P244 **EVALUATION OF PEANUT DISEASE DEVELOPMENT FORECASTING**

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1. INTRODUCTION

The economic impact of weather on agriculture is undeniable. Growers seek ways to improve their yields, reduce irrigation costs, and prevent disease based on climate information. Growers must often make production decisions before variables such as weather are known. The uncertainties associated with weather can however be mitigated with the use of decision support tools. As research makes known the specific relationships of weather, disease development and crop maturity, the value of climate-based decision support tools becomes more evident. Demonstrable value may provide an incentive to growers to consider climate information in management decisions thereby reducing costs and promoting more efficient use of resources.

The State Climate Office of North Carolina (SCO), at North Carolina State University in Raleigh, is leading efforts to develop weather-based decision support tools in the state. One such tool is the peanut disease mitigation tool. Each morning, during the growing season, disease risk advisories for peanut leaf spot and Sclerotinia blight are distributed to growers and County Extension Agents in North Carolina (Brooks et al., 2006). Recently, the SCO began forecasting disease risk using various numerical weather models. Evaluating the model performance is critical for providing the agricultural community increased warning time for potentially devastating diseases.

2. PEANUT CROP IN NORTH CAROLINA

North Carolina produces about $60-80 million of peanuts annually, ranking 4th in the nation. But two major diseases concerning peanut growers are peanut leaf spot and Sclerotinia blight. If uncontrolled, peanut leaf spot can cause yield losses of 50 percent or more in one season. Sclerotinia blight can spread rapidly under a peanut canopy and result in yield losses of up to 80 percent in severe cases.

Disease prevention is an integral part of crop management. Appropriately timed chemical applications can mitigate yield losses by preventing disease onset, but should only be used when environmental conditions favor disease development. Over-application can exacerbate non-target problems. Weather-based disease advisories take advantage of the close relationships between disease outbreaks and weather by allowing growers to skip or delay fungicide sprays during periods of unfavorable disease development.

3. PEANUT LEAF SPOT ALGORITHM AND ADVISORY CONDITIONS

Cu and Phipps (1993) determined that the growth and presence of peanut leaf spot could be determined using meteorological variables. To be considered a favorable hour for growth, the air temperature must be between 60°F and 90°F and the relative humidity must be at least 95%. The favorable counts of the past four day period are summed up, and spraying advisories are issued when these counts are more than 48 hours. Growers should spray if the last fungicide application was on or before 14 days ago, the last effective spray date.

4. PEANUT DISEASE PREDICTION

Since 2004, the SCO has been running numerical prediction models to help forecast peanut disease development during the growing season, typically May 1 through October 31. Up until the 2008 growing season, we have exclusively run the PSU/NCAR MM5 model to provide us with the weather forecasting component. In 2008 we brought our real-time WRF model online to assist us in this process. During the 2008 peanut growing season, we ran both numerical weather models, MM5 and WRF. The next

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few sections focus on the evaluation of the performance of these models and how they compare to observations and the National Digital Forecast Database (NDFD).

5. MODEL DESCRIPTION

WRF and MM5 simulations were performed every 6 hours over the 2008 growing season and the first 48 hours for each of the model runs was used in this study. Each simulation was initialized with the Global Forecast System (GFS) data. MM5 used a single 12km 100x115 horizontal domain with 31 vertical layers (Figure 1). The WRF model utilized 2 domains, an outer 15km 135x135 domain and a nested 5km 162x82 domain centered over North Carolina (Figure 2). The MM5 and WRF model configurations are shown in Table 1.

Model	MM5 v3.7	WRF 2.2.1 (Outer)	WRF 2.2.1 (Inner)
Microphysics	Reisner 1	WSM5	WSM5
Surface Model	Noah LSM	Noah LSM	Noah LSM
PBL Scheme	MRF	YSU	YSU
Radiation Scheme	RRTM	RRTM	RRTM
Convection Parameterization	KF2	Kain-Fritsch	Explicit

Table 1. Model configuration for the models that are run at the State Climate Office.

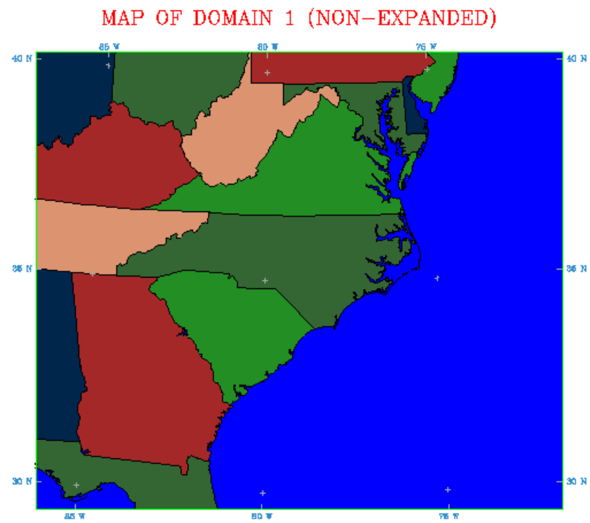

Figure 1. Domain of the MM5 model run by the NC State Climate Office.

Figure 2. Outer and inner (small box) domains of the WRF Model run by the NC State Climate Office.

6. DATA AND METHODS

Collection and organization of all models and observations proved to be a difficult task. The datasets had a variety of different timescales. Observations, along with the MM5 and WRF models provided hourly data, while the NDFD forecasts were only available every 3 hours. Thus, extrapolation of a time frame was done on the NDFD data: Three hours of favorable leaf spot disease development were accumulated only if the three-hour period between two forecasted times was above the thresholds for leafspot development. Also, the NDFD also does not provide an initial forecast/analysis for each forecast, so an initial onset of disease valid to 3 hours out from the model run would not be detected. In order to maintain consistency, all models will be validated from initialization to 48 hours out.

Our evaluation of the model performance is focused on 9 stations in the Coastal Plain in North Carolina as listed in Table 2 and Figures 3 and 4. Evaluation consisted of individual station statistics as well as area averaged outcomes. The following discussion centers on model performance as a whole to highlight the strengths and weaknesses of each forecast model. The best metrics to illuminate the differences between each prediction include absolute error and bias of observed verses modeled leafspot favorable hour counts.

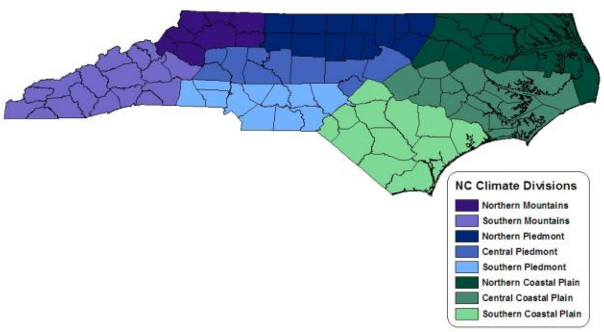

Figure 3. Climate divisions of North Carolina.

Station	Climate Division
Goldsboro (GOLD)	Central Coastal Plain
Kinston (KINS)	Central Coastal Plain
Rocky Mount (ROCK)	Northern Coastal Plain
Williamston (WILL)	Northern Coastal Plain
Lewiston (LEWS)	Northern Coastal Plain
Plymouth (PLYM)	Northern Coastal Plain
Buckland (BUCK)	Northern Coastal Plain
Clinton (CLIN)	Southern Coastal Plain
Whiteville (WHIT)	Southern Coastal Plain

Table 2. Locations of stations used for this study.

Figure 4. Map of stations used for this study.

7. DISCUSSION

For the 2008 growing season, the occurrence of favorable leaf spot hours increased as the season advanced. To better understand how these conditions varied across the season we segregated the counts by month as well as generating an average over the course of the season. The average observed favorable hours counts were the lowest in May (0.99 hours per day), increasing through June (2.07), July (5.06) and August (5.92). The maximum daily index for leaf spot in May was only 4.8 (May 30th), compared to the higher maximum daily indices of 6.6 (June 21st), 10.6 (July 23rd), and 12.2 (August 13th).

The point bias (May - August) averaged for all stations shows that the WRF models had a bias of under-predicting leaf spot by -0.98 (WRF5) to -1.13 (WRF15), compared to the higher under prediction of the MM5 (-4.36) and NDFD (-4.21) as shown in Table 3.

Model	Obs	MM5	NDFD	WRF5	WRF15
May	0.99	-3.40	-3.61	-0.92	-1.08
June	2.07	-3.23	-2.93	-0.20	-0.17
July	5.06	-5.74	-5.08	-1.26	-1.66
August	5.92	-5.06	-5.23	-1.51	-1.60
Average Point Bias	3.51	-4.36	-4.21	-0.98	-1.13

Table 3. Point Bias for all 9 stations averaged

As the season progressed, all four models showed an increasing absolute error of Leaf Spot disease forecasts through July, with only the NDFD worsening in August as shown in (Table 4). These results suggest that the models are comparable in performance with the WRF model showing a slight improvement in performance over MM5 and NDFD.

Model	Obs	MM5	NDFD	WRF5	WRF15
May	0.99	+3.49	+3.64	+2.80	+2.77
June	2.07	+3.35	+3.45	+3.22	+3.24
July	5.06	+5.79	+5.62	+5.00	+4.93
August	5.92	+5.08	+5.81	+4.09	+4.04
Averaged Abs Bias	3.51	+4.43	+4.63	+3.78	+3.74

Table 4. Absolute Error for all 9 stations averaged.

Leaf spot hour data were binned into categories of leaf spot hours of less than two, two (inclusive) to four, four (inclusive) to six, and six or more hours. Broken down by station, stations such as BUCK (100 days), GOLD (99) and PLYM (114) were mostly confined into the lowest bin, while WHIT (55), WILL (64), and LEWS (64) had a majority of days within the highest bin. These stations all represent different climate divisions, with LEWS and PLYM both in the Northern Coastal Plain. ROCK had 30 of the 123 days having a leaf spot hour count between 2 and 6.

Using station-averaged bins, 40% of days had less than two observed favorable leaf spot hours, followed by two to four (24%), six or more (22%), and between four and six (14%). It is also important to note that no days in May had six or more favorable hours observed. The average absolute error, when comparing the models within each bin, generally increased with higher leaf spot bins as shown in (Table 5). A similar trend can be observed in the point bias bins with the MM5 and NDFD, but the WRF models do not strongly exhibit this signature shown in (Table 6). The MM5 was generally best for days with two or less leaf spot hours, in terms of absolute error. But other analyses (not shown) indicated MM5 and NDFD did considerably better than WRF in the early part of the season.

The WRF models had the lowest absolute error for days with four or more leaf spot hours. The WRF models were also the only models to overpredict leaf spot occurrence (positive point bias), and had the lowest bias when more than two hours of leaf spot occurred. The MM5 and NDFD only outperformed the WRF models, based on point bias, in May with two or less leaf spot hours occurring. This may be due to the consistent underprediction of these models, thus "correctly" forecasting little, if any, favorable hours of leaf spot. Further investigation demonstrated the need evaluate the models on how they handle favorable or unfavorable weather conditions for disease development.

8. CONCLUSIONS AND FUTURE WORK

Our results suggest that the MM5 model, using its aforementioned configuration, is the least accurate for predicting leafspot favorable hour counts when conditions are most favorable for disease development. NDFD does not fare much better and in a few instances has higher biases that MM5. The WRF model tends to be the least biased overall and for each of the months.

Future work of this project will include an in-depth look at Sclerotinia blight for 2008, as well as analysis of a multi-season time period, to test the conclusions of this research.

9. ACKNOWLEDGEMENTS

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10. REFERENCES

Brooks, Mark, B. Shew, A. Sims, A. Baker, R. Boyles and S. Raman, 2006: Development of weather and climate decision support tools for agricultural applications. *Extended Abstracts, 22nd International Conference on Interactive Information Processing Systems for Meteorology, Oceanography, and Hydrology,* Atlanta, GA, American Meteorological Society, 12.6

Cu, R. M., and Phipps, P. M. 1993. Development of a pathogen growth response model for the Virginia peanut leaf spot advisory program. *Phytopathology,* **83**, 195-201.

LS: [0,2)	OBS	MM5	NDFD	WRF15	WRF5	# of Days
May	0.48	+0.49	+0.52	+1.24	+1.19	26
June	0.71	+0.65	+0.88	+1.15	+1.01	15
July	1.35	+1.27	+1.46	+2.37	+2.29	6
August	1.10	+1.09	+1.00	+1.24	+1.41	2

a. Bins for two Leaf Spot hours or less of daily occurrence

LS: [2, 4)	OBS	MM5	NDFD	WRF15	WRF5	# of Days
May	2.93	+2.94	+2.89	+2.46	+2.46	3
June	2.70	+2.61	+2.80	+2.86	+2.84	11
July	3.16	+3.15	+3.16	+3.70	+3.54	7
August	3.00	+3.00	+3.05	+3.36	+3.19	9

b. Bins of 2 to 4 favorable hours of daily Leaf Spot occurrence.

LS: [4, 6)	OBS	MM5	NDFD	WRF15	WRF5	# of Days
May	4.80	+4.31	+4.76	+3.30	+3.24	2
June	4.40	+4.41	+4.29	+4.10	+4.34	2
July	5.08	+5.06	+4.80	+4.48	+4.40	8
August	5.38	+5.31	+5.23	+4.56	+4.61	5

c. Bins of 4 to 6 favorable hours of daily Leaf Spot occurrence.

LS: 6+	OBS	MM5	NDFD	WRF15	WRF5	# of Days
May	No Leaf Spot of 6+ observed					
June	6.40	+6.32	+6.14	+4.36	+4.32	2
July	8.61	+8.21	+7.99	+6.33	+6.33	10
August	8.49	+6.26	+7.65	+4.38	+4.36	15

d. Bins of 6 or more favorable hours of daily Leaf Spot occurrence.

Table 5. Bins with absolute error averaged for all nine stations.

LS: [0,2)	OBS	MM5	NDFD	WRF15	WRF5	# of Days
May	0.48	-0.41	-0.40	+0.84	+0.79	26
June	0.71	-0.63	-0.41	+0.30	+0.12	15
July	1.35	-1.22	-1.02	+0.83	+0.71	6
August	1.10	-1.09	-1.00	-0.56	-0.48	2

a. Bins of point bias for two Leaf Spot hours or less of daily occurrence

LS: [2, 4)	OBS	MM5	NDFD	WRF15	WRF5	# of Days
May	2.93	-2.91	-2.84	-1.19	-1.21	3
June	2.70	-2.51	-2.26	-0.14	-0.13	11
July	3.16	-3.06	-2.62	+1.46	+1.00	7
August	3.00	-2.98	-2.57	-1.18	-1.30	9

b. Bins of point bias for 2 to 4 favorable hours of Leaf Spot hours

LS: [4, 6)	OBS	MM5	NDFD	WRF15	WRF5	# of Days
May	4.80	-4.14	-4.76	-0.52	-0.89	2
June	4.40	-4.13	-3.94	-1.62	+0.38	2
July	5.08	-5.06	-3.87	+0.42	-0.29	8
August	5.38	-5.28	-4.75	-0.37	-0.19	5

c. Bins of point bias for 4 to 6 favorable hours of Leaf Spot hours

LS: 6+	OBS	MM5	NDFD	WRF15	WRF5	# of Days
May	No Leaf Spot of 6+ observed					
June	6.40	-6.27	-5.63	+0.93	-0.97	2
July	8.61	-8.17	-7.78	-4.50	-4.62	10
August	8.49	-6.23	-6.98	-2.08	-2.25	15

d. Bins of point bias for 6 or more favorable hours of Leaf Spot hours

Table 6. Bins with point bias averaged for all nine stations.