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An integrated crop and hydrologic modeling system to estimate hydrologic impacts of crop irrigation demands☆

R.T. McNider [a,*], C. Handyside [a], K. Doty [a], W.L. Ellenburg [a], J.F. Cruise [a], J.R. Christy [a], D. Moss [a], V. Sharda [b], G. Hoogenboom [b], Peter Caldwell [c]

[a] Earth System Science Center, University of Alabama in Huntsville, Huntsville, AL 35899, USA
[b] AgWeatherNet, Washington State University, Prosser, WA 99350-8694, USA
[c] U.S. National Forest Service, Coweta, GA, USA

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ABSTRACT

The present paper discusses a coupled gridded crop modeling and hydrologic modeling system that can examine the benefits of irrigation and costs of irrigation and the coincident impact of the irrigation water withdrawals on surface water hydrology. The system is applied to the Southeastern U.S. The system tools to be discussed include a gridded version (GriDSSAT) of the crop modeling system DSSAT. The irrigation demand from GriDSSAT is coupled to a regional hydrologic model (WaSSI). GriDSSAT and WaSSI are coupled through the USDA NASS CropScape data to provide crop acreages in each watershed. The crop model provides the dynamic irrigation demand which is a function of the weather. The hydrologic model responds to the weather and includes all other anthropogenic competing uses of water. Examples of the system include an analysis of the hydrologic impact of future expansion of irrigation and the real-time impact of short-term drought.

Software availability

The GriDSSAT model presented in this paper was developed with the Decision Support System for Agrotechnology (DSSAT), a software application program that comprises crop simulation models for over 28 crops and is supported by data base management programs for soil, weather, and crop management and experimental data, and by utilities and application programs. The latest version can be obtained free at: http://www.dssat.net. The WaSSI model is an integrated, process-based model that was originally developed by the U.S. Forest Service. More information is available at: http://www.forestthreats.org/tools/WaSSI.

1. Introduction

As irrigated agriculture has expanded around the world because of improved productivity, it is recognized that water demands of irrigation must be weighed against hydrologic availability (Postel, 1992; Rosegrant et al., 2002; Gleick et al., 1995; de Villiers, 2000). In the past, when irrigated agricultural lands were first put into production, competing uses of water for public water supply and industry were often virtually non-existent (Solomon, 2010; Reisner, 1986). Additionally, there was little thought given to ecosystem water needs (Poff et al., 2010; Tavernia et al., 2013). Consequently, without the ability to foresee the future, many watersheds around the world have seen irrigation and other water demands outpace supply.

In order to avoid (or correct) past mistakes and prepare for the future, integrated agricultural, hydrologic, and sectoral withdrawal models that can calculate irrigation demand and the impact of this demand on hydrology will be required (Jia et al., 2011; Bithell and Brasington, 2009; Flores-Lopez and Yates, 2013). These systems should also be able to estimate the costs of various agricultural and hydrologic options. These integrated models can be used as tools to: (1) examine historic vulnerability of expanded irrigation or other water demands to past climate extremes (2) examine the future sustainability of irrigation under expansion or future climate scenarios and (3) to allow real-time dynamic water resource management (Bithell and Brasington, 2009). In retrospect if such tools had been available in the West the oversubscription and environmental impairment of the Colorado River (Powell, 2008; Solomon, 2010) might have been avoided.

To that end, this paper describes a coupled crop model and hydrologic model that can be used as a regional planning tool to determine when and where hydrologic flows may be threatened by irrigation withdrawals. Development of integrated simulation

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* Corresponding author. Tel.: +1 256 961 7756.
E-mail address: mcnider@nsstc.uah.edu (R.T. McNider).

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models for sustainable agriculture has received much attention in the recent literature (Bergez et al., 2013; Bithell and Brasington, 2009; Liu, 2009; De la Rosa et al., 2004). In particular the inclusion of biophysical crop growth algorithms within hydrology models has become a common practice, particularly as evidenced by the family of models developed by the US Agricultural Research Service (Williams et al., 1984, 1985; Young et al., 1995; Neitsch et al., 2005; Srinivasan et al., 2010). Another approach would be to integrate otherwise stand-alone crop and hydrology models into a common simulation system (Bithell and Brasington, 2009). Jia et al. (2011) linked the World Food Studies (WOFOST) crop model with the Water and Energy Transfer Processes (WEP) hydrologic model to examine the impacts of climate variability and change on crop yields in China. In their system, the crop model received input from the hydrologic model as to the hydrologic state of the water and moisture availability in the ecosystem. An alternative approach, one advocated here, would be to allow the crop simulation model to determine water requirements for a particular crop and the data to be fed to the hydrologic model, thus determining the degree to which the needs could be met by the available water in the basin. This approach allows for determination of water stress levels associated with various crops, climate and agricultural management plans for a given area.

The modeling system described here can examine past, present (real-time) and future scenarios. This system is formulated and tested in a regional setting – the Southeast U.S. The Southeast is unique in that it lost a large part of its agricultural production because its rain-fed agriculture could not compete with the arid Western irrigated agriculture or agriculture in the deep water holding soils of the Midwest. Given almost certain future reductions in Western irrigated agriculture due to reduced water availability and the threat to Midwest grain production from regional drought; it is therefore reasonable that irrigated agriculture within the Southeast with much greater water availability should play an expanded role in U.S. agriculture (McNider and Christy, 2007). In humid regions such as the Southeast both irrigation demand (Salazar et al., 2012) and hydrologic water availability can be dynamic with large swings due to seasonal and inter-annual precipitation (Keim, 1996). Given the lessons learned from the destruction of watersheds in the West and over-subscription of rivers for irrigation, it is clear that irrigation expansion in the Southeast should be carefully analyzed.

While historical simulations or long-term climate simulations can provide information for agricultural and water planning, there is also a need to have real-time modeling systems. For example a real-time system can see when water sheds become stressed and provide information that irrigation or other water restrictions need to be implemented. The modeling system discussed below is a relatively complex system that links crop irrigation demand to watershed water availability. While it includes many important details, there are still simplifications that can be relaxed in the future. Thus, the present description of the system should be considered as a work in progress. As an example, the current system is being run with maize as the only crop considered. We are currently expanding to other crops. However, even the single crop acting as a surrogate for all crops gives an indication of the demands of irrigation as a function of weather on water supply. In the same vein maize is currently modeled with a single cultivar. This will be relaxed in the future.

2. DSSAT-GriDSSAT system and calibration

2.1. DSSAT description

The Decision Support System for Agrotechnology Transfer (DSSAT v4.5) model (Jones et al., 2003; Hoogenboom et al., 2010) is a framework for biophysical modeling that includes a suite of more than 28 different cropping and fallow system models. DSSAT simulates crop growth and yield in response to management, climate, and soil conditions and requires a minimum set of inputs such as weather, soil type and profile variables, cultivar specific parameters and field management strategies including planting dates, irrigation and fertilization. In use for over 25 years, this widely used crop model has been applied to predict crop yield and water use, to develop management strategies and to study nitrogen cycling dynamics under many different soil and climate scenarios (Liu et al., 2011; Soler et al., 2011; Thornton et al., 2009; Soler et al., 2007; Yang et al., 2006; Jones et al., 2003; among others).

2.2. GriDSSAT description

The DSSAT crop model was designed to analyze a wide range of agricultural impacts but was originally conceived to run at a field scale. A large scale spatial model becomes necessary when analyzing crop yields and environmental impacts at the watershed, state and regional level (Mineter et al., 2003; Liu, 2009; Priya and Shibasaki, 2001). For example, Mineter et al. (2003) provided a framework for scaling-up field level agricultural models to a gridded format using interpolated weather data. Similarly, the DSSAT system was configured to run in a gridded mode at a grid spacing of approximately 4.75 km associated with the NCEP Stage IV precipitation analysis grid. This grid consists of 36,877 individual points at which the model must be run to cover the Southeastern region. This gridded crop model is referred to as "GriDSSAT" (McNider et al., 2011). An input data file that defines the location, weather, cultivar, soil type and other input parameters for each grid cell was developed. Temperature, solar insolation and precipitation are provided as weather inputs following the methodology of McNider et al. (2011) and a detailed description of the cultivar calibration can be found Section 1.4. Soil profiles are defined at a county level and selected as the dominant agricultural soils based on Soil Survey Geographic (SSURGO) soil data. Currently, there is only one soil per county but this will be upgraded to three soils per county to better reflect variability (Sharda et al., 2013). A batch process then runs DSSAT for every point in the grid. GriDSSAT is configured to run every day, based on the most current, observed weather data (a real-time daily mode) and in a historic weather data mode. Currently the model is configured to run a regionally calibrated maize cultivar as a proxy for all irrigated crops because of maize's high water demand. In the future, a more realistic crop rotation will be implemented that includes regionally important crops. Soybeans, wheat and cotton are all grown in major portions of the Southeast; as well as peanuts in smaller but still substantial areas. Each of these crops have varying water demands which will have an impact on local water supplies.

2.3. Crop growth simulations

The crop and water demand simulation modeling was conducted using the Cropping System model (CSM)-Crop-Environment Resource Synthesis (CERES)-Maize model (Ritchie et al., 1998 and Jones et al., 2003) in the DSSAT v4.5 suite (Jones et al., 2003; Hoogenboom et al., 2010). Many studies have evaluated the CSM-CERES-Maize model in various soil types and a range of climates (Hodges et al., 1987; Carberry et al., 1989; Jagtap et al. 1993; Asadi and Clemente, 2003; Jones et al., 2003; Soler et al., 2007).

2.4. Cultivar calibration

In the broad geographic context of GriDSSAT the selection of the cultivar is different than in a specific field mode. Cultivar characteristics which broadly mimic the type of cultivars that are employed across the region perhaps are desired, at the expense of the specific cultivar response at the field level. In general, early to medium maturing hybrids are preferred across the Southeast. As such, an initial maize hybrid cultivar was developed in a field mode but one that had generic attributes of a broad range of cultivars. Next, a regional test of the cultivar was made at locations across a broad range of soils and weather. Finally, the model was evaluated against southeast regional NASS county level crop data.

The cultivar-specific coefficients were modified by generalized likelihood uncertainty estimation (Beven and Binley, 1992) to determine a set of coefficients that reduced the difference between simulated and observed grain yield and anthesis date resulting in a best fit (lowest RMSE) for the experimental maize cultivar used.

The base cultivar used in GriDSSAT was calibrated against field trial yield data conducted at the Tennessee Valley Research and Extension Center (TVREC) located in Belle Mina, Alabama - an agricultural experiment station operated by the Auburn University Agricultural Extension Service. Dynagro 58K02 was selected as the TVREC target cultivar with 6 irrigating years (2004–2009) of data available (observed standard deviation = 159 kg/ha (20 bu/ac)). The Dynagrow 58K02 hybrid fit the overall maize average of the TVREC Variety Trials for both irrigated and rain fed trials well with a coefficient of determination of 0.9609 and an RMSE of 647 kg/ha (10 bu/ac, which represents 8% of the mean). Crop management profiles were created for each of the 6 years of data from the Variety Trial report and the soil used a silty clay loam representative of the TVREC fields. A medium to full season default maize hybrid cultivar (McCurdy 84aa) was selected as the base cultivar for calibration as it was well suited to the area and has been used in previous studies in the Southeastern United States (Ma et al., 2009; Cabrera et al., 2007; Ma et al., 2006). The goal of the calibration process was to derive a set of parameters for the McCurdy 84aa cultivar that would best mimic the target (Dynagrow 58K02) cultivar.

The results of the DSSAT model calibration on yield are shown in Fig. 1. The yield calibration resulted in a coefficient of determination of 0.7235 and an RMSE of 817 kg/ha (13 bu/ac, 8%). The means for the observed and simulated grain weights were 10184 kg/ha (161 bu/ac) and 10586 kg/ha (168 bu/ac) respectively. The higher variance in the observed data suggests water and nitrogen stressors were present in the irrigated trials. Cultivar coefficients are best calibrated under optimal growing conditions with no stress. However, taking into account the assumption of unequal variances, a *t*-test of the observed and simulated yields suggests that the difference of the means is not significant with a *P*-value of 0.532.

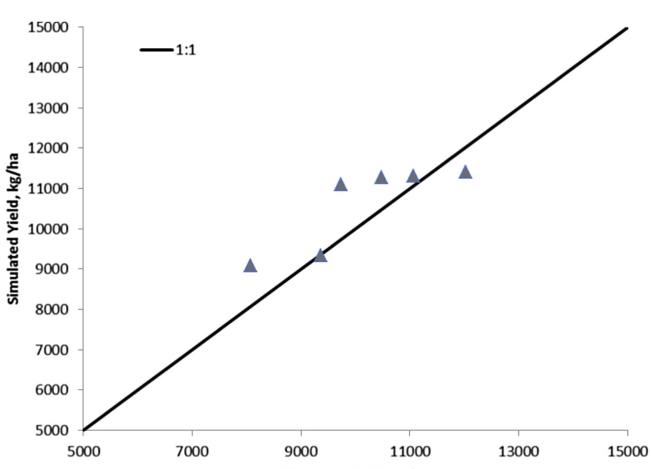

Fig. 1. Cultivar calibration results for 2004–2009: DSSAT simulated yields compared to observed TVRC Variety Trial yields of DnyaGro 58K02.

The next step was to evaluate the performance of the calibrated cultivar in simulating the overall yield averages in the region. To achieve this, 11 years (2000–2011) of Alabama Maize Hybrid Variety Trials from Auburn University Agricultural Extension Service's TVREC, and the Sand Mountain Research and Extension Center (SMREC) at Crossville, AL were employed. Irrigated and rain-fed trial averages were used from TVREC while only rain-fed trials were available at SMREC. The results of the evaluations can be seen in Fig. 2. The model performed well in simulating the measured regional variety trial averages. The overall coefficient of determination for the evaluation was 0.7887 and a RMSE of 1603 kg/ha (25 bu/ac, 19%). The regression slope was 0.9968 with an intercept of 848 kg/ha. The TVERC and SMREC simulations performed equally well resulting in RMSEs of 1906 kg/ha (22%) and 1367 kg/ha (23%) respectively. However, it does appear that the simulations more consistently under predicted the rain-fed scenarios.

3. Masking DSSAT with CropScape

The GriDSSAT spatial crop model was originally developed to provide spatial depictions of crop stress occurring due to real-time weather (McNider et al., 2011). Thus, it was assumed the crop was grown at every grid cell over the entire region. While this is useful in providing a spatial depiction of generalized crop stress or yields; it is not realistic when attempting to determine final yields and/or irrigation demand for an area (county, watershed, etc) due to the large sub-county variations in stress and yield. Therefore, there is a need to understand the actual location of crops in order to scale up to county-level yields and to determine irrigation demand for a watershed. Thus, additional spatial information is needed to allow a weighting of GriDSSAT output based on the actual location of the crops.

The Cropland Data Layer (CDL; Boryan et al., 2011) developed by the USDA NASS Spatial Analysis Group (http://nassgeodata.gmu.edu/CropScape/) formed the basis of the scaling exercise. The CDL is a raster image classified to most crops available for a given growing season and combines satellite imagery with ground truth information available through the NASS (USDA, 2011).

The CDL provides very detailed information about crop location but it is limited to crop type and acreage and the specific crop grown on a particular field for a given year is not available until late in the growing season. It also does not provide information about crop management practices. However, it does provide critical information on where crops are grown. In the current GriDSSAT we are focusing

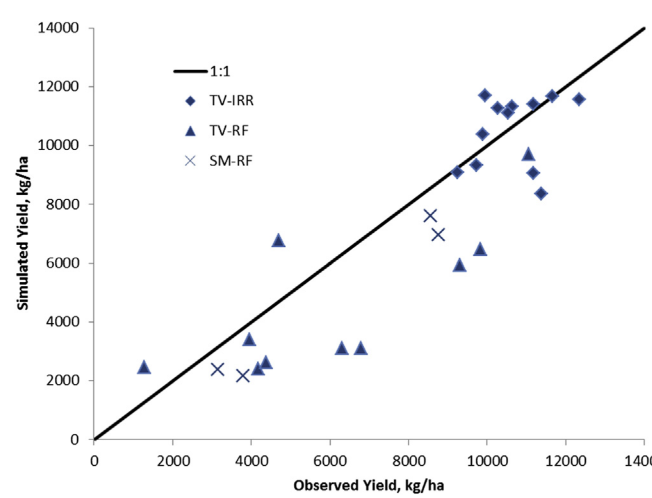

Fig. 2. Cultivar evaluation results for 2000–2011: DSSAT simulated yields compared to observed TVRC irrigated (TV-IRR), TVRC rain-fed (TV-RF), and SMREC rain-fed (SM-RF) Variety Trial average yields.

on maize. To limit the map to fields that would realistically grow maize, a filter is applied to extract only land classified as maize, cotton and soybeans (since these are in common rotation).

In order to map GriDSSAT with CropScape the raster image is converted to vector objects (polygons) and then assigned the crop model information (in the current case, yield and irrigation demand) from the nearest GriDSSAT point. The GriDSSAT crop model data are assigned to approximate field-level maps and can be aggregated based on output requirements. For example, water stress and yields may be aggregated by county for updates and reports. Fig. 3 shows the masking of GriDSSAT yield through the crop data layer.

A critical component to estimate the hydrologic impact of crop irrigation is the amount of irrigation water required based on the weather conditions. The DSSAT model includes an automatic irrigation mode which tracks moisture levels in the soil column and estimates irrigation requirements when soil moisture drops below a user defined variable, currently set at 40%. The crop model attempts to minimize water stress constantly through the growing cycle by applying irrigation based on soil water content. However, optimizing irrigation for maximum demand is not the only factor farmer's use when deciding when and how to irrigate. We are currently working with actual on-farm data for the region to make decisions on practical, optimal water use. In the present study we employ automatic irrigation but at a level which mimics the irrigated yields in field trials and in yields reported by farmers. Thus, it is in part a practical economic irrigation demand not a theoretical optimal yield demand.

Fig. 4 shows a schematic of how GriDSSAT irrigation demand is mapped to the hydrologic units which are the base geographic entity in the WaSSI hydrologic model (see below). The irrigation demand is then passed to the hydrology model as part of the agricultural sector withdrawal. In summary, the CDL is used to map GriDSSAT gridded yield information to the county level for comparison to reported agricultural statistics or irrigation demand to the hydrologic unit used in WaSSI.

4. GriDSSAT spatial evaluation

To evaluate the performance of the GriDSSAT spatial model, simulated yields were compared against the 2011 and 2012 USDA NASS yearly agricultural survey county averages. NASS provides a number of agricultural statistics for counties, regions and states that include yield, as well as planted and harvested acres for most agricultural crops (http://www.nass.usda.gov/). Since GriDSSAT is run on an approximately 5-km spatial grid, data points were collected and averaged by county based on those points that were contained by or closest to agricultural areas in maize production. The agricultural areas in maize production for both 2011 and 2012 were obtained from NASS Cropland Data Layer of CropScape as discussed above.

The region of North Alabama was considered first; since this was the region in which the cultivar calibration was conducted as described in Section 2 above. NASS county level yields include both irrigated yields and non-irrigated yields. Unfortunately, due to privacy concerns NASS county yield data is not divided into irrigated and non-irrigated yields. Thus, we ran the GriDSSAT system in both a non-irrigated mode and irrigated mode and later will attempt to weight the county yields by estimated irrigation acreage.

Fig. 5 provides comparisons of the 2011 and 2012 simulated and NASS averages using only non-irrigated GriDSSAT yields, and it can be seen that the model is not simulating the NASS average county yield very well, especially in the dry year 2012. The 2011 observed and simulated means were 8018 and 6540 kg/ha (127 and 104 bu/ac) respectively (st. dev = 75 and 147 kg/ha). The 2012 observed and simulated means were 5867 and 2496 kg/ha (93 and 39 bu/ac) respectively (st. dev. = 164 and 40 kg/ha). The overall RMSE is 2479 kg/ha (39 bu/ac, 36%). In the Southeast NASS does not separately provide irrigated and rain-fed yields. The lack of model performance can be explained in part due the fact that the NASS yields comprise both the irrigated and the rain fed yields within each county, while the simulated GriDSSAT yields shown in Fig. 5

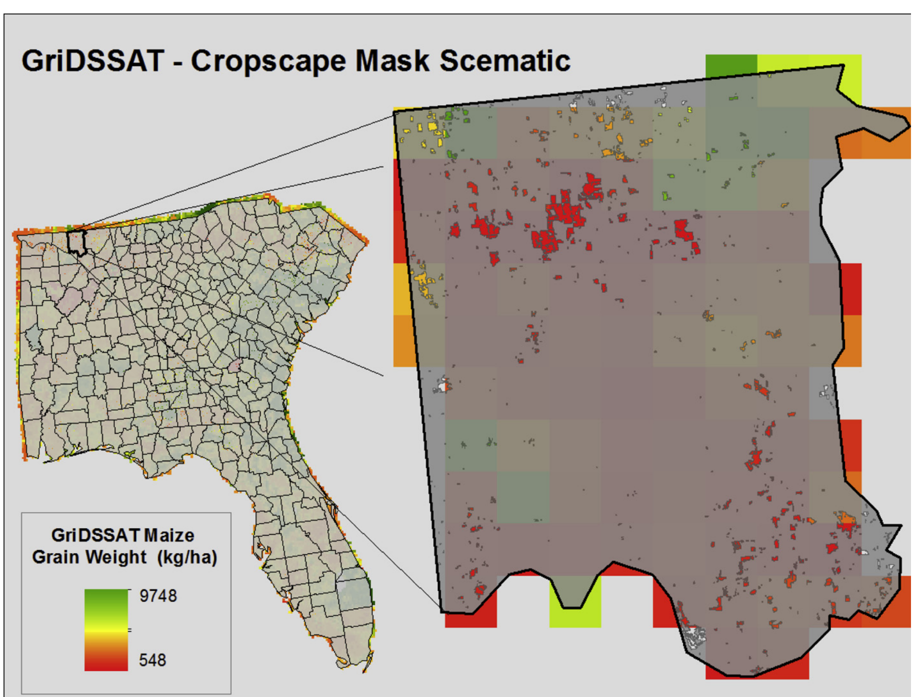

Fig. 3. GriDSSAT yield displayed through the Crop Data Layer.

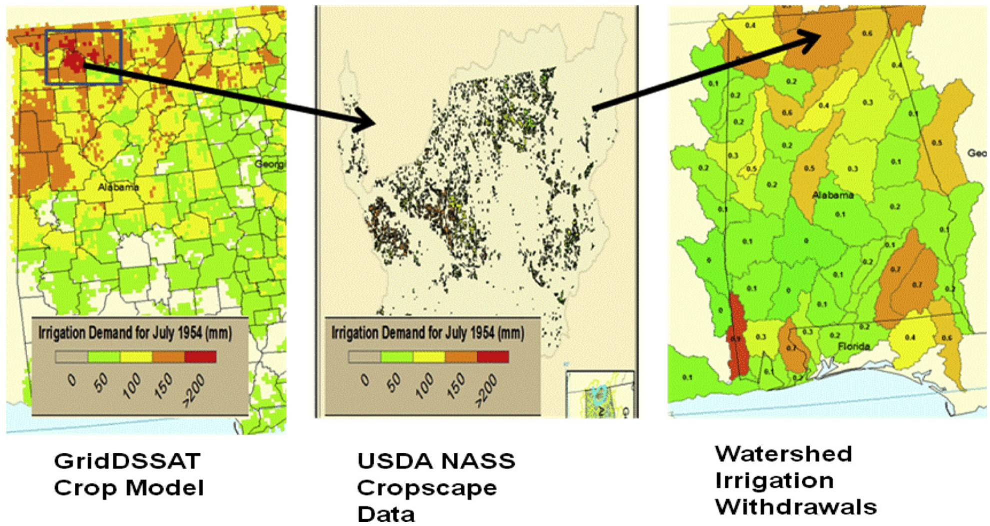

Fig. 4. A schematic of how GriDSSAT irrigation demand is mapped and passed to the hydrologic model (WaSSI). On the left is irrigation demand in mm from GriDSSAT. In the middle is the demand mapped through the CropScape Data Layer. On the right is a depiction of the watersheds where the withdrawals are taken.

did not incorporate irrigation. Mishra et al. (2013) demonstrated that DSSAT simulations can be dramatically improved in North Alabama through use of an integrated rain-fed and irrigated soil moisture signal. In our case, the yields for 2011 were better predicted than in 2012 with an RSME of two thirds that of the latter year (20% vs. 59%). This reinforces the hypothesis of the model performance, given that 2011 was a wetter year and rain fed fields would reflect yields closer to that of irrigated fields than in 2012 when drought persisted in the region. A *t*-test on the means assuming unequal variances shows that the means for both 2011 and 2012 are significantly different.

While NASS does not provide the partition of rain-fed and irrigated yields in the southeastern region, the most recent USDA NASS Agricultural Census (2007) does provide insight into the amount of irrigated land in each county. In Alabama, because of relatively favorable commodity prices and State incentives for expansion of irrigation, the 2007 irrigated acreages do not reflect current conditions. For example, Mishra et al. (2013) found that irrigated acres in Limestone and Madison counties had increased by around 35% since 2007 based on observations of center pivot fields in the area.

In the absence of the 2012 NASS Census, based on informal surveys in the State, we believe it is reasonable to assume that the total irrigated crop land in Alabama has increased by approximately 40470 ha (100,000 acres) above the 45,326 ha (112,000 acres) reported in 2007. To apply this assumption we must also assume this acreage is distributed in the same proportion as previously irrigated lands. If so, a current estimate of irrigated lands by county can be made and a fraction of the irrigated land relative to rain-fed land can be developed. Following this procedure, we estimate irrigated land in Limestone County to be 13,955 acres compared to 4047 ha (10,000 acres) reported by Mishra et al. (2013). However, the acreage obtained in the latter study was based exclusively on center pivot observations and thus would constitute an underestimate of total acreages as other forms of irrigation were ignored. Based on these computations, we estimate that the procedure is accurate to 20% or better, at least in North Alabama.

Total county GriDSSAT yields are then found by a weighted average of GriDSSAT rain-fed and irrigated yields using the weighted fraction of irrigated and rain-fed acreages.

By including irrigated yields into the evaluation process, the comparison of simulated yields to NASS county averages improves (Fig. 6). The irrigation weighted data have an overall RMSE of

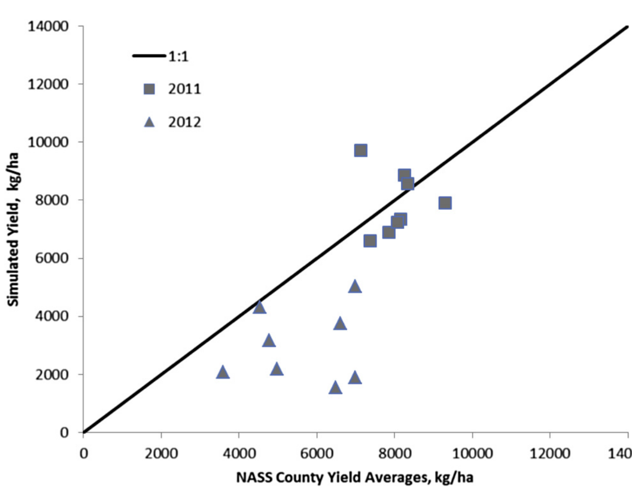

Fig. 5. Cultivar evaluation results for 2011–2012: GriDSSAT simulated yields compared to NASS County average yields for the North Alabama area. Note each county contains many GriDSSAT points.

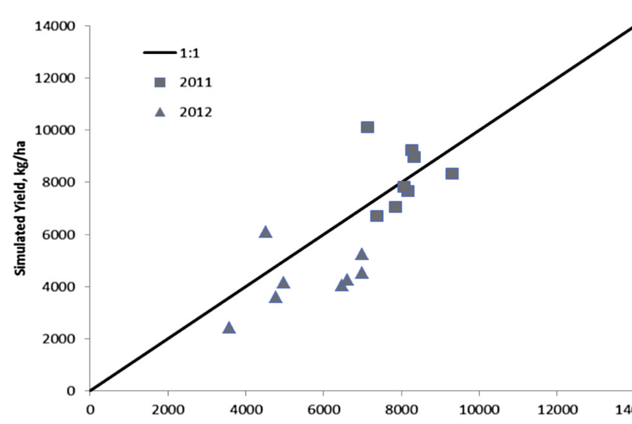

Fig. 6. Cultivar evaluation results for 2011–2012 GriDSSAT adjusted for irrigation simulated yields compared to NASS County average yields for the North Alabama area. Note each county contains many GriDSSAT points.

1560 kg/ha (24 bu/ac, 22%). In particular for 2012 the RMSE improved from 2890 to 1814 kg/ha.

Figs. 7 and 8 display the GriDSSAT model's performance over the entire Southeast region. The same weighting procedure for irrigated acreage was applied to all counties in the region that have NASS reported maize yield and a combined harvested acreage of maize, cotton, soybean and peanuts greater than 810 ha (2000 acres). The RMSE for the Southeast model runs in 2011 and 2012 are 3097 kg/ha and 2650 kg/ha (45% 49.3 bu/ac and 29%, 42 bu/ac), respectively.

In summary, in evaluating the regional model we must deal with an imperfect NASS data set both in our ability to know the location in a county where maize yields were reported and in knowing the actual location of irrigated land. Thus, we must inherently accept some irreducible scatter in the results. After coarse adjustment for irrigation we are heartened that predictions are near the 1:1 line despite scatter. We feel that given these uncertainties in the observational data base and the lack of bias, the model's regional performance is adequate for our purposes of estimating the regional economic return on irrigation and for water demand.

5. Water supply stress index (WaSSI) model

The Water Supply Stress Index (WaSSI) model developed by the Eastern Forest Environmental Threat Assessment Center of the USDA Forest Service (Sun et al., 2008; Caldwell et al., 2012) forms the hydrologic component of the integrated model. The Water Supply Stress Index is defined simply as the ratio of the total water demand for a period of time in a basin to the total water supply for that time (including return flows from all withdrawals). The WaSSI

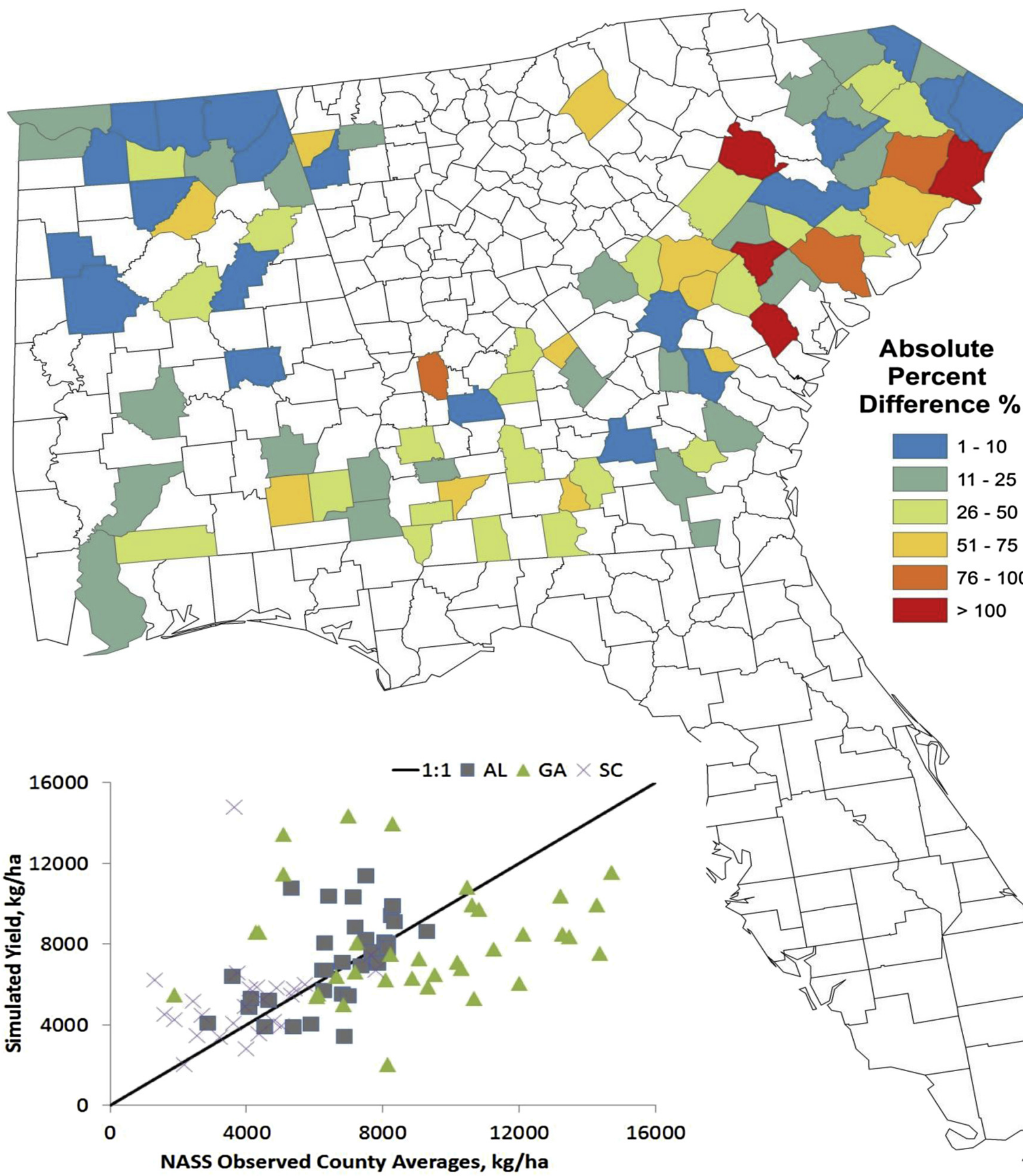

Fig. 7. Regional evaluation results for 2011: GriDSSAT combined rain-fed and irrigated simulated yields compared to NASS County average yields over the Southeast after correction for irrigated acreage described in the text. The map shows the spatial error in terms of absolute difference between the NASS county average and the GriDSSAT county estimate. The scatter plot shows the aggregated performance across the region.

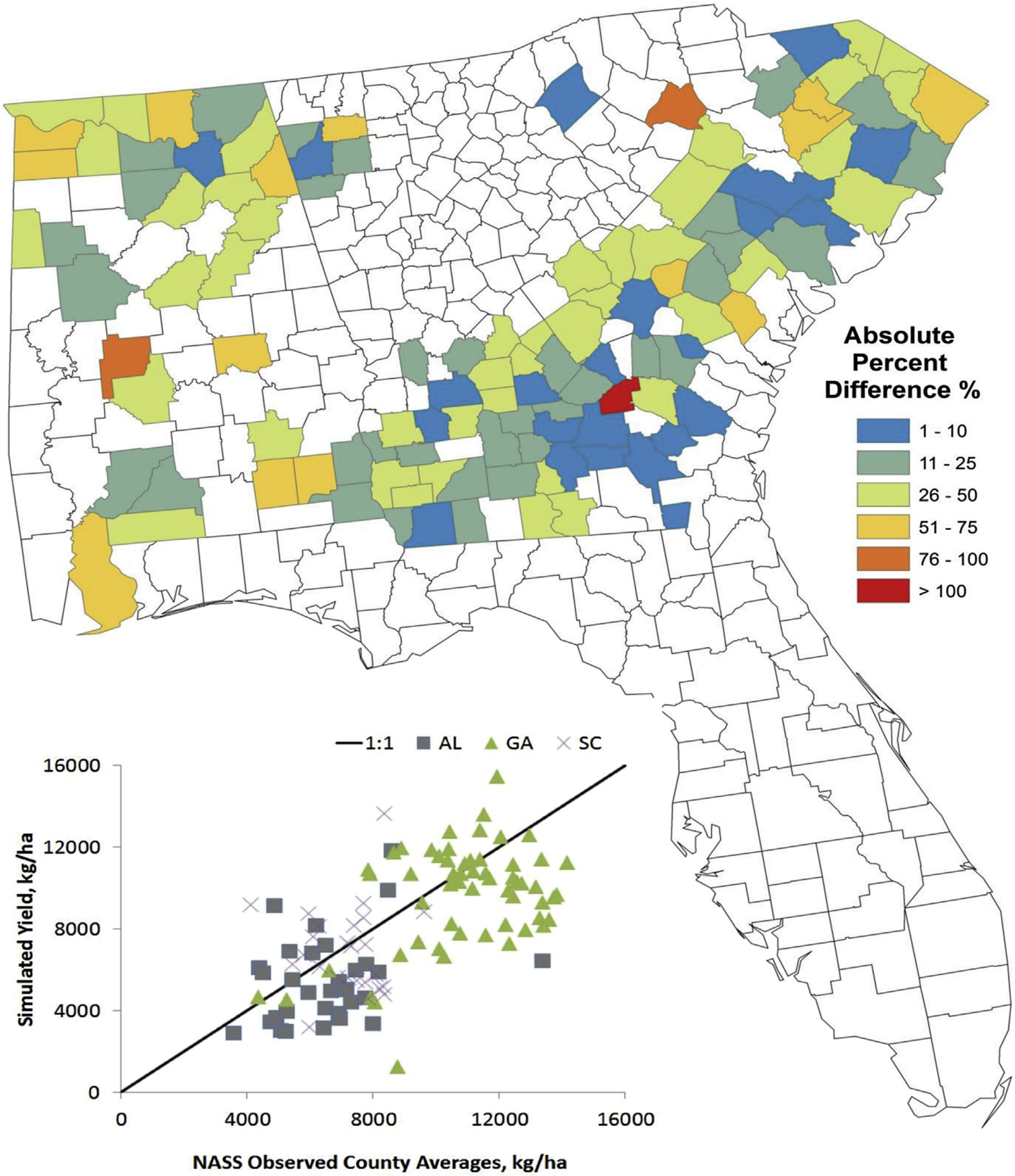

Fig. 8. Regional evaluation results for 2012: GriDSSAT combined rain-fed and irrigated simulated yields compared to NASS County average yields over the Southeast after correction for irrigated acreage described in the text. The map shows the spatial error in terms of absolute difference between the NASS county average and the GriDSSAT county estimate. The scatter plot shows the aggregated performance across the region.

model currently operates over the coterminous US at the 8-digit HUC level (approximately 1800 km^2) with an aggregated temporal resolution of 1 month.

The WaSSI model is composed of a hydrologic model to compute the water supply term together with a module to estimate water demand for the HUC. The hydrologic model computes the monthly water balance for each of ten land cover classes independently in each HUC watershed. Evapotranspiration (ET), infiltration, soil storage, snow accumulation and melt, surface runoff, and baseflow processes are calculated in each basin based on spatially explicit 2001 MODIS land cover, and discharge (Q) is instantaneously routed through the stream network from upstream to downstream watersheds. ET is estimated with an empirical equation based on multisite eddy covariance ET measurements using MODIS derived monthly leaf area index (LAI), potential ET (PEThamon), and precipitation (PPT) as independent variables (Sun et al., 2011). PET by Hamon's method is computed using only the daylight hours in the month (related to the mean latitude of the HUC) and the saturated vapor density computed from the mean monthly temperature (Hamon, 1963). Estimation of infiltration, soil storage, and runoff are accomplished through integration of algorithms from the Sacramento Soil Moisture Accounting Model using STATSGO-based soil parameters (Koren et al., 2003).

As originally constituted by the National Forest Service the model did not include streamflow regulation by reservoirs. However, reservoirs, due to their ability to provide water yields to downstream HUCs, are important to reflecting stress especially during the growing season. We are currently in the process of incorporating reservoir regulation into the model for the entire Southeast and the process is completed for the Alabama HUC's. The regulation effects are simulated through the incorporation of the area-capacity and operating (rule) curve relationships for the reservoirs of significant size to impact streamflow at the 8-digit HUC level. Inflow to the reservoir is computed by the WaSSI hydrologic model and the resulting reservoir elevation is computed from the area-capacity relationship. The operating curve is then consulted to determine the desired elevation for the time of year and the required reservoir release is computed to bring the reservoir back to its desired elevation.

The water demand component of the WaSSI model uses county-level 2005 annual U.S. Geological Survey (USGS) water demand and groundwater withdrawal estimates for eight water use sectors (Kenny et al., 2009). The sectors include domestic use, industrial demand, public needs, irrigation, mining, livestock, thermoelectric power, and aquaculture. In the original development runs the reported irrigation demands from the USGS report were used. However, as discussed below, later runs were done using irrigation demands supplied by GriDSSAT. Note that in the present version we are using maize as the surrogate crop for irrigation demand. That is, we assume all land defined by CropScape as currently in production is in maize. In the near future we expect to relax this assumption by running GriDSSAT for the main row crops in the region - maize, soybeans, cotton and peanuts. Then this irrigation demand will be determined by the CropScape allocation of these crops.

Based on DSSAT runs and farmer input, the water use for maize is greater than soybeans and cotton but slightly less than for peanuts grown mostly in sandy soil. Thus, the present withdrawals are perhaps slightly overstated on average. But, the coupled WaSSI-GriDSSAT system provides to first order the irrigation variability due to weather and plant needs.

The USGS data are rescaled to the 8-digit HUC watershed level, adjusted for population, and disaggregated to the monthly scale using regional regression relationships based on survey results. Return flows by sector were computed using return flow percentages from the 1995 USGS report (Solley et al., 1998). With the exception of the thermoelectric sector, the return flows are included in the model at the downstream node of the HUC and so are not considered to be available for use within the HUC where the withdrawal occurred, but are available in downstream HUC's. Since most thermoelectric plants merely cycle the water through the plant and return it in close proximity to the withdrawal point, those returns are considered to be available within the HUC and so are included in the supply term. The total water supply in each HUC watershed is the sum of surface water supply at the watershed outlet predicted by the hydrologic model, total groundwater withdrawals, and the return flow from the thermoelectric plants. Total water demand is the sum of the water use by all sectors in each watershed. The water supply stress index (WaSSI) is computed as the ratio of water demand to water supply (Sun et al., 2008).

5.1. Model verification

Since the reservoir regulation effects have only been implemented in Alabama thus far, detailed analysis of model accuracy has been confined to stream gages in that state. The long term climate data set (1950–2010) of Maurer et al., 2002 was used to drive the hydrological model. A total of nine stream gages were identified in Alabama whose locations were in close proximity to model nodes and whose period of record were sufficient for significant comparison statistics to be generated. The Nash-Sutcliffe

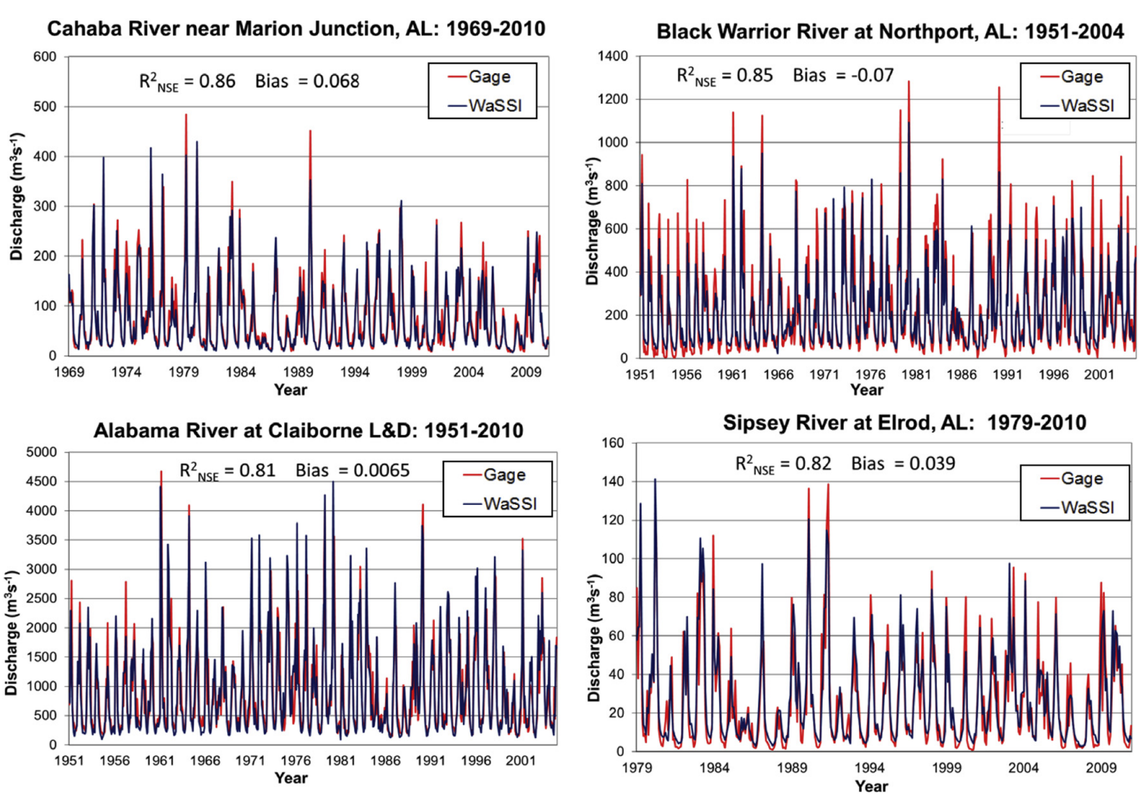

Fig. 9. A representative subset of the WaSSI modeled monthly stream discharge as compared to USGS stream gages for four rivers in Alabama. The lengths of record are determined by the available USGS gage data.

Efficiency Statistic (R^2_{NSE}) is recommended by the American Society of Civil Engineers for measurement of model prediction accuracy (ASCE, 1993). The NSE statistic is a function of the ratio of model error to variance of the observations and can vary from -∞ to 1. Any positive value denotes some predictive capability compared to use of the simple observed mean. A survey of literature results reported by Moriasi et al. (2007) found that, based on 33 surveyed studies, the reported R^2_{NSE} statistics for monthly streamflow evaluation varied from 0.14 to 0.91 with a median value of 0.79.

Typical results of the verification analysis are shown in Fig. 9 where discharge in units of cubic meters per seconds (m^3s^{-1}) is plotted against time. The R^2_{NSE} statistic and the relative bias are shown on the graph for each stream comparison. Overall, the R^2_{NSE} ranged from 0.86 to 0.77 with a median value of 0.82. The relative bias ranged from 0.108 to −0.07 with a median value of 0.039. Based on these figures, it appears that the WaSSI hydrological model is at least as accurate as those reported in the literature cited above, if not more so.

5.2. *WaSSI results*

As mentioned above, the WaSSI model has been executed on a monthly time step for the period 1951–2010 using the long term climate data set. The model produces the WaSSI Index for each 8-digit HUC for each month of the simulation period. Recall that the index value is the ratio of water demand from all sectors for the month to the water supply, which is a function of the surface streamflow generated by the hydrologic model, the groundwater resources derived from the USGS data, and the return flows from the thermoelectric withdrawals. A WaSSI value of 0.4 has been used as a threshold for indicated stress in a watershed (Vörösmarty et al., 2000; Raskin et al., 1997). Fig. 10 shows the average WaSSI Index for the period and also the maximum WaSSI Index (most stressed) for the period with the year that it occurs. Note that 1954, one of the driest years on record in the SE, produced the maximum in many areas but other extreme drought years such as 2007 also produced the maximum WaSSI index of record in some basins.

5.3. *Use of the combined GriDSSAT – WaSSI system to examine hydrologic impacts of increased irrigation*

Here we provide an example of how the coupled GriDSSAT and WaSSI system can be used to assess the hydrological impact of expanded irrigation and perhaps provide limits on a sustainable level of irrigation. The example is for Alabama in the heart of the Southeast. Alabama lags most states in the U.S. in irrigated acreage despite having large surface water assets, e.g. the Alabama River in south Alabama alone has nearly twice the flow of the Colorado

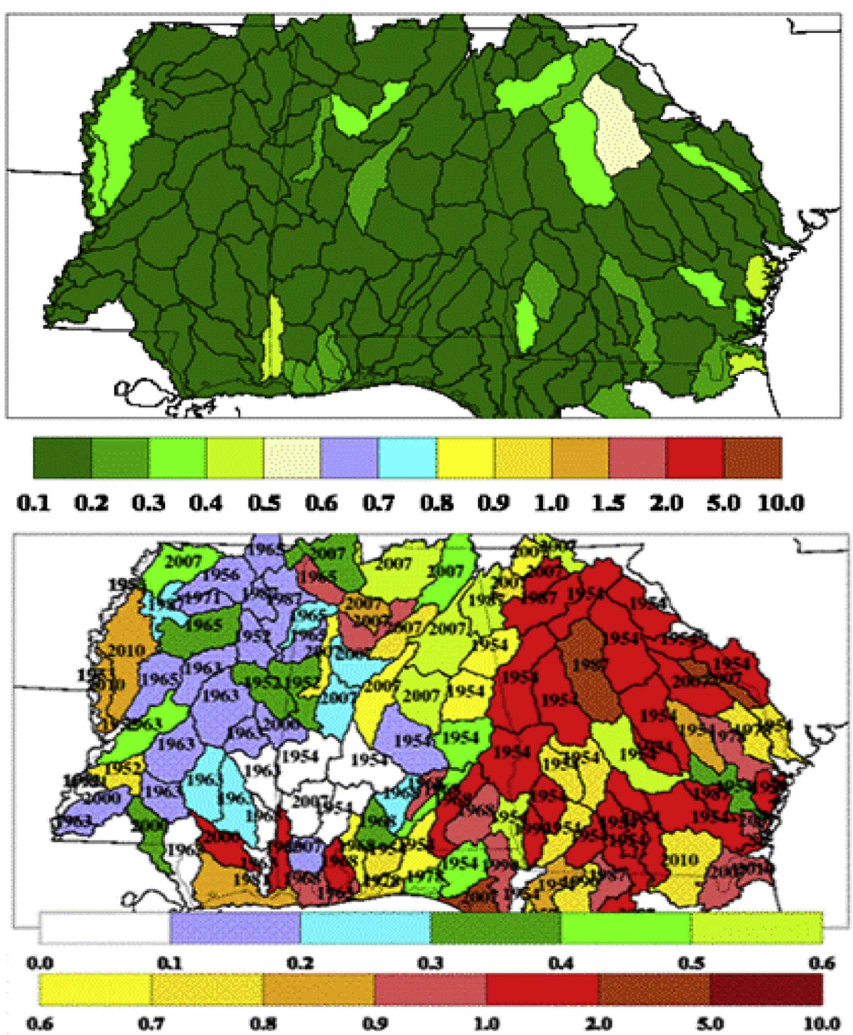

Fig. 10. Monthly WaSSI statistics for the period 1951–2010. Top panel shows the average WaSSI index (demand/supply) and the bottom panel shows the maximum WaSSI index (most stressed for the period.

River when it enters Arizona. An adjacent state, Georgia, has about 50% of its cultivated land irrigated while Alabama only has about 10% irrigated. With generally abundant water, favorable commodity prices and tax credit incentives available for investment in irrigation, it is likely that irrigated acres in Alabama will increase in the future. In advance of this increase the key question is how many acres might be irrigated before stressing the surface water availability. Here we examine the hydrologic impact due to expanded irrigation in Alabama. These set of runs are for the time period 1951–1999 and utilize the Maurer et al. (2002) dataset. The GriDSSAT-derived irrigation demands discussed in Section 3 replace the static 2005 USGS values which were in the original WaSSI model. The results are shown in Fig. 11 where all plots are with respect to the total of 245 warm season months of April–August for the period 1951–1999. Fig. 11a shows the number of warm season months (and the respective percentages) when the

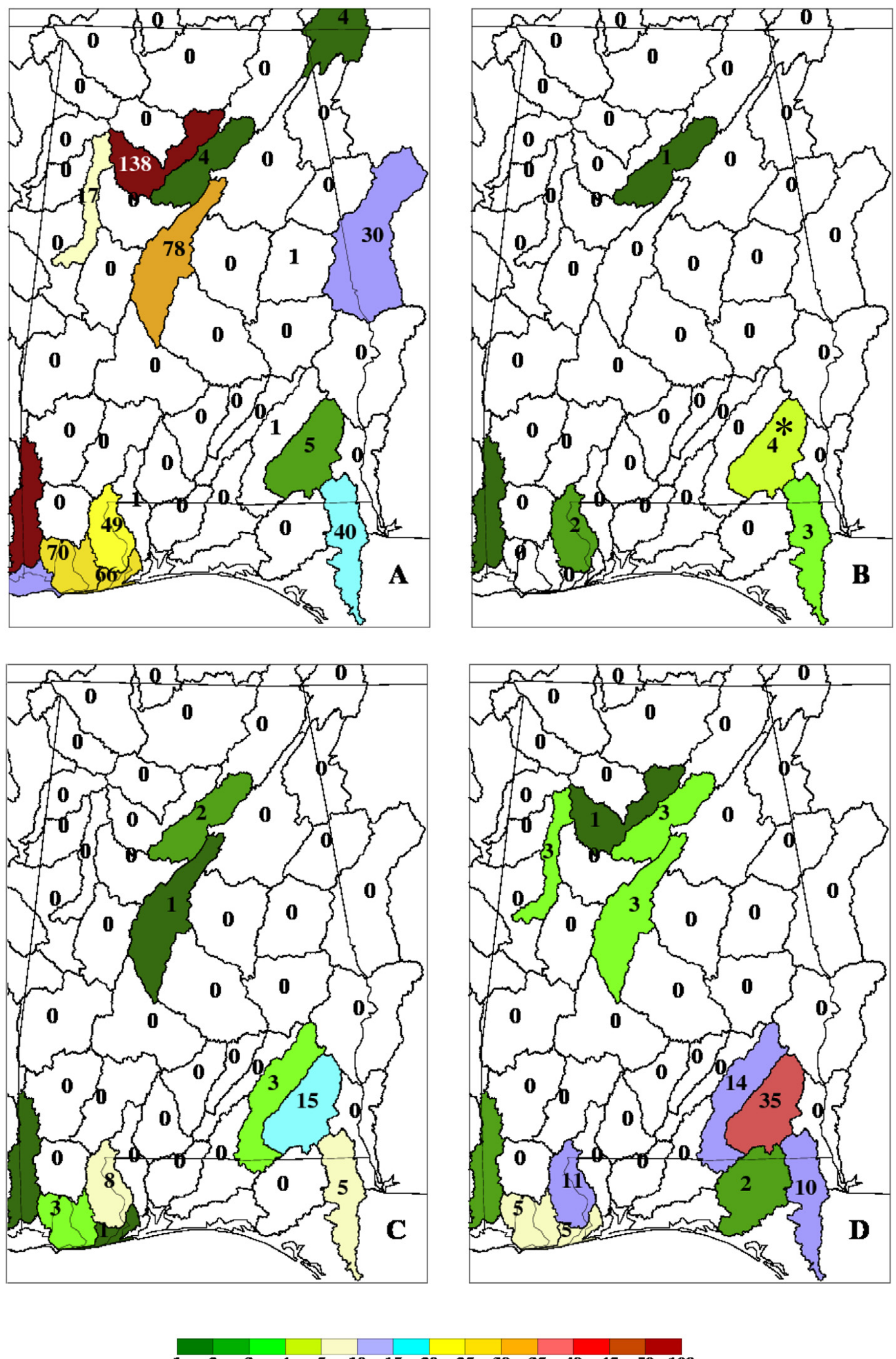

Fig. 11. Colors show percentage when the WaSSI stress index exceeded 0.4 with respect to the total of 245 warm season months of April–August for the period 1951–1999. The numbers show the number of times the stress index exceeded 0.4. 11a shows the number of warm season months (and the respective percentages) when the WaSSI exceeded 0.40 with all irrigation set to zero. 11b–d then show the impact of irrigating 10%, 25%, and 50% of the combined acreage of maize, cotton, soybeans, and peanuts, respectively In 11b–d the number of months is the increase over the baselines values given in Fig. 11a. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

WaSSI exceeded 0.40 with all irrigation set to zero (along with respective groundwater and return flows, as well). Some HUCs in the central, southwestern, and southeastern portions of the state show some water stress without irrigation, but in most places the number of stressed months was zero. Fig. 11b–d then show the impact of irrigating 10%, 25%, and 50% of the combined acreage of maize, cotton, soybeans, and peanuts, respectively. In these plots the number of months is the increase over the baselines values given in Fig. 11a. Even for the 50% scenario in Fig. 11d the impacts are generally small except for the southeastern corner of the state.

As mentioned in the introduction, the unique aspect of the modeling system presented here is the ability to examine the impact of the irrigation demand on the hydrology of a watershed. Fig. 12 illustrates the direct irrigation demand compared to the hydrology for the case above. It shows a time series of the irrigation demand for 1951–55 compared to the water availability as captured in the WaSSI index (ratio of demand to water supply) for the starred watershed in Fig. 11b above. This period is an extraordinarily dry period. It shows that in 1952 and 1953 while there was strong irrigation demand water availability is still high (i.e. a small WaSSI index). However, in 1951 and 1954 the high irrigation demand coincides with low water availability. In fact, 1954 is one of the driest years on record for many parts of the Southeast (see Fig. 10). But, for this particular watershed it was not the WaSSI hydrological drought of record which was 1968 (see Fig. 10). Note also because irrigation demand is in the numerator of the WaSSI index that the increased index value is in part due to the irrigation demand.

6. Real-time operation of the GriDSSAT- WaSSI model

The long-term historical coupled GriDSSAT – WaSSI runs described above can determine when watersheds might have high water demand. Also, these historical runs can determine the number of times watersheds might be stressed by irrigation and help define actuarial information for water insurance should withdrawals be curtailed. However, to actually manage water withdrawals requires that the system be run in real-time. The following describes the real-time system which differs from the historical mode only in terms of weather inputs. The models are run under script control which automatically collects the required real-time weather data and runs the GriDSSAT model. The soil and other GriDSSAT settings are the same as for the historical mode described earlier.

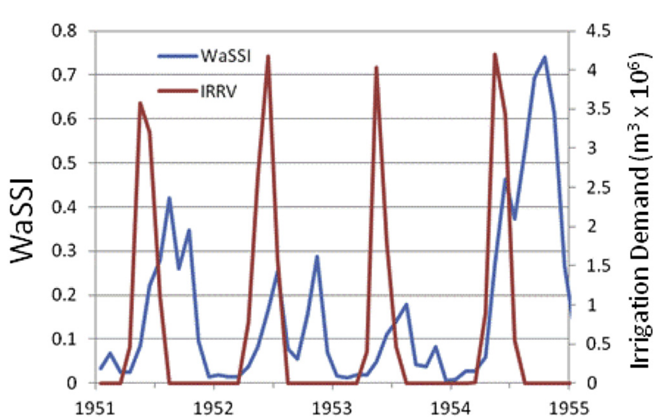

Fig. 12. Time series of irrigation demand and WaSSI index for the starred watershed in Fig. 11b. WaSSI is the ratio of anthropogenic demand to water supply. IRRV is the total irrigation volume for the watershed in millions of cubic meters as determined by GriDSSAT.

6.1. Real-time GriDSSAT/WaSSI inputs

The GriDSSAT crop model has been run in real-time since 2008 (McNider et al., 2011) although some of the weather inputs as described here have been changed. The spatial model runs on an approximately 5-km grid for a major portion of the Southeast. A primary county-level agricultural soil was provided for each grid cell (Sharda et al., 2013).

The following describes the meteorological forcing of the real-time system. Note this will be the same real-time daily forcing to be used in the WaSSI hydrologic model discussed below. It also includes an 8-day forecast component.

6.1.1. Temperature

Temperature is important in the crop model for plant processes such as respiration. It also is a major factor in ET. Temperature for the GriDSSAT system is provided by a real-time land surface modeling system run by the NASA Marshall Space Flight Center's group (SPoRT Center) that supports transition of NASA satellite and science products to the National Weather Service. The NASA MSFC SPoRT Center has been operating a real-time configuration of the NASA Land Information System (LIS) (Kumar et al., 2006; Peters-Lidard et al., 2007; Kumar et al., 2007) that runs the Noah Land Surface Model (LSM; Ek et al., 2003) in an uncoupled, or off-line mode, since summer 2010 (see Case et al., 2012; White and Case, 2013 for details). In an off-line mode, the LSM is run apart from a numerical weather prediction model, with input variables provided by atmospheric analyses. The land surface scheme provides ET that will be compared to WaSSI ET values.

6.1.2. Satellite Derived insolation

Solar forcing is a major factor which drives photosynthesis in the crop and also controls ET, and yet is not a regular NWS observation. UAH and NASA MSFC have developed an operational system that uses the physical retrieval method (Gautier et al., 1980; Diak and Gautier, 1983) with geostationary satellite visible imagery to recover insolation at high resolution (4 km grid) for use in regional-scale models (McNider et al., 1995). This satellite derived insolation has been shown to be superior to methods generating solar insolation from standard meteorological observations (McNider et al., 2011).

6.1.3. Precipitation

Precipitation is one of the most important parameters in both the crop and hydrologic models. Precipitation used in the real-time GriDSSAT and WaSSI models are the gridded radar gage-corrected hourly precipitation estimates from the NOAA NCEP Stage IV product (Lin and Mitchell, 2005; A complete technical description is available online: www.emc.ncep.noaa.gov/mmb/ylin/pcpanl/stage4/). This high resolution product is critical to capturing spatial variations in precipitation data not available from the standard surface rain-gage network.

6.2. Real-time GriDSSAT outputs

The real-time GriDSSAT model provides several automated outputs including crop water stress and grain weight that are produced daily. Such real-time information is most useful if it can be put in a historical context. Because of the previously derived historical runs the cumulative water stress and grain weight can be compared to historical values. Both outputs can be accessed through the GriDSSAT website (http://gridssat.nsstc.uah.edu) where users may access daily data, including the archive going back to 2008. The website also provides the user with the 8-day forecast mentioned earlier.

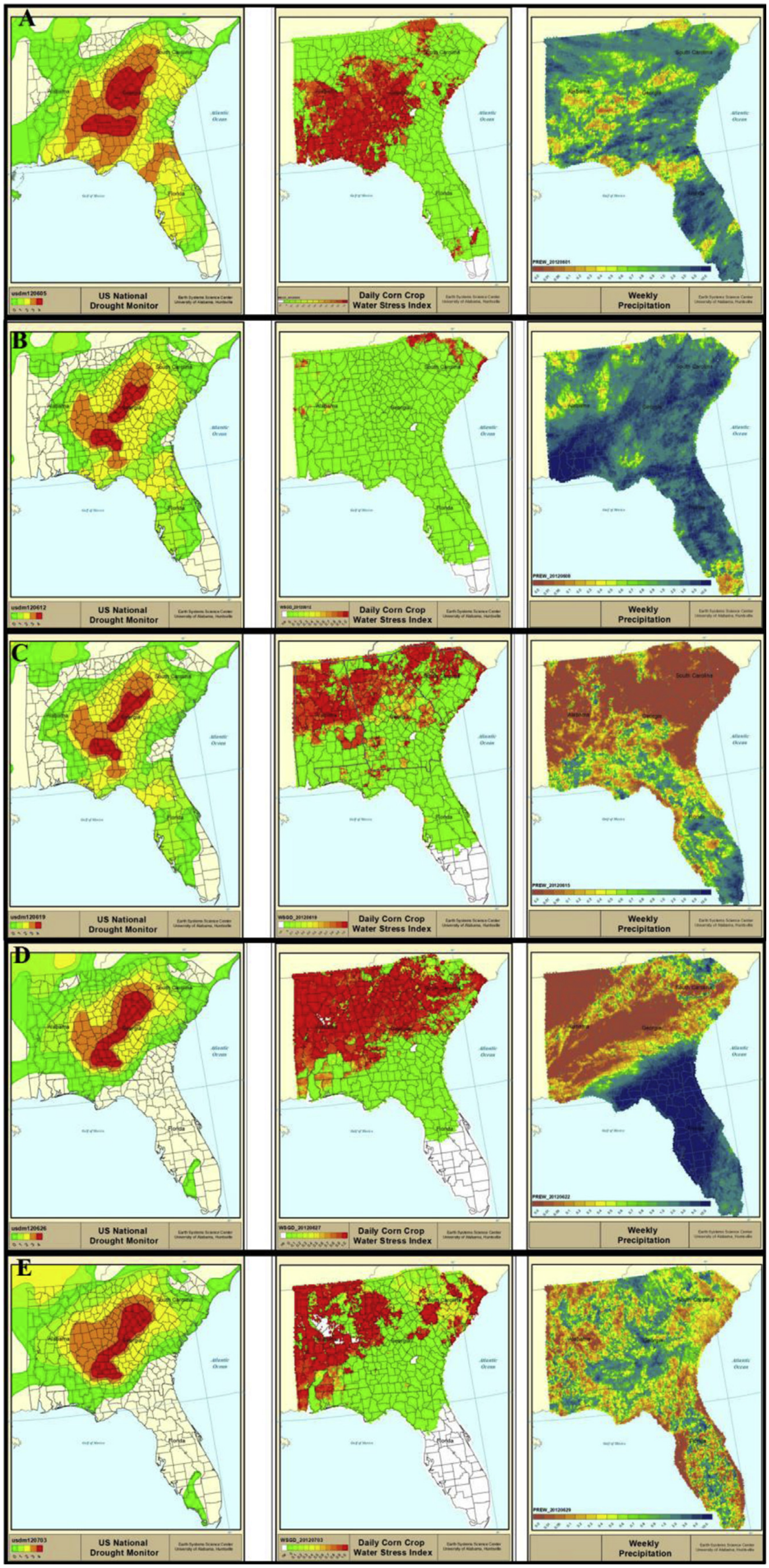

Fig. 13. A five week analysis of the "flash drought". Left panel gives the Drought Monitor. Middle panel gives the water stress index from GriDSSAT. The right panel gives the radar derived precipitation.13A: Week of June 5th, 2012, 13B: Week of June 12th, 2012, 13C: Week of June 19th, 2012, 13D: Week of June 26th, 2012 and 13E: Week of July 3rd, 2012.

6.3. GriDSSAT real-time example – June 2012 flash drought

Here we provide an example of a brief but intense drought in the Southeast in 2012 captured by the GriDSSAT that was devastating to the maize crop. The impact on the hydrology is evaluated below using the real-time irrigation demand from GriDSSAT.

The short duration and timing of the drought meant that other crops and sectors were not as adversely affected as maize. In Fig. 13, the US Nation Drought Monitor (droughtmonitor.unl.edu/), the GriDSSAT Corn Crop Water Stress Index and radar derived 7-day cumulative precipitation are all mapped to the same format and region. The time period is for 29 May to 10 July 2012. Note that as the precipitation levels fall, the crop stress increases to the point that by July the maize crop is severely stressed and in many locations, lost (Fig. 13d). However, the Drought Monitor only slowly responds to the "flash drought". A region like northwest Alabama was classified in the lower drought designations even though they suffered high maize losses. This designation can have an impact on farmers' ability to qualify for Federal disaster relief or low-interest loans. Final yields in the crop model in the drought stressed area were 2830–3460 kg/ha (45–55 bu/ac) much below normal yields of 7547–9435 kg/ha (120–150 bu/ac). These low yields were also verified in observed county yields approximately 3145 kg/ha (50 bu/ac).

6.4. Irrigation demand

A critical component of the coupled crop/hydrology model is the irrigation demand based on real-time weather conditions. Fig. 14 provides the irrigation demand during the 2012 North Alabama Flash drought. This will be later used as withdrawal data in the real-time WaSSI.

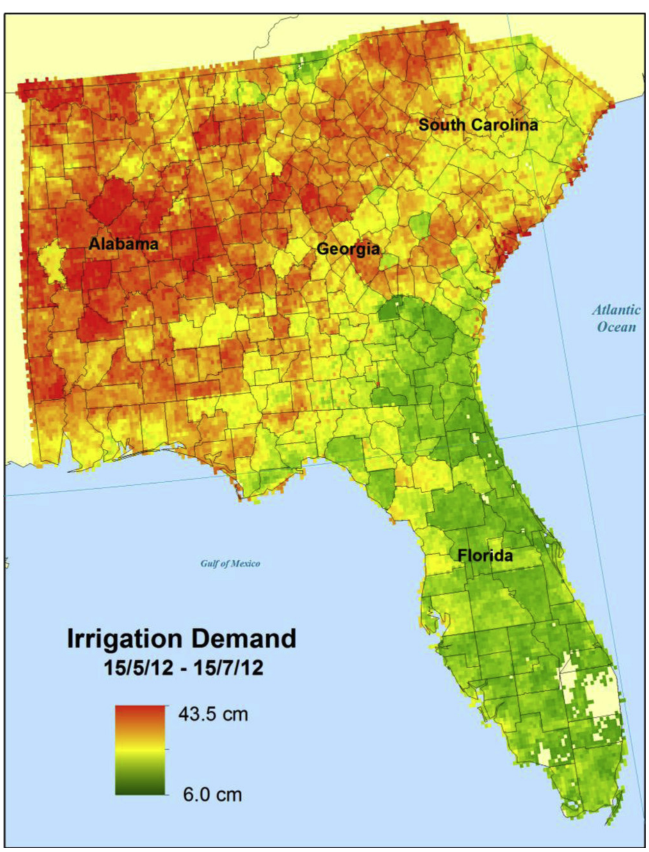

Fig. 14. Irrigation demand from GriDSSAT during the flash drought episode of June 2012.

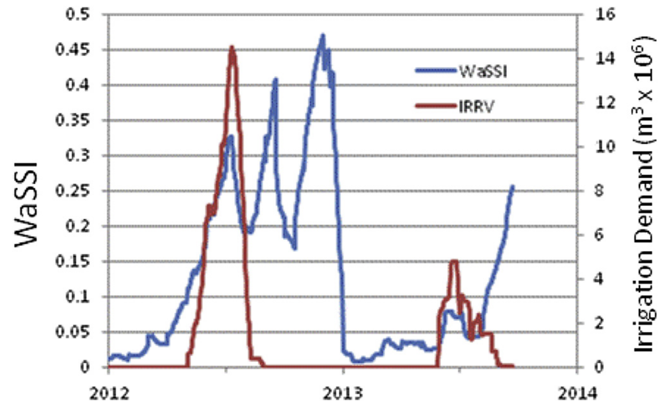

Fig. 15. Time series of irrigation demand and WaSSI index for 2012–2013 including the 2012 flash drought. WaSSI is the ratio of anthropogenic demand to water supply. IRRV is the total irrigation volume for the watershed in millions of cubic meters as determined by GriDSSAT.

6.5. Water availability during the flash drought – real-time WaSSI results

The WaSSI model has been run in the real-time mode using the weather inputs described above. The integrated model is run in a real-time daily mode with GriDSSAT coupled to a running 30 day WaSSI index computed for each day along with an eight day forecast period. The irrigation demand from GriDSSAT (such as in Fig. 14) was used as irrigation withdrawal in WaSSI.

The hydrologic availability from the real-time model for this flash drought period can also be examined. Fig. 15 shows the irrigation demand and the corresponding WaSSI index for 2012–2013 period including the flash drought in June 2012 for the HUC in North Alabama where the flash drought was most intense. It shows that during the actual flash drought there was modest water availability. The WaSSI value was at about 0.32. In 2013 there was plenty of available water and irrigation demand was also low.

7. Summary and conclusions

As noted in the introduction, in humid climates irrigation demand can be highly variable both inter-annually and intra-seasonally depending on natural rainfall, crop state and evaporative losses. Additionally, surface water availability also has large variations due to rainfall and to seasonal evaporative demands.

In the past irrigation was developed in many areas without consideration of the ultimate limits of the impact of irrigation demand on watersheds or other competing water interests including protection of environmental flows. Today it is becoming increasingly clear that irrigation cannot be sustained without consideration of over-demand of watersheds and competing interests for water (Postel and Richter, 2003; Poff et al., 2010).

The modeling system presented in this paper addresses the need of considering irrigation demand with hydrologic variability. Thus, the paper describes irrigation demand models within a hydrologic framework (the GriDSSAT-WaSSI tool) that can determine in conjunction with all other water uses when water sheds might be stressed. The models are coupled in both a long-term historical mode and in a real-time short-term mode.

In the long-term mode it was illustrated that the framework can be used to determine limits on expanded irrigation in a regional setting. For example, how many acres can be irrigated under past or future climates without threatening environmental flows (Srivastava et al., 2010; Mondal et al., 2011 for single watersheds)?

In a short-term real-time mode, the GriDSSAT system can determine crop state due to the rainfall and weather for that year. As such, it can contribute to drought declarations as well as make estimates of yield and drought losses.

When coupled with WaSSI in real-time, the system can provide information on when water sheds may not be able to support all of the anthropogenic demands and thus offer a framework to support intermittent withdrawal restrictions. In the historical mode it can also provide actuarial information on how many times watersheds might be threatened to determine whether irrigation is viable given that water withdrawals restrictions might be imposed.

In summary, in this paper crop models that can reflect the dynamic irrigation demand are coupled to hydrologic models that can reflect the water availability. Such models are the type that can provide critical information for regional water management and water planning in the coming century.

Acknowledgments

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