A Real-Time Gridded Crop Model for Assessing Spatial Drought Stress on Crops in the Southeastern United States

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ABSTRACT

The severity of drought has many implications for society. Its impacts on rain-fed agriculture are especially direct, however. The southeastern United States, with substantial rain-fed agriculture and large variability in growing-season precipitation, is especially vulnerable to drought. As commodity markets, drought assistance programs, and crop insurance have matured, more advanced information is needed on the evolution and impacts of drought. So far many new drought products and indices have been developed. These products generally do not include spatial details needed in the Southeast or do not include the physiological state of the crop, however. Here, a new type of drought measure is described that incorporates high-resolution physical inputs into a crop model (corn) that evolves based on the physical–biophysical conditions. The inputs include relatively high resolution (as compared with standard surface or NOAA Cooperative Observer Program data) (5 km) radar-derived precipitation, satellite-derived insolation, and temperature analyses. The system (referred to as CropRT for gridded crop real time) is run in real time under script control to provide daily maps of crop evolution and stress. Examples of the results from the system are provided for the 2008–10 growing seasons. Plots of daily crop water stress show small subcounty-scale variations in stress and the rapid change in stress over time. Depictions of final crop yield in comparison with seasonal average stress are provided.

1. Introduction

The severity of drought has many implications for society, including its impacts on the water supply, water pollution, reservoir management, and ecosystem. However, its impacts on rain-fed agriculture are especially direct. The development of information that relates the...
The basis of a drought index is to assess the availability of water for a particular or general use at a given time. This can be done using budget models that track gains and losses of water or from inferring soil moisture from auxiliary information such as temperature (Wetzel 1984; McNider et al. 1994; Norman et al. 1995), or the greenness of vegetation (Sellers 1985; Kogan 1995, Brown et al. 2008), or combinations of the above (Carlson et al. 1994; Nemani and Running 1989). Early drought indices relied on a water budget. The Palmer drought severity index (PDSI; Palmer 1965; Alley 1984) was originally based primarily on coarse rain gauge precipitation for gain and a simplified evaporation calculation based on temperature for losses to accrue a drought status for large areas (originally climate divisions on the order of 10 000–500 000 km²). It was recognized that the PDSI, while perhaps capturing a longer definition of drought, failed to respond quickly to drought stress on crops that were primarily responding to moisture sometimes in the first few inches of top soil. Palmer (1968) developed a shorter-term index called the crop moisture index (CMI). While the PDSI and CMI can accept higher-resolution inputs, they have primarily been driven by the National Weather Service (NWS) Cooperative Observer Program coarse-resolution data for rainfall and soil characteristics and retained the simplified evaporative loss parameterization.

As measures of drought intensity became the basis of important societal decisions from drought response plans to eligibility for relief programs, the need for finer-scale and more accurate measures of specific types of droughts (Wilhite and Glantz 1985) increased. In response to this need, many new drought indices have been developed (Heim 2000; Niemeyer 2008). Keyantash and Dracup (2002) provide a robust summary of drought indices, their basis, and performance. Some of the more advanced approaches estimate direct physical losses (transpiration; Senay 2008) and runoff (Narasimhan and Srinivasan 2005). Because drought can be highly localized, satellite data with high spatial resolution compared to standard in situ data have been employed. Anderson et al. (2007) and Anderson et al. (2011) utilized a combination of geostationary and polar-orbiting data to recover model root-zone moisture within a simple boundary layer. One of the more advanced examples is the soil moisture deficit index (SMDI) developed by Narasimhan and Srinivasan (2005). Recognizing the critical role of soil moisture and its spatial variability in agricultural losses, Narasimhan and Srinivasan (2005) used the framework of a hydrological model (Soil and Water Assessment Tool, or SWAT) to determine soil moisture. SWAT is a basin-scale hydrologic model that incorporates spatial variability in terrain, soil characteristics, and rainfall (see Arnold et al. 1998). Narasimhan and Srinivasan (2005) used the root zone moisture averaged over a 7-day period to develop a soil dryness that could be compared against long-term soil dryness from historical runs. This provided a natural method for putting a drought period into some historical context. The derived soil moisture index compared well to selected locations of satellite-derived greenness (Sellers 1985).

Recently, Senay (2008), using a combination of radar-derived high-resolution precipitation and high-resolution land-use estimates of evapotranspiration (ET), provided a 5-km estimate of vegetative ET (VegET) for the United States. For agricultural land, they employed relationships for generic cereal crops for several stages of development. The present investigation uses a direct approach to crop physiology by employing a specific crop model and utilizes satellite data to determine insolation as a driver of ET.

The present investigation builds upon the ideas of Narasimhan and Srinivasan (2005) and Senay (2008) to conceptualize and construct a system that can capture the high-resolution impacts of drought on specific crop agricultural production. It moves beyond the approach of soil moisture being a correlative measure of agricultural loss to a direct computation of specific crop responses to water availability. This is accomplished by directly running a crop model [the Climate System Model (CSM)–Clouds and the Earth’s Radiant Energy System (CERES)–Maize model of the Decision Support System for Agrotechnology Transfer (DSSAT); see below] in real time at high spatial resolution. We will refer to this real-time crop model as CropRT (for gridded crop real time). In the SMDI, only a generic plant biomass model was used, and in VegET, water uptake relations were used for a generic cereal crop. The CropRT further incorporates radar-derived precipitation that had been envisioned by Narasimhan and Srinivasan (2005) for use in SWAT and includes high-resolution satellite estimates of insolation, which is a critical component of biomass production and water loss. While DSSAT provides additional details on plant and local soil moisture interaction, it does not accumulate or spatially aggregate runoff. Given the rapid advancements in remote sensing, there are now many opportunities for linking crop models with remotely sensed data for both historical analysis and yield forecasting (Hoogenboom 2000; Bannayan et al. 2003; Fang et al. 2008).

The following describes the system and its potential uses. Major emphasis is given to high spatial variabilities in rainfall, temperature, and insolation that have been incorporated into the model. In this prototype setting, we have not included the spatial variation in soil characteristics that is needed to further advance and refine...
the system. The spatial variability of the local soil parameters and soil profiles needed for DSSAT is currently under development and will be reported upon later. The goal of this paper is to present a prototype of a real-time crop model and the potential that such a system might have for estimating agricultural drought effects and for projecting crop yield through the growing season. Because of the omission of spatial variation in soil characteristics, the gridded crop model provides an interesting display of the variation in stress and yield entirely due to both the temporal and spatial variabilities of weather.

2. Development of high-resolution drought products in the Southeast

The NWS Cooperative Observer Program’s irregular coverage amounts to a much coarser resolution than 5 km, which can be achieved with remotely sensed datasets. Here, we refer to the 5-km resolution as the high-resolution product. In the Southeast (SE), small-scale air mass convection is often the major source of growing-season rainfall. Additionally, soil characteristics vary on extremely small spatial scales. Thus, significant variations in soil moisture can occur on the subcounty scale and even the subfarm scale. Unlike the West, which is largely insulated from drought by irrigation and the Midwest, which is partially immune to short-term drought by deep-water-holding soils, the SE is sensitive to droughts even on the scale of a week due to its relatively poor water-holding capacity of soils, especially for the coastal plain region.

To capture some aspects of this finescale drought, a lawn and garden index (LGI) was developed using high-resolution radar-derived precipitation. The original LGI was developed by the Alabama Office of State Climatology and was expanded to Florida and Georgia. It is a semi-empirical attempt to characterize the current soil moisture in its capacity to sustain healthy lawns and gardens. The index is computed in two stages.

First, an estimate is made on how much recent precipitation contributes to current soil moisture. It assumes that any precipitation over the past 21 days should be included in the computation. It also assumes that more recent precipitation is more significant than less recent events. All precipitation during the previous 7-day period is considered to be equally important, but precipitation before that time is discounted according to a linear sliding scale. A more robust soil water model is needed here. The key input in this product, which differs from most large-scale analyses, is that the precipitation used is radar-derived precipitation at nearly 5-km resolution. Thus, finescale (almost to the farm scale) data are available to define small-scale droughts. Second, an estimate is made of average water requirements for the current day. The LGI uses a simple daily mean annual cycle of “needs amount,” varying from 10 mm during the winter and ramping to 50 mm during the summer for the 21-day tapered index input, based on shallow rooted vegetation responses to rainfall. The needs amount is a critical weakness in the system. The needs amount depends on the specific crop and phenological state of the plant. The difference between the water needs and the current effective rainfall from above is the daily lawn-and-garden moisture index (in inches). Figure 1 shows an example of the LGI for the SE.

While the empirical approach of the LGI has grossly simplifying assumptions, its inclusion of the key input of high-resolution precipitation and physical units of moisture deficit has made it a highly effective and useful tool in conveying spatial characteristics of agricultural drought to decision makers. It was expanded from Alabama to Georgia and Florida under a Southeast Climate Consortium (SECC) activity and was integrated into the SECC’s AgroClimate Web site (www.AgroClimate.org) delivery system (Fraisse et al. 2006).
The success of the LGI and its use by the Drought Monitor to refine drought categories at the county and even subcounty levels has led to the view that other high-resolution drought products could have value to the agricultural community. The SECC had long embraced crop models (e.g., DSSAT) to evaluate the impacts of climate variability and seasonal climate forecasts on agricultural yields (Garcia y Garcia et al. 2006; Paz et al. 2007). Thus, it was planned to merge components of the LGI with the DSSAT crop models to provide high-resolution information on drought stress for the critical agronomic crops of the SE.

In looking at prior agricultural drought indices, it was felt that three aspects were important to the development of a more useful agricultural drought product in the SE.

1) Use of high-resolution radar-derived precipitation: The coarse spacing of Cooperative Observer Program rain gauges is not sufficient to capture the rainfall variability during the growing season in the SE. Available radar composites provide continual spatial coverage at a resolution of 4.76 km × 4.76 km or approximately 22 km². Narasimhan and Srinivasan (2005) had proposed this scale for the SMDI but in their paper used interpolated rain-gauge data. Senay (2008) used this precipitation product in VegET.

2) Improved specification of water loss due to plant uptake and surface evaporation: While the LGI included the high-resolution radar-derived precipitation, its treatment of water loss and water use were largely heuristic and simple. The approach in Narasimhan and Srinivasan (2005) of using a Penman–Monteith method in the SWAT model (Ritchie 1972) provides a more realistic water loss representation. However, such an approach requires estimates of incoming net energy, which drives the evaporative losses especially under full canopies. For historical cumulative long-term drought studies, surrogates for incoming energy based on sun angle and average cloudiness have been used. However, for short-term results actual daily incoming solar energy (insolation) is desired. Surface observations of insolation are generally not available and surface-based cloud observations at high resolution are also not available. Historically, only NWS first-order stations reported cloud cover. Errors in insolation over short-term periods, though perhaps less critical than precipitation, can introduce errors in water loss. Satellite data, however, can provide relatively robust measures of insolation and these data are now becoming readily available (see below). Thus, the preferred path was to use Penman-type evaporation loss driven by satellite-derived insolation. A simplification of the Penman-type evaporation is contained within the DSSAT soil moisture budget calculations (Priestley and Taylor 1972; Ritchie et al. 1998).

3) Incorporation of plant physiological stage and moisture: The coincident moisture and phenological stage of the plant are important to both water loss by the soil through soil evaporation and plant transpiration and to crop yield. The stage of the plant in terms of canopy development and expansion is important to the amount of water lost from the soil by evapotranspiration. This canopy-dependent loss was estimated in the SMDI SWAT system by the use of a generic plant module. However, in some crops, such as corn, there are times when the Penman relationships for plant water needs using only a mean canopy area fail. As an example, when corn reaches maturity, it can retain water for kernel development even though transpiration drops. Thus estimates of actual to potential evaporation based on the canopy may not capture the real stress on the crop yield.

In addition to the role of the plant in impacting water loss, the root-zone moisture is also critical to plant development and final yield. Plants do not simply control water loss but are directed in their physiological development by available water. Early available water may impact the number of leaves that are initiated and potential leaf expansion, changing the ultimate evapotranspiration potential of the canopy. As another example, at the stage when corn is in the kernel filling stage, final yield is not as sensitive to moisture as in the pollination stage or in the physiological decision stage for the number of kernels. This is because at the final kernel growth stage the plant will sacrifice water and nutrients to support the kernel at the expense of the leaves and stalk. But if the full complement of kernels is not set early during reproductive development or if moisture is insufficient for full pollination, the final yield will be significantly impacted even if plenty of soil moisture is available near the final maturity date (Ritchie et al. 1998). Other crops such as soybeans may not be as sensitive since their phenological window for decisions on yield may be longer and not as time critical.

To develop a system that would capture these three desirable attributes requires 1) a crop model that identifies the various physiological stages of a plant, 2) high-resolution radar data in real time, and 3) high-resolution insolation values on a daily basis. The following sections describe this system.
a. Crop model component

DSSAT is a computer software system designed to predict growth and yield for more than 25 crops, and to assist in producing successful crop management techniques, and to provide alternate options for decision making (Tsuji et al. 1998; Hoogenboom et al. 2004). The DSSAT models use variables such as weather, soil type, and soil profile properties, as well as cultivar-specific inputs and management including irrigation and amount and type of fertilizer among others for simulating growth, development, and yield. DSSAT also has a soil hydrological model that estimates soil water flow and root water uptake as a function of soil surface and soil profile properties (Ritchie et al. 1998; Jones et al. 2003). The atmosphere can limit transpiration by low solar radiation and cool temperatures, the canopy can limit it by low leaf area index (LAI), and the soil can limit it by low soil water content or low root length density. Each simulation for a single growing season provides a large amount of data output, including rooting depth, plant transpiration, soil temperature and moisture, nitrogen levels in soil, plant growth, and development, as well as a final water, nitrogen, and carbon balance. The models can be run for a single year or multiyear climate mode to account for both the seasonal weather variability and interannual climate variability (Thornton and Hoogenboom 1994; Garcia y Garcia et al. 2006).

SECC is a collaborative group of state climatologists, agricultural researchers, atmospheric scientists, economists, anthropologists, and hydrologists in Alabama, Florida, Georgia, and North Carolina. The SECC strongly embraced the use of the DSSAT crop models as a method to evaluate the value and utility of seasonal forecasts and in crop management practices such as irrigation through the use of long-term climatology (Paz et al. 2007).

b. High-resolution rainfall data

The coarse spacing of rain gauges compared to the scale of convective precipitation events has lead to uncertainties in the amount of rainfall at discrete points. With the development of the national Next Generation Doppler Radar (NEXRAD) network came the opportunity to establish a national radar-derived precipitation product. Radar returns have the advantage of acquiring information that relates to rainfall in an almost continuous spatial and temporal domain. The NWS River Forecast Centers (RFCs) took the lead in establishing procedures to use this radar information to develop derived rainfall products. The products are, in fact, a combination of radar information and rain gauge data. Using regional radar–rainfall relationships in each of the 12 RFCs in the continental United States, these relationships are continually calibrated by automatic rain gauge data at 6-h intervals. This combined product is referred to as a multisensor precipitation analysis. The 12 regional RFC 6-h rainfall products are collected into a continental U.S. multisensor rainfall analysis product that is accumulated to produce a 24-h (daily) continental U.S. rainfall analysis on a nearly 5-km (4.7625 km) grid. (A complete technical description is available online: http://www.emc.ncep.noaa.gov/mmb/ylin/pcpanl/stage4/)

This NOAA/NWS daily rainfall product is used as the basic precipitation input to the LG1 and into the gridded crop mode system. It is automatically acquired and archived for this purpose by the Alabama Office of State Climatologist.

c. Satellite-derived insolation

The University of Alabama in Huntsville (UAH) and the National Aeronautics and Space Administration Marshall Space Flight Center (NASA MSFC) have developed an operational system that uses the physical retrieval method (Gautier et al. 1980; Diak and Gautier 1983) to employ Geostationary Operational Environmental Satellite (GOES) visible imagery in recovering insolation at high resolution (4-km grid) for use in regional-scale models. These data are publicly available online (http://satdas.nsstc.nasa.gov/). Satellite techniques are relatively robust in their ability to recover surface values of insolance. While there are other statistical techniques for recovering insolance from GOES imagery (Tarpley 1979; Pinker et al. 2003), the physical retrieval technique has advantages in that it calculates cloud transmittance and absorption, which can then be incorporated in more complex radiative transfer models (Pour-Biazar et al. 2007).

The amount of solar energy reaching the earth’s surface (insolation) is estimated from the broadband visible channel on GOES. It is desirable to estimate both direct and diffuse radiation (scattering from the atmosphere and clouds). The albedo of the surface is required to accurately compute these components. The surface albedo (for each hour) is calculated using a short-term history of GOES visible channel reflectance measurements from cloud-free images (minimum visible value over the history), the solar constant, and an estimate of the water vapor content of the atmosphere. In cloudy regions, a historical estimate of the albedo (from cloud-free data) is used. The procedure includes three processes: 1) attenuation of the downward flux of solar radiation in cloud-free regions by molecular scattering and absorption by atmospheric water vapor, 2) absorption and scattering of solar radiation by clouds, and 3) attenuation of solar radiation by the atmosphere below the
clouds. Atmospheric absorption is calculated with a parameterized radiative transfer model appropriate for shortwave radiation and is dependent on water vapor (total precipitable water in our case) and satellite and solar-viewing geometry. Cloud absorption is parameterized solely on visible reflectance and Rayleigh scattering with a molecular pathlength. A comparison to surface pyranometers is found in McNider et al. (1995).

These insolation products have been applied in air quality and weather forecast settings (McNider et al. 1994, 1995). The use of this insolation product was explored to improve the spatial specification of water loss in the LGI. Figure 2 shows an example of the use of the satellite-derived insolation values in estimating the evapotranspiration loss based on insolation using the Priestley and Taylor (1972) formulation. The spatial variation in estimated evapotranspiration shows that on short time scales these variations may impact the spatial distribution of soil moisture. The 4-km insolation product used here and in DSSAT is based on hourly GOES images but only a single daily value of average insolation is used. That is, the summed hourly values are divided by 24. The 4-km insolation product is interpolated to the 4.7-km precipitation grid.

Insolation is a key input into DSSAT for determining the rates of biomass production and reference evapotranspiration. Photosynthetic active radiation (PAR) is deduced from the daily insolation as one-half the daily radiation. For many crops, the model’s biomass production is related to a radiation use efficiency (RUE) parameter and the fraction of radiation intercepted, which depends on the canopy LAI [see Ritchie et al. (1998) for a description of daily radiation use for the grain cereal models].

Because insolation is not as readily available as an observable parameter, a procedure was developed that generates insolation based on daily maximum and minimum temperature and precipitation similar to the data

![Fig. 2. Daily estimates of water loss based on the Priestley and Taylor (1972) evapotranspiration loss using satellite-derived insolation (in.)](image)

![Fig. 3. Daily estimates of DSSAT-generated incoming solar radiation (MJ m\(^{-2}\) day\(^{-1}\)) in comparison with in situ pyranometer data observed at Camilla, GA, during the period 2003–05 based on the technique of Garcia y Garcia and Hoogenboom (2005). Standard deviation is 3.7 and mean bias is −0.45.](image)
that are available for NWS Cooperative Observer Program sites (Garcia y Garcia and Hoogenboom 2005; Garcia y Garcia et al. 2008). While such a system makes DSSAT easy to use at places where insolation data do not exist, the generated data are not as desirable as direct observations of insolation. With the advent of satellite insolation products, the possibility exists to replace the generated insolation with data that are observed by

FIG. 4. Daily satellite-derived incoming solar radiation (MJ m\(^{-2}\) day\(^{-1}\)) in comparison with in situ pyranometer data observed at Camilla during the period 2003–05 based on the technique of Diak and Gautier (1983) as applied by McNider et al. (1995). Standard deviation is 1.95 and mean bias is 0.47.

FIG. 5. Flowchart overview of data inputs and processing for the LGI and CropRT models.
satellites. Figures 3 and 4 show a comparison of generated data versus in situ data and of satellite insolation compared with in situ data. Obviously, the space and time attributes of the satellite allow for better agreement than the generated data. However, in statistical tests it was shown that the seasonal distribution (probability density function, or PDF) of the generated insolation compared favorably to the in situ PDF and to the satellite data.

3. Gridded crop model system

The DSSAT system was configured to be run in a gridded mode at a horizontal grid spacing of approximately 5 km. An input data file that defines the location and soil type for each grid was developed. In this initial testing, all soil parameters were set to be the same for all grid points. Also, because of the data cutoff time of 1200 UTC in the operational system, the full dataset was
not included in the model runs until the following day. Thus, rainfall recorded after 1200 UTC was included in the next day’s crop model run. The present system reflects the water stress and yield impacts due only to meteorology (i.e., the local weather conditions). The temporal data required by DSSAT are daily minimum and maximum temperatures, daily insolation data, and daily precipitation data. All data were set to be run in real time with scripts controlling the automatic acquisition of temporal data. Figure 5 provides a flowchart schematic of the CropRT and the LGI systems and their common inputs.

a. Minimum and maximum temperature data

Minimum and maximum temperatures were taken from the NOAA Rapid Update Cycle (RUC) analysis. The RUC is a NOAA/National Centers for Environmental Prediction (NCEP) operational weather prediction system that includes a numerical forecast model and an analysis-assimilation system (information online at http://maps.fsl.noaa.gov). The current operational version has a horizontal mesh size of about 13 km. The 2008 simulations were conducted using a horizontal mesh size of about 40 km and it was run every hour. Minimum and maximum temperatures were extracted for each model grid point over a 24-h period ending at 1200 UTC from the hourly RUC initialization analysis fields. These minimum and maximum temperatures were then interpolated onto the grid that was used in the crop model (which was the same grid as was used for the precipitation data, 4.7625 km). Figure 6 shows an example of the maximum and minimum temperatures as used in the DSSAT gridded system.

b. Daily insolation

Daily insolation needed in DSSAT was obtained from insolation values at a horizontal resolution of 4 km from the UAH–MSFC satellite physical retrieval and averaging the hourly insolation data to obtain a daily value. Figure 7 shows an example of the satellite-derived insolation as was used in CropRT.

c. Radar-derived multisensor precipitation

The national 24-h multisensor precipitation analyses (see above) were extracted consistent with the CropRT

![Figure 7. Example of the average daily insolation used as input into the DSSAT gridded model. Insolation (W m\(^{-2}\)) is for the 24 h ending 1200 UTC 27 Jun 2008.](image-url)
system and used as the precipitation data needed in DSSAT. Figure 8 shows the multisensor precipitation as it was used in the CropRT simulations.

For the initial operational test, corn (maize) was taken as the crop to be simulated with DSSAT. Corn is an especially complex plant whose physiological development is highly determined by temporal data. Its final yield depends on the local weather and soil conditions and genotypic characteristics. The DSSAT gridded system (CropRT) was run on a daily basis under script control to produce daily water stress maps and final yield data. The next section describes the initial tests of the system for the 2008 growing season in the SE.

4. Gridded crop model seasonal runs

The gridded crop modeling system was set up for a generic corn cultivar that is common in the SE. The soil type was a medium silty loam. Future operational runs will use soil data at least at the county level.

The gridded DSSAT was run from 1 January until 8 September 2008, using the input data described above.
in and after the fact analysis (i.e., not in real time). The planting date was made a function of latitude that approximates planting guidance from agricultural extension programs. It may not be robust in the subtropical areas of Florida where soils are warm enough year round to support germination. The planting date is given by

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\text{Planting day\_of\_year} = (6.2 \times \text{latitude}) - 126.
\]

This formula yields day 60 at latitude 30 and day 91 at latitude 35. Once the soil data have been added to the system, these planting dates can be varied based on soil color which, impacts soil warmup in the spring. In addition, actual temperatures from the temperature analysis might also be used to modify this. In the real-time version, DSSAT is run to the current date using actual observations; then, a forecast period to the predicted final harvest date is conducted. At present this forecast period is based on climatology, and improved forecast strategies are under development. For example, future versions might incorporate 10-day forecasts from NWP products, then, using seasonal outlooks, go beyond 10 days. We do not report on any of the forecast data here but only provide data driven by actual observations.

a. Water stress parameter

Many variables are available from DSSAT including crop characteristics such as total plant biomass, soil water information, nutrient levels, etc. In the current exercise we only extracted and plotted the daily water stress parameter. This is a physiological parameter indicating the limitation of growth rates by water (Tsuji et al. 1998; Hoogenboom et al. 2004). It is based on a soil water deficit parameter that is taken from the ratio of potential uptake to potential transpiration (Ritchie 1998). The values are in index form from 0 to 1 with 0 indicating no stress and 1 maximum stress. The stress factor is highly variable through the crop’s life cycle. It can rapidly decline after a precipitation event, depending on the amount of precipitation. However, under hot and clear conditions it can also rapidly increase during periods without precipitation. The rate of increase depends on plant water needs at a particular physiological state and the available water in the root zone. Figure 9 shows an example of the variation of the water stress index for a coastal plain soil in a wet (1961) and a dry year (1954) for a long-term single-point run of DSSAT. This is the same soil type used as is used in the current CropRT.

The water stress parameter was extracted at each grid point and plotted for each day of the DSSAT simulation period. Figure 10 shows an example of the DSSAT water stress index for 28 June. It can be compared to the insolation and precipitation in Figs. 7 and 8. In reality, corn would not be planted at all the pixels in the spatial domain. Not all land is suitable for crop production and farmers could grow other crops, such as cotton, peanut, soybean, or wheat, rather than corn. The interpretation of these gridded maps is that this would be the stress if corn had been planted at that location using the planting date that was provided to the model planting day. Thus, a producer or agricultural specialist could look at the locations in which they were interested and see the

![Fig. 9. Example of the DSSAT water stress parameter for corn at a coastal plain site in Alabama for a wet year (1961, pink) and a dry year (1954, blue). For this index, 0 indicates no stress and 1.0 shows large stress.](image-url)
relative stresses of these locations compared to other locations. Additionally, we expect that coarse-resolution long-term runs can put this stress into temporal climatological perspective.

Figure 11 shows the evolution of the daily stress values over a week-long period in June 2008. It can be seen that on 9 June 2008, northwest Alabama did not have very high stress levels due to recent rains. On the other hand, south Alabama, south Georgia, and central Florida all had high stress values except for a few scattered places where convective storms (almost at the grid-scale level) provided additional moisture, resulting in lower stress values. During the week the pattern changed drastically. By 16 June, most of the areas in Alabama that had low stress values, were in moderate to extreme stress. Central Florida, which had been a mostly high-stress area, was changed to low-stress values because of rainfall. These images illustrate the postulate in the introduction that relatively poor water-holding soils and scattered rainfall can lead to small-scale and rapid changes in stress level for crops.

The variation in rainfall and evapotranspiration leads to strong spatial variations in average stress levels during the simulation period. Figure 12 shows the average stress values during the growing season for the years 2008–10.

b. Final yield

The CropRT model was run through the predicted final harvest maturity. Thus, a map of final yield was available from the gridded run. However, final crop yield in DSSAT depends on many interactive factors during the modeling process. Thus, the recommended path is to use experimental data and on-farm data for calibration and evaluation of the simulated yield data. This is normally done using field specific data or variety trials (Soler et al. 2007; Bannayan and Hoogenboom 2009). However, in this application, we were interested in general aspects of yield encompassing broad geographic regions. As part of the studies conducted by our group related to the impacts of irrigation on corn yields in Alabama, several tests of DSSAT yields compared to corn field trials yields were made (see Fig. 13). These tests included actual soils for the sites and specific crop management inputs. The result was a calibration curve,
where \( x \) is the DSSAT yield and \( y \) is the adjusted yield in units of bushels (bu) per acre. To make an independent test of this relationship, the calibration was applied to long-term (56 yr) DSSAT yields for three sites in Alabama. The sites represented three major climatological and soil regions and ranged from an Alabama coastal plain to a prairie setting in the Blackbelt region in the middle part of the state to the Tennessee Valley area in northern Alabama. The three sites were averaged to give a pseudostatewide average. This statewide average was then compared to statewide yields from the USDA’s National Agricultural Statistics Service (USDA/NASS). The NASS data were detrended to mitigate systemic increases in yields as a result of cultivar improvements and agricultural practices through the 56-yr period. This comparison is given in Fig. 14. While the average of the three sites has a larger variance than the statewide NASS data, the calibration appears to capture the year-to-year patterns of variability in the NASS data. The smaller variance in the NASS statewide numbers would be expected since it is averaged using numerous different weather conditions over many areas rather than just three sites. The increase in variance in the NASS statewide data in recent years may be due to the drastic decrease in corn acreage in Alabama (from 2.5 million acres in 1950 to 300 000 in 2006) and the concentration of corn production in north Alabama.

The calibration of crop model yields based on the Alabama tests were applied to the gridded DSSAT runs made for 2008–10. The calibrated yields for 3 yr are given in Fig. 15. The Alabama-based calibration may not be applicable to the other areas, especially Florida. The blue areas of very low yields in southeast Georgia and in south Florida are due to a failure to germinate that was predicted by DSSAT due to inadequate soil moisture. This picture is interesting in that it shows the estimated variation in yields due to weather (temperature, insolation, and precipitation). The comparison of the yield (Fig. 15) and average water stress (Fig. 12) is especially noteworthy as it shows that the integrated model stress is a good indicator of final model yield, although additional comparisons are needed against actual yields. Thus, daily stress values (before crops reach maturity) have some skill in projecting final yields. While DSSAT water stress is tied to crop requirements and to canopy area, the water stress may not give the full picture at critical times in the plant’s life cycle. Concurrent maps of water stress and plant stage, such as flowering, may be better measures of impact on yield; therefore, this relationship needs to be further analyzed (Garcia y Garcia et al. 2009).

5. Summary and conclusions

This paper describes a first attempt to include relatively high-resolution input data and plant physiological behavior in a new type of spatial agricultural drought index based on the stress level produced by a physiological-based crop model. Multisensor high-resolution precipitation products and high-resolution insolation products were used in a gridded version of the DSSAT crop modeling system. Corn was chosen as the specific crop. The system was run for the 2008 and 2009 growing seasons in

\[
y = 0.791x + 35.147,
\]
an after-the-fact analysis. The same system is currently being evaluated for the real-time performance during the 2010 growing season.

The output from the model gives a map of daily water stress that reflects a reduction in the potential growth rate of corn and kernel development. End-of-year results provide a spatial estimate of corn yield. The results indicate (as postulated in the introduction) that even in years where large-scale drought is not present, significant crop losses are present.

The current version reported here is a first-generation system that only includes spatial variations in atmospheric inputs. Future versions will include spatial variations in soil types and profiles (Engel et al. 1997; Heinemann et al. 2002). Additional work relating DSSAT water stress to final yield is needed. The product

![Fig. 13. Summary calibration chart from field trial data across three years 2000-03 and across all geographic sites. The largest outlier (offline point) is from a wet year (2003).](image)

![Fig. 14. Application of calibration to DSSAT yields in comparison with Alabama statewide NASS yields. DSSAT yields are an average of three sites in Alabama representing three major soil and climatological regimes (bu acre^{-1}).](image)
should be useful for anticipating drought impacts on final yields and for quantifying the spatial extent of drought impacts.

Once actual soils are included, a detailed evaluation of CropRT can be made against NASS county-level data. In addition, the ability to run DSSAT in a climate mode (30–50 yr) will allow current droughts to be put in a historical context.

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