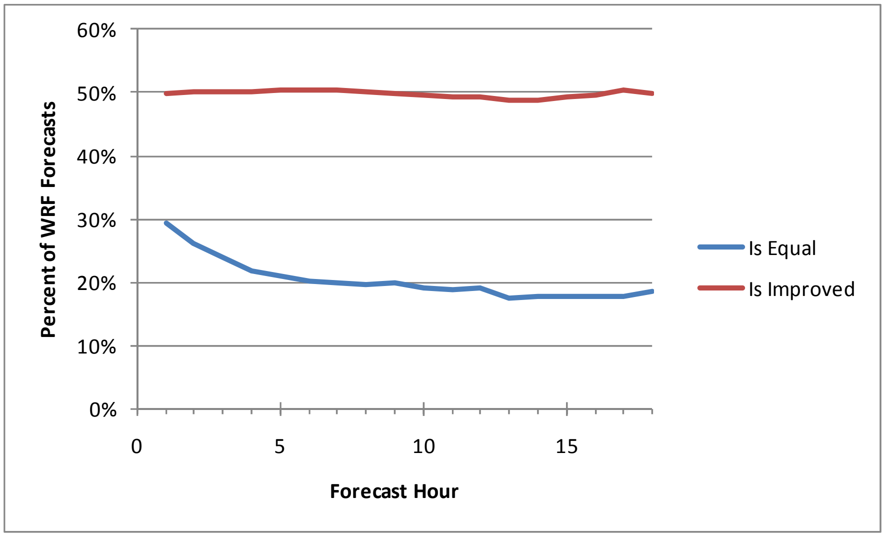


Figure 45. Performance Metrics for WRF Temperature Forecasts by Forecast Hour

As with the overall performance metrics, the Is Improved metric does not show any appreciable negative or positive impact on the WRF forecasts, regardless of the forecast hour. There is a general trend for the Clarus data to more frequently impact the forecasts during later forecast hours – for the hour 1 forecasts, the Clarus data impacted about 70 percent of the forecasts, with the impact increasing to about 80 percent of forecasts for later forecast hours.

Similar conclusions are drawn from the WRF air pressure forecasts depicted in Figure 46 – including Clarus data in the WRF forecasts does impact the forecasts, but did not result in appreciable improvements to the forecasts.

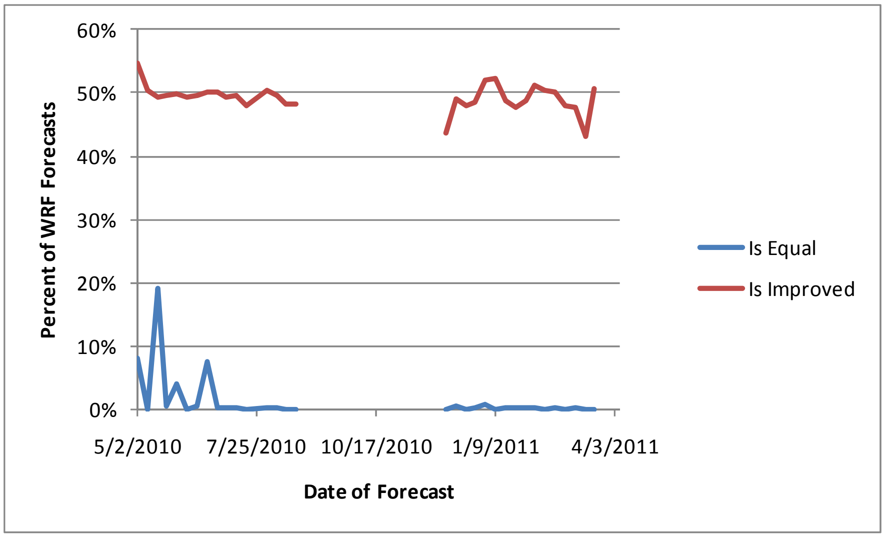


Figure 46. Performance Metrics for WRF Air Pressure Forecasts by Forecast Date

Figure 47 shows similar results, though there is a small increase in the agreement between forecast and observed air pressure values during the later hours of the forecast with a small decrease during the early forecast hours.

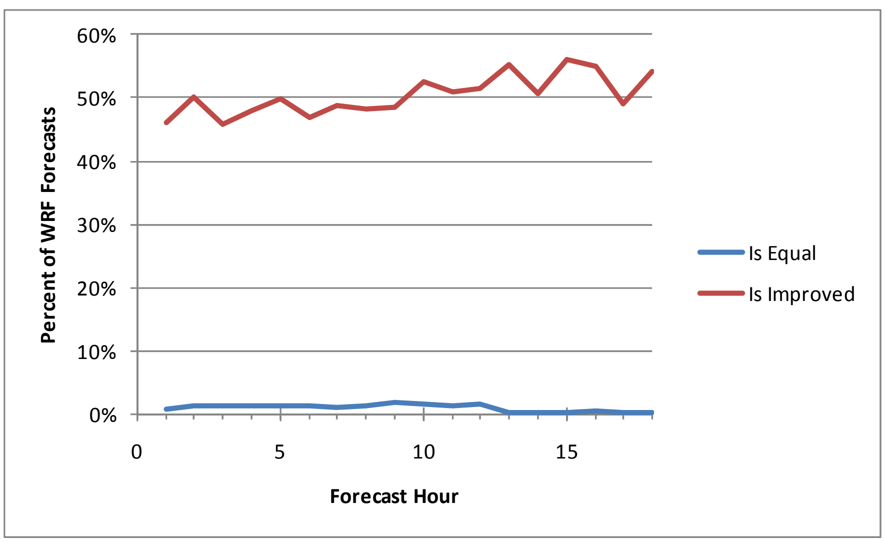


Figure 47. Performance Metrics for WRF Air Pressure Forecasts by Forecast Hour

Forecasts during the Hurricane Ike Test Case

In September 2008, the remnants of Hurricane Ike moved through the study area, resulting in high wind speeds in the area, particularly on September 13 and 14, as shown in Figure 48.

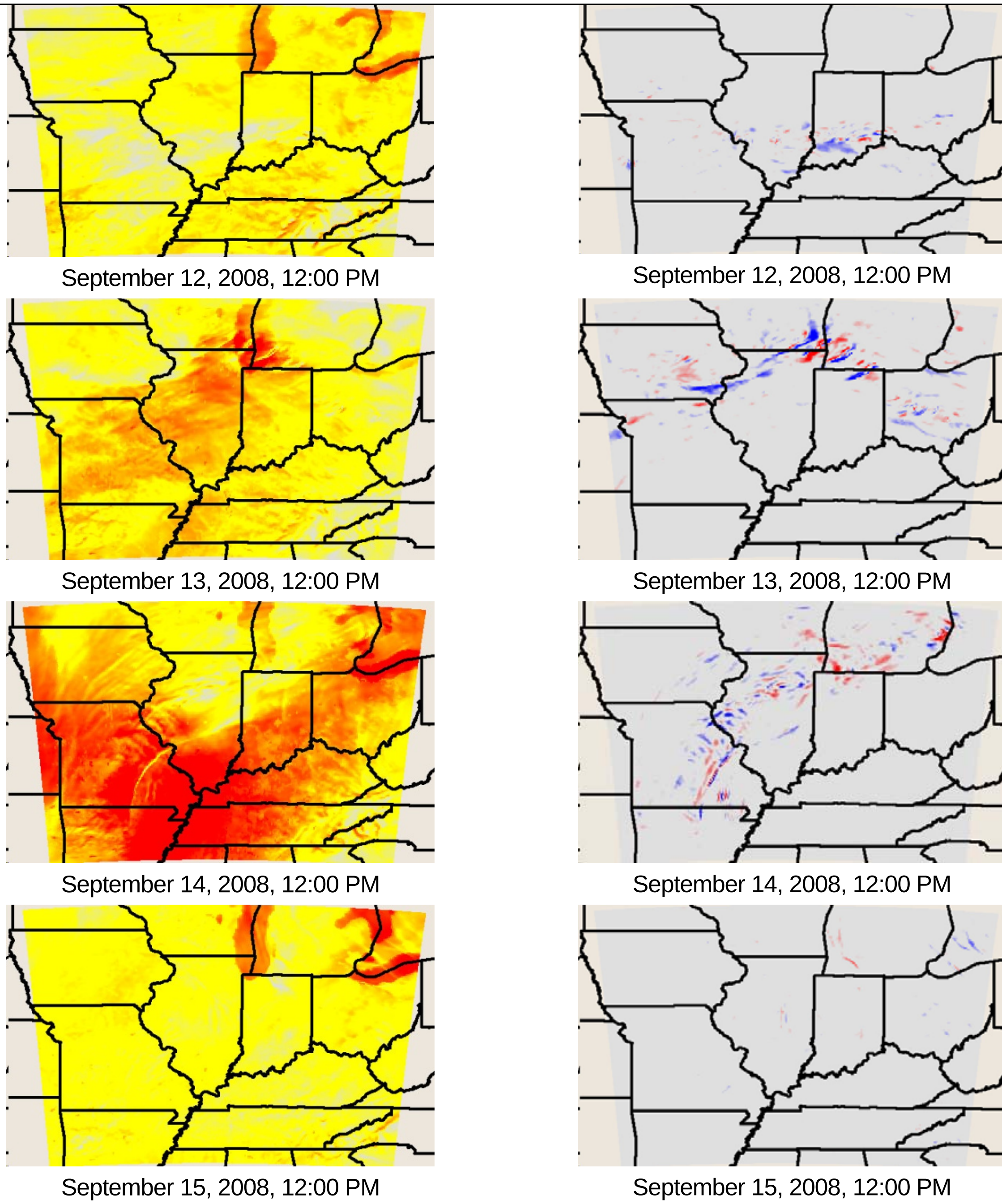
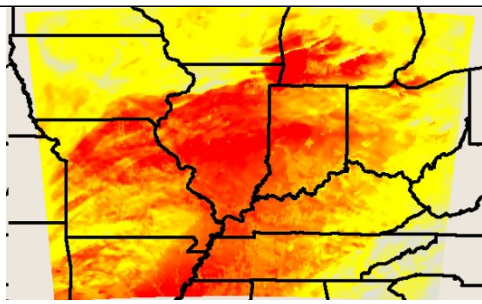
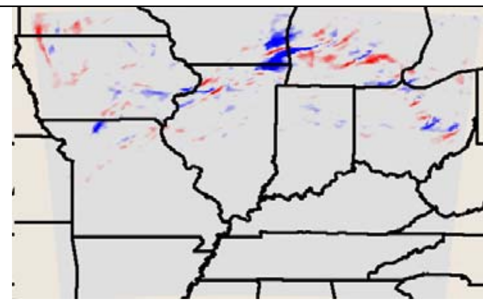


Figure 48. Windspeed Forecasts (left) and Forecast Difference (right) During the Hurricane Ike Test Case

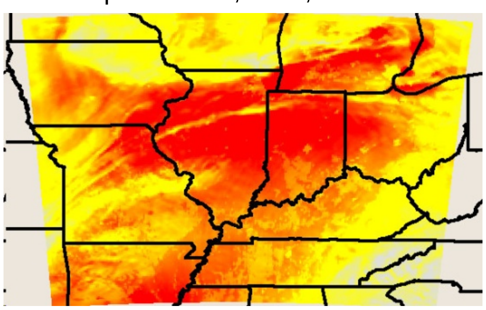
In these figures, the windspeed forecasts from one model run are shown on the left and show large areas of high wind speeds (red areas) on September 13 and 14, with lower wind speeds on days preceding and following these days. The maps on the right show the difference between the windspeed forecasts made with and without Clarus data, with differences of less than 1 mph colored gray and differences of 4 mph or greater colored blue or red, depending on whether the forecast made with Clarus data was higher (red) or lower (blue) than the forecast made without Clarus data.Note that, as with the forecasts examined in the previous sections, the differences between the forecasts are small in most area, though larger differences do exist in some concentrated areas. In fact, the areas where the differences existed tended to be clustered around areas where the windspeed was changing. This observation is reinforced by the maps below in Figure 49, which depict results for 3-hour intervals on September 13, 2008. These results appear to suggest that the WRF is accurate on large, synoptic scales, but less so on the smaller, meso scales. Even though WRF is a mesoscale model, there appear to be challenges in characterizing small spatial scale wind effects.



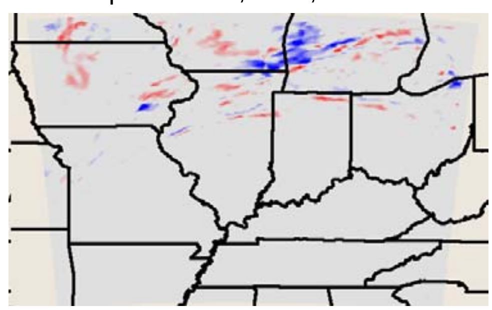
September 13, 2008, 3:00 PM



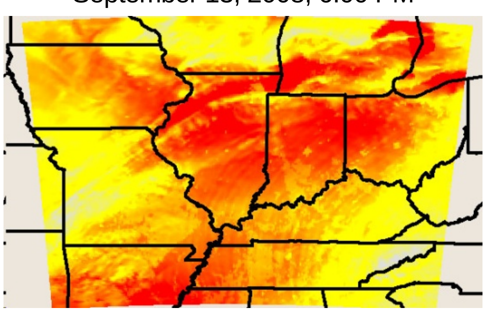
September 13, 2008, 3:00 PM



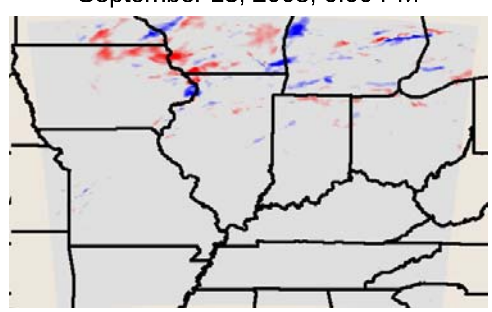
September 13, 2008, 6:00 PM



September 13, 2008, 6:00 PM



September 13, 2008, 9:00 PM



September 13, 2008, 9:00 PM

Figure 49. Windspeed Forecasts (left) and Forecast Difference (right) During the Hurricane Ike Test Case, September 13, 2008

As with the previous charts, the locations where a difference in the windspeed forecasts exists define the edge of the area of high windspeeds. In other words, the differences exist exactly where the weather conditions are the most dynamic. Also, the amount of difference appeared to be the same from forecast valid time to subsequent valid time as shown above from 3 to 9 pm.

Analyses performed by the NCAR team indicated that, as with the forecast data produced by the Meridian team2, the inclusion of the Clarus data, while it impacted the forecasts, neither significantly improved nor significantly degraded the agreement between the forecasts and Clarus observations as a whole.

Summary and Conclusions

The inclusion of Clarus data in the WRF forecasts impacted the forecast results, but did not significantly improve or significantly degrade the agreement between the forecasts and Clarus observations. This was demonstrated in the detailed analysis of the forecasts from the week of January 16, 2011, the performance metrics summarized throughout the study period, and the observations of the NCAR team in their analysis of the impact of the Clarus data on the atmospheric weather forecasts.

There was some evidence that this resulted from the “spin up” of the forecast models. Observations from the forecasts made during the week of January 16, 2011 provided several examples where the initial forecast included anomalies indicating that the WRF model was not producing stable forecasts. In each of these examples, there was very little difference between the 0 hour forecasts made with and without Clarus data, suggesting that the impact of the weather physics and other factors built into the model were over-riding the impact of the Clarus data on the models through changes in the LAPS estimates.

This was not isolated to just that week. In order to prevent the anomalous data from impacting the performance metrics, methods were devised to identify forecasts that included anomalous data so that those forecasts could be excluded from performance metric calculations. Anomalous data was common during the 0 hour forecasts and much less common for the other forecast hours. This is consistent with the interpretation that a “spin up” period was often present in the forecast data.

[2] Presentation by Mike Chapman at the 2011 Road Weather Management meeting.

5 The Impact of *Clarus* Data on Road Condition Forecasts

This section describes the results of evaluating the impact of Clarus data on the site-specific weather and road condition forecasts.

How *Clarus* Data Impacts the Road Condition Forecasts

Changes to the pavement surface temperature are driven by two often competing factors: the atmospheric conditions above the pavement and the subsurface conditions beneath the pavement. For example, on a cold winter day, solar radiation absorbed by the pavement often heats the pavement while convective heat loss to the atmosphere (i.e., cold air absorbs heat from the pavement) and conductive heat loss to the sub-base (i.e., the cooler sub-base absorbs heat from the warmer pavement surface). Other atmospheric and sub-surface phenomenon can also impact the pavement surface temperature. Snow falling on warm pavement or sub-surface ice beneath the pavement can melt, absorbing heat from solar radiation that would otherwise warm the pavement. Standing snow on pavement can reflect solar radiation, preventing it from being absorbed.

Road condition models forecast future road conditions by estimating initial conditions for the pavement and sub-surface conditions, forecasting future atmosphere conditions, and using a pavement and sub-surface model to estimate the impact of the forecast atmospheric conditions on the pavement and sub-surface conditions. The Clarus observations were used in the first two steps of this three-step process:

- Clarus observations were used to estimate the initial pavement and sub-surface conditions. When historical Clarus observations of pavement surface conditions were available, they were used with the sub-surface condition model to generate an estimate of sub-surface conditions at the start of the forecast period. When no Clarus observations were available (i.e., the Clarus observations were omitted from the model), historical weather forecasts were used with the pavement and sub-surface condition models to estimate the pavement and sub-surface conditions at the start of the forecast period. In this way, the use of Clarus observations helped improve the estimate for the pavement and sub-surface conditions at the start of the forecast period.
- Clarus observations were used to improve the atmospheric weather forecasts at the site. Rather than use a single atmosphere weather forecast model to estimate weather conditions at the site, a group of such forecasts (known as an ensemble) was collected. When Clarus observations were available, forecasts for previous periods were compared to recent Clarus observations to determine which models provided forecasts that best matched recent observations, and the models providing the best fit for recent observations were used for future forecasts. Thus, the Clarus observations were used to make site-specific customizations to the atmospheric weather forecasts. When no Clarus observations were used at a site, the same process was used, but averaged over other Clarus stations in the vicinity of the site. So, with no Clarus observations, regional customizations to the atmospheric weather forecasts were used.

In summary, the use of *Clarus* observations in the road condition forecasts was expected to result in estimates for road conditions that (a) more closely matched actual conditions at the start of the forecast period (because of the improved initialization process) and (b) more closely matched actual conditions during the forecast period (because the *Clarus* observations were used to create site-specific weather forecasts).

Impacts of *Clarus* Data at *Clarus* Station 512-10

To exemplify the impacts of the *Clarus* data on road condition forecasts, first consider a specific station, *Clarus* station 512-10, during the Cold Test Case. Figure 50 depicts the air temperature forecasts made with and without Clarus data for the January 12, 2009 model run, along with the *Clarus* observations during the forecast period.

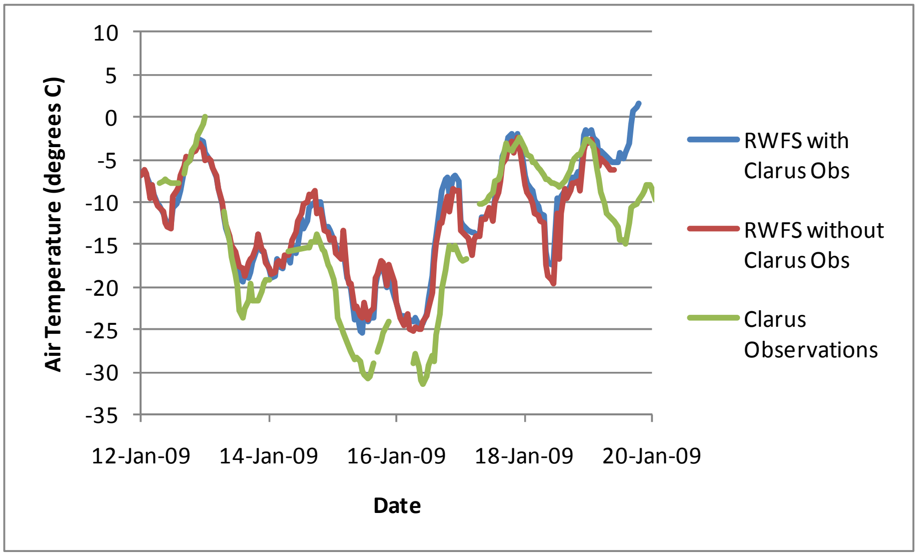


Figure 50. Air Temperature Forecasts and Observations from the 1/12/2009 Forecasts for Station 512-10

Note that the air temperature forecasts are in fairly good agreement early in the forecast period, within 1 degree of observations about half the time. The model forecasts differ more from the observations later in the forecast period. Also, there are only slight differences between the atmospheric air temperature forecasts made using Clarus data and those made without it. In other words, the site-specific atmospheric weather forecasts in this example made using Clarus observations were only slightly different than the atmospheric weather forecasts made without the use of Clarus observations.

A similar chart, but for road temperature, is shown in Figure 51.

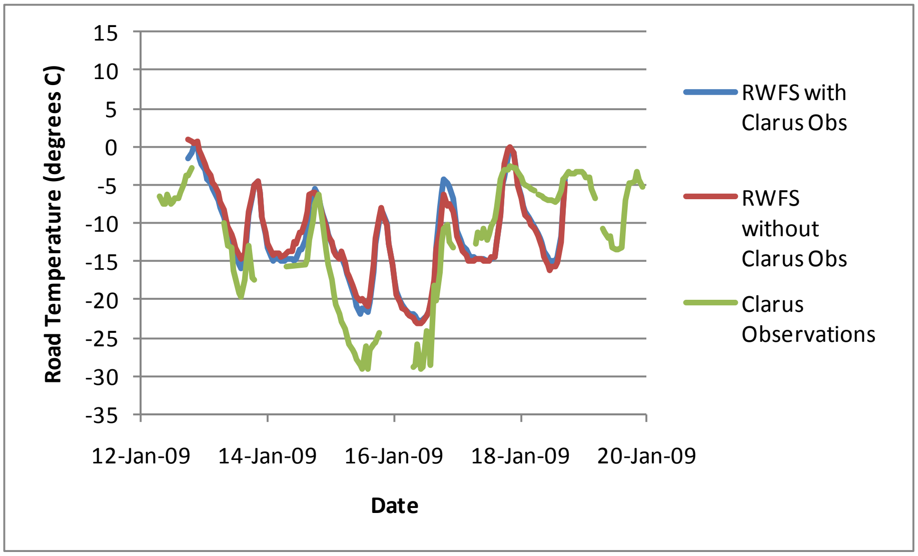


Figure 51. Road Temperature Forecasts and Observations from the 1/12/2009 Forecasts for Station 512-10

This chart shows similar tendencies as the previous one – fairly good agreement between forecasts and observations early in the forecast period, less agreement later in the forecast period, and only small differences between the forecasts made with and without Clarus observations. There is a difference during the first several hours of the forecast period that is difficult to identify because of the long time scale of this chart. Figure 52 reproduces this chart, but restricting the time scale to the first 18 hours of the forecast.

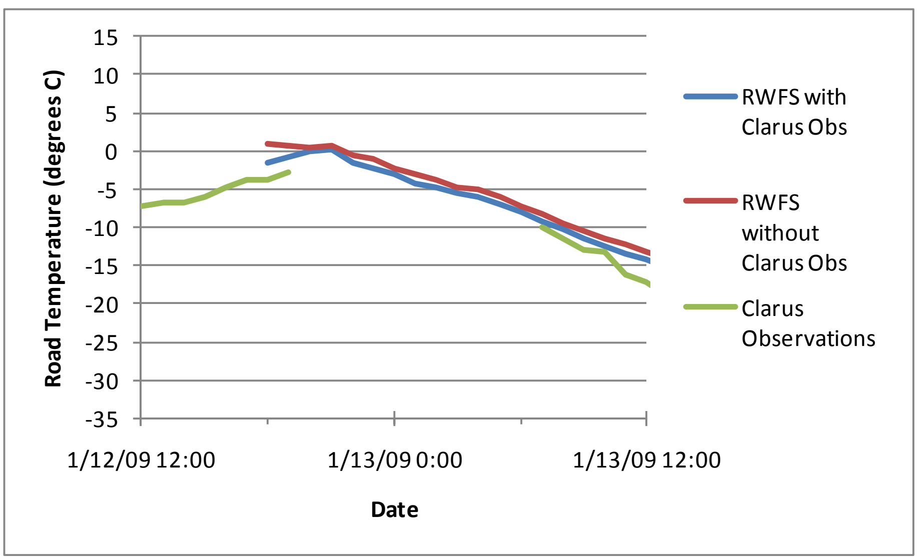


Figure 52. Road Temperature Forecasts and Observations from the First 18 Hours of the 1/12/2009 Forecasts for Station 512-10

Note the different starting point for the road temperature forecasts due to the use of Clarus observations in estimating initial pavement and sub-surface conditions.

These results can be summarized across all the forecasts produced at this station by considering the difference between the forecast and observed temperatures and averaging across the forecast hour. The difference between air temperature forecasts and observations is depicted in Figure 53.

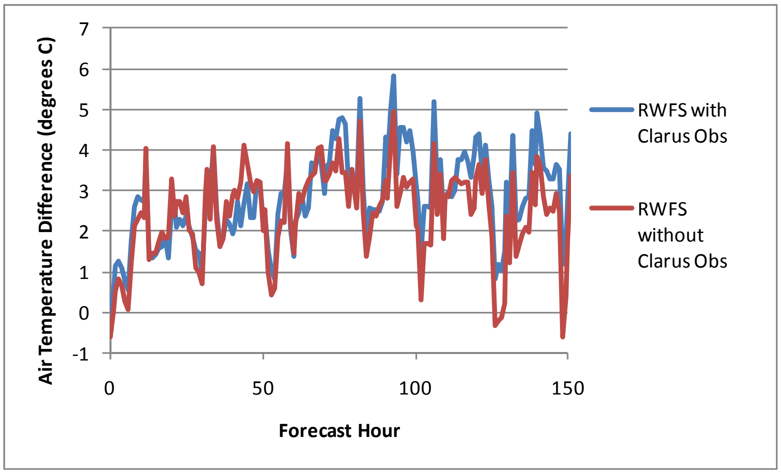


Figure 53. Difference Between Air Temperature Forecasts and Observations for Station 512-10

This chart reinforces the results previously noted: (a) the forecasts show better agreement with observations early in the forecast period than later in the forecast period and (b) the difference between the forecasts made with and without *Clarus* observations is smaller than the difference between those forecasts and observations. Figure 54 shows the difference between the forecast and observed road temperatures at this station, averaged over the forecast hour. At the start of the forecast period, the forecast made with the *Clarus* data is much closer to the observed values – more than 3 degrees Celsius closer.

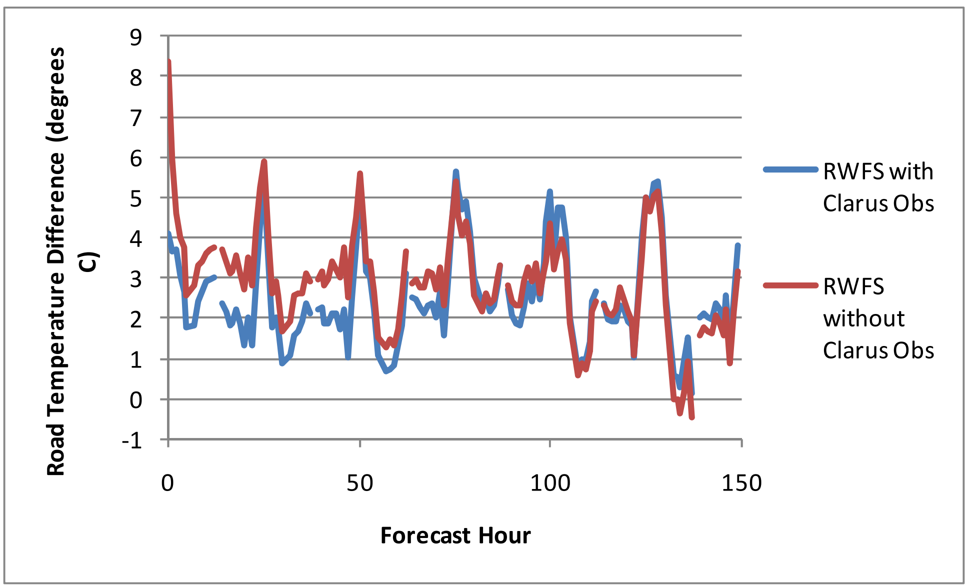


Figure 54. Difference Between Road Temperature Forecasts and Observations for Station 512-10

The forecasts made using *Clarus* data continue to be closer for the first 100 hours of the forecast period, and are little different after that time.

Note that the key to determining whether the forecasts made with or without *Clarus* data provides better agreement with observations is identifying which of the lines in the above graph is closer to zero – the line closer to zero provided better agreement. Define the observation agreement metric as the absolute value of the difference in the model forecast made without *Clarus* data and the observations minus the difference in the model forecast made with *Clarus* data. If this metric is positive, it indicates that the forecasts made with *Clarus* data provided closer agreement to the observations. If it is negative, the forecasts made without *Clarus* data provided better agreement. Figure 55 depicts the observation agreement metric by forecast hour for Station 512-10.

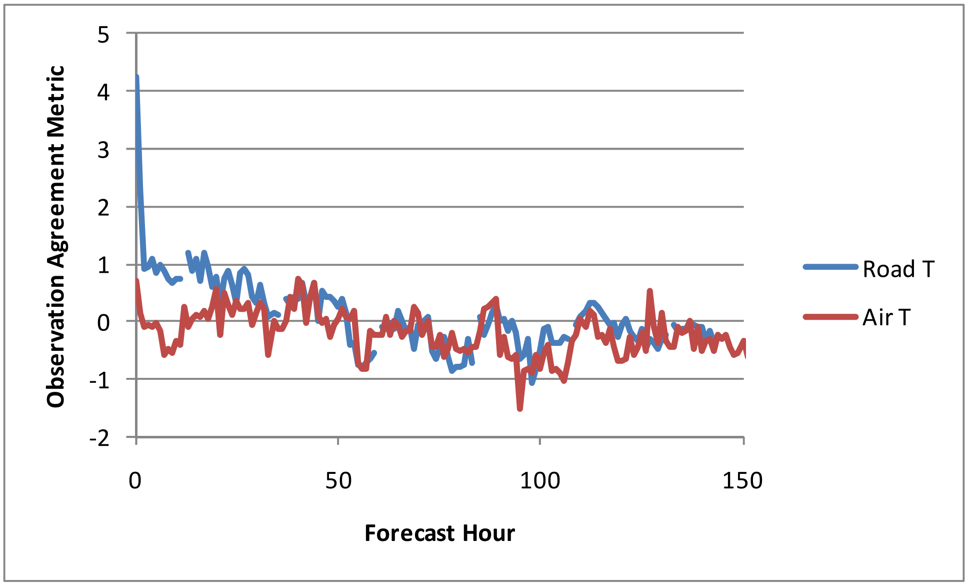


Figure 55. Observation Agreement Metrics for Station 512-10

Note the large, positive value for the road temperature observation agreement metric early in the forecast period because the forecast made with *Clarus* data was much closer (just over 4 degrees C) to the observations than the forecast made without *Clarus* data. The road temperature forecasts made with *Clarus* data continues to provide about a 1 degree Celsius better agreement with observations for the first 24 hours, but then is worse than the road temperature forecast without *Clarus* observation past the 60 hour point. However, for air temperature, the *Clarus* data degrades the forecast earlier (about the fifth hour) and, after the 60 hour point, generally degrades the forecasts.

Average Impacts of *Clarus* Data during the Cold Test Case

The charts and metrics described in the previous section can be used to summarize the impact of *Clarus* data on the air and road temperature forecasts by averaging those values across all the stations included in the study. Figure 56 shows the absolute value of the difference between the air temperature forecasts and the *Clarus* observations, averaged across all stations.

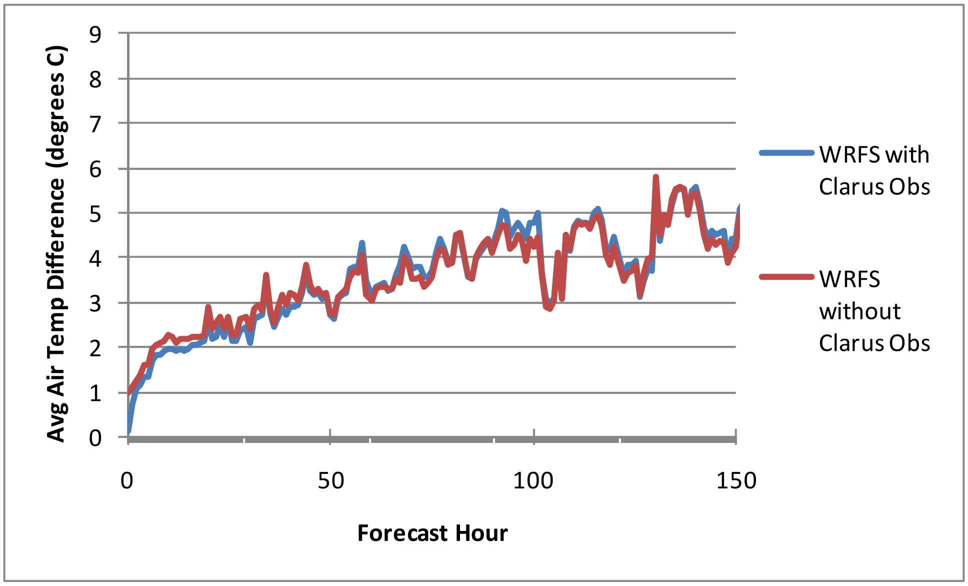


Figure 56. Average Difference Between Air Temperature Forecasts and Observations

For the first 50 hours of the forecast, the forecasts made with *Clarus* data are slightly better than the forecasts made without *Clarus* data. Also, the forecasts become progressively less accurate as the forecast hour increases, ranging from about a 1 degree Celsius difference early when the forecast begins to about a 4 degree difference 100 hours into the forecast period – this loss of accuracy is not surprising for numerical weather predictions.

Figure 57 is a similar chart for road temperature forecasts. This chart indicates that the road temperature forecasts made with *Clarus* data are closer to the *Clarus* observations by an average value of about 1 degree Celsius early in the forecast period, with this difference disappearing by forecast hour 24. After the 50 hour point, the forecasts with *Clarus* data are worse than or equal to those without *Clarus* data. As with the air temperature forecasts, the accuracy of both the forecasts degrade with the forecast hour.

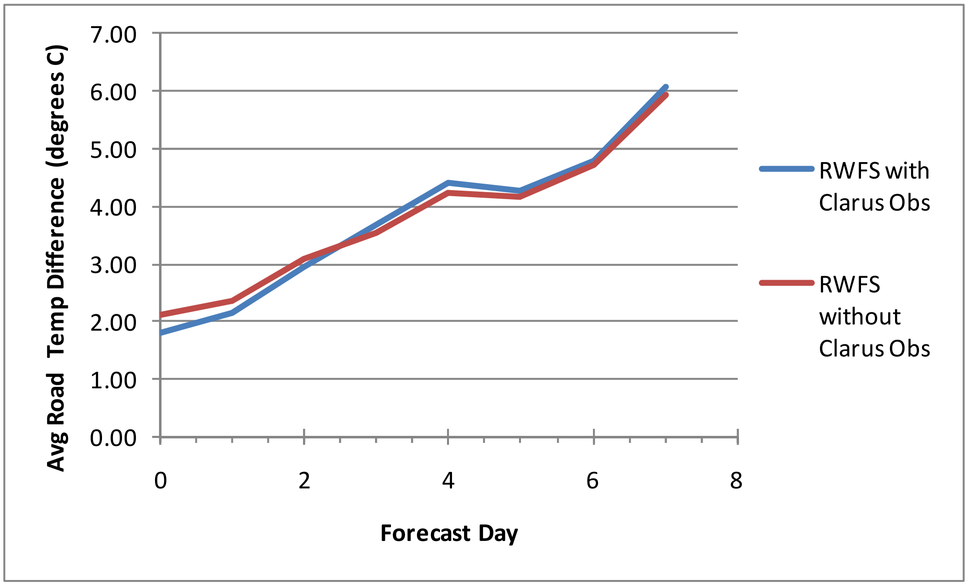


Figure 57. Average Difference Between Road Temperature Forecasts and Observations

Figure 58 depicts the observation agreement metric, which summarizes these results. At the start of the forecast period, the road temperature forecasts made with Clarus data average almost 2 degrees Celsius closer to the observations than those made without Clarus data and continues to provide better agreement with observations for the first 24 hours of the forecast.

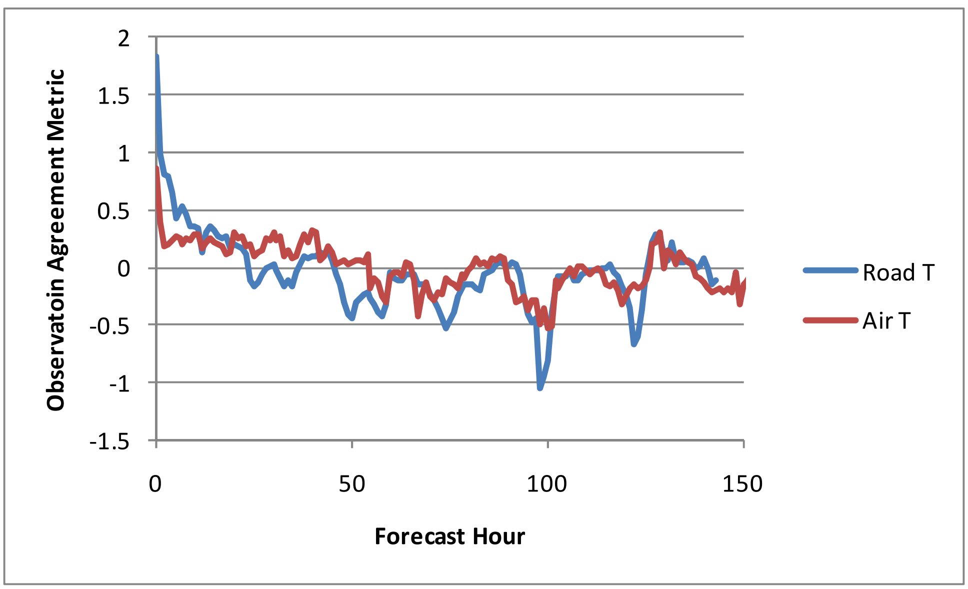


Figure 58. Average Observation Agreement Metrics for Road and Air Temperature

Similar results hold when examining the windspeed forecasts, as shown in Figure 59, which depicts the average absolute value of the difference between windspeed forecasts and observations. As with the temperature forecasts, the windspeed forecasts are better when made with Clarus data – in this case, throughout most of the forecast period – and the accuracy of both the forecasts degrade with the forecast hour.

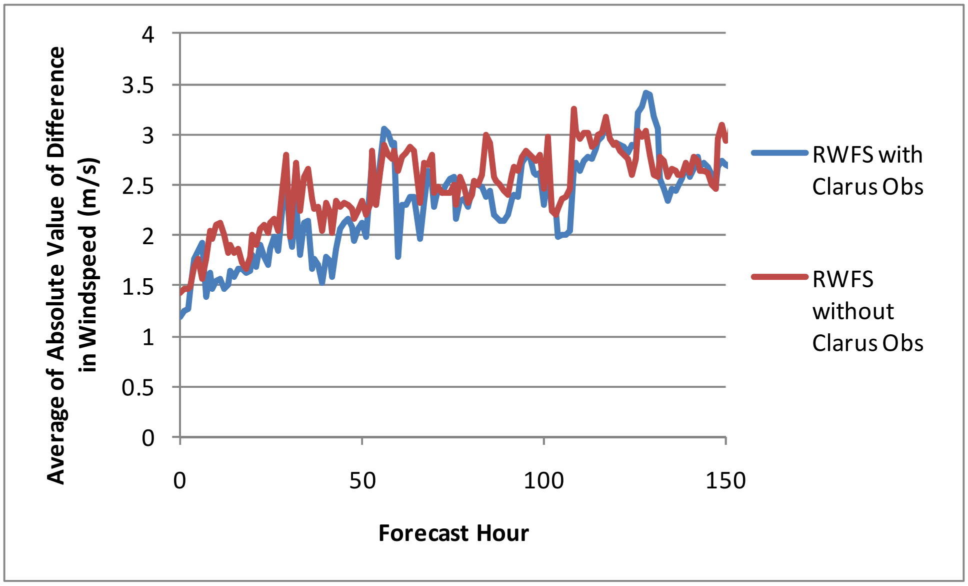


Figure 59. Average Difference Between Windspeed Forecasts and Observations

Summary and Conclusions

Including Clarus data in the site-specific air and road temperature forecasts provided improved agreement between the forecasts and the Clarus observations. During the early hours of the forecast, the average improvement was almost 2 degrees Celsius, probably because the availability of observations resulted in much more accurate estimates for the model initial conditions and also resulted in more accurate forecasts of atmospheric conditions early in the forecast period. The forecasts made using Clarus data continued to be better on average than those made without Clarus data for the first 24 hours.

6 The Impact of *Clarus* Data on the PPAES Analysis

This section describes the results of evaluating the PPAES analysis.

The Expected Performance of the PPAES Analysis

The PPAES is intended to enhance precipitation observations by using weather model analysis, satellite, and surface observation data to improve on radar-based observations. Radar detects precipitation by emitting radio signals and detecting the return signals generated when the emitted signals bounce off snow, ice particles, water vapor, and droplets in the air. The time delay between when the radar signal was emitted and when the return pulse is received provides an indication of the distance to the object. The amount of signal returned provides a measure of the size and reflectivity of the object. For airborne water vapor and droplets, the reflectivity is related to the amount of water vapor in the air. Taken together, this information allows weather radar to make indirect estimates of precipitation rates (amount/hour) and accumulation (amount/3, 6, 12 hours or storm). Weather radar also has the advantage of taking measurements horizontally and vertically over a large space of the atmosphere as compared to just a single point for a surface station.

However, radar data has limitations. One of the most common forms of errors in radar precipitation measurements is caused by overshoot. Because the surface of the earth curves and radar signals travel in essentially straight lines, radar signals emitted from a station do not reach parts of the atmosphere close to the earth's surface. This fact means that radar observations do not detect conditions in an envelope near the earth's surface, with the height of that envelope increasing with distance from the radar station. In other words, the radar "overshoots" the lower part of the atmosphere. When atmospheric and surface conditions differ, this condition can result in radar measurements that differ from ground observations. Other factors that limit the accuracy of radar are the low reflectivity of snow particles to radar signals, high reflectivity of melting snow, and low reflectivity for very small water droplets (e.g., drizzle).

The PPAES analysis attempts to remove some of this source of error by using supplemental data to augment the radar observations. This approach should result in improved performance where radar observations are weakest:

- Greater improvement at locations a greater distance from radar stations
- Greater improvements in colder months (when snowfall is more prevalent) than in warmer months
- Greater improvements in northern locales (where snowfall is more prevalent) than in southern locales.

The evaluation assesses the impact of including *Clarus* observations in the PPAES analysis, initially focusing on the PPAES analysis estimates as a whole, then reporting on the impacts at locations more distant from radar stations and during cooler weather.

The Performance of the PPAES Analysis

The PPAES analysis was run twice per hour from December 30, 2009, through August 27, 2010, once including *Clarus* data in the analysis run and once excluding it. For each run, a set of about 200 control stations were excluded from the analysis inputs, with different control stations excluded during different analysis runs. The performance of the PPAES analysis was measured by comparing the PPAES estimates of whether precipitation occurred at the control station locations with precipitation observations at these stations using metrics appropriate for binary observations (see Appendix A). For these metrics, an observation was termed a "Hit" if the surface station observation indicated that precipitation was present and the PPAES analysis estimate also indicated that precipitation was present.

Figure 60 depicts the percent of *Clarus* control stations where precipitation was estimated to be present using the PPAES analysis that included *Clarus* data ("w Clarus"), using radar ("Radar"), and the percent of those control stations at which precipitation was observed. This provides a good summary of the difference between radar precipitation estimates and precipitation estimates made with the PPAES analysis using *Clarus* data. In the winter months, the percent of locations with precipitation estimated by radar only is often much lower than the same percentage from surface observations, considered "truth" or reality in this study. In December and through January, the estimate using the PPAES analysis is much closer to observations, but is a bit higher than that indicated by surface observations. However, the radar estimates appear to outperform the PPAES estimates from late February to May (the red line being closer to the green line in Figure 60). Overall, during the spring months, the radar estimates correspond closely with the ground observations and the PPAES estimates continue to be a bit higher. During the summer months, both the radar and the PPAES estimates for the percent of control stations with precipitation present closely agree with the surface observations.

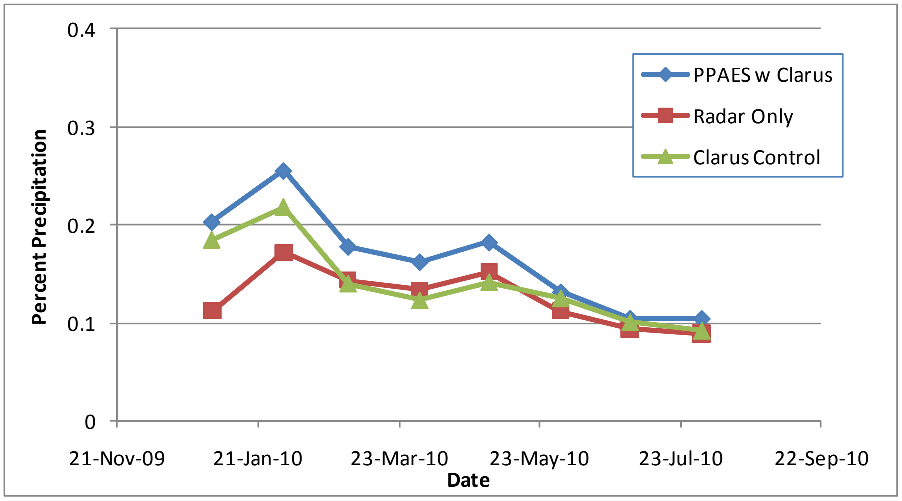


Figure 60. Percent of Control Stations with Precipitation by Date

The remainder of this section examines this in more detail through commonly used weather forecast performance metrics. Figure 61 summarizes the effectiveness of the PPAES analysis for the entire period, showing the percentage of the PPAES and radar only estimates that agreed with observations at the control stations (i.e., the percent correct).

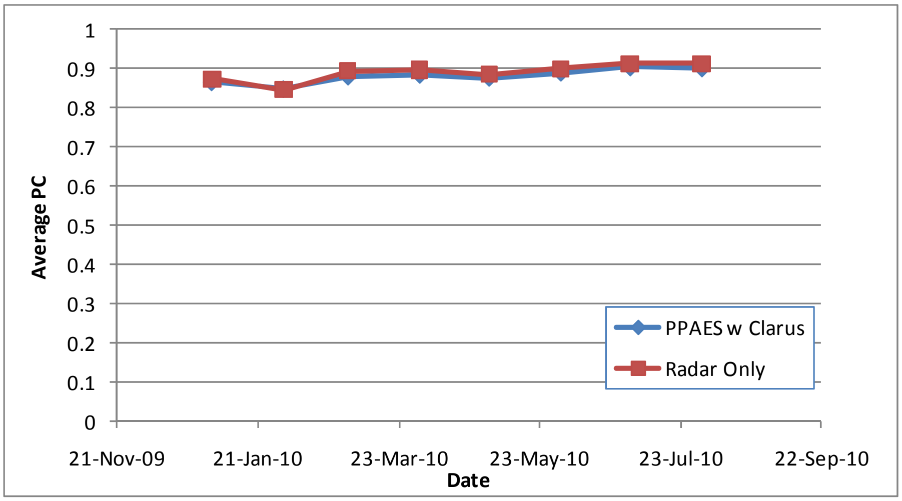


Figure 61. PPAES Percent Correct by Date

There is little difference between the PPAES analyses and radar data in the overall percentage of estimates that are correct. For the entire period, whether precipitation was present or not, the radar data was correct 89 percent of the time and the PPAES analysis with *Clarus* data was correct 88 percent of the time. A difference appears when comparing the percent correct when precipitation was observed at the station and when it was not, as shown in Figure 62.

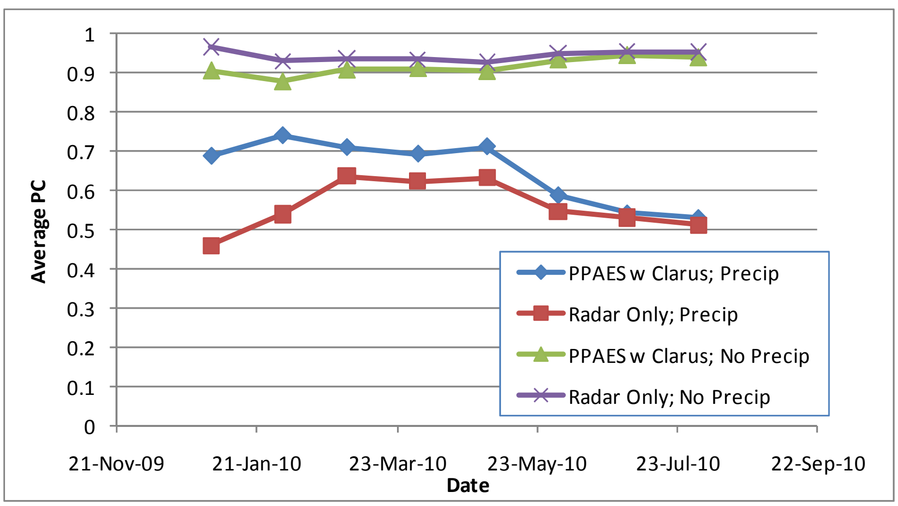


Figure 62. PPAES Percent Correct by Date for Precipitation and Nonprecipitation Events

Compared to the control stations where precipitation was observed, the PPAES analysis with Clarus data was much more likely to correctly identify when precipitation was observed than radar-based estimates, as shown by the blue line being above the red line. This finding was pronounced particularly during the winter months, when radar is known to overshoot snow produced low in the atmosphere. The lower radar estimation can also be explained by the radar not detecting very light or drizzle precipitation, which most surface instruments detect. In January, the PC value for precipitation was about 70 percent for the PPAES analysis with Clarus data and only about 45 percent for radar. During the spring months, the PC remained about 70 percent for the

PPAES analysis, with the PC for radar estimates increasing to just above 60 percent, with the PC for both estimates dropping to just above 50 percent in July and August.

However, the PPAES analysis with Clarus data was more likely to indicate precipitation was present when it was not. The much higher PC for precipitation events and the slightly lower PC for non-precipitation events exhibited by the PPAES analysis averaged out to about the same PC for all events because non-precipitation events were more frequent than precipitation events.

This finding is reflected in the FAR shown in Figure 63. For the PPAES analysis with Clarus data, about 44 percent of the instances where the model indicated precipitation would be present, it was not observed. This percentage was only 38 percent for radar-based estimates.

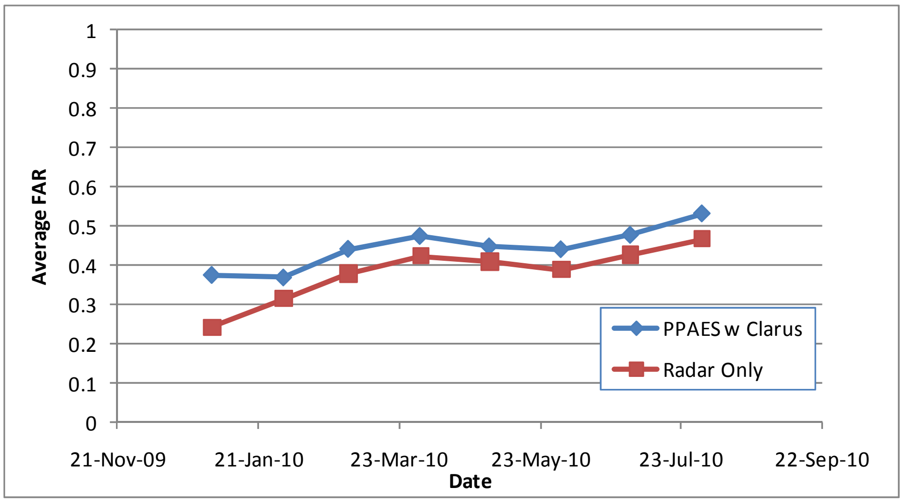


Figure 63. PPAES False Alarm Ratio by Date

This tendency is confirmed in Figure 64, which shows the BIAS in the estimates.

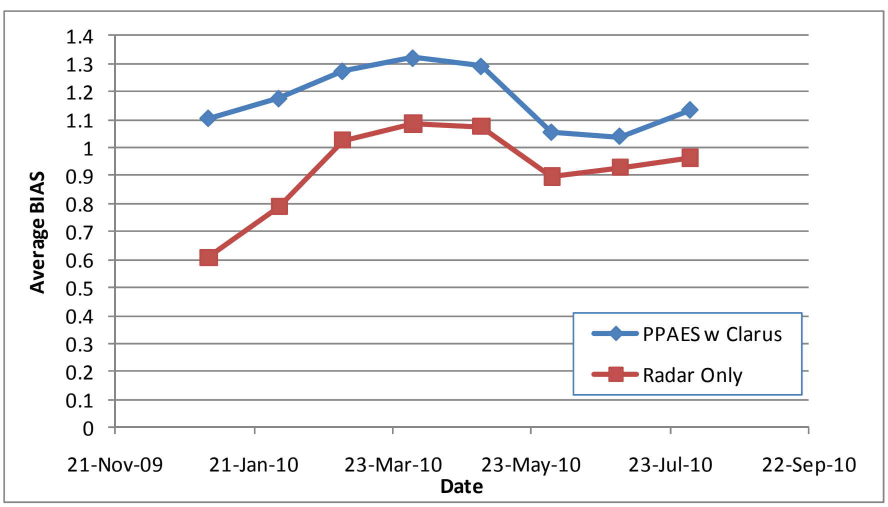


Figure 64. PPAES BIAS by Date

The BIAS indicates whether a model is more likely to generate false positives (reporting precipitation when not actually present) or false negatives (not reporting precipitation when it is present), with a value of 1 indicating that the model produces an equal number of false positives and negatives—in other words, it is not biased toward either. As with other metrics, the difference is most pronounced in the winter months, when the radar-based estimates show a strong bias toward false negatives, and the PPAES analysis shows only a slight bias toward false positives. In other words, the PPAES analysis with *Clarus* data improved the bias during this period. For the entire period, the average BIAS for the radar-based estimates was 0.9 and that for the PPAES analysis with *Clarus* data was 1.16, so the radar-based estimates tended to miss precipitation events while the PPAES analysis with Clarus data tended to indicate precipitation existed when it did not.

Another measure of the effectiveness of a model is the Equitable Threat Score (ETS). For this measure, depicted in Figure 65, a value of 0 indicates that an estimate does no better than if done by chance, and a value close to 1 indicates that the model is very effective at identifying when precipitation occurs.

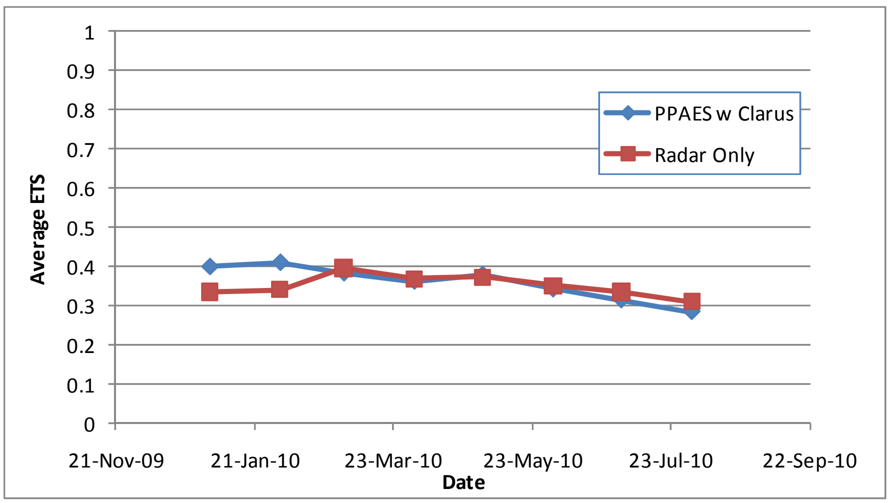


Figure 65. PPAES Equitable Threat Score by Date

The PPAES analysis has a higher ETS value during January and February than radar alone, with similar values from March through May and lower values in June and July. This finding provides further confirmation that the PPAES analysis improves precipitation estimation during winter months.

Factors Affecting PPAES Performance

The results of the previous section indicated that the PPAES analysis with *Clarus* data was more effective at identifying when precipitation occurred than radar-based estimates, particularly in the winter months. This finding was consistent with a known weakness of radar-based estimates—they can miss snow produced in the lower atmosphere due to overshoot. This section of the evaluation report examines how other factors, such as latitude and proximity to radar, affect the relative performance of the PPAES analysis with *Clarus* versus radar-based precipitation estimates.

Figure 66 depicts the percentage of precipitation estimates that were correct for precipitation and nonprecipitation events that occurred between December 30, 2009, and March 31, 2010, averaged across observation stations with similar latitudes.

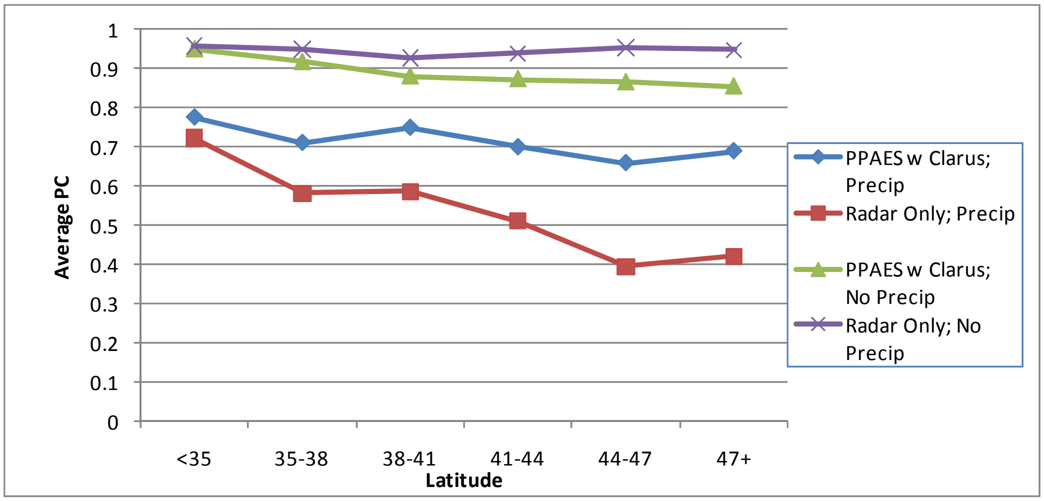


Figure 66. PPAES Percent Correct by Latitude for Precipitation and Nonprecipitation Events

This analysis, focused on the winter months when overshoot of snow-producing clouds would be greatest, revealed that the performance of radar-based precipitation estimates was much worse at higher latitudes. At lower latitudes, radar-based estimates of whether precipitation occurred agreed with observations at the control stations about 70 percent of the time. This value dropped to about 40 percent at higher latitudes. The PPAES analysis with Clarus data showed much less drop in its effectiveness at identifying precipitation events at higher latitudes, although the number of false positives did increase. This finding is reflected in the change in BIAS by latitude, as shown in Figure 67.

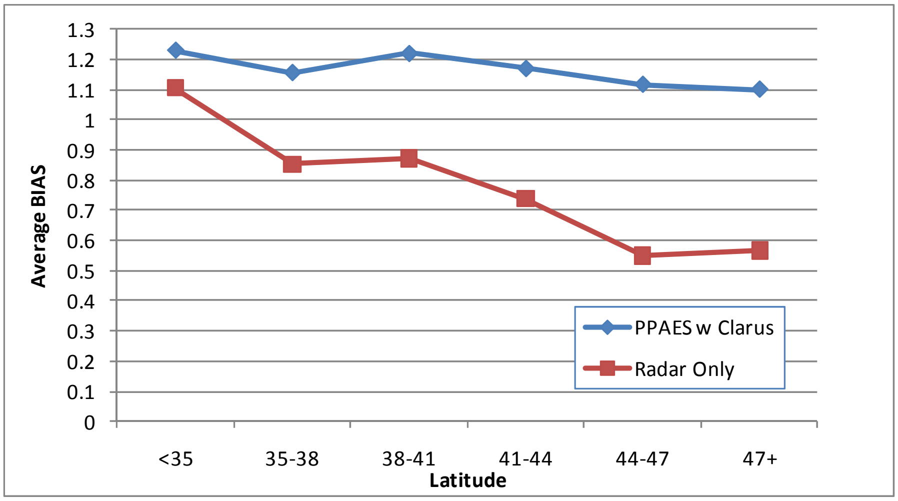


Figure 67. PPAES BIAS by Latitude

At higher latitudes in the winter months, radar-estimates alone had a strong bias toward false negatives; in other words, radar-based wintertime precipitation estimates often missed precipitation events. For the PPAES analysis with Clarus data, the bias was more consistent.

The ETS provides additional confirmation that the PPAES analysis with Clarus data provides better performance at higher latitudes during the winter, as shown in Figure 68. The ETS is similar for the observation stations at lower latitudes, but the ETS is higher for the PPAES analysis at higher latitudes.

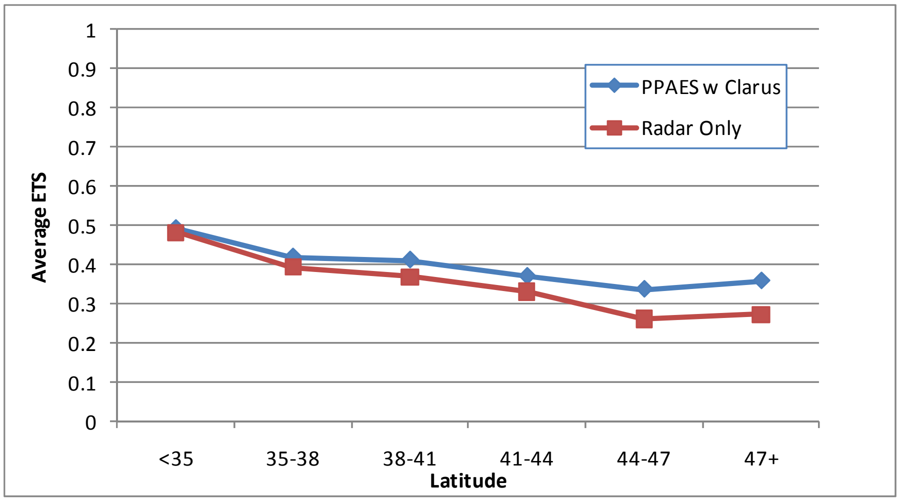


Figure 68. PPAES ETS by Latitude

The next set of charts examines the impact of the proximity of the locations to the nearest NexRad radar station on the effectiveness of the radar-estimates and the PPAES analysis. Figure 69 shows the percent of estimates that were correct for precipitation and non-precipitation events plotted against the distance from the observation point to the closest NexRad station. (For this analysis, the observations were restricted to those at stations located in the United States and that occurred between December 31, 2009, and March 31, 2010.

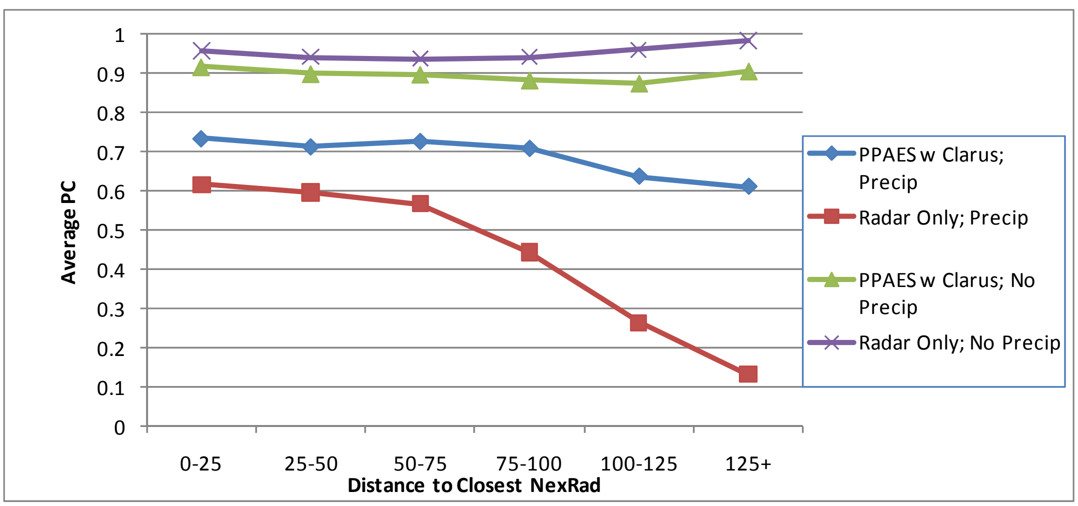


Figure 69. PPAES Percent Correct by Distance to Radar for Precipitation and non-Precipitation Events, Winter Observations

The performance of radar at estimating when precipitation will occur drops rapidly at distances greater than about 75 miles from the radar station, and the PPAES analysis with Clarus data helps maintain better performance farther away from the radar station. For comparison, the same metrics were computed for nonwinter months (after May 1, 2010) and stations located below 41 degrees latitude. These results are shown in Figure 70.

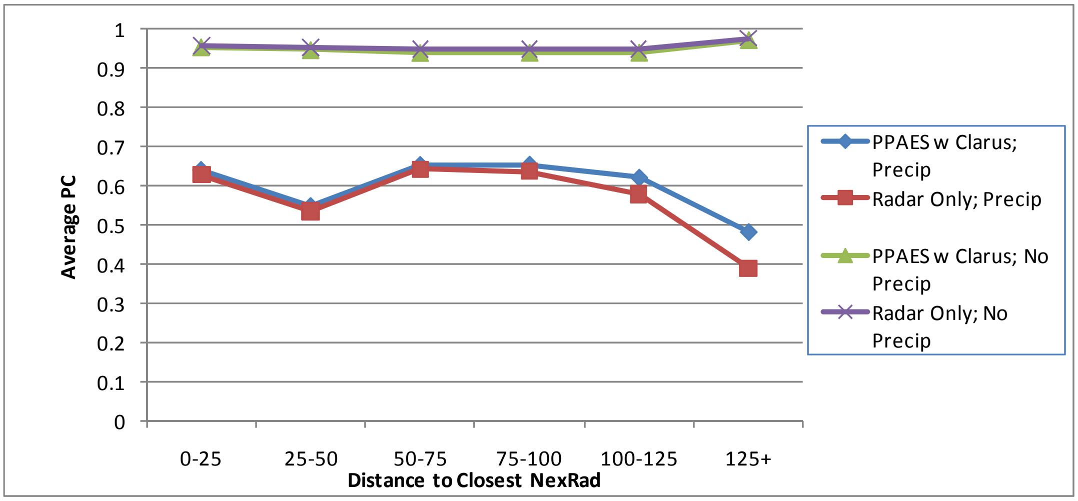


Figure 70. PPAES Percent Correct by Distance to Radar for Precipitation and non-Precipitation Events, Non-Winter Observations at Low Latitudes

In this case, the degradation in radar performance in estimating precipitation at long distances from the radar station is much less severe than for the winter observations previously assessed. This finding provides an additional indication that the primary benefit of PPAES is for improving wintertime precipitation estimates.

The last factor considered was the impact of the number of nearby observation stations on the PPAES estimates. Figure 71 shows the percent correct charted against the number of observation stations within 20 miles of the control station.

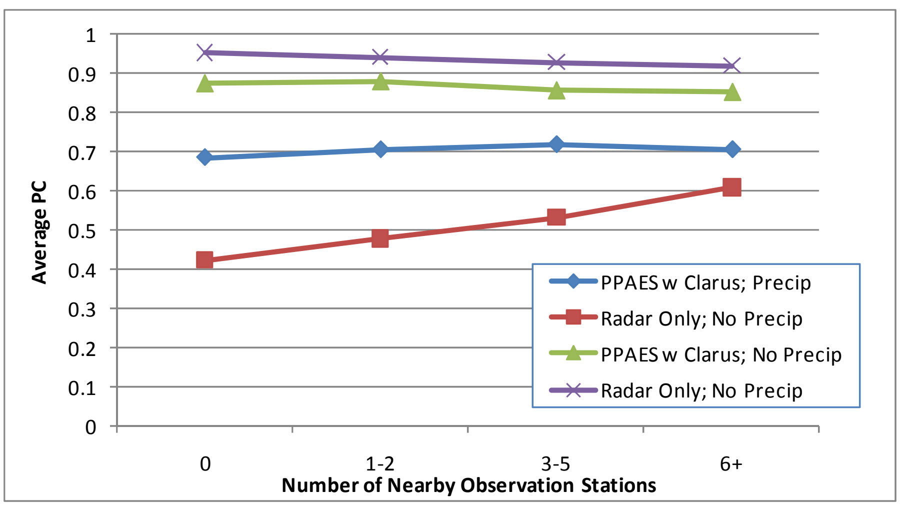


Figure 71. PPAES Percent Correct by Number of Nearby Observation Stations for Precipitation and non-Precipitation Events, Wintertime Observations at High Latitudes

Figure 72 is a similar chart for the ETS.

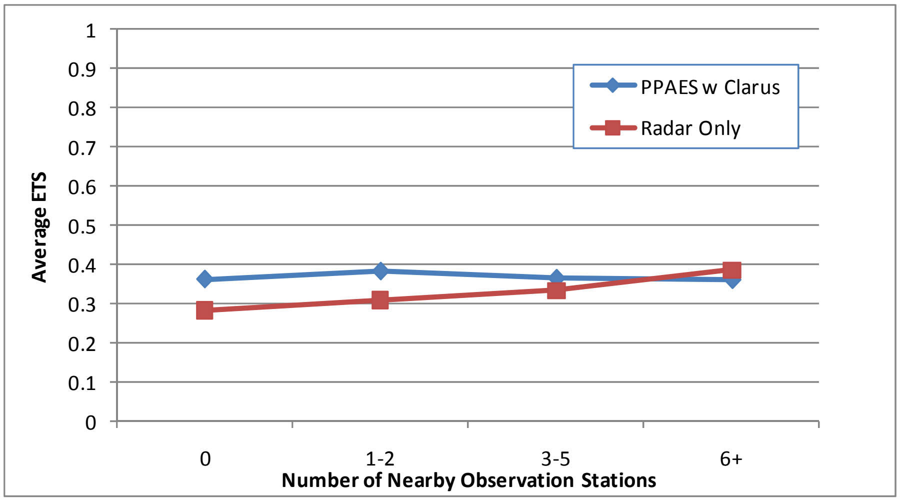


Figure 72. PPAES ETS by Number of Nearby Observation Stations, Wintertime Observations at High Latitudes

The performance of the PPAES analysis does not seem to improve based on the number of nearby observation stations – the percent correct (from Figure 71) and the ETS (from Figure 72) are about the same regardless of the number of nearby observation stations. In other words, the PPAES analysis appears to perform about as well with only a few nearby observation stations as it does when there are many nearby observation stations.

Summary and Conclusions

Weather radar is one of the most common forms of real-time precipitation data used. The PPAES analysis attempts to improve on radar-based precipitation estimates by using satellite observations, model forecasts, and surface observations – specifically, in this study, Clarus surface observations – to supplement radar precipitation estimates. The results of this evaluation indicate that the use of Clarus data and the PPAES analysis does enhance real-time precipitation estimates, but only under some circumstances:

- The PPAES analysis with Clarus data was more effective than radar alone at estimating when and where precipitation occurred during winter months, particularly at higher latitudes and for locations relatively far from the nearest NexRad weather radar station. This finding is reflected in both the percentage of precipitation events that were identified correctly and in the equitable threat score.
- The PPAES analysis with Clarus data tended to overcorrect for the fact that weather radar underestimates wintertime precipitation. The PPAES analysis was more likely to indicate that precipitation occurred where it did not (i.e., generate false alarms) than to indicate that precipitation did not occur where it did.

7 Summary and Conclusions

This report documented the impacts of Clarus data on five types of weather analysis and forecasts. First, it reported on the impacts of Clarus data on the LAPS estimates used by the Meridian team to initialize the WRF weather forecast model. This assessment identified that including Clarus data in the LAPS estimation process did result in LAPS estimates that agreed more closely with observations than LAPS estimates made without Clarus data. The Clarus data impacted the LAPS estimates about half the time. When it did impact the LAPS estimates, the result was closer agreement between the estimates and observations about 70 percent of the time.

The next set of results examined whether this improvement in the LAPS data used by the Meridian Team to initialize the WRF model resulted in improved weather forecasts. The results indicated that the inclusion of Clarus data in the WRF forecasts impacted the forecast results, but did not significantly improve the agreement between the forecasts and Clarus observations, though it did not significantly degrade that agreement, either. There was some evidence that this resulted from the "spin up" of the forecast models, with weather physics and other factors built into the model over-riding the impact of the Clarus data entering the model through changes to the LAPS estimates.

The Clarus data was also used to help produce site-specific atmospheric and road condition forecasts at the locations of each observation station. Including Clarus data in the site-specific air and road temperature forecasts provided improved agreement between the forecasts and the observations at those sites. During the early hours of the forecast, the average improvement was almost 2 degrees Celsius, probably because the availability of observations resulted in much more accurate estimates for the model initial conditions and also resulted in more accurate forecasts of atmospheric conditions early in the forecast period. The forecasts made using Clarus data continued to be better on average than those made without Clarus data for the first 24 hours.

The last area in which Clarus data was used was to improve on radar-based precipitation estimates by using satellite observations, model forecasts, and surface observations – specifically, in this study, Clarus surface observations – to supplement radar precipitation estimates. The results indicate that the use of Clarus data and the PPAES analysis did enhance precipitation estimates, but only under some circumstances. In particular, the PPAES analysis with Clarus data was more effective than radar alone at estimating when and where precipitation occurred during winter months, particularly at higher latitudes and for locations relatively far from the nearest NexRad weather radar station. This finding is reflected in both the percentage of precipitation events that were identified correctly and in the equitable threat score. The PPAES analysis with Clarus data was more likely to indicate that precipitation occurred where it did not (i.e., generate false alarms) than to indicate that precipitation did not occur where it did

Appendix A. Description of Metrics

The following list describes metrics used to evaluate the effectiveness of weather forecasts.

Binary Observation – This term applies to estimates and observations that take values of either true or false. A binary estimate or observation is often created by determining whether an estimate or observation has exceeded a specified threshold (e.g., did the precipitation rate exceed 0.1 inch per hour). Each combination of binary observation and estimate is classified into one of the four categories—hit, miss, false alarm, and nonevent—depending on whether the estimate and observation agree and whether the observation was true. The total number of observations is equal to the sum of hits, misses, false alarms, and nonevents:

$$Observations = Hits + Misses + False\ Alarms + Nonevents$$

Bias (BIAS). This metric measures the tendency for the system to either produce an excessive number of false alarms or produce an excessive number of misses.

$$BIAS = \frac{Hits + False\ Alarms}{Hits + Misses}$$

If BIAS is less than 1, it produces fewer false alarms than misses. If BIAS is greater than 1, it produces fewer misses than false alarms. Values close to 1 indicate that the false alarms and misses do not introduce a lot of mistakes into the forecasts. This condition could be because false alarms and misses are relatively balanced or because both false alarms and misses are much less frequent than hits.

Critical Success Index (CSI). This metric measures the fraction of events for which the forecast hits.

$$CSI = \frac{Hits}{Hits + Misses + False\ Alarms}$$

The values range from 0 to 1. A low value indicates that the forecast seldom hits. A value near 1 indicates that the forecast almost always hits.

Equitable Threat Score. The Equitable Threat Score is similar to the Threat Score, but is adjusted for values that would occur purely by chance. It is intended to correct for the fact that the Threat Score tends to give poorer scores for rare events.

$$ETS = \frac{Hits - Hits\ Expected\ by\ Chance}{Hits + Misses + False\ Alarms - Hits\ Expected\ by\ Chance}$$

The value of *Hits Expected by Chance* is computed by

$$Hits\ Expected\ by\ Chance = \frac{(Hits + False\ Alarms)(Hits + Misses)}{Hits + False\ Alarms + Misses + Nonevents}$$

False Alarms – This term applies to estimates and observations that are binary in nature – either true or false. (See Binary Observation for more information.) A False Alarm means that the estimate was true but the observation was false (e.g., the event of interest did not occur, but the estimate incorrectly indicated that the event did occur). For example, the forecast precipitation exceeded the threshold, but the observed precipitation did not. The term False Alarms refers to the number of observations that are classified as a False Alarm.

False Alarm Ratio (FAR). This metric measures the likelihood that an estimate indicated an event occurred when it did not. It is the number of false alarms divided by the number of hits plus false alarms.

$$FAR = \frac{False\ Alarms}{Hits + False\ Alarms}$$

The values range from 0 to 1, with 0 indicating that the estimate is never wrong and 1 indicating that the estimate is never right.

False Alarm Rate (F). This metric measures the fraction of time when an event did not occur but the estimate indicated that it did occur. It is the number of False Alarms divided by the number of False Alarms plus the number of Nonevents:

$$F = \frac{False\ Alarms}{False\ Alarms + Nonevents}$$

The values range from 0 to 1. A value close to 0 indicates that False Alarms are not often generated when an event does not occur, and a value close to 1 indicates that False Alarms often occur when an event does not occur.

Fraction Skill Score – The fraction skill score (FSS) is computed according to the following formula:

$$FSS = 1 - \frac{\frac{1}{N}\sum_N (P_F - P_O)^2}{\frac{1}{N}\sum_N P_F^2 + \frac{1}{N}\sum_N P_O^2}$$

This score can be considered a correlation coefficient where the base model is the worst-case model (i.e., P_F is zero whenever P_O is nonzero and vice versa).

Fraction Spread Score – The fraction spread score (FSPS) is:

$$FSPS = 1 - \frac{\frac{1}{N}\sum_N (P_F - P_{CF})^2}{\frac{1}{N}\sum_N P_F^2 + \frac{1}{N}\sum_N P_{CF}^2}$$

Where P_{CF} is the control forecast (i.e., the forecast resulting from the nonshifted initial conditions).

Hits – This term applies to estimates and observations that are binary in nature, either true or false. (See Binary Observation for more information.) A Hit means that the observation was True and the estimate was True (e.g., the event of interest occurred AND the estimate correctly indicated that the event occurred). For example, both the measured and the forecast precipitation exceeded the threshold. The term Hits refers to the number of observations that are classified as a Hit.

Misses – This term applies to estimates and observations that are binary in nature, either true or false. (See Binary Observation for more information.) A Miss means that the observation was True, but the estimate was False (e.g., the event of interest occurred, but the estimate incorrectly indicated that the event did not occur). For example, the measured precipitation exceeds the threshold, but the observed precipitation does not. The term Misses refers to the number of observations that are classified as a Miss.

Nonevents. This term applies to estimates and observations that are binary in nature, either true or false. (See Binary Observation for more information.) A Nonevent means that the observation was false and the estimate was false (e.g., the event of interest did not occur, and the estimate correctly indicated that the event did not occur). For example, the measured precipitation did not exceed the threshold, but the observed precipitation did not either. The term Nonevents refers to the number of observations that are classified as a nonevent. (The term Nonevents is often labeled Z.)

Percent Correct (PC) – The Percent Correct is the percentage of time that the estimate and the observation agreed:

$$PC = \frac{Hits + Nonevents}{Hits + False\ Alarms + Misses + Nonevents}$$

Post Agreement – The Past Agreement (PS) is 1 – FAR.

Probability of Detection (POD). This metric measures the likelihood that the algorithm will detect an event if it occurs. It is the number of Hits divided by the number of Hits plus Misses.

$$POD = \frac{Hits}{Hits + Misses}$$

The values range from 0 to 1, with 0 indicating the forecast never hits and 1 indicating that the forecast never misses.

Probability of Detection - Inverted (PODI). This metric measures the likelihood that the algorithm will correctly identify when an event did not occur. It is the number of Nonevents divided by the number of Nonevents plus False Alarms.

$$PODI = \frac{Nonevents}{Nonevents + False\ Alarms}$$

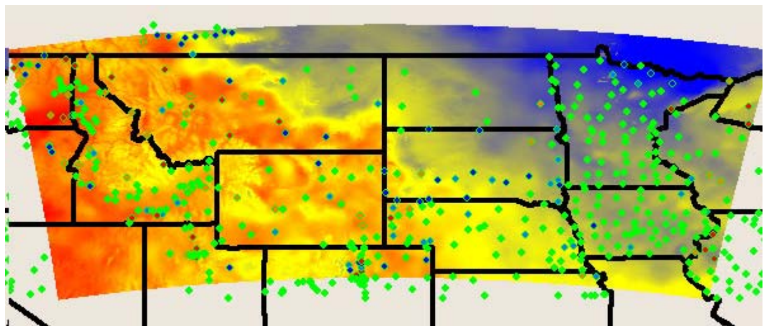
The values range from 0 to 1, with 0 indicating that the forecast never correctly identifies when an event does not occur and 1 indicating that the forecast always correctly identifies when an event does not occur.

Threat Score. The Threat Score is the same as the Critical Success Index.

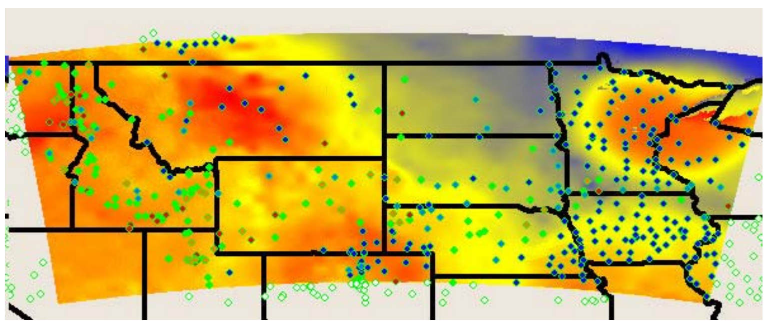
Appendix B. Temperature Forecasts from the WRF Forecast on January 16, 2011 at 12:00 PM

The charts below show the temperature forecasts produced by the WRF forecast from January 16, 2011 at 12:00 PM.

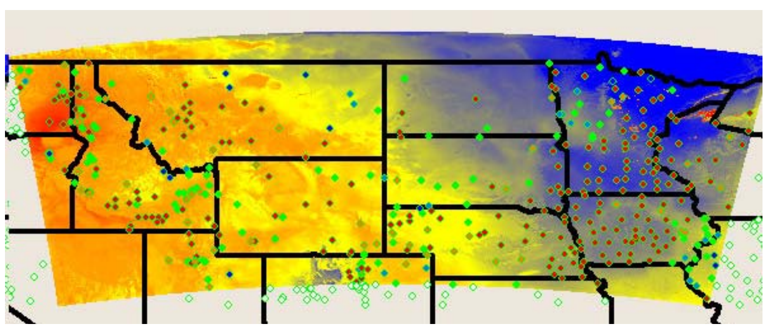
LAPS estimate for 1/16/2011 at 12:00 PM



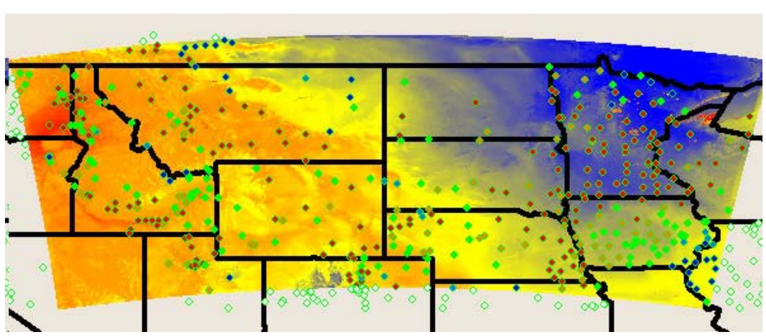
WRF forecast for 1/16/2011 at 12:00 PM



WRF forecast for 1/16/2011 at 2:00 PM



WRF forecast for 1/16/2011 at 3:00 PM



Appendix C. Glossary of Acronyms

Acronym	Definition
ARW	Advanced Research Weather Research and Forecasting
BIAS	A metric used to determine whether a forecasting tool is biased towards producing false positives or false negatives
DOT	Department of Transportation
ESS	environmental sensor stations
ETS	Equitable Threat Score
F	Fahrenheit
F	False Alarm Rate
FAR	False Alarm Ratio
FHWA	Federal Highway Adminstration
FSS	fraction spread score
knt	knots
LAPS	Local Analysis and Predictions System
m/s	meters per second
MADIS	Meteorological Assimilation Data Ingest System
mb	millibar
NCAR	National Center for Atmospheric Research
NexRad	NEXt generation RADar
OBSGRID	An objective analysis program used to incorporate observations into meteorological analyses
PC	Percent Correct
POD	Probability of Detection
PODI	Probability of Detection – Inverted
PPAES	Pavement Precipitation Accumulation Estimation System
REBS	Roadway Environment Blowing Snow
RTFDDA	Real-Time Four-Dimensional Data Assimilation
RWFS	Road Weather Forecasting System
RWIS	Road Weather Information Systems
SOW	statement of work
STWRC	Surface Transportation Weather Research Center
SWR	Seasonal Weight Restriction
UND	University of North Dakota
USDOT	U.S. Department of Transportation
WPS	Weather Research and Forecasting Preprocessing System
WRF	Weather Research and Forecast

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