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SATELLITE AND NUMERICAL MODEL DATA-DRIVEN CLOUD CEILING AND VISIBILITY ESTIMATION

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1. INTRODUCTION

The Federal Aviation Administration's (FAA) Aviation Weather Research Program (AWRP) National Ceiling and Visibility (NCV) product development team is researching and developing automated cloud ceiling and visibility (C&V) products for operational users – pilots, dispatchers, controllers, etc. These products include current analyses and forecasts (up to 12 hours) of ceiling, visibility, and flight category conditions. Improvements in air safety, flight planning, and in-flight guidance are expected as a result of the implementation of these new algorithms and procedures supporting the timely analysis and forecast of C&V conditions and the improved access to the resulting products for the operational users. More information on the NCV analysis and forecasting techniques can be found in Herzegh, et al (2004).

For current C&V analyses, rapid (15 minute) updates of C&V conditions in graphical form will be provided. The graphic output will be a result of the use of developed tools for the examination and analysis of METARs, TAFs, AIRMETs, and satellite, radar, and numerical model data. One of the current areas of research is the use of Knowledge Discovery from Databases (KDD) methodology to develop algorithms to better estimate C&V where direct observations are not available. In addition to the modeling of weather phenomena driven by physical laws (verified by data), some sensible weather elements can be modeled through a data-driven approach. KDD methods allow for development of a simple model from existing data and application of that model on "new" data. Within the context of the KDD approach, data mining of historical satellite, numerical model, and METAR data will uncover the data relationships in order to estimate C&V through satellite and/or numerical model data.

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2. BACKGROUND

For the NCV product development team, filling in the spatial or temporal holes ("gap-filling") of ceiling and visibility observations is a key challenge. Previous work (Bankert, et al, 2004) demonstrated the potential usefulness of cloud ceiling height estimation algorithms developed through the KDD approach. Figure 1 is an example of the real-time output being generated by the Naval Research Laboratory (NRL) GOES-10 cloud ceiling algorithm. Using GOES-10 data from a 3-year period, relationships between the satellite data and METAR observations were discovered to generate this cloud ceiling height estimation algorithm. Table 1 is a comparison of METAR ceiling height and the KDD GOES-10 estimated ceiling height at various locations for the example in Figure 1.

Table 1. Observed cloud ceiling heights (METAR) and NRL KDD GOES-10 cloud ceiling height estimation (from Figure 1).

LOCATION	METAR CLOUD CEILING HEIGHT (FT)	NRL KDD GOES-10 CEILING HEIGHT (FT)
Santa Barbara	1300	1204
Van Nuys	1800	1915
Los Angeles	1800	1525
Long Beach	1400	1315
Santa Ana	1600	1355
Oceanside	1900	2014
San Diego	1600	1630

Data collection, data processing, data mining, and algorithm development are all part of the KDD methodology. Since the KDD-developed algorithms are ultimately used in assessing cloud ceilings in real-time situations, the choice of data sources and data mining tools is very important.

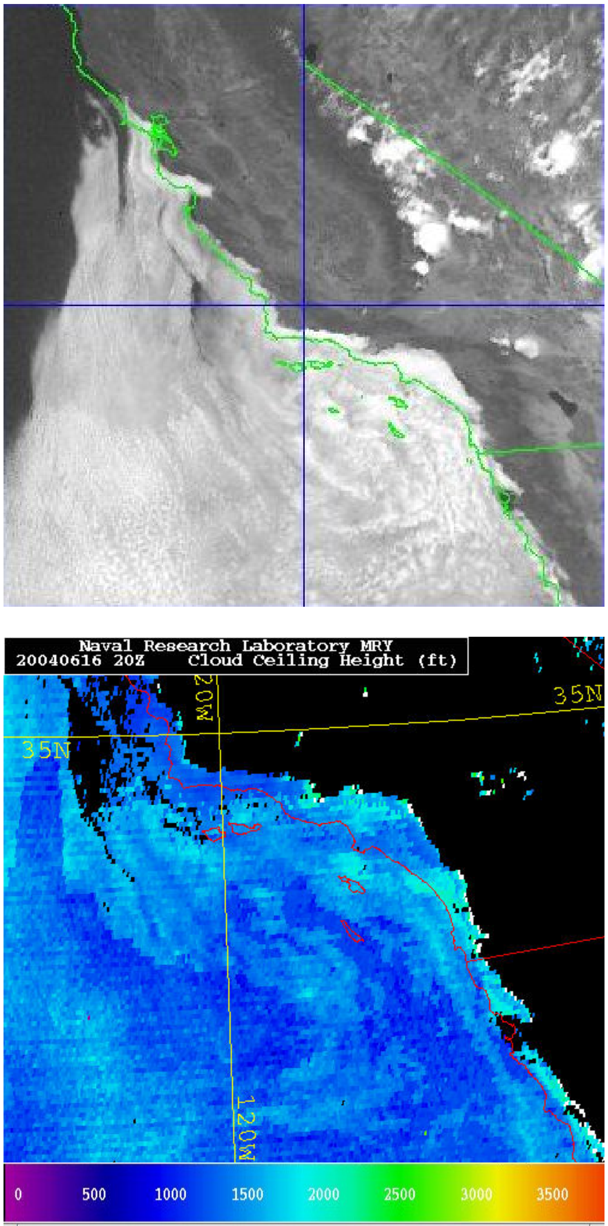

Figure 1. 16 June 2004 2000 UTC visible image (top) and corresponding KDD GOES-10 cloud ceiling image (bottom) of Southern California and adjacent water with ceiling heights estimated in feet.

3. DATA AND ALGORITHMS

Based upon the success of the NRL KDD cloud ceiling research and development, C&V estimation algorithms are currently being developed and tested in a similar manner as part of the NCV product development team's research. Archived (from 2004) hourly Rapid Update Cycle (RUC) model and Geostationary Operational Environmental Satellite (GOES-12) data are being used to create a database of model and satellite parameters. Four geographic regions within the continental U.S. are being studied separately: Iowa, Northeast Texas, Gulf Coast (Texas to Florida), and Mid-Atlantic (Connecticut to Virginia) regions. These areas provide a sufficient quantity and density of METAR stations to train and test the KDD-developed algorithms.

Table 2. RUC parameters – stored in hourly, location dependent database records – to be used in finding relationships between them and observed cloud ceiling (C) and visibility (V).

RH at lowest model level (C&V)
Dewpoint temperature at lowest model level (C&V)
Emperical ceiling (using lowest level T and Td) (C)
LCL (C)
Temperature at lowest model level (C&V)
u-wind component at lowest model level (C&V)
v-wind component at lowest model level (C&V)
Total wind speed at lowest model level (C&V)
Sensible heat flux at surface (C&V)
Latent heat flux at surface (C&V)
Bowen ratio (C&V)
Height of lowest model level with RH > 90% (C)
Terrain height (C&V)
Cloud base height (C)
Cloud top height (C&V)
Cloud top temperature (C&V)
Cloud / No cloud (yes/no) (C&V)
Snow cover depth (V)
Snow cover / No snow cover (yes/no) (C&V)
Height model level with max vapor mixing ratio (C)
u-wind component in 0-30 mb AGL layer (C&V)
v-wind component in 0-30 mb AGL layer (C&V)
Total wind speed in 0-30 mb AGL layer (C&V)
Average RH in lowest 150 mb (C&V)
Temp diff (top and bottom) in lowest 150 mb (C&V)
Precipitable water (C)
Precipitable water ratio (C&V)
Richardson number (lowest 4 levels) (C&V)
PBL depth (C&V)
Vertically-averaged TKE in PBL (C&V)
Stoelinga-Warner ceiling (C)
Soil temperature (C&V)
Net longwave radiation (C&V)
Net shortwave radiation (C&V)
Stoelinga-Warner visibility (V)
Categorical rain (V)
Categorical snow (V)
Categorical freezing rain (V)
Categorical ice pellets (V)
Ground moisture availability (C&V)

Each record in the database is a set of RUC, GOES-12, and METAR parameter values for a given time at a selected METAR location. A list of

RUC parameters can be found in Table 2. GOES-12 parameters include channel and channel-differencing data. In the near future cloud property data computed from a combination of GOES-12 and RUC data will be added.

Data mining was performed on the database to uncover relationships among the RUC and/or GOES-12 variables that balance predictive skill with model generality for the generated C&V algorithms. Classification models (represented as decision trees) were produced through use of the Rulequest Research (1997-2005) C5.0 data mining tool (Quinlan, 1993). Rule-based predictive models (numerical output) were produced through use of Rulequest's Cubist algorithm.

To evaluate the performance of these algorithms, the data is split into training and testing sets for a given region with all records for a specific METAR station in either the training or testing set. C5.0 and Cubist are applied to the training set to uncover patterns and relationships within the RUC and GOES-12 data that can be used to assess cloud ceiling and visibility. The KDD-derived cloud ceiling algorithm is a three-step procedure to, ultimately, identify and estimate the height of low cloud ceilings at a specific location:

Step 1: Yes/No Ceiling Classification
If ceiling exists (yes class), proceed to step 2
Step 2: Low/High Ceiling Classification (1000 m)
If ceiling is low (below 1000 m), proceed to step 3
Step 3: Compute Ceiling Height.

Similarly, the visibility algorithm is currently a two-step process to identify and estimate low visibilities at the surface:

Step 1: Low/High Visibility Classification (5 mi)
If visibility is low (less than 5 mi), proceed to step 2
Step 2: Compute Visibility Distance.
These algorithms are then evaluated on the testing set.

4. INITIAL RESULTS

At the time of this writing, only RUC data has populated the database to a significant level for performance evaluation of the proposed C&V estimation algorithms. RUC-only C&V algorithms have been developed and tested for all four regions using approximately 11 months of hourly data from 2004. Selected METAR stations are used for testing and not involved in the data mining – development of the algorithm - for each region. As an example, the selected Iowa stations are shown in Figure 2.

4.1 Cloud Ceiling Height

Each of the three steps within a KDD cloud ceiling algorithm can be evaluated. For this RUC-only data, day and night data records are combined. Future research that includes GOES-12 data will separate day and night records. Figure 3 is a graph representing the performance for each algorithm in Step1 (yes/no ceiling) for each of the four regions. Four types of performance measures are examined: Overall Accuracy, Probability of Detection (POD) of ceilings, False Alarm Ratio (FAR), and True Skill Score (TSS). While the overall accuracy is similar (over 80%) for all regions, less skill was demonstrated within the Gulf Coast testing. These results are expected to improve with the introduction of GOES-12 data and computed cloud properties. Previous work (Bankert, et al, 2004) has shown that satellite data is a more reliable source for determining the existence of a cloud ceiling.

Performance measures for Step 2 – low/high ceiling classification are displayed in Figure 4. POD, FAR, CSI, TSS are measured with respect to low ceilings – which is of most interest in the aviation community. These results demonstrate fairly high accuracy and skill for the RUC-only algorithms estimating whether a ceiling is high or low. Once again, the algorithm developed for Gulf Coast locations showed the least skill. The Gulf Coast stations may be less homogeneous in terms of relating RUC parameters to cloud ceiling than the other regions.

Figure 5 is a graphical display of the performance measures for Step 3 – low ceiling height estimation. Similar results were found for all four regions. Each of the four region algorithms (all three steps) developed through the data mining process can and will be further analyzed in future work to evaluate any physical meaning of the decision trees and rules that were produced. Region independence will also be examined – can one algorithm be developed for all regions?

4.2 Visibility

The initial test for a RUC-only visibility estimation algorithm suggests some skill, but improvement is needed. As with the cloud ceiling study, each region for each step is analyzed. For the classification of high/low visibility, performance

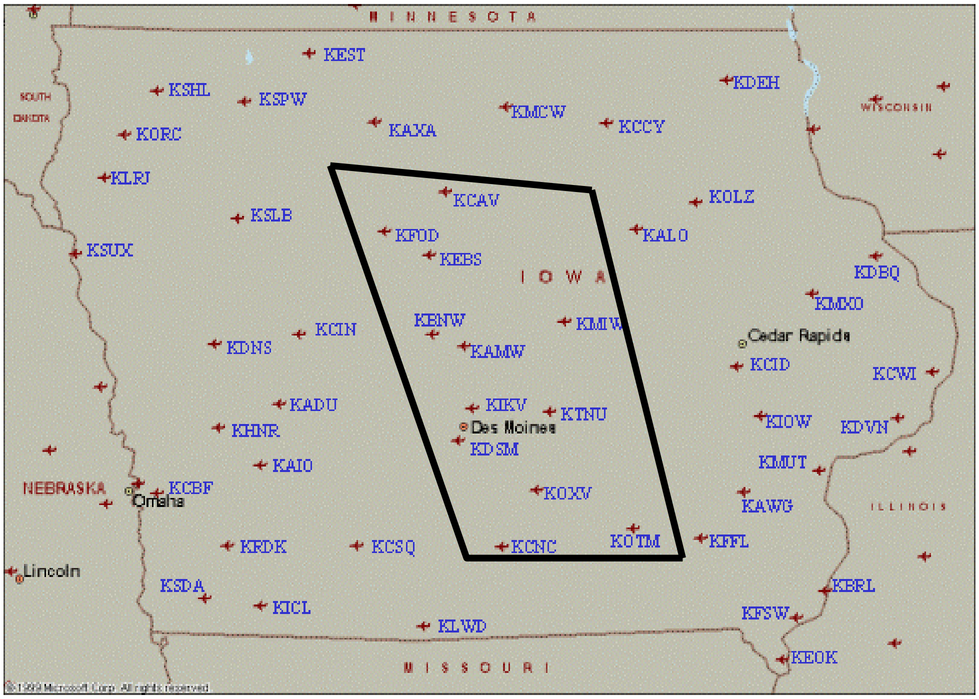

Figure 2. Iowa METAR station locations with testing set of METARS enclosed by black border. All other station data are used to train the specific algorithm through the data mining process.

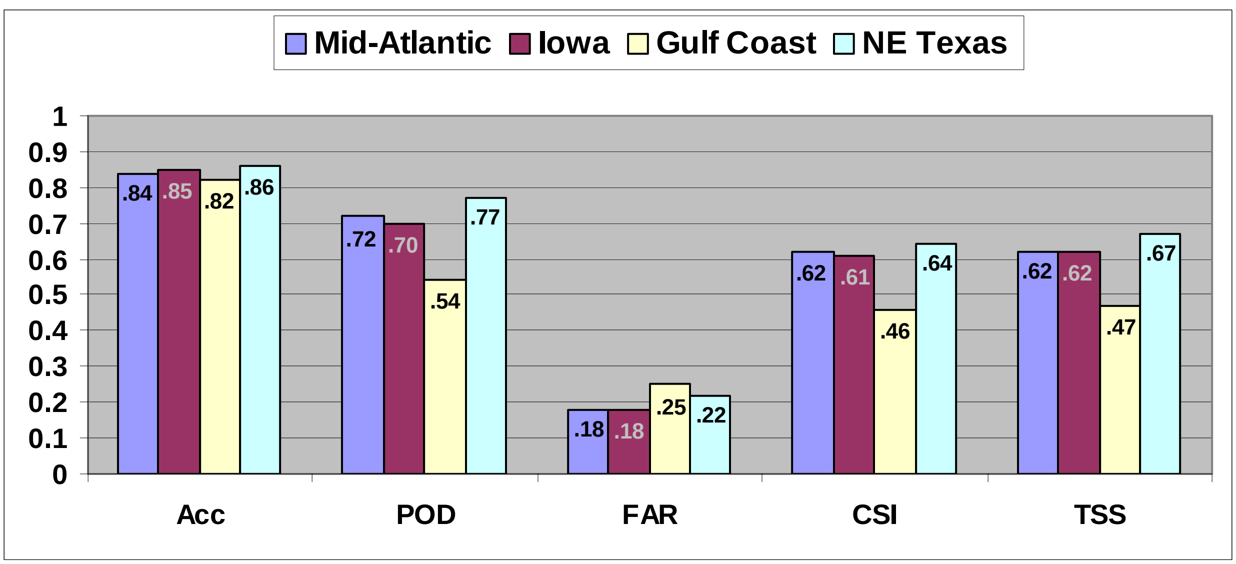

Figure 3. For each region – performance measures for cloud ceiling yes/no (Step 1) for RUC-only algorithms. Acc: Overall Accuracy, POD: Probability of Detection, FAR: False Alarm Ratio, CSI: Critical Success Index, TSS: True Skill Score.

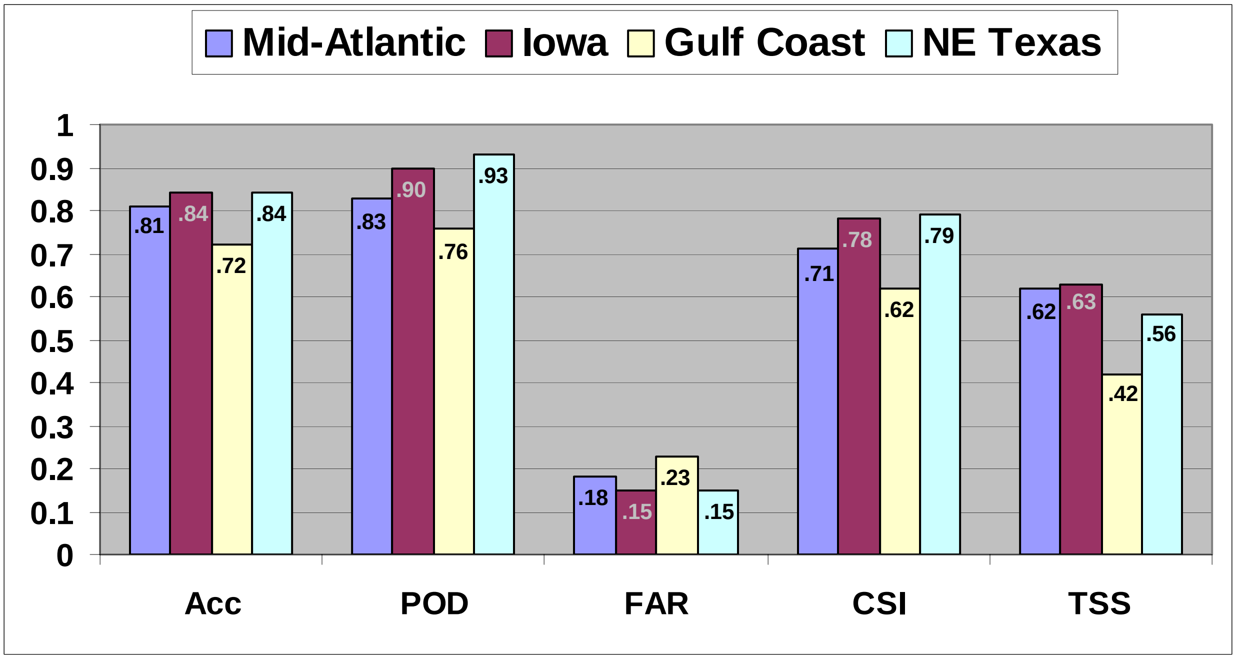

Figure 4. For each region – performance measures for cloud ceiling low/high (Step 2) for RUC-only algorithms. Acc: Overall Accuracy, POD: Probability of Detection, FAR: False Alarm Ratio, CSI: Critical Success Index, TSS: True Skill Score.

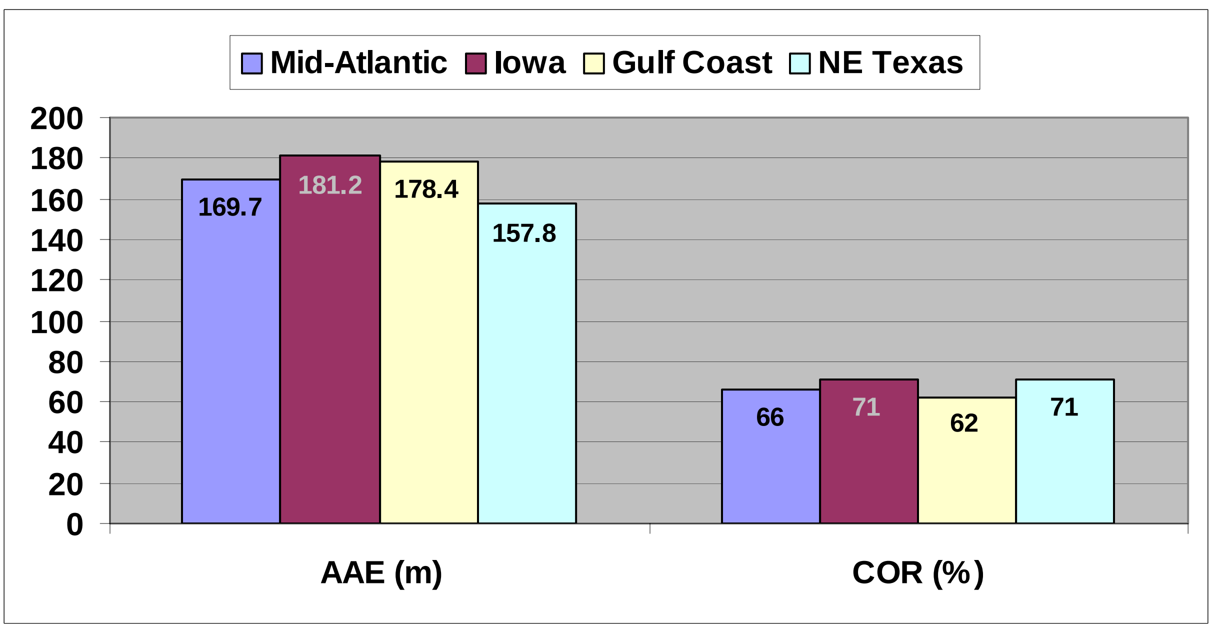

Figure 5. For each region – performance measures for low ceiling height estimation (Step 3) for RUC-only algorithms. AAE: Average Absolute Error (meters), COR: Correlation Coefficient (%).

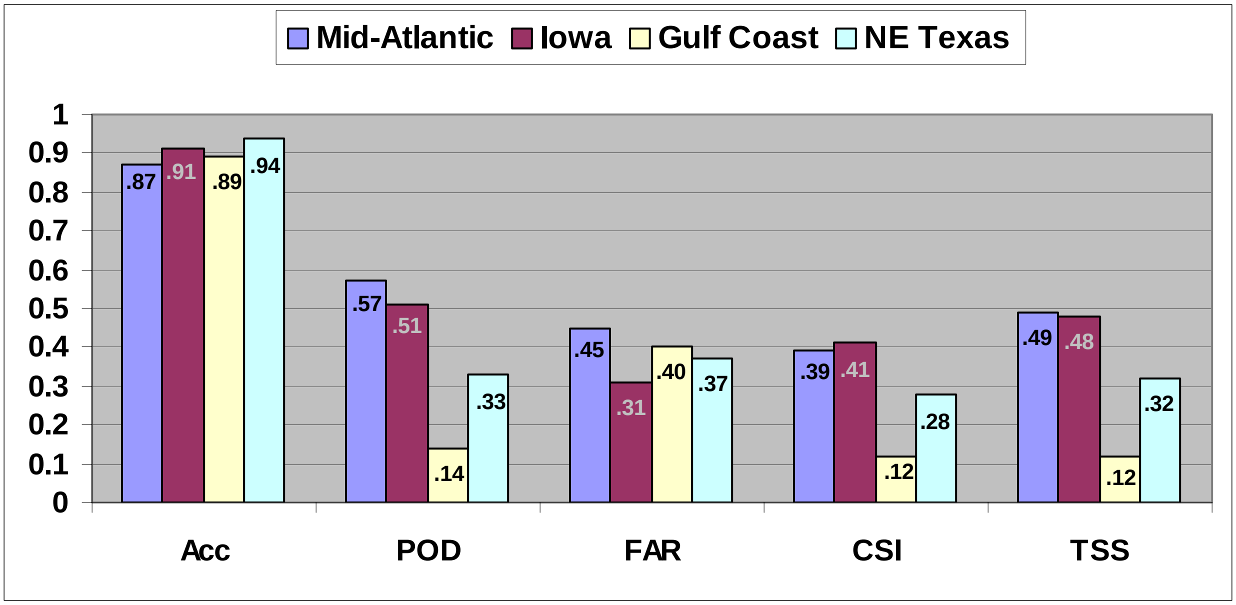

Figure 6. For each region – performance measures for visibility low/high (Step 1) for RUC-only algorithms. Acc: Overall Accuracy, POD: Probability of Detection, FAR: False Alarm Ratio, CSI: Critical Success Index, TSS: True Skill Score.

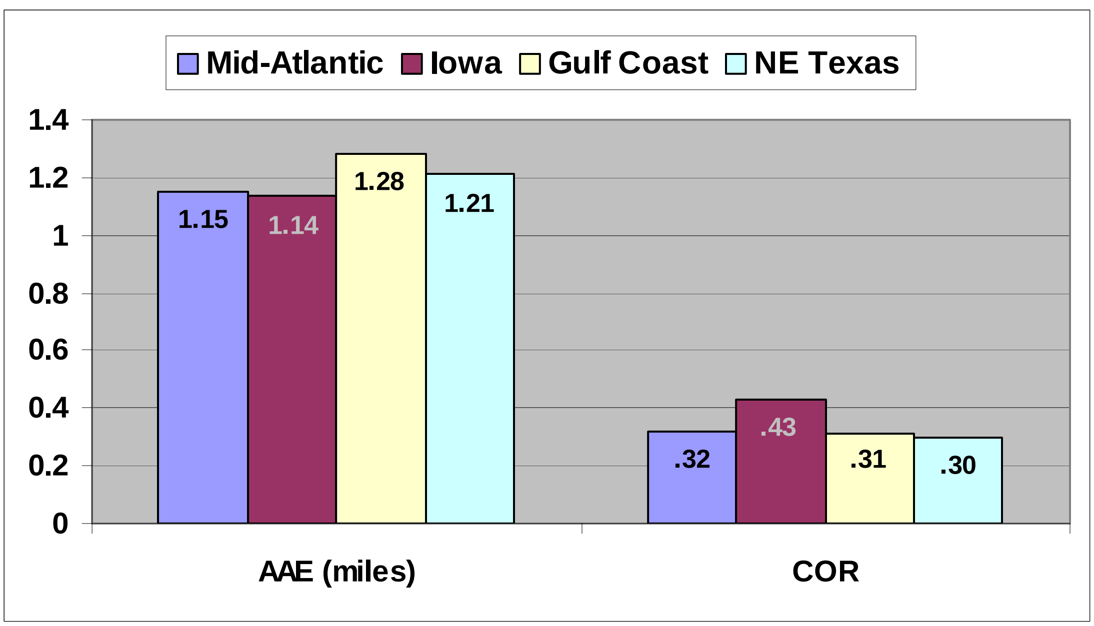

Figure 7. For each region – performance measures for low visibility estimation (Step 2) for RUC-only algorithms. AAE: Average Absolute Error (miles), COR: Correlation Coefficient.

measures are displayed in Figure 6. While the overall accuracy for this classification is high in all four regions, the skill for low visibility identification is relatively low. This is particularly true for the Gulf Coast stations. Some adjustments can be made to possibly improve this result. These include using a different threshold for separating low and high to create a more even distribution of low and high cases (currently there are many more high than low) or a different end-system design (e.g, one step instead of two).

The algorithm's performance in estimating the visibility distance for low visibility cases (Step 2) is presented in Figure 7. Similar error and correlation values were produced for all four regions. The addition of GOES-12 data and RUC/GOES-12 cloud properties may improve these results. An experiment was performed using a much smaller data set of GOES-12 channel values combined with RUC data that produced better performance measures than RUC data alone.

5. FUTURE WORK

The next step necessary as this research moves forward is completing database development to include GOES-12 and cloud properties data. For robust data mining and to build confidence in the algorithms to generalize to real-time data, a minimum 1-year database of hourly records is necessary and will be collected. More algorithm training and testing experiments are subsequently needed for all four geographic regions being studied. Each of the following items will be investigated to complete a thorough study and to find ceiling and/or visibility algorithm enhancements….

1) Train and test algorithms that use a combination of data from two or more regions for testing KDD algorithms for region independence
2) Compare C&V results to Stoelina-Warner (1999) C&V values (current RUC translation algorithm for visibility) to measure relative performance
3) Add cloud properties (liquid water path, cloud optical depth, etc) – some computed from GOES-12 alone and some from a combination of RUC and GOES-12 – to parameter list

Some additional questions that need to be addressed…

1) For each step in either a ceiling or visibility algorithm, does it make sense to use just one of the data sources (GOES or RUC) or a combination? What criteria should be used to judge this?
2) Can these algorithms be applied to mountainous areas or are separate algorithms needed and what is best way to deal with western U.S. (different GOES satellite)?
3) What criteria will be used to determine if any KDD algorithms demonstrate enough skill for transition to an operational setting?

Finally, further analysis in terms of the physical reasoning implicit in the KDD-algorithms may prove insightful and beneficial to future research.

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