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AgClimate: A climate forecast information system for agricultural risk management in the southeastern USA

C.W. Fraisse [a,*], N.E. Breuer [b], D. Zierden [c], J.G. Bellow [c], J. Paz [d], V.E. Cabrera [b], A. Garcia y Garcia [d], K.T. Ingram [a], U. Hatch [e], G. Hoogenboom [d], J.W. Jones [a], J.J. O'Brien [c]

[a] *Department of Agricultural and Biological Engineering, University of Florida, FL, United States*
[b] *Rosenstiel School of Marine and Atmospheric Science, University of Miami, United States*
[c] *Center for Ocean-Atmospheric Prediction Studies, Florida State University, FL, United States*
[d] *Department of Biological and Agricultural Engineering, The University of Georgia, GA, United States*
[e] *Environmental Institute, Auburn University, United States*

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Abstract

Seasonal climate variability plays an important role in the production risks faced by producers. The majority of crop failures in the USA are associated with either a lack or excess of rainfall. Climate forecasts can be used to reduce risks faced by an agricultural enterprise, but simply providing better climate forecasts to potential users is not enough. Climate information only has value when there is a clearly defined adaptive response and a benefit once the content of the information is considered in the decision making process. *AgClimate* is a response to the need for information and tools on proactive adaptations to seasonal and interannual climate variability forecasts in the southeastern USA. Extension agents, agricultural producers, forest managers, crop consultants, and policy makers may use this decision support system to aid in decision making concerning management adjustments in light of climate forecasts. Adaptations include those that might mitigate potential losses as well those with the potential to produce optimal yields. *AgClimate* is a web-based climate forecast and information system that was designed and implemented in partnership with the Cooperative State Extension Service. It has two main components: the front-end interface and a set of dynamic tools. The main navigation menu includes the AgClimate tools, climate forecasts, and management options for crops, forestry, pasture, and livestock. It also includes a climate and El Niño section with background information. The tools section contains two applications that allow a user to examine the climate forecast for individual counties based on the ENSO phase and to evaluate yield potentials for certain crops. Applied outlooks for individual agricultural sectors are also provided on a quarterly basis. AgClimate is now operational under the Southeast Climate Consortium and several upgrades are under development and consideration.

Keywords: Crop models; Climate variability; Decision making; ENSO; El Niño; Extension

1. Introduction

Agricultural producers face a number of risks in their operations. The United States Department of Agriculture's Risk Management Agency has defined five primary categories of risk: production, marketing, finance, legal, and human risk

* Correspondence to: 239 Rogers Hall, P.O. Box 110570, Gainesville, FL 32611-0570, United States.
E-mail address: cfraisse@ufl.edu (C.W. Fraisse).

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(Harwood et al., 1999). Seasonal climate variability is a major source of production risks. The majority of crop failures in the USA are associated with either a lack or excess of rainfall (Ibarra and Hewitt, 1999). Climate variability is also associated with other sources of production risks such as pest and disease incidence. Weather patterns, including high temperature and humidity, and the potential for daily rainfall, can create a near perfect environment for the outbreak of fungal diseases. They can also impact the reproductive cycle of other pests and insects that function as disease vectors. Climate variability is also greatly associated with marketing risks. Unanticipated forces, such as inclement weather, drought conditions, crop failure or abundance, or pest or disease outbreak, can lead to dramatic changes in crop and livestock prices. A good market plan requires an analysis of supply and demand projections throughout the cropping season. Expectations early in the season are highly uncertain. However, commodity markets respond decisively to these projections and seasonal climate variability can play an important role in modifying the balance between supply and demand.

Based on the abundant evidence that seasonal climate variability plays an important role on the risks faced by producers, it is natural to conclude that climate forecasts can be used to reduce risks faced by an agricultural enterprise. In fact several studies have evaluated the potential benefits of using seasonal climate forecasts on the decision making process in agriculture (Lamb, 1981; Sonka et al., 1987; Stern and Easterling, 1999; Jones et al., 2000; Hansen, 2002). Climate variability often is portrayed as negatively impacting agricultural systems and the inability to predict or adapt to it has led to the development of conservative management approaches. These approaches may be of limited effectiveness in buffering against severe downside conditions and more importantly they may fail to take advantage of potential opportunities to capitalize on seasonal variability (Meinke and Stone, 2005).

The potential for producers to benefit from seasonal forecasts depends on factors that include the flexibility and willingness to adapt farming operations to the forecast, the timing and accuracy of the forecast, and the effectiveness of the communication process. A common perception is that advances in seasonal climate prediction alone will be enough for societal benefits to accrue. However, simply documenting the effects of climate variability and providing better climate forecasts to potential users are not sufficient (Jones et al., 2000). Meinke and Stone (2005) discussed the importance of differentiating between the quality of a forecast and its value or impact. Climate information only has value when there is a potential response and a clearly defined benefit, once the content of the information is applied. It is important to recognize that its effective application means making a decision that takes a probabilistic forecast into account. The inherent probabilistic nature of seasonal climate forecasts presents particular challenges. Visual representations of probability have had mixed results. Early experience shows that ‘terciles’ were poorly understood by a sample of farmers in South Africa and in the southeastern USA (O’Brien and Vogel, 2003; Breuer et al., 2000). Underestimating the accuracy of the forecast system leads to lost opportunities that can prepare decision makers for adverse conditions and permit them to take advantage of favorable conditions. Overestimating the accuracy of a forecast system can lead to excessive responses that are inconsistent with decision makers’ risk tolerance, and can damage the credibility of the forecast provider (Hansen et al., 2004).

The determination of the potential for using climate forecasts to reduce agricultural risks in the southeastern USA requires addressing the previously discussed points. To what extent is climate variability predictable in the southeastern USA? Are the predictions accurate? Does climate variability impact the major commodities produced in the region? Are there management responses that can mitigate losses or exploit opportunities? Would agricultural producers be interested in and use climate forecast information if it was made available in a timely basis? What information should be communicated to agricultural decision makers and how should it be communicated for effective and routine use? Jagtap et al. (2002) discussed the implementation of a climate information system in Florida. They defined a framework for the implementation of the system and reviewed previous research that addressed the important questions raised above. This research has identified key issues and resulted in considerable understanding of the process. More recently, in an effort to integrate all aspects of applying seasonal climate forecasts in agriculture, climate scientists, agricultural engineers, agronomists, anthropologists, and extension specialists from six universities in the states of Alabama, Florida, and Georgia formed the Southeast Climate Consortium (SECC). The mission of the SECC is to provide scientifically based climate, climate impact, and response option knowledge for decision makers in agriculture, water resources, and forestry management. An important component of this joint effort is to provide decision makers with information that is relevant and useful in a timely fashion and on a continuous basis. A web-based climate information system (http://www.agclimate.org) was developed to provide extension agents, producers, and natural resource managers with tools to aid their decision making processes in reducing risks associated with climate variability.

The main hypothesis of this research is that a climate forecast information system could be effectively implemented to help agricultural producers reduce risks associated with climate variability in the southeastern USA. The main goal of this paper is to present the design and implementation of a web-based climate forecast information system that informs producers in a timely, routine, and effective way.

1.1. Climate variability impacts on the southeastern USA agriculture

The El Niño Southern Oscillation (ENSO) phenomenon is the strongest driver of interannual climate variability around the world (Ropelewski and Halpert, 1996) and affects crop production in many regions. ENSO phases are characterized by sea surface temperature anomalies in the eastern equatorial Pacific Ocean. When sea surface temperature is higher than normal the phenomenon is referred as El Niño. Associated with the warmer surface temperatures is an increase in convective activity, and at a certain stage, a persistent reduction of the normally westward flowing winds (Cane, 2001). When the sea surface temperature is lower than normal, the phenomenon is referred to as La Niña. During La Niña events, the equatorial trade winds strengthen, resulting in colder water being brought up from the ocean's floor. Neutral is the term for when neither El Niño nor La Niña are present in the Pacific. Under neutral conditions, trade winds blow from east to west near the Equator in the Pacific Ocean.

Previous research has demonstrated that ENSO exerts a substantial influence on the climate of the southeastern USA. El Niño years tend to be cool and La Niña years tend to be warm between October and April (Kiladis and Diaz, 1989; Sittel, 1994; Mearns et al., 2003). Although the influence on rainfall is spatially less consistent, El Niño years tend to be wet and La Niña years dry during these months. The ENSO signal in the region is strongest in the fall and winter months; some evidence exists that La Niña summers tend to be slightly wetter than normal (Sittel, 1994). Table 1 summarizes the impacts of ENSO phases on the climate of the southeastern USA.

El Niño is known to cause low grain yields in south Asia and Australia, and high grain yields in the North American prairies (Garnett and Khandekar, 1992). Cane et al. (1994) associated ENSO-related sea surface temperatures (SST) with rainfall and corn yields in Zimbabwe, where SST a full year before planting explained 57% of the variability in yields. ENSO events have also been found to influence corn yields in the midwestern and southeastern USA (Handler, 1990; Carlson et al., 1996). Hansen et al. (1998) analyzed the historical (1960–1995) response of total production value and its components (yield, area harvested, and price) to ENSO phases and quarterly SST for six crops (peanut, tomato, cotton, tobacco, corn, and soybean) in four southeastern states (Alabama, Florida, Georgia, and South Carolina). ENSO phase significantly influenced corn and tobacco yields, the areas of soybean and cotton harvested, and the values of corn, soybean, peanut, and tobacco. ENSO phases explained an average shift of US$ 212 million, or 25.9%, of the value of corn. They also identified significant responses of corn, soybean and cotton yields, and peanut value to SST across the region. Additionally peanut and tobacco yields, and tomato and soybean values in particular states were significantly affected.

Table 1
Impacts of ENSO phases on the climate of the southeastern USA

ENSO phase	Region	Seasons			
		October–December	January–March	April–June	July–September
El Niño	Peninsular Florida	Wet and cool	Very wet and cool	Slightly dry	Slightly dry to no impact
	Tri-State Region	Wet	Wet	Slightly wet	No impact
	Western Panhandle	No impact	Wet	Slightly dry	No impact
	Central and North Alabama and Georgia	No impact	No impact	No impact	Slightly dry
La Niña	Peninsular Florida	Dry and slightly warm	Very dry and warm	Slightly wet	Slightly cool
	Tri-State Region	Slightly dry	Dry	Dry	No impact
	Western Panhandle	Slightly dry	Dry	Dry	No impact
	Central and North Alabama and Georgia	Dry	Dry in the south, wet in NW Alabama	No impact	Slightly cool and wet in NW Alabama
Neutral	All regions	No impact	No impact	No impact	No impact

1.2. Climate forecasting and decision making in agriculture

Forecasts of seasonal climate variability have been historically based on statistical analysis of weather records. However, much has changed during the last two decades. Climatic anomalies caused by El Niño events of 1982/1983 and 1997/1998 have focused attention on the economic and social impacts of El Niño Southern Oscillation events. The improved capability to forecast seasonal climate variability based on ENSO provided an opportunity for the development of decision aid systems. Several regional systems were established to undertake research and assessment of ENSO events and develop and apply tools to aid decision makers (Glantz, 2001). A central challenge facing these systems is to make forecasts based on global climate models usable at the local levels, and integrate climate sciences with hydrology, agronomy, and fisheries sciences (Cash et al., 2003). Nevertheless, the emerging ability to probabilistically forecast future seasons in terms of climate and its consequences on agricultural systems has started to influence decision making at many levels (Meinke and Stone, 2005).

Management decisions based on seasonal climate forecasts will have positive outcomes in some years and negative outcomes in others. According to Meinke and Stone (2005), this should not be regarded as either a win or a failure of the strategy employed, since each season only represents one sample from a not very well-defined distribution of possible outcomes. Nevertheless, the potential damage for the credibility of the system in the eyes of stakeholders can result in a delay of technology adoption that may take years to be reversed. An education process that clarifies the probabilistic nature of climate forecast to stakeholders must be an important component of any effort to increase its use in decision making.

Producers make decisions on a daily basis that are often based on some type of forecast such as price, weather, or climate. Price-based decisions are associated with changes in the price of output or of inputs that may eventually occur and require a broad understanding of both domestic and international markets. Weather-based decisions are generally operational by nature and involve activities that should happen in the very near future, most of the time in less than a week. Examples are irrigation, freeze protection, application of chemicals, and harvesting. Climate-based decisions are normally pre-season decisions and tend to be more strategic in nature. Examples of climate-based decisions can be the choice of the variety that will be planted, planting dates, land use allocation, pre-season purchase of inputs, and marketing (Fraisse et al., 2004).

A significant effort was undertaken by SECC researchers to understand the potential benefits and needs of climate forecasts for the main agricultural commodities in the southeastern USA (Hildebrand et al., 1999; Jones et al., 2000; Messina, 2000). Many questions needed to be answered before climate forecasts could be used with confidence in agriculture. If producers have a reliable climate forecast 3–6 months ahead of time, what changes can they make in their strategies and for what crops? What are the risks associated with these changes? Realizing that forecasts can never be perfect or deterministic, are they a feasible tool for producers and extension agents? The results of this effort (Breuer et al., 2005) indicated that, in addition to climate information, some of the more notable potential use of climate forecasts in the southeastern USA include cropping strategy (variety, maturity group, and planting date), pest management, irrigation and drainage management, pasture management, herd size management, and adaptive forestry operations (plantation establishment, controlled burning, harvest planning, pest management, and wildfire threat monitoring).

2. Methods and procedures

An important aspect of the design methodology used for developing *AgClimate* was a strong interaction with outreach institutions such as State Cooperative Extension Services. It ensured that the information provided in the system is relevant for user needs and that the language and formats used are appropriate. While a number of activities did not necessarily require interactions with end users, such as the development of regional climate and agronomic databases, the design of layouts and functionalities were based on an intense interaction with end users for testing and evaluation. Once an initial climate and agronomic database was implemented, prototypes of decision aid tools were designed for evaluation by stakeholders and feedback sessions were organized across the three states involved in this effort.

2.1. Climate and weather data

The first step for implementing the *AgClimate* information system was the development of a climate database for the region. Weather observations were compiled from the National Weather Service's Cooperative Observer network

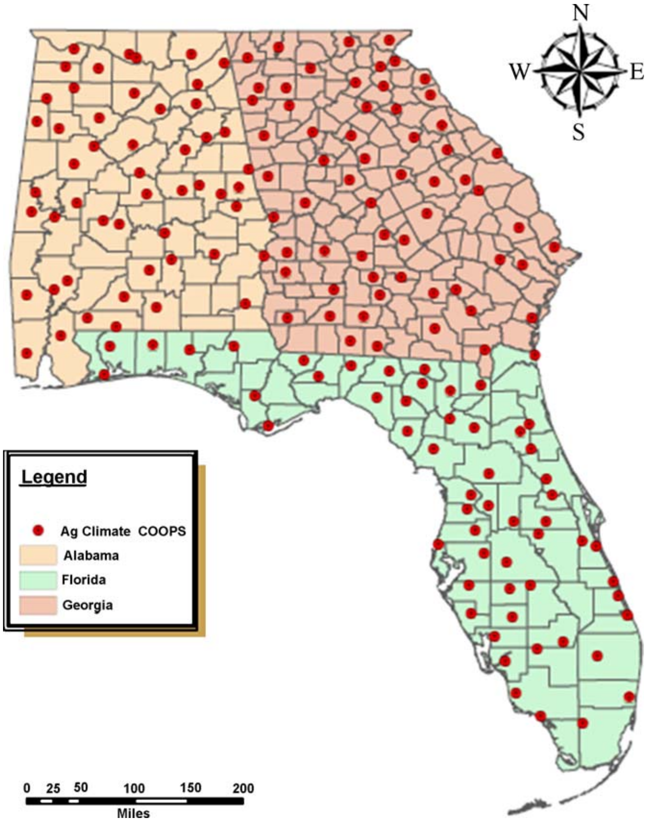

Fig. 1. National Weather Service's Cooperative Observer Network of Meteorological Stations (COOPS) in Alabama, Florida, and Georgia.

(NCDC TD 3200), which contains daily values for maximum temperature, minimum temperature, and precipitation for a period of record of at least 50 years extending through December of 2004. The stations (Fig. 1) were selected based on (1) length of record, (2) data completeness, (3) homogeneity, and (4) representativeness of surrounding agricultural areas. The final data set contained historical weather records from 91 stations in Florida, 62 stations in Georgia, and 56 stations in Alabama.

The daily weather observations were compiled into monthly values of average minimum temperature, average maximum temperature, and total precipitation. These monthly values were then stratified by ENSO phase and composites were made of ENSO phase monthly averages and deviations from normal for each of the climate variables. The phase and event of ENSO events are normally defined by an index; however, there are many such indices. The ENSO index developed by the Japan Meteorological Agency (JMA), that is based on regional SST, was used in this study. The JMA index is a temperature-based index and uses mean SSTs within the equatorial Pacific region that extends from 4°N–4°S to 150°–90°W. The JMA definition of a warm (cold) ENSO event requires the SST in this region to be greater than 0.5 °C (less than −0.5 °C) for six consecutive months and the months must include October, November, and December (Hanley et al., 2003).

A bootstrapping methodology (Efron and Tibshirani, 1993) was used to resample the raw weather data, creating a bootstrap sample of 1000 years of monthly data for each weather station and for each ENSO phase. Daily values of temperature and precipitation were randomly chosen from the subset of historical weather observations in a similar ENSO phase. For example, to construct an "El Niño" January, January 1st may be pulled from 1983. January 2nd may have come from 1977, and January 3rd from 1998, etc. The randomly chosen daily observations were then compiled into monthly values as described above. While the resampling of non-independent values such as daily weather observations may present problems in some applications, the recompiling of the observations into monthly values renders the need for independence unnecessary (Liu and Singh, 1992; Zwiers, 1991). These bootstrapped data were used to generate smooth probability density functions and exceedence curves for the climate variables, which are displayed in *AgClimate*.

While ENSO phase is a useful way to forecast daily weather realizations that can then be linked with biophysical models to predict crop yield, water use, and other variables of interest, there is a need to reduce the uncertainty associated with the forecasts. SECC researchers are currently investigating the use of numerical climate model outputs as a basis for climate forecasts. A key aspect of this research is the creation of daily weather variables from the numerical outputs that are reliable predictors over time and space. Once the methodology is improved and validated, forecasts based on numerical models will be implemented in *AgClimate*.

2.2. Crop modeling

A crop modeling effort was undertaken for selected commodities with the objective of providing base lines for evaluating crop production risk under alternative climate forecasts. The crops that were initially selected are peanut (*Arachis hypogaea* L.), tomato (*Lycopersicon esculentum* Mill.), and potato (*Solanum tuberosum* L.). The Decision Support System for Agrotechnology Transfer-Cropping System Model (DSSAT-CSM) suite of crop models (Jones et al., 2003) was used for this effort. DSSAT-CSM includes models for 16 crops derived from the old DSSAT CROPGRO and CERES models (maize, wheat, soybean, peanut, rice, potato, tomato, drybean, sorghum, millet, pasture, chickpea, cowpea, velvet bean, brachiaria grass, and faba bean). The DSSAT-CSM Version 4.0 (Hoogenboom et al., 2004) crop models are process-based models that simulate crop growth and development, soil water processes, and nitrogen balances. Long-term historical weather compiled from the National Weather Service was used for the simulations. A solar radiation generator, WGENR, with adjustment factors obtained for the southeastern USA (Garcia y Garcia and Hoogenboom, 2005) was used to generate daily solar radiation data. Soil profile characteristics for the main agricultural soil types in each county were obtained from the soil characterization database of the USDA National Resource Conservation Service.

The CSM-CROPGRO-Peanut (Hoogenboom et al., 1992; Boote et al., 1998; Jones et al., 2003), CROPGRO-Tomato (Scholberg et al., 1997), and SUBSTOR-Potato (Ritchie et al., 1995) crop models were used to simulate crop yield under different management scenarios using weather data from 1950 to 2004 for several counties in Georgia, Florida, and Alabama. In the case of peanut, the Georgia Green peanut cultivar, a medium maturing runner-type peanut variety, was selected as the representative variety for the main peanut producing counties in each state. The typical planting window for peanuts is between mid-April and mid-June. Peanut responses were simulated with and without irrigation. Potatoes are grown commercially in Florida in the winter and spring months when the days are warm and the nights are cool. Potato simulations were performed for the variety Atlantic which is a standard variety for processing with high yield potential. Tomato simulations focused initially on the fresh market tomato crop produced in Fall–Winter–Spring in south Florida. A common tomato cultivar, Sunny, was selected to represent the range of cultivars grown in south Florida.

2.3. Prototype systems

Prototype systems were developed for evaluation by potential end users of the proposed climate information system. First a prototype web site was created in-house to allow SECC researchers to evaluate layouts and contents. This system was then introduced to several groups of potential end users, primarily composed of County Extension agents and producers, for evaluation. The decision on how to organize the information and decision aid tools in a format that would be both appealing and functional was facilitated by a number of modifications proposed during feedback sessions with potential end users.

At the same time, prototype dynamic tools were developed as stand alone systems using Microsoft VisualBasic® for the purpose of demonstration and eliciting feedback. Two tools were developed: (1) climate risk tool: that allowed users to analyze forecasts of climate variables such as monthly precipitation, average minimum, and maximum temperature at the county level and (2) yield risk tool: simulated crop yield at the county level based on selected soil type and management practices could be evaluated for different planting dates and climate scenarios. An important aspect of the evaluation process was to test different ways of presenting probabilistic results. Although the initial idea called for the presentation of results for either climate variables or crop yields only in the form of probabilities, it was soon made clear in the evaluation sessions that potential end users would also like to have results in the form of averages for different climate scenarios or ENSO phases together with anomalies or deviations from long-term averages. Typical observations or requests obtained during the evaluation sessions included ideas such as the need to add varieties to the yield risk tool or the necessity of including explanatory materials with the tools explaining how to interpret probabilities. Some feedback was more specific such as adding simulation results for a late maturity peanut variety such as C-99R or more information about weather patterns during the harvest season.

3. Results and discussion

The resulting web-based *AgClimate* system includes information and a set of dynamic applications or tools that interact with a database system. The information and tools are available across the tri-state region of Alabama, Florida, and Georgia with county specific resolution.

3.1. AgClimate database systems

The MySQL (V.4.0.18) relational database management system was chosen to support the dynamic applications due to its ability to efficiently store, search, and retrieve data in large databases. The AgClimate database system is composed of a main database, a web administration database, and smaller, customized databases that support specific applications (Fig. 2). The main database stores climate data, crop model outputs, and crop yield statistics. It will also be able to store outputs generated by other models that can be used to support additional decision making applications. The web administration database was implemented to store information related to users' statistics and administration records. A spatial database will eventually be implemented to store geo-referenced datasets that will be used to display interactive map-based information. Customized databases containing only a subset of the main database and some pre-calculated statistics were created to serve specific dynamic tools in order to optimize and speed up database access by the dynamic tools.

Fig. 3 shows an example of the probability of occurrence for various ranges of rainfall for the month of January in Jackson County, Florida, that are based on the climate database. The top graph shows the probabilities calculated by using all years of data available from the local meteorological station. The probability for Jackson County receiving different amounts of rainfall in January varies from 2.0% for 1 in. or less to 15.1% for 3–4 in. The question to ask is: will the probabilities change if the ENSO phase for the coming year is El Niño, La Niña, or Neutral? The bottom graph provides the user with clear indications of significant changes according to ENSO phases. The probability distribution for total rainfall during La Niña years shifts towards lower rainfall amounts; the chance for 3–4 in. of rainfall in January

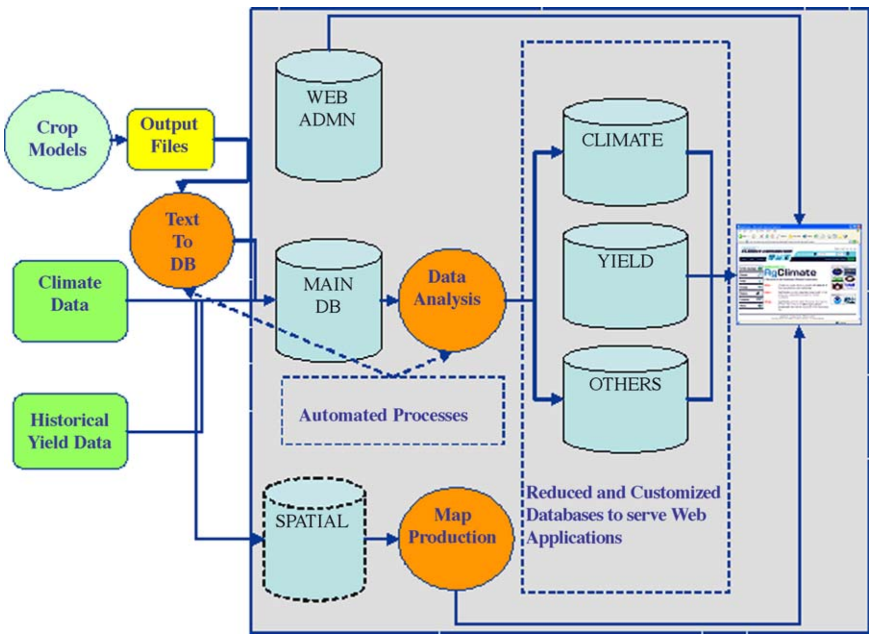

Fig. 2. AgClimate database system designed to support decision aid applications.

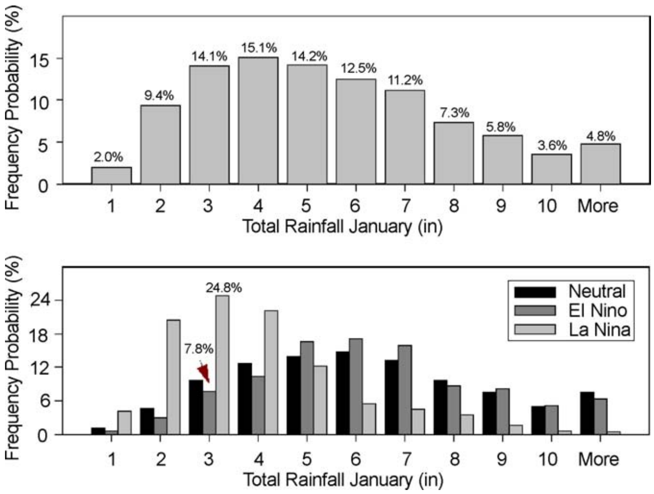

Fig. 3. Probability distribution for total rainfall in January for all years (top) and Neutral, El Niño, and La Niña years (bottom) for Jackson County, Florida.

is about 25% as compared to 7.8% during El Niño years. Conversely, the probabilities for greater amounts of rainfall are higher during El Niño years. Similar probability distributions for rainfall and minimum and maximum temperature are available on *AgClimate* for each county in Alabama, Florida, and Georgia.

3.2. Overall design and web layout

Information available in *AgClimate* includes climate forecasts combined with risk management tools and information for selected crops, forestry, pasture, and livestock. The system was developed to allow easy expansion of the topic areas, number of commodities, and risk management tools available for users. This modularity is a very important aspect of the overall design and a commercial web development company was contracted for development. *AgClimate* contents are added and maintained by SECC members and new menu items can be easily added by modifying an *xml* file without any required knowledge of web programming languages. Administration of the site and its contents is decentralized, facilitating the delegation of responsibility for maintenance and updates of the different sections by individual groups within the SECC.

AgClimate was deployed in a Linux environment with specific applications and Perl modules installed. Dynamic tools were developed using the PHP web programming language interacting with FLASH movies and MySQL databases. Fig. 4 shows the main AgClimate web page. Its navigation menu includes the following items:

1. *AgClimate tools*: (a) Climate risk: expected (probabilistic) and historical climate information (precipitation and average min/max temperature) at the county level (Fig. 2) and (b) yield risk: expected yield based on soil type, planting date, and basic management practices for peanut, potato, and tomato. Yield forecasts are available for selected locations depending on the crop selected.
2. *Climate forecasts*: Includes forecasts produced by the SECC and links to external sites for national and international climate forecasts. The sub-menu items are: (a) county; (b) regional (not implemented to date); (c) national, linking to the National Oceanic Atmospheric Administration (NOAA); (d) international, linking to the International Research Institute for Climate Prediction (IRI); (e) ENSO phase forecast, reports current SST conditions and what ENSO phase is expected to prevail during the next months, and (f) hurricane forecasts, a summary of hurricane forecasts from several sources.
3. *Crops*: This section provides producers with management options and yield risk evaluation tailored to climate forecasts, in addition to links to extension resources, market information and commodity related industry web sites. Currently there are three crops in the system (peanut, potato, and tomato), under different degrees of implementation and completion.

Fig. 4. The main web page for AgClimate.

4. *Forestry*: The main product under the forestry section is a wildfire activity potential forecast that is based on the Keetch–Byram Drought Index (KBDI). It also includes management options for alternative climate scenarios as well as links to extension resources and to industry sites.
5. *Pasture and livestock*: The pasture and livestock sections include documentation on the effects of climate variability on pasture/hay and livestock production activities such as the establishment of cool and warm season grasses, fertilization, grazing and stocking rates, forage quality, and pasture renovation.
6. *Climate and El Niño*: The climate and El Niño section provides extensive background information about the El Niño phenomenon in the tropical Pacific and how it affects the climate of the southeast USA, graphics and animations showing El Niño impacts on temperature and precipitation across the region, and links to general climate and weather resources available in the world wide web.
7. *Your feedback and About*: The main purpose of the feedback section is to quantify knowledge, perceptions, attitudes, and potential use of seasonal climate forecasts among potential users. The about section provides information about *AgClimate* and the SECC.

3.2.1. AgClimate tools

Dynamic tools were not implemented in *AgClimate* before prototypes were demonstrated to extension agents in Florida, Georgia, and Alabama. Prior to implementation of *AgClimate*, their suggestions and observations were taken into consideration for the development of the final web versions. The ability to plot monthly averages and deviations from long-term averages of climate variables, such as rainfall and temperature, is an example of features that were incorporated in the system based of the feedback of the stakeholders. This tool is currently being upgraded to allow the analysis of absolute minimum and maximum temperatures in addition to monthly minimum and maximum temperature averages. This upgrade represents the responsiveness possible by considering feedback from users of the system. The yield risk tool provides users with the opportunity to evaluate yield potential based on crop model simulation results. The user must select the crop, location (state and county), soil type, and basic management practices such as irrigated or not before a table and graph are displayed showing the probabilities for various yield ranges as a function of the planting date and ENSO phase. *AgClimate* dynamic tools always default to the current forecast of ENSO phase for the evaluation of climate or crop related variables. However, the user can also evaluate the results for alternate ENSO phases as a means for considering forecast accuracy.

Table 2
Management options for tomato production in south Florida

Practice	Adaptation to seasonal climate variability
Field allocation	Variety selection should take into account tolerance to climate-related stress. See the varieties section
Land preparation	Special attention to drainage is important during El Niño years
Varieties	Heat tolerance is important characteristic in La Niña years. Genetic tolerance to soil-borne pathogens is important in El Niño years
Planting date	Adapting planting dates may have the greatest impact on reducing yield risk. Check our crop yield risk tool to evaluate potential yield levels for your county
Fertilization	Additional slow-release nitrogen may be planned for El Niño years
Disease pressure and pesticide application	Most soil-borne pathogens and fruit quality problems increase in El Niño years. White flies may be more prevalent in La Niña years
Harvest	Getting a good picking from first fruit set is very important in La Niña years. Fruit quality problems like gray wall are more prevalent in El Niño years

3.2.2. Climate forecasts

Climate forecasts produced by the SECC include; an ENSO phase forecast, probabilistic climate forecasts for rainfall and temperature at the county level, and a freeze forecast. The ENSO forecast is an assessment and prediction of conditions in the tropical Pacific Ocean. It is this assessment that provides the basis for all other forecast products. Regional forecasts in the form of maps that inform about probabilities for winter freezes, monthly drought, precipitation and temperature in the southeast are under development. The site also provides links to national and international forecasts from NOAA and IRI, respectively.

3.2.3. Crops

Under the “Crops” section, the user can find discussions on management options that are intended to highlight important management aspects as related to climate variability. Table 2 shows an example of management options for tomato management in south Florida based on ENSO phase forecasts. Users can click on any practice to obtain more detailed information. The main goal of this table is to provide users with a quick overview of the main highlights and potential actions. The more interested user can access additional in-depth information based on his/her interests and time availability.

Links to extension resources and industry related web sites are also provided for each crop that is listed in the system. *AgClimate* focuses on climate-related information, but links to other available resources that can be of interest to the user are also provided. Normally the links refer to extension publications from the land grant universities that are members of the SECC and regional commodity organizations.

3.2.4. Forestry

The main forecast product available under the forestry section is a wildfire risk forecast. In addition, the web site also includes a discussion on other factors that depend largely upon climate conditions, such as forest plantation establishment, growth, quality and pest, and disease control. The wildfire activity potential forecast available in *AgClimate* is based on the Keetch–Byram Drought Index (Byram and Keetch, 1988). The Division of Forestry of the Florida Department of Agriculture and Consumer Services offers excellent primers on KBDI-based Drought classification as well as its use as an indicator of potential wildfire activity (http://www.fl-dof.com). It has been shown that increased wildfire risk is linked with the deviation of the KBDI from seasonal normals. The KBDI tends to be at its peak in May, so values around 400 or 500 are not unusual at this time and do not indicate an increased threat. The substantial threat instead occurs when the values for the KBDI are 1–1.5 (or higher) standard deviations above the seasonal average. In *AgClimate*, the wildfire threat forecast is presented in a series of color-coded maps that show the probability of the KBDI for the following threat categories: (1) abnormally dry (450 or above); (2) moderately dry (500 or above); (3) severely dry (550 or above); and (4) extremely dry (650 or above). Since the KBDI is driven by daily weather and can change drastically based on one or more rainfall events, the maps show the probability of exceeding the threat level at least 7 days during the month, rather than for the month as a whole. Fig. 5 shows the individual KBDI forecast maps with the probabilities for achieving the four threat categories for April 2005. These probabilities are available at the county level for Alabama, Florida, and Georgia.

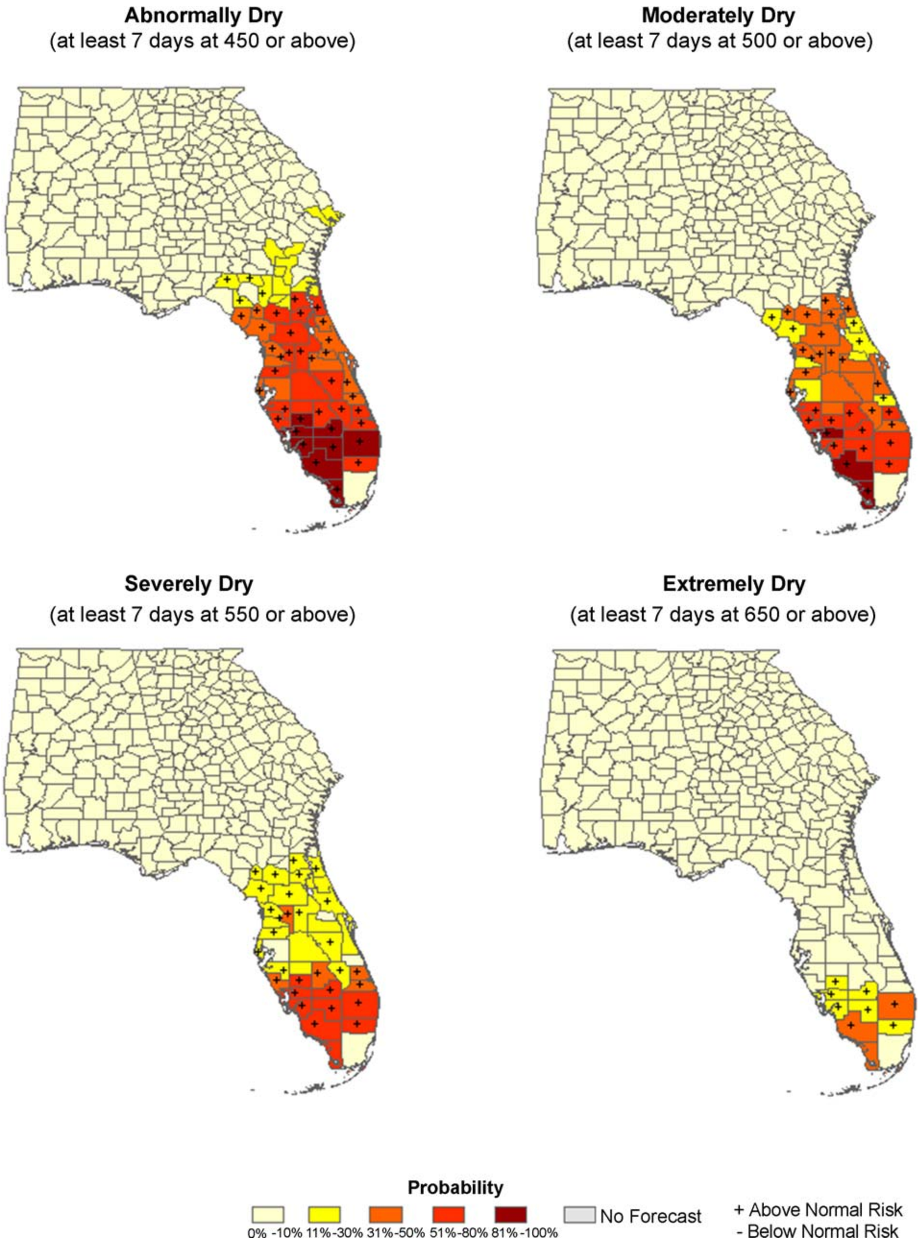

Fig. 5. Keetch–Byram Drought Index (KBDI) forecast for April 2005 as published on AgClimate.

3.2.5. *Pasture and livestock*

The pasture and livestock sections of *AgClimate* provide a number of summarized discussions about management strategies that should be considered depending on the ENSO phase forecast. Table 3 shows basic information provided for the management of season grasses for El Niño and La Niña phases. Additional information will be added to the system as the knowledge about impacts of seasonal climate variability on both pasture and livestock increases.

3.2.6. *Your feedback and About*

A survey is available under the feedback section of *AgClimate*. Its purpose is to quantify knowledge, perceptions, attitudes, potential use of seasonal climate forecasts among users. A form based e-mail tool allows users to submit questions, suggestions, and comments directly to the extension team. Information gathered in this online survey allows

Table 3
Management options for season grasses as a function of ENSO phase

Management	El Niño	La Niña
Establishment of cool season grasses	Generally good for planting	Tends to be too dry for good establishment
Establishment of warm season grasses	Little influence in summer plantings	Tends to be too dry for good establishment in later winter plantings
Fertilization	N and K may have to be repeated due to leaching	Little response expected from plantings in winter–spring
Grazing and stocking rates	Up to 10% more cattle can typically be stocked	Stocking might be reduced by 12–15%
Making hay	Spring harvest abundant	Spring cutting usually not worthwhile
Forage quality	May be higher due to cooler temperatures	May be roughage quality due to persistently high temperatures
Pasture renovation	Desiccation of old growth may be difficult	Desiccation of old growth easier due to dry conditions

the SECC and its partners to expand or shift current work and to identify new potential uses and evolving user perceptions and needs over time. It can also facilitate evaluation of new products such as experimental forecasts; and use of our climate forecasts for improved management in agriculture, forestry, and water resources. The *About* section contains information about the SECC, its mission, objectives, programs, and additional information about its members. SECC members can also login to perform administrative tasks by clicking on the link to administration under this section.

3.3. AgClimate updating procedures

The *AgClimate* database contains a very large amount of climate data. As new weather stations are added to the existing network of stations, more site-specific information may be added to the county level database. The gatekeepers of weather and climate data are the State Climatologists for Alabama, Florida, and Georgia. More recently, discussions were started with the automated networks of weather stations in the states of Florida, Florida Automated Weather Network (FAWN; http://fawn.ifas.ufl.edu), and Georgia, Automated Environmental Monitoring Network (AEMN; http://www.Georgiaweather.net) to explore opportunities for the integration of weather and climate databases. This important step will largely expand the opportunities to serve our stakeholders by allowing the decision aid tools to use real time, in-season weather data. Real time weather data collected by the network of automated stations would be used to update the simulations during the cropping season. Combining real time weather data with the climate forecast can result in improved yield forecasts, with a reduced range of probabilistic results.

3.4. AgClimate evaluation and future directions

The use of participatory methods to interact with clientele was a continuous feature in the design and implementation of *AgClimate*. More recently the attention has shifted to the evaluation of potential benefits and assessment of impacts. A web-based survey of 200 extension agents in Florida and Georgia provided baseline data as to knowledge of ENSO and other climate phenomena and its effects in the region. The survey found that precipitation effects were better known than temperature effects for each extension agents' specific county. The survey also helped point out potential intervention points in different agricultural systems and pertinent information was subsequently included in the text sections of *AgClimate*. *AgClimate* was shown and discussed at some 25 association meetings with nearly 1000 attendees in 2005. Much has also been learned by the feedback provided online by users of the system. Subject matters ranged from queries about specific rainfall or temperature information missing for a specific county (or state outside the SECC) to requests to add new crops to the system. An impact evaluation of use and types of adaptations to the seasonal climate forecasts is also planned. This will be conducted after at least three cropping seasons will have passed. Adoption of strategies based on information from *AgClimate* is strategic in nature and as such, implemented only a few times a year (if at all). Thus, a full-scale assessment will have to wait for dissemination efforts to snowball and reach a critical mass of users. In the meantime, positive (but anecdotal) reports are being received during interviews, workshops, meetings, and focus groups. They suggest that the potential for adoption and the numbers of possible adaptations in farm management practices based on decision aids in AgClimate is encouraging.

As important as evaluating the use and potential benefits of the system is to continue to identify opportunities for engaging stakeholders and for the development of customized solutions. Seasonal outlooks have been found to be one of the preferred forms of communicating with stakeholders. Seasonal outlooks are provided four times during the year, matching the agricultural decision calendar. As an example, the seasonal outlook released during the fall emphasizes the discussion on the upcoming ENSO phase, summer crop harvests and winter freeze forecast. Outlooks released during the winter focus on the upcoming planting season, potential soil moisture levels, and forest fire risks. New dynamic tools, including a Growing Degree Days and Chilling Units forecast tools, are in the development process and will soon be ready for further stakeholders evaluation. The constant interaction between SECC extension specialists and stakeholders provides an opportunity to identify knowledge gaps that need to be addressed by SECC researchers and information gaps that should be added to the system. The SECC response to these needs is prioritized based on resources and importance to the economic and environmental welfare of the southeastern USA.

4. Conclusions

AgClimate was designed with the participation of potential end users, including agricultural producers and extension agents from its inception. It is intended to be a user-friendly and interactive decision support system that translates seasonal climate forecasts into information that can help users make decisions in their operations in the face of uncertainty. The tools embedded in *AgClimate* are interactive and site-specific at the county level. While *AgClimate* can be considered user-friendly because its interfaces and tools were designed in close collaboration with end users, much is learned through the continuous feedback and interface with cooperative extension services. Improving the system and identifying stakeholders priorities must also be a continuous process. SECC researchers are involved in projects related to a broad range of subjects, from downscaling global circulation models to the development of new crop simulation models. As results from ongoing research are incorporated in *AgClimate*, we expect the system to better serve extension agents and decision makers involved in agriculture and natural resource management. The main hypothesis of this research was that a climate forecast information system could be effectively implemented to help agricultural producers reduce risks associated with climate variability in the southeastern USA. While initial evaluation reports and feedback are positive, completion of an ongoing formal evaluation process will be required to validate our main hypothesis. The system is now in the process of being transferred to the Florida State Extension System and efforts are under way to duplicate the transfer to Extension Services in Georgia and Alabama. The transfer of *AgClimate* to State Extension Services aims at further integrating the system into the decision making process of agricultural and natural resource decision makers, thus ensuring its long-term sustainability.

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