Downscaling of NWP based meteorological variables for potential applications

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A general problem with output from weather forecasting models is that modeled variables often do not compare well with ground-based weather variables and complex downscaling procedures are necessary to convert Numerical Weather Prediction (NWP) weather variables into realistic weather variables on the ground. NWP models have now firmly established as major forecasting tool and there is increasing use of Ensemble Prediction Systems (EPS) based probabilistic information in support of decision-making by forecasters as well as other special users. However, the challenges in down scaling the model forecasts, normally applicable for a grid area commensurable with the model resolution, to a meaningful location-specific product are by no means trivial. An attempt has been made in this study to down scale coarse resolution NWP based meteorological parameters to fine resolution products. The meteorological parameters considered for this study are temperature and downward surface shortwave radiation (DSSR) as important for ecological studies at regional scale. The comparisons have been carried out for the DSSR and temperature from satellite with that of in situ data. The NWP based fine grid data were found to be in good agreement with satellite and in situ data as compared to that of coarse resolution NWP parameters. The variations of these remapped fine grid parameters have also been studied at local and regional scale over India.

Keywords: Weather forecasting, Meteorological variables, Downward surface shortwave radiation (DSSR)

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1 Introduction

The Global Modeling and Assimilation Office (GMAO) have been established as a core resource in the development and use of satellite observations through the integrating tools of models and assimilation systems. Global ocean, atmosphere and land surface models are developed as components of assimilation and forecast systems as well as for addressing the weather and climate research questions identified in NASA's science mission. Research quality assimilated datasets, including trace gas, aerosol and climate products, ocean and land surface products, are generated for use by NASA instrument teams and for research analyses. The GMAO generates assimilated data products in near real-time to support the EOS-Terra, Aqua and Aura instrument teams and field experiments. The GMAO also undertakes periodic re-processing of satellite-era observations for research analyses, especially in support of instrument teams and other NASA investigations.

The spatial and temporal variability of weather conditions are an important source of uncertainty when applying crop simulation models over large areas. Nowadays, two important sources of weather variables are often applied:

(i) Weather variables derived from weather stations and interpolated to the locations where the ecology model is applied. Although the density of weather stations in many areas is often quit high, many stations do not report in near-real time making them unsuitable for near real time crop monitoring applications. Due to the limited density of weather stations, a considerable uncertainty is often present in gridded weather products derived from weather stations.

(ii) Weather variables provided by NWP models such as applied by the European Centre for Medium Range Weather Forecasts (ECMWF) and National Centers for Environmental Prediction (NCEP). NWP models suffered from poor spatial resolution for long time as the grid resolution of the model often was in the order of 0.5 to 2 degrees. Recent advances in computing have caused a steady increase of the spatial resolution of NWP models where grid resolution now approaches 25 km.
Many other downscaling algorithms have been developed. Most of the operational NWP models issue forecasts at either 2400 hrs GMT or 1200 hrs GMT, and IMD gauge analysis are available at 0300 hrs GMT. Time correction is applied using a three-hourly TRMM 3B42 diurnal cycle to align IMD gauge data with model forecast hours (i.e. 1200 hrs GMT). The recent study involves the continuation of downscaling and multimodal forecasting of precipitation, in order to examine the TRMM and rain gauge datasets over India.

Meteorological satellites such as the NOAA-AVHRR series or the MeteoSat series are capable of providing meteorological variables. In particular, MeteoSat provides good opportunities with its high spatial resolution to validate downscaled NWP model forecast. Further, MeteoSat imagery can be used for deriving estimates of global and net radiation derived from cloud cover and albedo, daily minimum and maximum temperature derived from day and night surface temperature and potential evapotranspiration derived from available radiation. Moreover, opportunities for rainfall estimates exist by integrating MeteoSat cloud cover estimates with rain gauge products. Application of MeteoSat derived weather variables in mechanistic crop simulation models has so far been limited.

2 Data and Methodology

The primary Data Assimilation Office (DAO) data set is a 3-hour global product with 1.0 x 1.25 degree (latitude x longitude) spatial resolution. It provides downward surface shortwave radiation, surface air pressure, air temperature and specific humidity. Detailed information on the Goddard Earth Observation System (GEOS) analysis system and DAO data set can be found with DAO and Global Modeling and Assimilation Office (GMAO). Temperature and humidity in the other data sets are reported at a height of 2 m above the surface whereas DAO is reported at 10 m. There are differences in temperature and humidity between 10 and 2 m, but these differences are negligible at kilometer scales. The day temperature data over India was obtained from weather stations of India Meteorological Department. The observed data from weather stations are influenced by local environmental conditions such as topography and land cover compared to Numerical Weather Prediction analysis data. Therefore, observed data are the only data to be used as a baseline. Four stations from different climatic zones were considered in the present study, viz. Hisar (Haryana), Raigarh (Orissa), Nagpur (Maharashtra) and Hasan (Karnataka). Hisar (Latitude 24°55´N, Longitude 75°45´55´E) has a continental climate, with very hot summers and relatively cool winters. Summer starts in April and lasts till the middle of October. May is the hottest month, with the maximum day temperature about 48°C (118°F). Hisar experiences a weak monsoon, from late June to September, with about 15 inches (380 mm) of rain. Hisar lies just 30 km north-east of the Thar Desert. Nagpur is located in Maharashtra state, between 21°45 north to 20°30 north and 78°15 east to 79°45 east. Nagpur lies on the Deccan plateau of the Indian Peninsula and has a mean altitude of 310 m above sea level. Nagpur receives an annual rainfall of 1205 mm (47.44 inch) from monsoon rains during June - September. Summers are extremely hot lasting from March to June, with maximum temperatures in May. Winter lasts from November to January during which temperature may drop below 10°C (50°F). Raigarh (Latitude 21°54´N, Longitude 83°24´E) has an average elevation of 215 m. The minimum-maximum temperature range is 29.5 - 49°C in summer and 8 - 25°C in winter. Hassan, lying between 12°13´ and 13°33´ and 75°45´ to 76°38´E longitude, has a total area of 6826.15 km² and is situated 934 m above sea level.

In order to compare these two data sets on a pixel-by-pixel basis, the DAO data was re-projected onto the 5 x 5 km grid using weighted averages. The similar results were obtained irrespective of whether 5 x 5 km pixels projected onto DAO space or vice-versa for this study. The four DAO cells surrounding a given 5-km pixel are used in the interpolation algorithm (Fig. 1).

Although there are many formulae for non-linear spatial interpolation, for simplicity, a cosine function, which constrains the result between 1 and 0 if the input variable is between 0 to k/2. As the function did not effectively eliminate DAO cell boundary lines in a image, hence it’s second, third and fourth power were used to increase the weighing value of the nearest DAO cell. Finally, it was found that its fourth power form successfully removed DAO footprint even in region with abrupt climatic gradients:

\[ D_i = \cos^4 \left[ \frac{(\pi/2) * (d/d_{max})}{\pi} \right] \quad \text{where } i = 1, 2, 3, 4 \quad \ldots (1) \]
This ensures that $D_i = 1$ when $d_i = 0$, and $D_i = 0$ when $d_i = d_{\text{max}}$. Based on the non-linear distance ($D_i$), the weighted value $W_i$ can be expressed as

$$W_i = \frac{\sum D_i}{\Sigma D_i} \quad \cdots (2)$$

And, for a given pixel, the corresponding smoothed variable $V$ (i.e., interpolated day temperature) is

$$V = \sum_{i=1}^{4} (W_i * V_i) \quad \cdots (3)$$

Theoretically, this DAO spatial interpolation improves the accuracy of temperature ($T_{2m}$) data for each 5 km pixel because it removes these abrupt changes from one side of a DAO boundary to the other. The plots of daily temperature on 12 February 2007 are shown in Fig. 2 (a and b) for coarse resolution ($1.0 \times 1.25$ degree latitude x longitude) and interpolated fine resolution ($5 \times 5$ km), respectively. Figure 2 shows how this method makes embedded DAO cell effects disappear from interpolated image. The degree to which this interpolated DAO will improve the accuracy of $T_{2m}$ inputs, however, is largely dependent on the accuracy of DAO data and local environmental conditions, elevation and weather patterns.

3 Results

3.1 Temperature at local scale

The time series of daily temperature from DAO (coarse grid), DAO (fine grid) and *in situ* observations for the year 2007 were evaluated at four specific sites namely Hisar (Haryana), Raigarh (Orissa), Nagpur (Maharasthra) and Hasan (Karnataka) across India. The annual variations of daily temperature from DAO (coarse grid), DAO (fine grid) and *in situ* are shown in Fig. 2.
in Figs 3(a-d). The DAO (fine grid) temperature is in close agreement with *in situ* observations compared to that of DAO (coarse grid) at all the four locations. The larger variations are noticed for Raigarh and Hassan compared to that of Hisar and Nagpur. This could be due to the fact that these two districts are near to sea coast and therefore, have unstable weather most of the year. It is clear that DAO fine grid data set represents the local conditions along with annual variations.

### 3.2 Temperature at regional scale

The monthly mean temperature from DAO (fine grid) were plotted for the month of January, April, July and October 2007 as shown in Figs 4 (a, b, c and d), respectively. These four months represents the seasonal variations in temperature across India. The interpolation of DAO coarse grid to fine grid has improved the data quality. Since there are no abrupt changes noticed in these figures. The temperature is found to be very high in the month of April compared to other three months especially over north-west and central part of India. In general, April month is dry and hot due to pre-monsoon heating over this part of India as shown in Fig. 4(b). However, with the onset of monsoon in the month of July, the values of T10m started decreasing as shown in Fig. 4(c) except the parts of Punjab and west Rajasthan. The temperature starts decreasing in October and January over north India as shown in Figs 4(d and a), respectively. Therefore, it may be stated that fine grid DAO data may be potentially used for models like ecology and weather model.

### 3.3 DSSR at local scale

The surface downward full-sky shortwave radiation from the latest ISCCP data set was used to assess the accuracy of DSSR from the DAO data sets. The ISCCP was generated from GISS/NASA at 280 km intervals for an 18-year period from July 1983 to

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**Fig. 3—Time series plot of daily temperature for the year 2007 at four locations**
June 2001. The equal-area ISCCP was first mapped to geographic projection at a 2.5 × 2.5 degree resolution, and then re-sampled to 0.5 × 0.5 degree resolution using spatial nonlinear interpolation as discussed earlier. Although ISCCP DSSR was derived from satellite and model data, it had been validated by ground observations and been proven highly accurate with a mean (RMSE) difference of 2.0 (18.5) W m\(^{-2}\) and a correlation coefficient 0.98 (ref. 9). DSSR from monthly mean ISCCP and from re-analyses for the same period were averaged for further comparison.

Similar to annual variations of temperature, the annual variations of daily DSSR from DAO (coarse grid), DAO (fine grid) and ISCCP are shown in Figs 5(a-d). The DAO (fine grid) DSSR is in close agreement with ISCCP data compared to that of DAO (coarse grid) at all the four locations. It is clear that DAO fine grid data set represents the local conditions along with annual variations.

### 3.4 DSSR at regional scale

The monthly mean DSSR from DAO (fine grid) were plotted for the month of January, April, July and October 2007 as shown in Figs 6(a, b, c and d), respectively. Similar to temperature, the interpolation of DAO coarse grid to fine grid has improved the data quality of DSSR data also. Since there are no abrupt changes noticed in these four figures. The DSSR shows a maximum over central and north-west India for the month of April and July. During the cold season, it is highest over central India, while the northern regions receives less DSSR due to the passage of winter disturbances from the west and the decrease in the length of the day with latitude and in the south due to cloudiness associated with disturbances in the Bay of Bengal and Arabian sea. As the year advances, till the onset of the monsoon in June, the region of clear skies and maximum DSSR shifts to the north India. Agricultural crop drying is
Fig. 5—Time series plot of daily DSSR for the year 2007 at four locations

Fig. 6—Seasonal variations of DAO DSSR fine grid over India
usually a good use for solar radiation. Solar heated air is not so hot that it spoils the produce, and the drying system protects food crops from rain, dirt and insects. The use of solar heat for timber seasoning can save large amounts of conventional energy.

4 Discussions
The important role of downscaled NWP products along with remote sensing in precision agriculture was well summarized in a recent paper. With the long list of NWP models and environmental satellites announced for launch in the coming years, and the increasing use of digital databases for farm management, the role of remote sensing cannot be ignored. In particular, many authors have demonstrated relationships between plant reflectance air temperature, solar radiation and agricultural parameters of crops. Previous studies were based mostly on hand held spectro-radiometer reflectance measurements above individual plants or small portions of a field. In particular, suggested that remotely sensed reflectance is a more efficient way of determining plant nitrogen status over large areas than taking costly and time consuming field measurements.

The importance of the solar radiation for the crop production process is understood especially on general level, i.e. that solar energy is the driving force and only source of energy for photosynthesis. The utilization of solar energy for photosynthetic activity is limited by low content of carbon dioxide in air especially during clear summer days, by unsuitable canopy structure (mutual shading of leaves) and by lack of water or (and) minerals. Solar radiation (DSSR) is one of the main factors influencing biomass and yield production and its quality, e.g. high 1000-grain weight is beside other factors associated with prolonged DSSR in the phase of stem elongation and grain filling while low intensity of DSSR during grain filling phase negatively influences grain yield. However, high level of DSSR in summer in combination with high temperatures and a high saturation deficit can cause marked reduction of tillers. Statistical analysis of the relationship between measured solar radiation and experimental data is complicated by many other factors which are mutually interrelated, e.g. amount of solar radiation is significantly influenced by cloud cover and rain distribution and DSSR is on other side the major determinant of the air temperature.

5 Conclusions
The results obtained illustrate a preliminary assessment of the ability of the methodology to downscale meteorological variables over India. This work is the initial phase of a larger project that is aimed at building a system that is able to downscale changes in the solar radiation resulted by a low-resolution atmospheric general circulation model. Visual comparison of the amount and geographic distribution of monthly meteorological variables reveal considerable skill in the downscaling methodology. The use of down scaled improved NWP products may potentially be in operational use in real time to a meaningful location-specific product. This scheme would enable synoptic NWP derived product and satellite capabilities for modeling and monitoring applications quickly, reliably, and accurately. Simple algorithms such as this could be easily implemented on inexpensive computers such that NWP and satellite observations can be translated to useful information such as estimates of evapotranspiration by using ecosystem models. Future work will involve this methodology that better represents the regional and local climate to run NWP model using downscaled lateral-boundary conditions for the impact study.

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