Forecast climate data use in irrigation scheduling models

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Abstract *Forecast climate data sets are increasing in their role in planning models for water resources. Irrigation scheduling models use solar radiation, air temperature, humidity, and wind speed to calculate reference evapotranspiration. The objective of the research was to determine the error caused by using forecast climate data in an irrigation scheduling model. Daily National Weather Service (NWS) forecast climate data was acquired for locations in New Mexico where an automated weather station was located. Monthly bias of measure-forecast data increases by a factor of 2 when the forecast time increases from 24 hours to 120 hours. Yearly maximum temperature bias ranged from -0.2 to -1.3 degrees C. Evapotranspiration monthly bias ranges are positive and range from 0 in the spring to 0.4 mm/day in midsummer. The main difference between forecast - measured reference evapotranspiration is caused by the overestimation of wind speed.*

Keywords Irrigation, climate, evapotranspiration, forecast

Introduction

The quality of climate and atmospheric data sets has been become more important now that they are being used in planning and prediction models for water resources, evapotranspiration calculations, and air-quality issues. This raises the priority of understanding spatial and temporal variability of the measured and predicted climate parameters. Ideally, the spacing between adjacent climate stations to measure these climate parameters should be such that the error in interpolating climate values for an intermediate station is comparable to the instrumental error at any single station. The recommended spacing for temperature measurements ranged from 160 km for uniform terrain to 15 km for non uniform terrain along the coast where climate conditions change rapidly (Linacre, 1992). Microclimate influences on temperatures observed at nearby (horizontally and vertically) U.S. Climate Reference Network stations were potentially much greater than influences that might be due to latitude or elevation differences between the stations (Gallo, 2005).

The climate element and the time period of the average of the data also affect the spacing to obtain a given accuracy (Wilmott et al., 1991; Hubbard, 1994a; Snyder et al., 1996;

Ashraf et al., 1997). Based on an analysis of climate data from the High Plains (Hubbard, 1994a), a 60 km spacing is required to explain 90% of the variation between sites for maximum daily air temperature. For minimum temperature, relative humidity, solar radiation, and potential evapotranspiration, that spacing reduces to 30 km, and for wind speed and precipitation, spacing of 10 km and 5 km are required, respectively. Spacing requirements varied with the time of year. Using the NWS Cooperative Observers Network, Greco and Smith (2011) determined that in more than 80% of the United States, the climate stations need to be less than a radius of 33 km from each other to resolve air temperature climate variability to within 5 degrees C for a 30-year normal mean monthly air temperature. Consequently, care must be taken in spacing climate stations and in using climate-station data to calculate reference Et or growing degree days over areas greater than 30 km. Forecast data from the NWS forecast office (Saha et al., 2006) is now available on a 2.5 km grid. Reference Et calculate from forecast climate data minus reference Et calculated from the measured CIMIS climate network (CIMIS, 2009) showed a percent difference on a year-time scale that ranged from -8% to 31%, with the largest error in San Diego on the coast of California and the smallest error of -1% in the San Joaquin valley in the center of California (Senay et al., 2008). The grid size of the forecast data used in the study was 100 km.

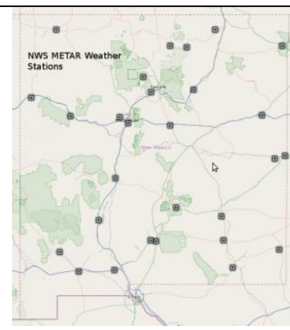
Automated station output must have quality control software (QC) that finds and corrects, or estimates, missing and bad data. The standard quality control software (QC) involves the use of multiple stations where a station's data is compared to the data from neighboring stations (Wade, 1987; Gandin, 1988; Eischeid et al., 1995; Hubbard, 2001). Thus, bad data can be replaced using various statistical approaches (e.g., multiple regression, Eicheid et al., 1995; linear regression, Hubbard et al., 2005). Often, the corrections are inverse distance-weighted interpolations using surrounding stations (Guttman, 1988; Wade, 1987). Camargo (et al., 1998) determined that seven years of data are needed to stabilize the variation between stations in order to develop models to replace missing data based on surrounding data.

The objective of the research was to determine if forecast data could replace missing measured data or replace measured data entirely in an irrigation scheduling model and still result in acceptable accuracy in scheduling irrigation dates.

Materials and Methods

Forecast data is available from the NWS Real-Time Mesoscale Analysis (RTMA), which is a gridded analysis of the meteorological variables (NOAA. 2011). The forecast system model is described by Saha et al. (2006). It produces a 12 km grid of data over the entire United States four times a day for temperature, dew point, relative humidity, wind speed, wind direction, and sky cover for every hour up to five days in advance. The RTMA on the NWS website has interpolated data to a finer grid (2.5 km) and hourly time step. This interpolated data can be obtained by a user by entering a latitude and longitude or selecting a map location (NWS forecast climate data, 2009). The data was captured starting in September 2010 using a python software package (Figure 1) from the 2.5 km grid and hourly interpolated data for locations where five automated climate networks are maintained in New Mexico (Table 1).

Mott (et al., 1992) describes the NMSU automatic climate network. The METAR automated stations are located at airports and represent the average of a two-minute time just before the hour, not the average for the entire hour, as is the case for the other automated networks (METAR Surface Weather Observations, 2011). Snotel is a high-elevation automate climate network operated by NRCS to measure both snow depth and climate data, and the climate network is described by Schaefer and Werner (1996). RAWS is a Remote Automated Weather Stations system maintained by the National Interagency Fire Center with most of the stations located on BLM land (RAWS, 2011). The NMSU Vineyard Network is a subset of the NMSU climate network and has a design similar to that network but is operated by the vineyard extension specialist.

Network name	Number of station and description of instrumentation and data logger	Description map of station location in New Mexico
METAR – airport weather stations (METAR Surface Weather Observations, 2011)	28 station, precipitation, wind speed at 10 m height, barometric pressure, air temperature and due point temperature.	
NMSU State Climate Network (Mott et al., 1992)	17 stations measure precipitation, temperature/relative humidity, wind speed at 3 m height and direction, solar radiation, soil temperature.	

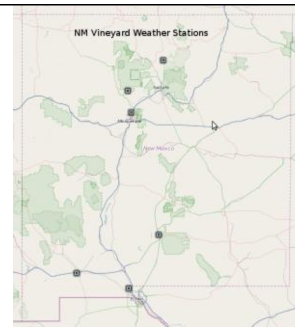
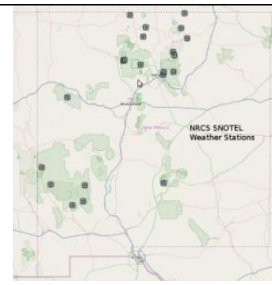
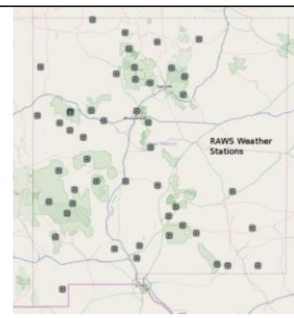
NMSU Vineyard Network	Six stations measure precipitation, temperature/relative humidity, wind speed at 3 m height and direction, solar radiation, soil temperature.	
NRCS Snotel Weather Station – weather stations to measure snowpack (Schaefer and Werner, 1996)	21 stations measure snow water content, precipitation, snow depth, air temperature.	
RAWS – Remote automated weather stations maintained by National Interagency Fire Center (RAWS 2011)	48 stations measure wind speed at 2 m height, precipitation, barometric pressure, soil moisture, air temperature/relative humidity, solar radiation.	

Table 1**.** Automated climate networks measure climate data in New Mexico.

Both measured and forecast databases were written to a database management system that allows importation of the data with different units into a common database. For each forecast location and weather station location, the mean and standard deviations were calculated for the climate variable of interest on a monthly basis. If missing data from either data set occurred, then that day was excluded from the analysis. The biases were calculated using Equation 1.

The mean bias of the forecast data to measure data is Equation 1.

$$\text{MBIAS}= \frac{\sum_{i=1}^{N} forecast - measured}{N} \qquad (1)$$

Consequently, two databases were created, one for measured data and one for forecast data predicted one day into the future. The climate data then was used to calculate reference evapotranspiration (Et_o) (Equation 2) using the standardized penman Monteith equation (Allen et al., 2005).

The Penman Monteith equation described by Allen is:

:

$$Et_o = \frac{0.408\Delta\,(R_n - G) + \gamma\,[900/\,(T+273)]\,U_2\,(e_s - e_a)}{(\Delta+\gamma)\,(1+0.34U_2)} \qquad (2)$$

Where: ET_o = (mm day^{-1})

R_n =net radiation at the crop surface (MJ m^{-2} day^{-1}).
G =soil heat flux density (MJ m^{-2} day^{-1}).
T =mean daily air temperature at 2 m height (°C).
U_2 =wind speed at 2 m height (m s^{-1}).
e_s =saturation vapor pressure (kPa).
e_a =actual vapor pressure (kPa).
e_s - e_a =saturation vapor pressure deficit (kPa).
Δ =slope vapor pressure curve (kPa °C^{-1}).
γ =psychrometric constant (kPa °C^{-1}).

In the case of solar radiation, the NWS day light hours average cloud cover forecast data was used to adjust the calculated clear-sky radiation to actual daily solar radiation (FAO 24) because the forecast model does not predict hourly or daily solar radiation levels. A second daily solar radiation product produced by NASA also was downloaded from the Internet (NASA 2011) and was used to replace the calculated total daily solar radiation from the forecast cloud-cover data and clear-sky calculated solar radiation. This solar radiation satellite data is available on a grid of 1 degree latitude by 1 degree longitude (approximately 100 km grid). The computed solar radiation data (Flashflux 2010) comes from the Terra and Aqua (Modis) satellite (Stackhouse et al., 2008). The Modis solar radiation data has a reported bias of plus 2.25%.

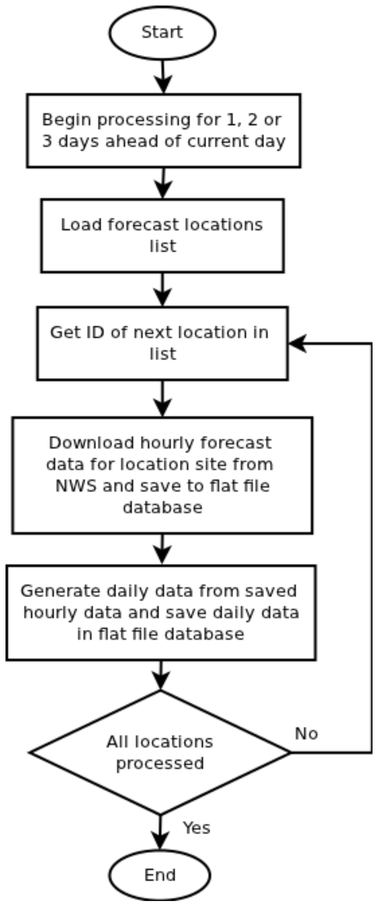


Figure 1. Flow chart of Python based NWS data capture and processing software package.

In Las Cruces, NM, two Campbell weather stations were set up side by side to evaluate the error between two measured climate stations.

The forecast data were compared to the automated climate METAR –airport weather stations station using the NWS analysis presented on its website for the entire United States. The meteorological variables evaluated by the NWS (NWS, 2010) are:

- Maximum highest temperature observed from 7 a.m. to 7 p.m..
- Minimum temperature lowest temperature observed from 7 p.m. to 8 a.m. .
- The ambient temperature observed at 2 meters above ground level.
- Relative humidity: computed from the ambient temperature and dew point 2 meters above ground level.
- Wind speed at 10 m height.

Results and Discussion

Because the NWS also used the METAR data to calibrate the forecast model, this comparison between measured and forecast data sets represents the best forecast data for those sites and is the standard against which to compare the other automated weather station data set. The NWS (NWS, 2010) reported that the 12 Greenwich Mean Time forecast showed decreased accuracy as the forecast data moves into the future with the first 24 hours having the best prediction compared to the measured METAR data for the entire United States (Figure 2). Figures 2, 3, and 4 were derived from data presented by the NWS website: http://www.weather.gov/ndfd/verification/. Because the bias calculation consists of over and under predictions of measured data, the absolute error will be larger than the bias, but the bias data gives information about the monthly or yearly error that will occur when calculating heat units, or evapotranspiration using the forecast data. Generally in agriculture, the daily error is not as important as the weekly, monthly, or seasonal error or bias because the climate data is used for a region, and spatial location within that region also can cause errors in daily values for a region but are consistent when averaged over time (Senay et al., 2008). The average over the years of maximum absolute error (MAE), was 1.29 C for 1,321 sites in the United States, and it increased to 2.03 C for a forecast 108 hours into the future (NWS, 2010). The mean bias calculated increased with the forecast into the future (Figure 2) with the bias being positive from July to January and negative from February to May, with a yearly average biomass of -0.05 C. Similar values of MAE and bias were determined for minimum temperature forecast versus measured data (not shown). The distribution of the absolute error and bias around the sites throughout the United States is consistent in all regions during the summer. In the winter, a higher increase in MAE of 1.1 degrees C occurs in the north-central states (see maps at http://www.weather.gov/ndfd/verification/), but the biases are the same around the United States.

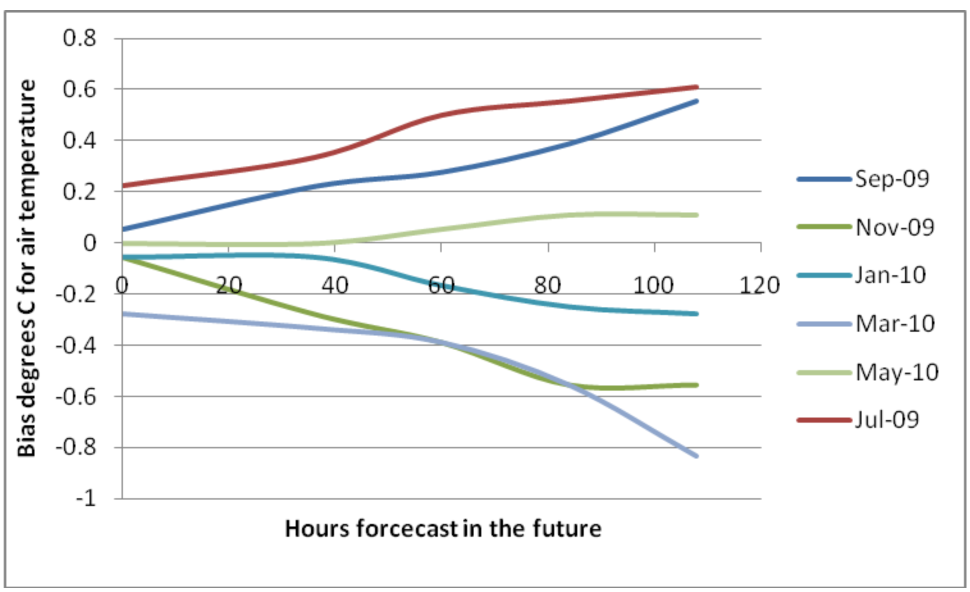


Figure 2. Bias of maximum air temperature in degrees Celsius calculated by the National Weather Service for 1,221 airport locations.

The hourly humidity bias also increases with forecast time (Figure 3) but has a cyclic nature unlike the temperature bias, which steadily increases with time.

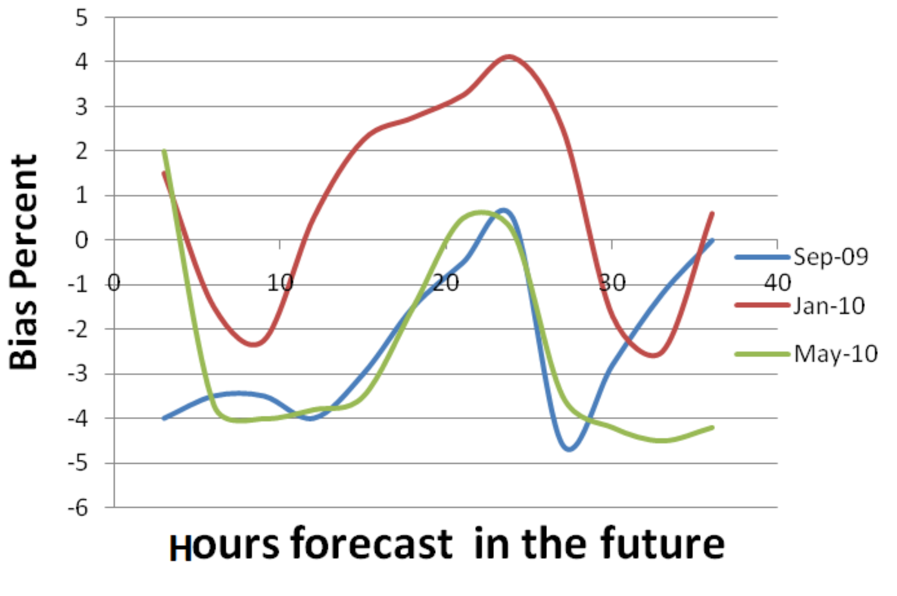


Figure 3. The hourly humidity-bias percent changes with increasing forecast time in the future is calculated by the National Weather Service for 1,221 airport locations.

The wind-speed forecast data at a height of 10 m had a bias that increased with forecast time but still was small (0.5 m/s). However, the forecast model also predicts a wind speed at a height to 2 m, which has a much higher positive bias, as is discussed later in this paper.

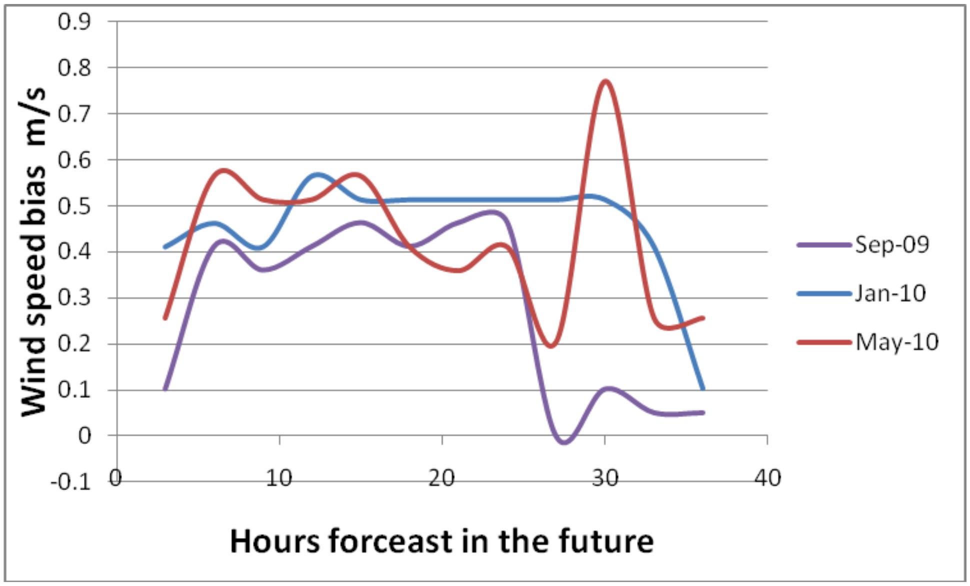
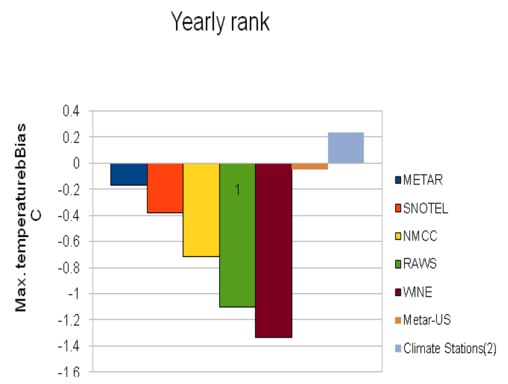


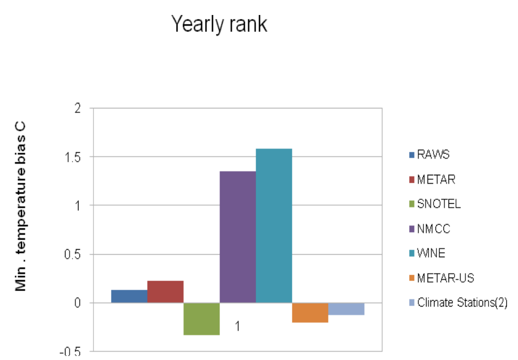
Figure 4. The hourly wind-speed (m/s) bias change with increasing forecast time in the future is calculated by the National Weather Service for 1,221 airport locations.

In general, the forecast error and bias for all of the climate variables are similar across the United States, with only the north-central states requiring more careful analysis before using the forecast data in place of measured data. Because more errors occur in the future, the latest forecast for the current day should be used to predict the climate for the next day, and that forecast data should be used in any crop or irrigation simulation model. The latest forecast run in any given day will depend on the location of the desired simulation. Consequently, the latest run time of day that should be captured will be different for East Coast states compared to West Coast states. All data must be captured for the next 24 hours and stored in the database. Because url data is updated hourly throughout the day, the time of capturing the data is important.

The different networks in New Mexico then were analyzed for comparison between forecast-measured data, and the yearly comparison of the maximum air temperature for the METAR stations only in New Mexico shows a bias of -0.17 C compared the METAR U.S. bias of -0.05 (Figure 5), which is expected when biases are averaged over a larger area. However, the biases between forecast-measured data for the other automated climate networks are larger than for the METAR climate network, increasing from -0.38 for the SNOTEL climate network to -1.3 C yearly bias for the WINE network. The largest network is the RAWS network, which has 48 stations and a yearly maximum temperature bias of forecast-measure data of 1.1 C. The minimum temperature bias is similar to the maximum temperature bias (Figure 5).

The wind speed in the forecast data, in addition to being interpolated temporally and spatially, is interpolated to a 2 m height through the use of a log-wind profile equation (Campbell and Norman, 1998). Consequently, because the roughness length which is a function of the vegetation height in this interpolation equation may not represent the vegetation condition at the other network sites, the wind-speed bias that is always positive for all networks needs to be adjusted before the data can be used in the evapotranspiration equation, or this bias (Figure 5) will lead to an overestimate of reference evapotranspiration (results shown later in this paper).





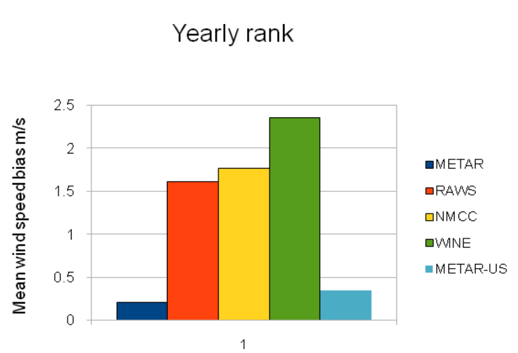
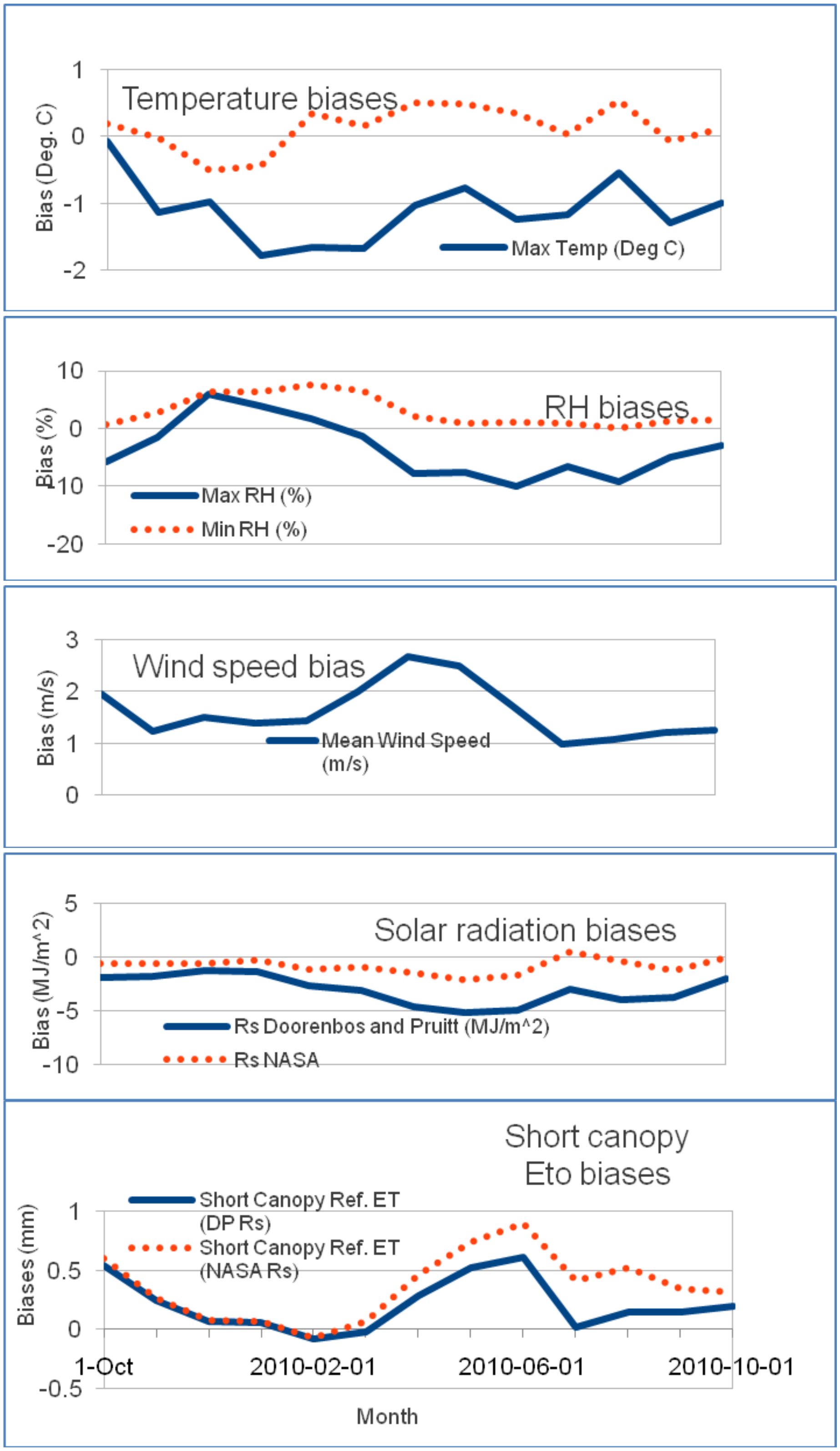


Figure 5. Yearly ranking of maximimum and minimum air temperature and mean daily wind speed bias for five climate networks. The SNOTEL network does not have wind-speed data.

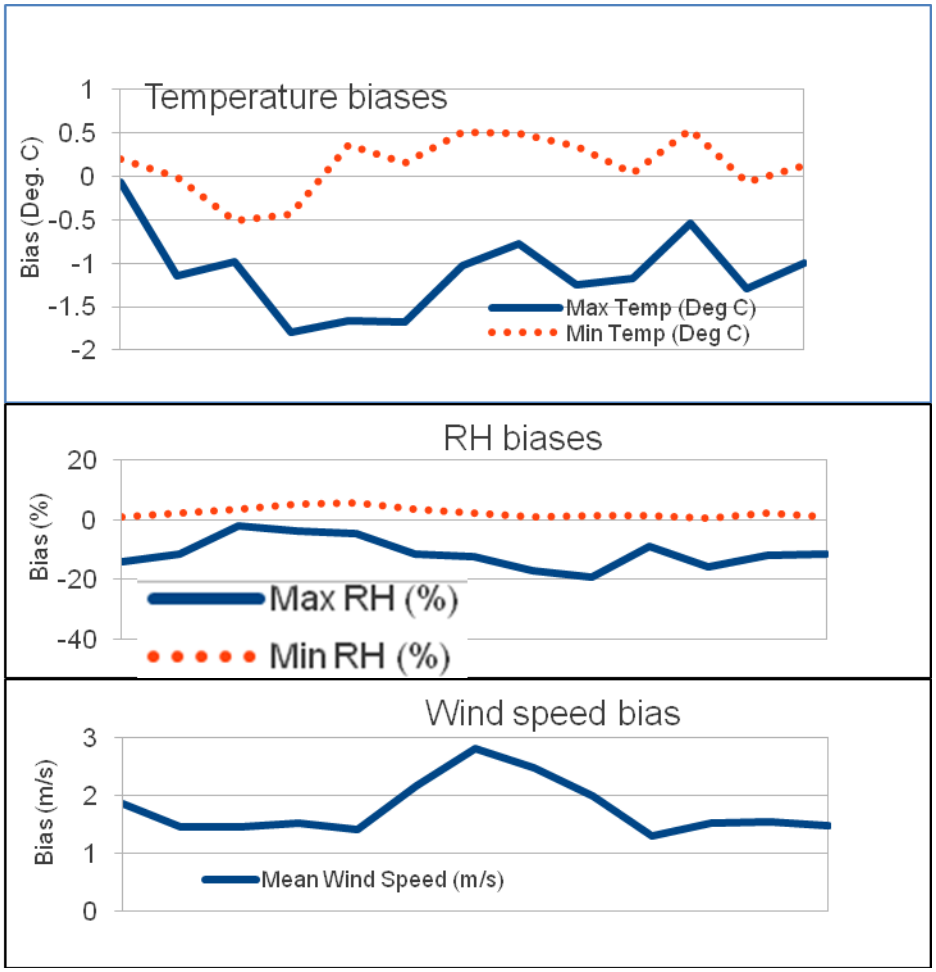
A complete climate data set, including maximum and minimum daily temperature, maximum and minimum daily humidity, average daily wind speed and total solar radiation, is needed to calculate evapotranspiration under non water stress conditions using the reference Et Penman-Montheith equation which is scaled for each crop using a crop coefficient (Equation 2). Consequently, only a comparison between forecast and measured data for the networks having a complete climate data set can be conducted. These include the RAWS, NWCC and the WINE climate networks. The other networks are lacking in one or more measured climate elements needed by Equation 2. Again, these represent a reason to use forecast data instead of measured data because many automated climate networks are missing one or more climate elements needed to calculate the Penman-Montheith equation. Simpler equations to calculate reference Et that use only temperature or temperature and solar radiation can be used with these climate networks, but research has shown that the simpler equations have more error than use of the Penman-Montheith equation.

The forecast monthly series deviates from the measured RAWS data more during the winter months for temperature and humidity compared to the summer months (Figure 6). The bias error for the NWS and WINE data is similar througout the years (Figures 7 and 8). However, wind-speed forecast estimates are more accurate during the winter than during the summer months for both RAWS and NWS, and WINE data sets (Figures 6, 7 and 8). The forecast solar radiation determined from the percent cloud cover has a larger bias during the summer months compared to the rest of the year for both data sets because during the summer months, solar radiation is affected by thunderstorm activity where part of the sky is covered with clouds and part is open sky. Consequently, this patchy cloud cover results in errors when using the simple regression model of FAO24 to reduce clear-sky radiation to cloud cover solar ratiation levels (Figures 6, 7 and 8).



Temperature biases
Bias (Deg. C)
1
0
-1
-2
Max Temp (Deg C)
RH biases
Bias (%)
10
0
-10
-20
Max RH (%)
Min RH (%)
Wind speed bias
Bias (m/s)
3
2
1
0
Mean Wind Speed (m/s)
Solar radiation biases
Bias (MJ/m^2)
5
0
-5
-10
Rs Doorenbos and Pruitt (MJ/m^2)
Rs NASA
Short canopy Eto biases
Biases (mm)
1
0.5
0
-0.5
Short Canopy Ref. ET (DP Rs)
Short Canopy Ref. ET (NASA Rs)
1-Oct
2010-02-01
2010-06-01
2010-10-01
Month

Figure 6. RAWS climate network monthly biases (forecast-measure from Oct. 1, 2009, to Oct. 31, 2010, for the different climate elements and reference ETcalculation. The solar radiation uses the FAO 24 formula or NASA-measured satellite solar radiation.



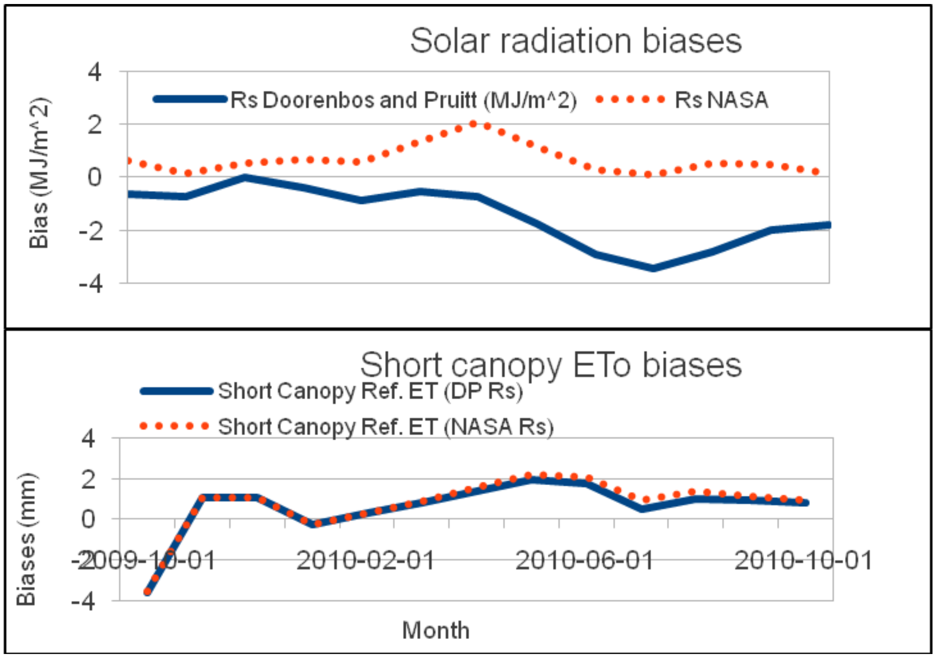
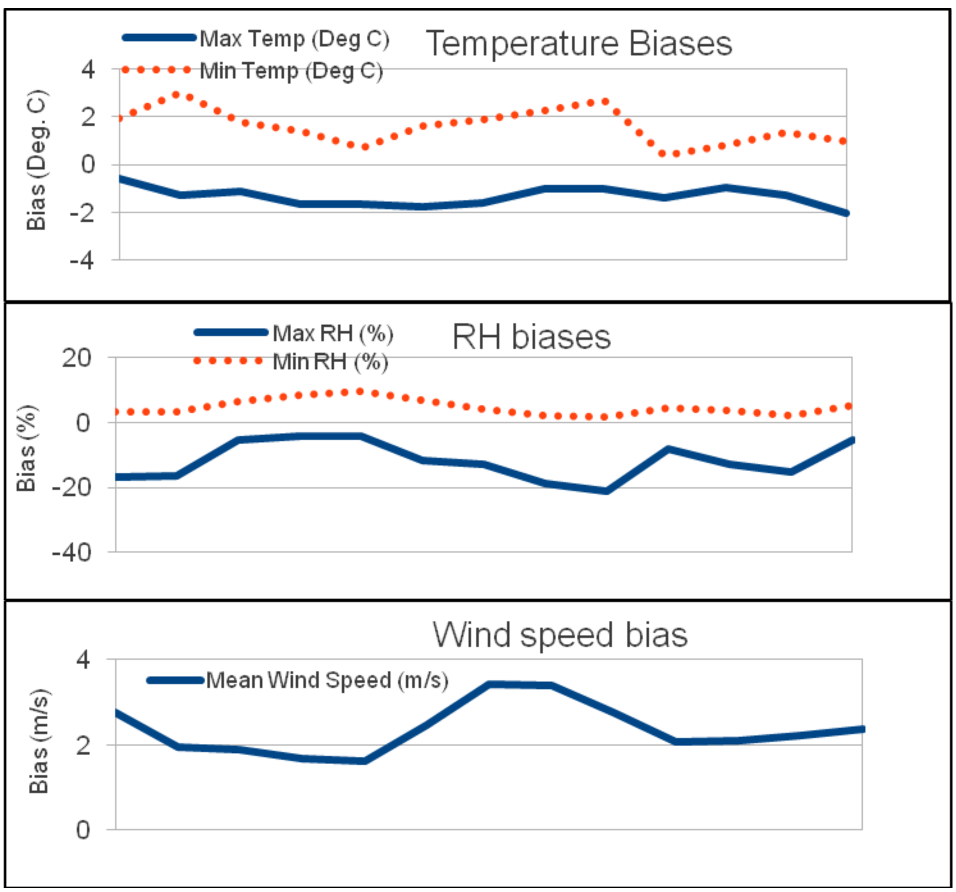


Figure 7. NMCC climate network monthly biases (forecast/measure) from Oct. 1, 2009, to Oct. 31, 2010.



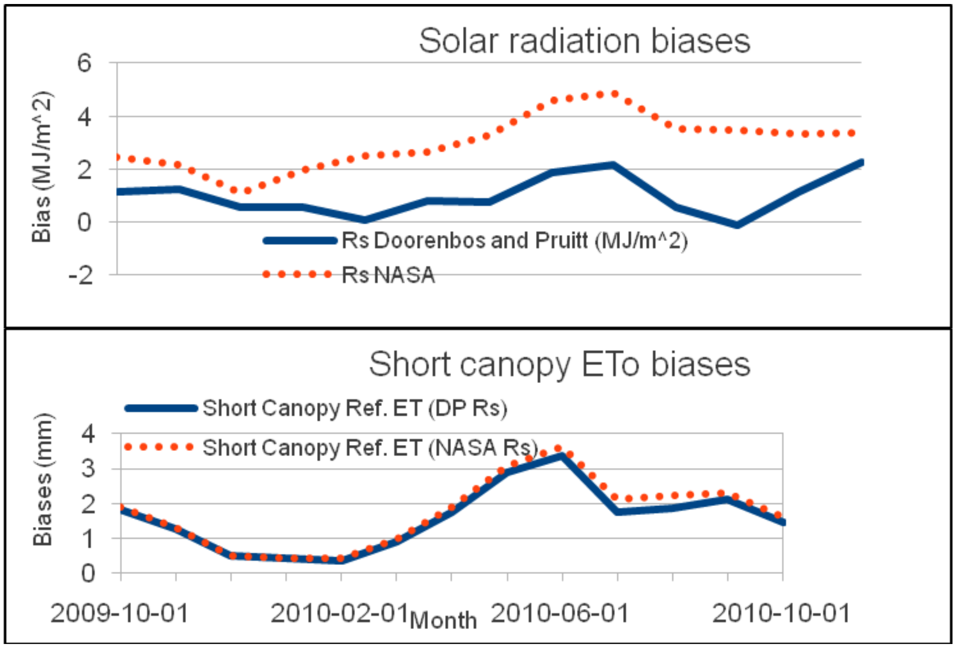


Figure 8. WINE climate network monthly biases (Forecast-measure from Oct. 1, 2009, to Oct. 31, 2010.

The solar radiation bias for all of the forecast data compared to the measured data is reduced when the radiation forecast estimated data is replaced by the measured solar radiation data from the Modes Satellite even though the footprint of the product is a grid of one degree. The yearly bias decreased from -2.99 MJ/m^2 day to -0.76 for the RAWS climate database and from -1.42 MJ/m^2 day to 0.66 MJ/m^2 day for the NWCC climate database. The decrease in bias still represents a higher bias than reported by Stackhouse et al., 2006 of 2.25% for the same product when comparing forecast-measure data. The increased bias is due to the measurement error associated with the use of Licore solar radiation instruments in the climate data sets compared to the use of Epply or equivalent solar radiation instruments used in the measured data set used by Stackhouse et al., 2006 when comparing measured to forecast solar radiation data.

The error in bias for the forecast data compared to measured data must be put into the context of the error between two adjacent climate stations. The bias for temperature and wind speed between two climate stations (data not shown) is in the same range as the difference between the forecast and METAR climate network (Figure 5). When all of the climate elements are combined in the reference evapotranspiration equation (2), and after correcting for wind bias, the average yearly bias of the difference between calculated daily reference evapotranspiration was two to two-and-a-half times larger for the forecast data minus measured data compared to the measured data of two climate stations (Figure 9). The bias of using forecast climate data goes from a plus bias to a small negative bias when wind a yearly wind speed reduction scaling factor is used in the calculations. Bias means that on an average during summer months when reference Et is 8 mm/day, the difference in calculated reference Et using two different climate stations located side by side is 2% whereas the difference between reference Et using measured climate data compared to reference Et using climate data from a forecast model is 5% . The error doubles during the winter months when reference Et is 4 mm/day (Figure 9).

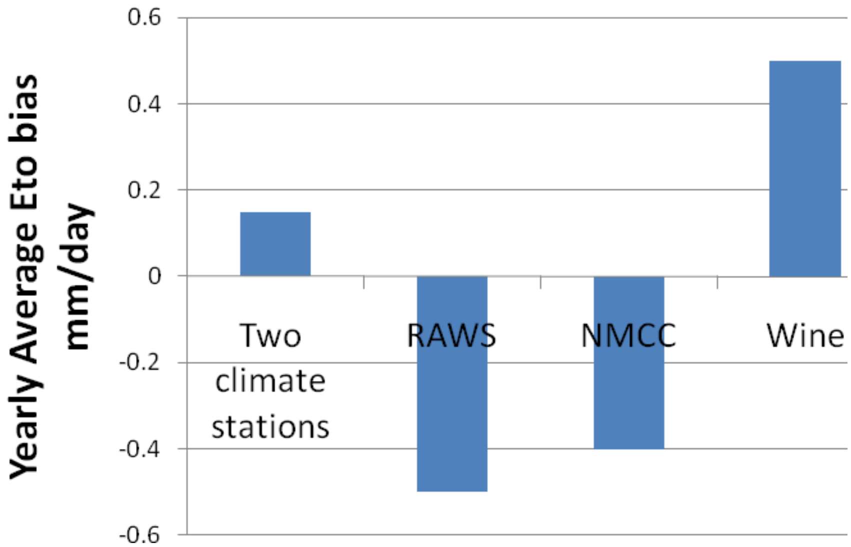


Figure 9. Reference evapotranspiration biases for different networks and for two adjacent climate stations corrected for the wind bias.

Irrigation Scheduling Model.

The forecast climate data was used to drive an irrigation scheduling water balance model to predict the evapotranspiration of alfalfa for Las Cruces, NM. The wind speed was corrected by scaling it by 0.56, the same scaling factor as used in figure 9, and the resulting daily Et was calculated with irrigation water being applied whenever soil-water stress occurred (Figure 10). The forecast data underestimates the Et in July through September, indicating that a monthly wind-correction factor should be used to adjust the forecast wind speed rather than a yearly correction factor. During those months, the correction factor should be 1.0. In Las Cruces, the July through September represent thunderstorm activity instead of frontal storms that occur during the winter months. The forecast wind data is not overestimated during this time period as it is during the rest of the year.

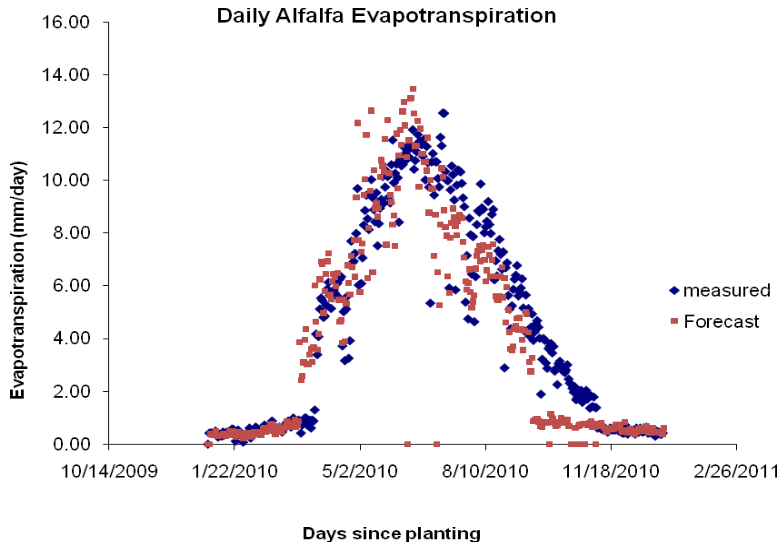


Figure 10. Simulated daily evapotranspiration of alfalfa for Las Cruces, using measured and forecast climate data.

Conclusion

Forecast climate data can be used to replace measured data to be used in agricultural support systems requiring climate data. The spacing of climate stations to measure climate parameters depends on topography, microclimate, vegetation in the surrounding area, and the geography of the area. Computer-based irrigation scheduling models use solar radiation, air temperature, humidity, and wind speed to calculate reference evapotranspiration and then schedule irrigation based on the water balance equation. The forecast data has the smallest bias when compared to measured data at METAR sites because this data is one of the major data sets used to calibrate the forecast model. However, the bias is smaller when comparing the biases over the entire United States to the bias of climate variables for New Mexico. As the climate network switches from the federal government-maintained stations to state networks, the bias error increases. Some of the increase could be due to the location of the climate stations, or the bias error could be due to poorer maintenance. Consequently, if funding is available to maintain the network and good quality control is performed on the measured data, then measured data is preferable to forecast data. Results indicate that monthly bias of forecast-measured data increases by a factor of two when the forecast time increases from a 24-hour forecast to a 120-hour forecast. Reference evapotranspiration's monthly bias ranges are positive and range from 0 in the spring to 1 mm/day in the middle of the summer for the RAWS network and 0-2 mm/day for the irrigated New Mexico Climate Network because of the overestimation of temperature, underestimation of humidity and overestimation of wind speed. However, the main difference in reference Et calculations when using forecast or measured climate data is caused by the overestimation of wind speed in the forecast climate data set. The forecast model is a large-scale macro model and does not represent the small irrigated areas in the valleys of New Mexico but represents the climate conditions in the large, surrounding dry-land mesa where wind speeds are high due to spares vegetation and consequent less wind surface drag. The forecast model is calibrated in the United States using airport data, and in the western United States, airports typically are on dry-land mesas, not in irrigated valleys. If the forecast climate data is used to calculate reference Et it in an irrigated scheduling model, then the wind speed needs to be adjusted downward.

Acknowledgements

This work was supported by the New Mexico Agricultural Experiment Station.

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