1.4 VALIDATION OF THE NWS MIAMI WEATHER RESEARCH AND FORECASTING SYSTEM MODEL FORECASTS DURING THE 2011 SOUTH FLORIDA CONVECTIVE SEASON

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Abstract

Advances over the past several years in high-resolution atmospheric weather modeling include the introduction of the enhanced RUC13 (13km), which assimilates 3-d level III radar reflectivity, the availability of NASA's Short-term Prediction Research and Transition Center (SPoRT) high-resolution Moderate Resolution Imaging Spectroradiometer (MODIS) Advanced Microwave Scanning Radiometer (AMSR-E) Sea Surface Temperature (SST) composites (providing superior details across surrounding ocean areas), and NASA's high-resolution Land Information System (LIS) surface datasets. In order to study the impact of these improvements and the performance of various local model configurations at WFO Miami, an experiment was conducted during the 2011 convective season using the Weather and Research Forecasting (WRF) Environmental Modeling System (WRFEMS) released and maintained by the National Weather Service (NWS) Science and Operations Officer Science and Training Resource Coordinator (SOO STRC). The experiment consisted of verifying and comparing against each other the performance of different model configurations using Equitable Threat Scores (ETS), Areal Bias (AB) Scores, and Percent Correct (PC) scores for different precipitation thresholds. The focus of the analysis was on short term convection. The model configurations consisted of a variety of local high-resolution WRF configurations and the RUC13. Emphasis was also given to the effect on the local WRF model configurations of NASA's SPoRT surface datasets as well as to the effect of using explicit convection versus convective parameterization. The skill scores were computed using Stage IV gridded precipitation data as ground truth. This paper presents the results of this experiment.

1. INTRODUCTION

During South Florida convective season (mid-May to mid-October) mesoscale weather features have a significant impact on day-to-day weather forecasts as they represent the primary forcing. Some of these features are: sea, land, and lake breezes, thermal troughs, and outflow boundaries. The warm waters of the Gulf Stream also play an important role on the thermodynamic properties of the local air mass. Also day-to-day fluctuations in the conditions of the land surface (temperature and moisture) associated with the spatial variability of day-to-day convection impact the observed thunderstorm activity. Unlike in the past, many of these features are represented in high-resolution models available to local offices from National Centers as well as from local models which are necessary to support local forecasts.

In fact, during the past several years significant improvements have been made with high-resolution diagnostic as well as prognostic tools. One of those tools is the 13 km Rapid Update Cycle (RUC13) model (Benjamin et al., 2007, 2010). The RUC13 incorporates assimilation of multiple high-resolution data sets including nationwide level III radar data. Another one of those tools is the Weather and Research Forecasting (WRF) Environmental Modeling System (WRFEMS; SOO/STRC, 2010) which is a packaged version of the WRF model distributed by the National Center for Atmospheric Research (NCAR). The WRFEMS enables the configuration of high-resolution model configurations for operational or research purposes at the local level while requiring little modeling expertise. Furthermore, collaboration between local Weather Forecast Offices (WFOs) and research groups such as NASA's SPoRT has resulted in accessibility by some WFOs to high-resolution land and surface datasets such as NASA's LIS (Case et al., 2009) and high-resolution SST composites from multiple instruments such as the Advanced Microwave Sensing Radiometer (AMSR) and the Moderate Resolution Imaging Spectroradiometer (MODIS) (Jedlovec et al., 2009, 2010; Schiferl et al., 2010). These new tools and data sets have opened the door for new experiments at the WFO level with the intent to study any potential improvement in local scale convective guidance driven by local high-resolution models.

This paper presents results of a validation study conducted during the 2011 convective season at the

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WFO in Miami to validate their local WRF high-resolution model configurations with emphasis on the effect of the tools described above on the model skill, comparisons against the RUC13, and effects of changing the convective parameterization scheme in the model. This work is the result of a summer internship project at WFO Miami sponsored by the University of Puerto in Mayagüez.

2. OBJECTIVES

The objectives of this paper are: 1) to verify the skill in forecasting summertime convection of WFO Miami WRF Advanced Research core model configurations as well as the RUC13, 2) to compare the skills of the various model configurations tested, 3) to assess the impact of using NASA's SPoRT SST/LIS high-resolution surface data sets, and 4) to verify the skill of the models relative to resolution and the convective precipitation scheme used (explicit versus convective parameterization).

3. DATA

In order to successfully fulfill the objectives stated in section 2, there are four sources of data needed: 1) archives of the models to be validated, 2) the source of initial and boundary conditions used to run the model in 1, 3) the source of surface datasets used for the model run, and 4) the source of observed precipitation data used against which the model skill scores will be computed. These data sources are briefly described in this section.

3.1 Model - WRF ARW

WFO Miami uses the Weather Research and Forecast Environmental Modeling System (WRF EMS). As stated on the WRF-EMS website "*this is a complete, full-physics, state-of-the-science numerical weather prediction (NWP) package that incorporates dynamical cores from both the National Center for Atmospheric Research (NCAR) Advanced Research WRF (ARW) and the National Center for Environmental Predictions' (NCEP) non-hydrostatic mesoscale model (NMM) releases into a single end-to-end forecasting system. All the capability of the NCEP and NCAR WRF packages are retained within the WRF EMS; however, the installation, configuration, and execution of the cores have been greatly simplified to encourage its use throughout the operational, private, and University forecasting and research communities*".

The WRF is run in two different configurations at WFO Miami: a 9/3 km WRF-ARW nest (also referred to in the text as arw09 and arw03) and a 6/2 km WRF-NMM nest. Table 1 shows the highlights of each of the model configurations. Figure 1 shows the model domains. For purposes of this experiment, and given the limited computational resources at the WFO level, only those configurations in red in Table 1 were evaluated in this study. For the same reason the ARW configurations ran out only to 18 hours 6 times a day.

Model: WRF- ARW **Forecast Length**: 18 hours/1 hour output interval **Resolution: 9/3 km nest (arw09/arw03)** **Cycles: 00Z**, 04Z, 08Z, **12Z**, 16Z, 20Z **Boundary Conditions:** 13 km RUC for 9km and outer nest for the 3km domain. **Convective Parameterization:** 3km explicit; 9km: two configurations tested, explicit and Kain-Fritsch (Kain and Fritsch, 1993).
Model: WRF-NMM **Forecast Length:** 36 hours/1 hour output interval **Resolution:** 6/2 km nest **Cycles**: 00Z, 03Z, 06Z, 09Z, 12Z, 15Z, 18Z, 21Z **Boundary Conditions:** Global Forecast System for 6km nest and 6km nest for the 2km domain. **Convective Parameterization:** None.
Common to both model configurations **Initial Conditions:** 13 km RUC outer nests **SSTs:** NASA's SPoRT high res MODIS/AMSR-E composite **Land Surface Temperature and Moisture:** NASA's SPoRT Land Information System

Table 1. WRF model configurations run locally at WFO Miami. Due to limited computational resources, only those configurations in red were looked at in this study.

3.2 13 km RUC (RUC13)

The RUC13 (Benjamin et al., 2007, 2010) is a numerical forecast model that uses an isentropic-sigma hybrid vertical coordinate system and assimilates data on a rapid update cycle run hourly out to 18 hours. Among others, some of its most notable enhancements introduced in recent years include assimilation of hourly nationwide level III radar reflectivity data which have resulted in marked improvements (Benjamin et al., 2007). For purposes of this project, the RUC13 was used for initial and boundary conditions of the WRF-ARW 9 km nest in part because we sought to compare the ARW configurations against those of the RUC.

3.3 NASA's Land Information System and High-resolution AMSR-E/MODIS Sea Surface Temperatures (SST)

NASA's SPoRT high-resolution MODIS/AMSR-E SST is a 1 km SST product that is created real time by compositing SST retrievals from MODIS polar orbiting (Aqua and Terra) satellites successive overpasses. However, when done using MODIS data alone, the accuracy of the data is affected by extended periods of cloud cover over any given particular area (Jedlovic et al. 2009). This is where the incorporation of the Advanced Microwave Sensing Radiometer (AMSR-E) retrievals helps as the microwave retrievals are not affected by clouds. This dataset is used to specify the SST going into the WRF model at Miami.

NASA's Land Information System (LIS; Kumar et al., 2006, 2007) is a high performance land surface modeling and data assimilation system that integrates satellite-derived datasets, ground-based observations and model reanalyzes to force a variety of land surface models (LSMs). By using scalable, high-performance computing and data management technologies, LIS can run LSMs offline globally with a grid spacing as fine as 1 km to characterize land surface states and fluxes. Case et al. (2008) presented improvements to simulated sea breezes and surface verification statistics over Florida by initializing the WRF model with land surface variables from an offline LIS spin-up run, conducted on the same WRF domain and resolution. NASA's LIS, provided by NASA's SPoRT Center is used as the land surface data used to initialize the WRF model at WFO Miami.

As stated earlier, one of the objectives of this study was to quantify the effect of using NASA's SPoRT SST and LIS data in the model simulation by looking at skill scores with model runs that used this data versus the same set without the dataset.

3.4 Stage IV Rainfall Data

The Stage IV precipitation data (NCEP, 2011) is a 4 km national mosaic from the regional hourly and 6 hourly multi-sensor (radar and gauges) precipitation analyses that are produced by the River Forecast Centers across the continental US (CONUS) (Lin and Mitchell, 2005). The data is freely available for download from NCEP's website.

4.0 METHODOLOGY

The model evaluation was based on analysis of grid scale calculations of a variety of skill scores including equitable threat score (ETS), areal bias (AB), and percent correct (PC) scores. Before ETS is defined, the concept of a threat score must be defined (TS) (Wilks, 1995). Conceptually, threat scores can be explained like this: given an Area Forecast (Af) of precipitation, an Area Observed (Ao) of precipitation, and the area over which both of these intersect, referred to as Area Correct (Ac), the threat score is defined as shown in Figure 2.

Therefore, the smaller the threat scores the less skill in the forecast. Notice also that if the areas of observed and forecast precipitation overlap by as much as 50%, the resulting threat score would be 0.33 assuming the Af and Ao are equal in size. A perfect forecast for which Af and Ao overlap entirely would result in TS=1. Conversely, if the Ac=0 (no overlap between Af and Ao), TS=0. It is important to mention that TS does not include null cases or cases for which rainfall is not forecast and not observed.

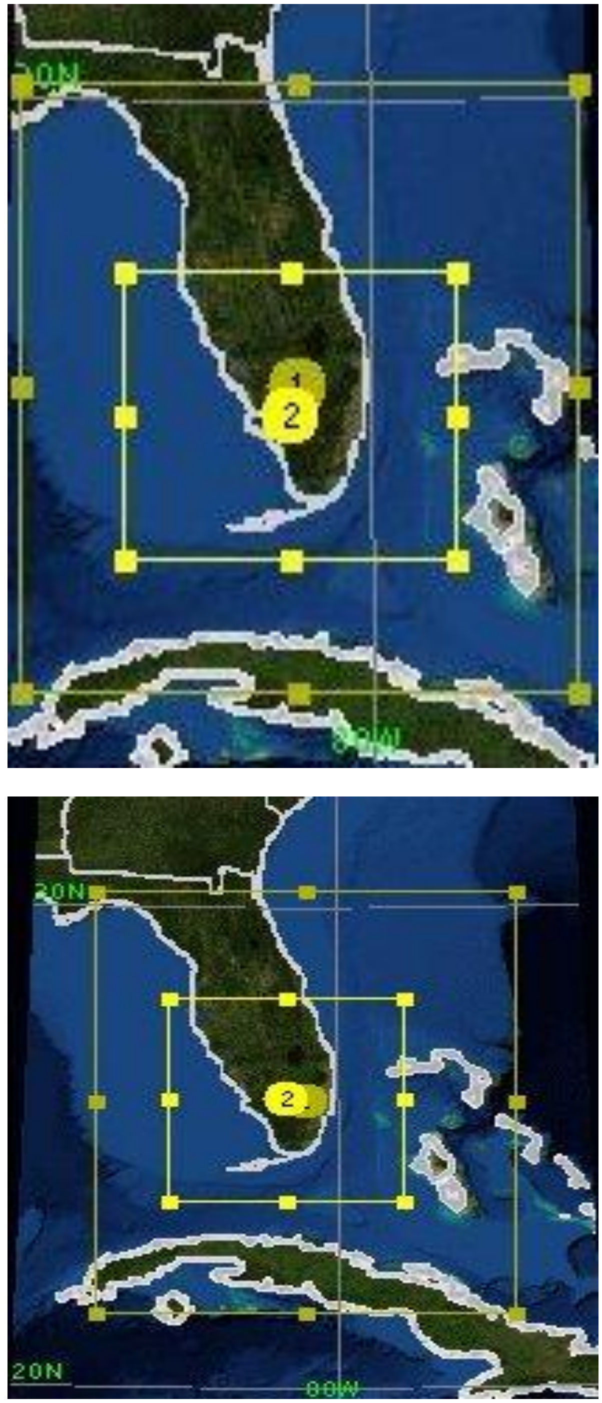


Figure 1. WFO Miami WRF-ARW nested domains (9/3 km or arw09/arw03) top and WRF-NMM (6/2 km) bottom. These are one way nests with inner nests getting their initial and boundary conditions from outer nests.

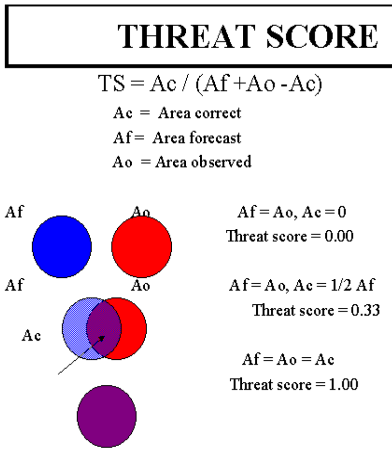


Figure 2. Schematic illustration of the definition of Threat Score.

In in terms of how one computes these on a grid, an equivalent definition is like this. Consider the following contingency table:

		Observed No	Observed Yes
Forecast	No	a	b
	Yes	c	d

Table 2. Contingency table used to illustrate how a variety of skill scores can be computed from Forecast/Observed Yes/No cases.

Given Table 2, threat score is then defined like this:

$$TS = d/(b + c + d)$$

Where d represents hits, c represents false alarms, and b represents misses. In this context, the traditional probability of detection (POD) and false alarm ratio (FAR) are computed as follows:

$$POD = d/(b+d) \quad ; \quad FAR = c/(c+d)$$

This definition of TS is equivalent to the definition in Fig. 2. Notice TS accounts for both POD and FAR and is also traditionally known as the critical success index. So if one has a list of model forecasts and observed data points matching in time, b, c, and d can be counted on a grid point by grid point basis and any of these scores computed for a given area from where data is extracted. The counts can be computed relative to different rainfall thresholds. **In this case we used 0.254 mm (0.01 inches) and 6.35 mm (0.25 inches) of rain for thresholds**. This means the rainfall event is considered to have been forecast or observed for any given point if it exceeded that threshold.

One limitation of the TS score is that if the model exhibits large areal biases it runs the risk of scoring yes forecast and yes observed events by chance and not necessarily skill. So a more commonly used metric in the modeling community for model skill is the equitable threat score (ETS; Rogers et al., 1996) defined as follows:

$$ETS = (Hits – E)/(Hits + Misses + False\ Alarms – E)$$

Where

$$E = (\#forecastpoints \times \#observedpoints/\#Total\ points)$$

Or in terms of how it is computed using Table 2:

$$ETS = (d-dr)/(b + c + d – dr)$$

where

$$dr = (c + d)*(b + d)/(a +b + c + d)$$

where E or dr is a measure of hits expected by chance. A negative ETS signifies no skill with a perfect score being 1.0. Figure 3 illustrates and example of what these scores look like for a bad and good forecast.

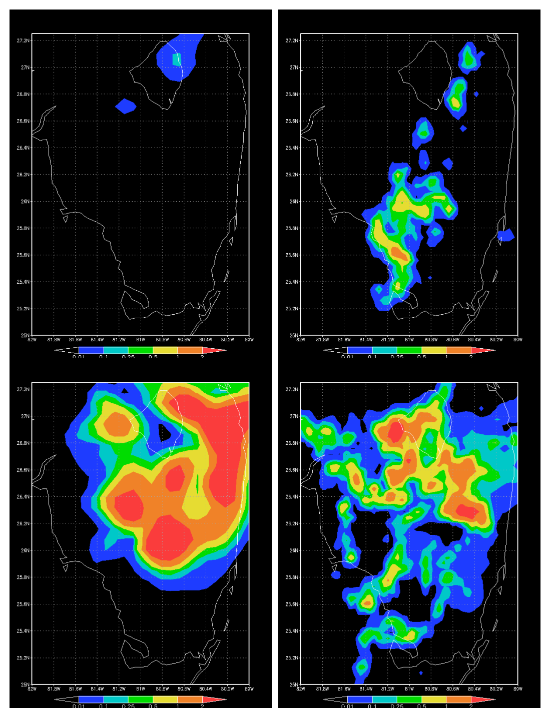
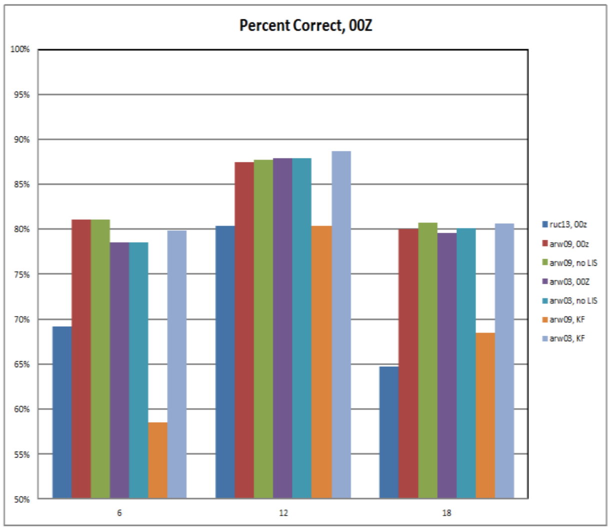


Figure 3. Illustration of how the TS/ETS scores vary between a bad forecast (top row) and a good forecast (bottom row). On the left column is a model precipitation forecast for a given time period and on the right is the observed rainfall for the same period. For this example, the bad forecast (top) exhibited a TS = 0.01 and ETS = -0.011. The good forecast (bottom) exhibited a TS = 0.583 and ETS = 0.334.



0.01 in threshold

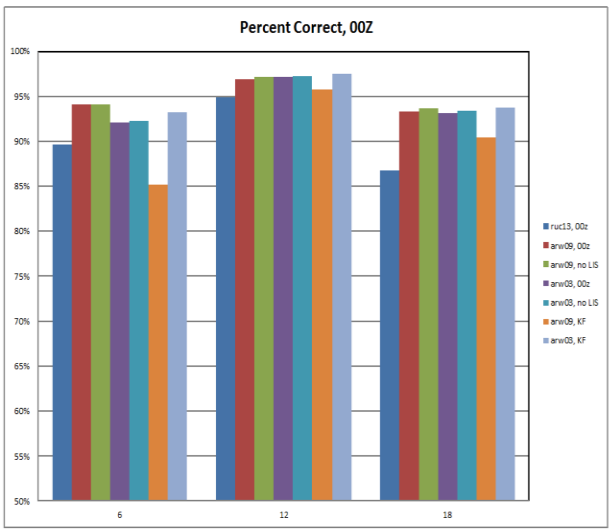


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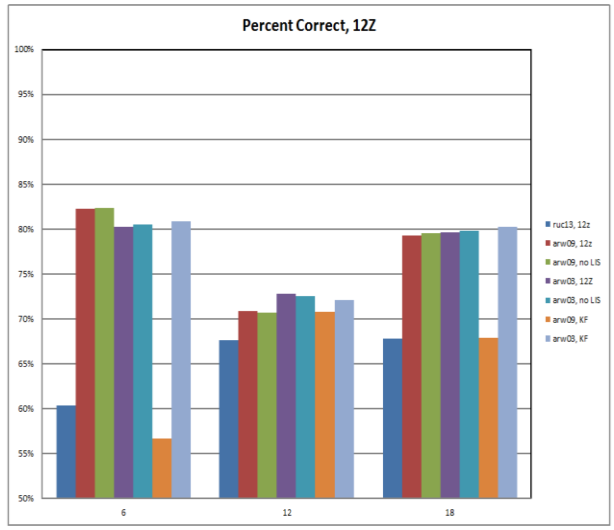
Figure 4a. Composite 00 UTC model cycle PC scores for the 00 to 06, 06 to 12, and 12 to 18 forecast periods for the 0.254 mm/0.01 in (top) and 6.35 mm/0.25 in (bottom) thresholds for the period of study stretching from May 15, 2011 to August 25, 2011. In blue is the ruc13, red is the arw09 (outer nest at the top of Fig.1), green is arw09 without NASA's SPoRT SST/LIS dataset, purple is arw03 (inner nest at the top of Fig.1), light blue is arw03 without NASA's SPoRT SST/LIS, and orange is arw09 using NASA's SPoRT dataset and Kain-Fritsch (KF) for convective parameterization, and cyan is arw03 which still uses explicit precipitation but is fed by the arw09 outer nest with KF.

Other scores that were computed given Table 2 are the percent correct (PC) and areal bias (AB) defined as:

PC = (a+d)/(a+b+c+d) and AB = (c+d)/(b+d)



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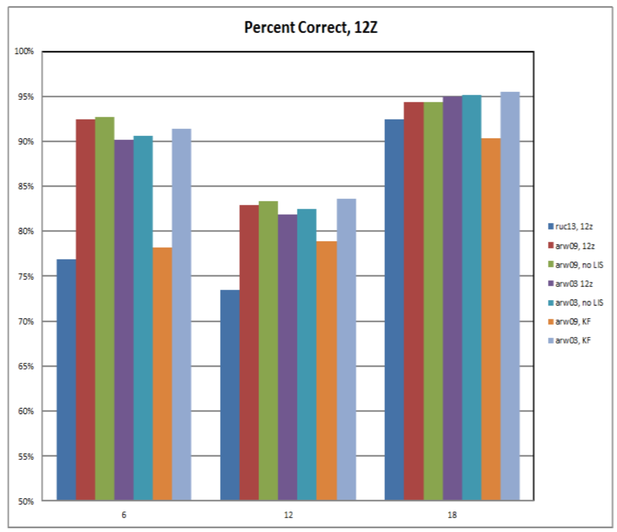
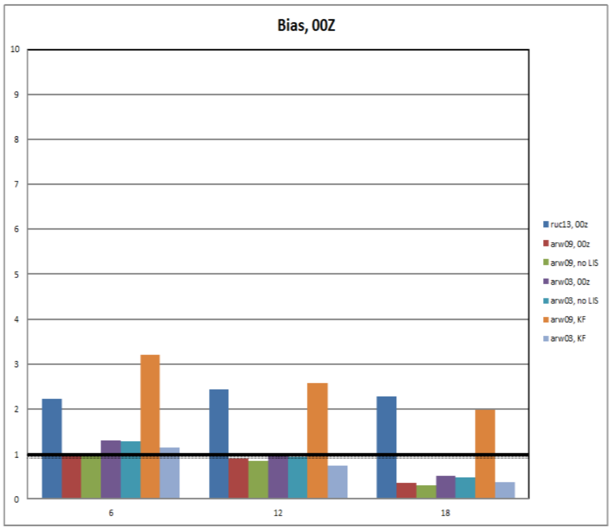


0.25 in threshold

Figure 4b. Same as 4a but for the 12 UTC model cycle.

PC is a measure of the percent of correct yes and no forecasts and AB is a measure of the areal or spatial bias in the model with respect to a given threshold.

In order to compute the skill scores, the model and/or stage IV rainfall data were interpolated on to the lower resolution grid between the two. Then the scores were computed as a function of forecast hour using 3 and 6 hours rain accumulations and composited for the study period stretching from May 15 to August 25 2011 and for the 00 UTC and 12 UTC model cycles. The total of model cycles included in the analysis through the period was 80 for 00 UTC, and 81 for 12 UTC. The thresholds for which the scores were computed were .254 mm/ .01 inches and 6.35 mm/0.25 inches of rain. The area over which scores were computed is the one shown in Fig. 3 which encompasses mainland South Florida despite the



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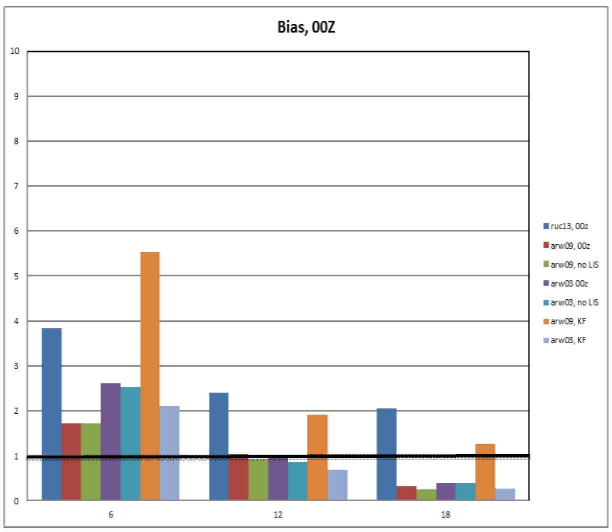
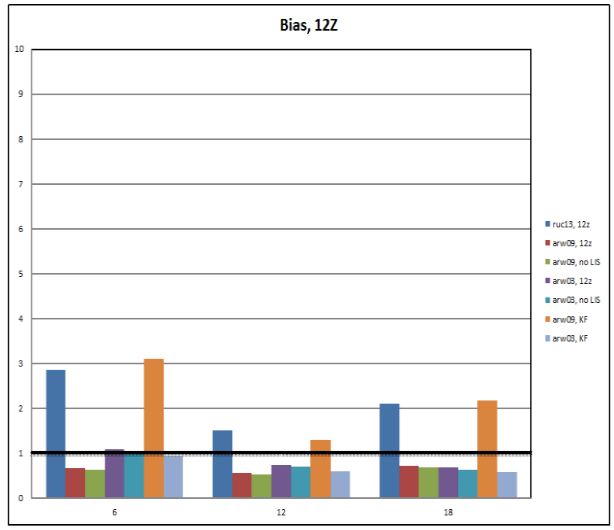


0.25 in threshold

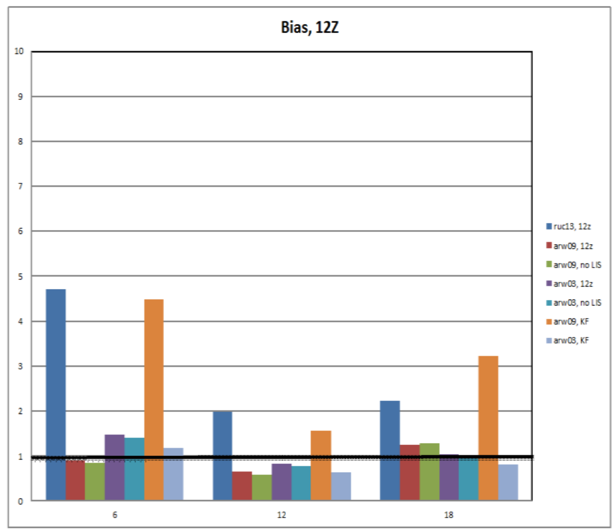
Figure 5a. As Fig. 4a but for AB scores.

model domain in Fig. 1 being much larger. This was due to limited computational resources.

In order to meet the objectives stated earlier, the scores were computed for the RUC13, arw09, and arw03 domains (with and without NASA's SPoRT SST/LIS dataset), and for the arw09 using both explicit convection as well as the KF convective parameterization scheme. This enabled us to compare the RUC13 against the different WRF-ARW local configurations, evaluate the impact of the NASA surface datasets, model resolution, the effect of the convective scheme used, and compare the performance with respect to different rain thresholds.



0.01 in threshold

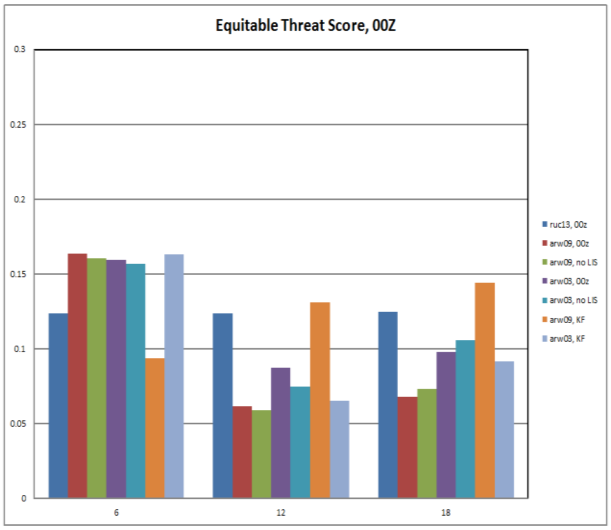


0.25 in threshold

Figure 5b. Same as 5a but for the 12 UTC model cycle.

5. RESULTS

Figure 4 shows the study period composite PC scores for the 0-6, 6-12, and 12-18 forecast periods for the different model configurations for the 00 UTC (4a) and 12 UTC (4b) model cycles. The top plots in Fig. 4 are the scores for the 0.01 in threshold and the bottom ones are for the 0.25 in threshold. This figure shows improvements of as much as 15% of the arw model configurations over the RUC13 in distinguishing areas where the event occurred or not. The improvement is greatest for the 0.01 in threshold. Also notable are the higher scores of the arw09 outer nest configuration that used explicit precipitation versus the runs using the KF convective parameterization scheme which exhibited substantially lower scores, particularly in the lower threshold. The differences in skill related to resolution appear to be not that discernible.



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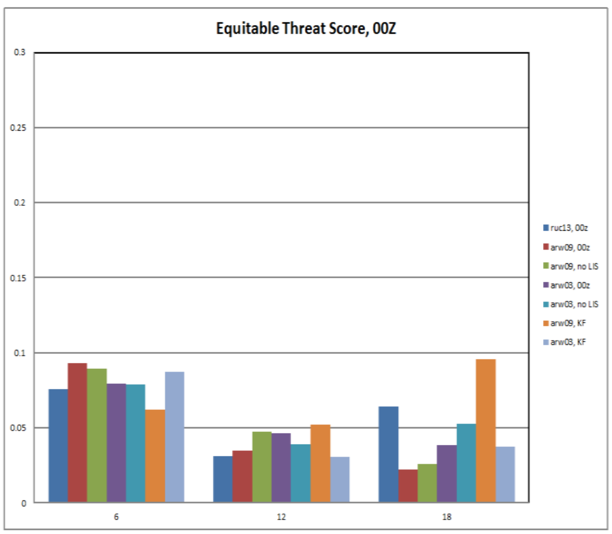


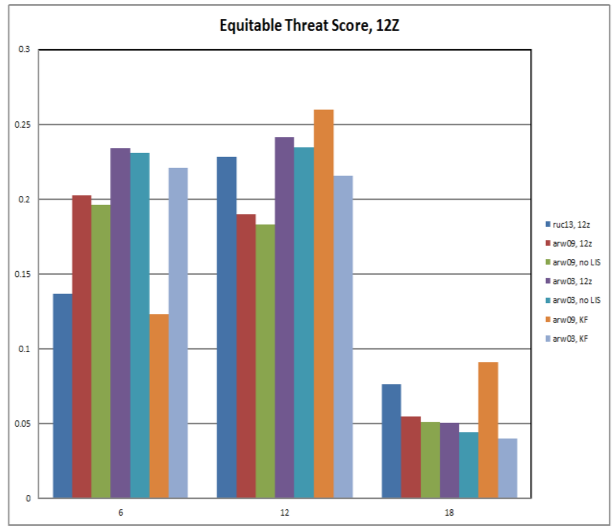
0.25 in threshold

Figure 6a. As Fig. 4a but for ETS scores.

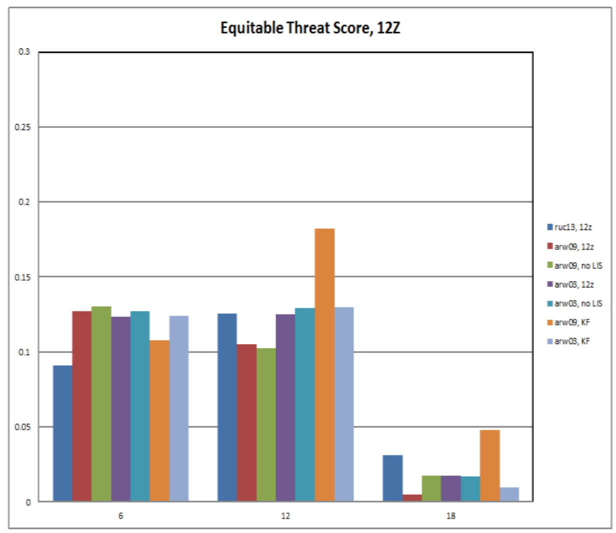
Figure 5 is as Fig. 4 but for the AB scores. It is evident that the RUC13 and arw09 configuration with the KF convective parameterization scheme suffer from a pronounced areal bias overestimating areas of rain by as much as a factor of 2 with individual forecast time periods as high as nearly 4 to 5.5. On the other hand, the arw configurations with explicit convection have a bias closer to 1 except for the latter forecast projections which reflect a dry bias.

Figure 6 illustrates the results for the ETS scores. These are mixed. None of the model configurations clearly outperforms the other although the high areal biases associated with the RUC13 and are09 KF configurations likely contribute to inflate these scores.

Collectively, all three scores clearly show the systematic effect of using NASA's SPoRT SST/LIS



0.01 in threshold

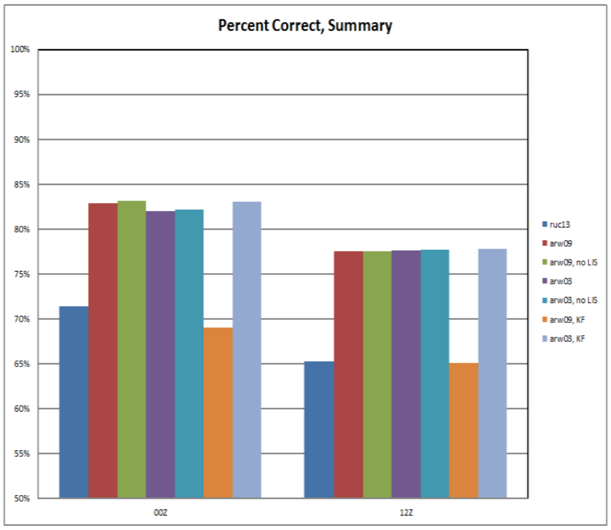


0.25 in threshold

Figure 6b. Same as 6a but for the 12 UTC model cycle.

datasets at the surface is nearly neutral over the convective season.

Figures 7, 8, and 9 show the PC, AB, and ETS scores, respectively, averaged for all forecast periods combined through the study period for the 00 UTC and 12 UTC cycles and the 0.01 in (top) and 0.25 in (bottom) precipitation thresholds. From the perspective of the PC score, and in the mean, the arw configurations outperform the RUC13 and arw09 with KF configurations. Also worth noting is that there appears to be no systematic difference in skill between the different arw model resolutions. The largest difference among the different model configurations stem from the change in the convective scheme with explicit precipitation outperforming the KF convective parameterization scheme with arw09.



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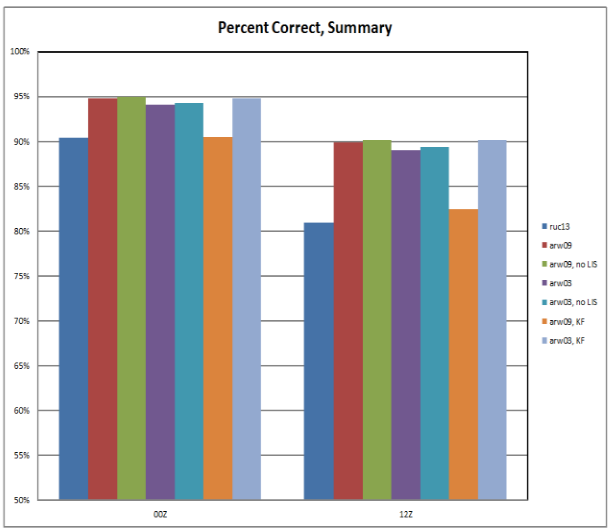


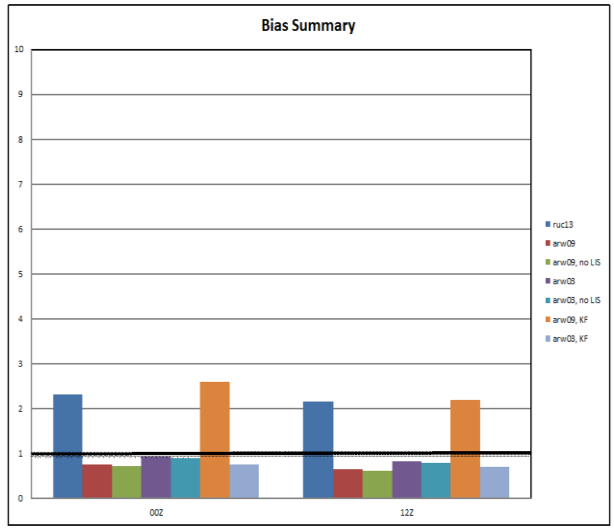
0.25 in threshold

Figure 7. Composite PC scores for all forecast periods combined for the 00 UTC and 12 UTC model cycles for the 0.01 in (top) and 0.25 in (bottom) thresholds.

From the perspective of the AB score, overall, the RUC13 and arw09 with KF configurations exhibit large systematic areal biases while the other arw configurations are much closer to 1. The ETS mean scores in Fig. 9 show no clear model configuration outperforming the other with the 12 UTC cycle exhibiting higher scores overall. This is likely related to the fact that the 12 UTC cycle, given the forecasts went out only 18 hours, is the cycle that best captured the peak of the diurnal convective cycle.

Overall the effect of using the NASA's SPoRT SST/LIS surface datasets is nearly neutral.

Although not shown, a similar sequence of results was analyzed based on 3 hours forecast periods



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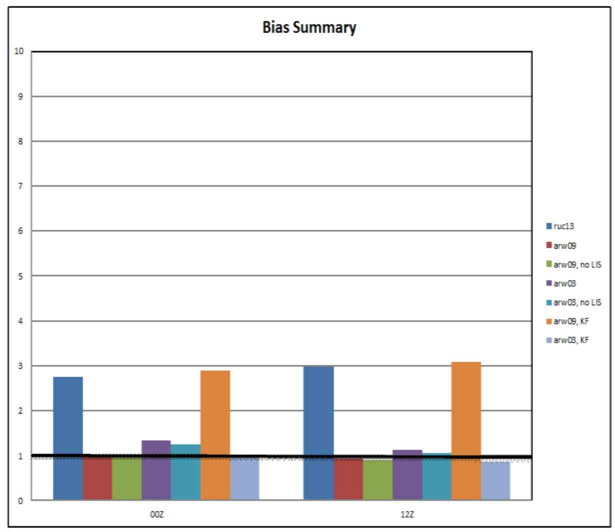
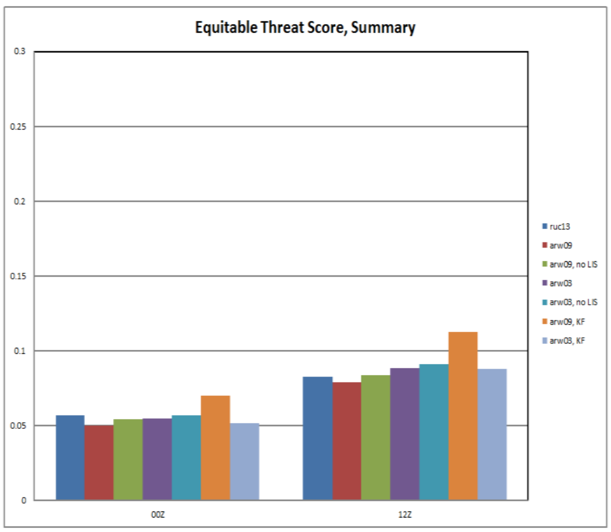


0.25 in threshold

Figure 8. As Fig. 7 but for AB scores.

instead of 6. The results were pretty similar to those summarized so far here based on the 6 hours forecast periods results. The one notable difference was that the RUC13and arw09 with KF configurations exhibited areal biases as high as a factor of 7 for individual 3 hours forecast period. Also, around the 3-hour forecast period ending at 06 UTC, all model configurations showed a very notable wet bias of 6 to 7 particularly on the 3 hour period ending at 06 UTC. This may indicate a problem with the high res models overestimating southeast Florida showers which typically have an overnight diurnal peak during the summer time in the predominant low level easterly flow.

0.01 in threshold



0.25 in threshold

Figure 9. As Fig. 7 but for ETS scores.

6.0 SUMMARY AND CONCLUSIONS

This paper summarizes the results of a verification study of RUC13 and local high-resolution models conducted at WFO Miami during the 2011 convective,season. The period of study stretched from May 15, 2011 to August 25, 2011. Various skill scores were computed to validate and compare different model configurations including the RUC13, and the WRF-ARW configurations shown in Fig. 1 and Table 1. The study also included a comparison of the model skills with and without NASA's SPoRT surface data sets as well as a comparison of using explicit precipitation versus the KF convective parameterization scheme with the arw09 model configuration. The skill scores used included percent correct (PC), areal bias (AB), and Equitable Threat Score (ETS) computed for the 0.01 in and 0.25 in precipitation thresholds.

Results indicate that generally the arw model configurations systematically outperformed the RUC13 in terms of PC scores with the exception of the arw09 with KF. The RUC13 and arw09 KF configurations exhibited a large systematic areal bias compared to the arw configurations. In terms of the ETS scores, the results were mixed with no clear model outperforming the other. Therefore, when looking at these results holistically, the arw configurations outperformed slightly the others.

The skill scores did not show systematic improvements between the outer and the inner nests of the ARW configurations. Whether higher resolution resulted in any systematic improvement or not cannot be answered based on these findings. This is perhaps due to the fact that the inner nest is driven by the boundary conditions flowing into it from the outer nest. Perhaps a more proper comparison would be to run different configurations with different resolutions independent of each other but still using the same initial and boundary conditions.

The greatest detriment in skill scores resulted from switching the convective scheme from explicit in the arw09 configuration to the KF convective parameterization scheme. This highlights that when modeling at these scales resolution is not the only important consideration but also physical configuration parameters.

Finally, NASA's SPoRT SST/LIS datasets do not appear to have any systematic effect in terms of skill (negative or positive). The authors believe this might be related to the fact that the results in this paper were composited for the entire season. This needs further investigation looking at individual cases where large scale forcing is weak. In that context a positive contribution signal might be more discernible from the use of these datasets. That would also be consistent with the findings of Case et al. (2009).

All high resolution model configurations considered in this study exhibited skill in forecasting convective precipitation. But limited as this study was, it highlights that there are still considerable differences among different high-resolution model configurations. Therefore, when one uses high-resolution models at the local level it is not because NCEP does not provide guidance at these resolutions (a valid arguments years ago but not any longer); but, more importantly, it is because their value reside in the combined use of different configurations – an ensemble approach. This is why we believe there is value for the continued use of local models in the field. Additionally it gives offices a tool for conducting case studies as well as to experiment with different configurations.

7.0 REFERENCES

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8.0 ACKNOWLEDGEMENTS

The authors would like to express their gratitude to Evelyn Rivera, Intern at WFO Miami, for her help with the preparation of the charts.