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AGCLIMATE: A CLIMATE FORECAST INFORMATION SYSTEM FOR AGRICULTURAL RISK MANAGEMENT IN THE SOUTHEASTERN USA

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Abstract. ***AgClimate*** **is a response to the need for information and tools on proactive adaptations to seasonal climate variability forecasts in the southeastern US. 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 maximize yields as well as others that might mitigate potential losses.** ***AgClimate*** **is a web-based climate forecast and information system that was designed and implemented in partnership with state Extension Services. It has two main components: the front end interface and a set of dynamic tools. The website was deployed in a Linux environment with specific applications and Perl modules installed. The main navigation menu includes the AgClimate tools, forecasts, crops, forestry, pasture, livestock, and a climate and El Niño section with background information. The tools section contains two applications or tools that allow a user to exam the climate forecast for his/her county based on the ENSO phase and to evaluate yield potentials for certain crops.**

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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 (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 the lack or excess of rainfall (Ibarra and Hewitt, 1999). Climate variability can also be associated with other sources of production risks such as pests and diseases. Weather patterns, including high temperature and humidity, and the potential for daily rainfall, create near perfect environment for the outbreak of fungal diseases. They can also impact the reproductive cycle of insect pests or insects that function as disease vectors. Climate variability is also greatly associated with marketing risks. Unanticipated forces, such as weather or government action, 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 large 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). However, the potential for producers to benefit from seasonal forecasts depends on factors that include the flexibility and willingness of adapting 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 will alone 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 clearly defined benefit, once the content of the information is applied. It is important to recognize that its effective application means making a decision taking into account a probabilistic forecast. The inherent probabilistic nature of seasonal climate forecasts presents particular challenges. Underestimating the accuracy of the forecast system leads to lost opportunity to prepare for adverse conditions and 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 main hypothesis of this research is that a climate forecast information system can be effectively implemented to help agricultural producers reduce risks associated with climate variability in the southeastern USA. The methodology used for the design and implementation of a web-based climate forecast information system to inform producers on a routine and effective way is discussed.

Climate Variability Impact on the Southeastern US Agriculture

The El Niño Southern Oscillation (ENSO) phenomenon is the strongest driver of inter-annual 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 temperature is lower than normal, the phenomenon is referred to as La Niña. During La Niña events, the equatorial trade winds instead strengthen, resulting in colder water being brought up from the ocean's floor. The effects and climate variations of a La Niña event are not the same as those of El Niño and oftentimes oppose each other. 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 US. 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). 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 wet than normal (Sittel, 1994). Table 1 summarizes the impacts of ENSO phases on the climate of the southeastern US.

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). ENSO events have also been found to influence corn yields in the midwestern and southeastern US (Handler, 1990; Carlson et al., 1996). Hansen et al. (1998) analyzed the historical (1960-1995) response of total 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 $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; and of peanut and tobacco yields, and tomato and soybean values in particular states.

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 1982/83 and 1997/98 focused attention on the economic and social impacts of El Niño Southern Oscillation (ENSO) events. Improved ability to provide forecasts of 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).

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

ENSO Phase	Region	Seasons			
		Oct-Dec	Jan-Mar	Apr-Jun	Jul-Sep
El Niño					
	Peninsular Florida	Wet & cool	Very wet & 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 & Georgia.	No impact	No impact	No impact	Slightly dry
La Niña					
	Peninsular Florida	Dry & slightly warm	Very dry & 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 & Georgia	Dry	Dry in the south, wet in NW Alabama.	No impact	Slightly cool & wet in NW Alabama.
Neutral					
	All Regions	No impact	No impact	No impact	No impact

A central challenge facing these systems is to make 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 probabilistic 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).

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 markets both domestic and international. Weather-based decisions are generally operational by nature and involve activities that should happen in the very near future, most of the times 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 variety planted, acreage 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 United States (Hildebrand et al., 1999; Jones et al., 2000; Messina, 2000; Breuer et al. 2003). Many questions needed to be answered before climate forecasts could be used with confidence in agriculture. If producers have a reliable climate forecast three to six 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 indicated that, in addition to climate information, some of the more notable potential use of climate forecasts in the southeastern U.S. include cropping strategy (variety, maturity group, planting date), pest management, irrigation and drainage management, pasture management, herd size management, and forestry (plantation establishment, controlled burning, harvest planning, pest management and wild fire forecast).

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 required interactions with end users such as the development of regional climate and agronomic databases to support both climate information systems and a crop modeling effort, 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 implemented for evaluation by stakeholders and feedback sessions were organized across the 3 states involved in this effort.

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 (NCDC TD 3200) and contain daily values of maximum temperature, minimum temperature, and precipitation for a period of record of at least 50 years extending through December of 2004. The stations were selected based on (1) length of record, (2) data completeness, (3) homogeneity, and (4) representativeness to surrounding agricultural areas. The final data set contains historical weather records from 92 stations in Florida, 64 stations in Georgia, and 58 stations in Alabama.

The raw weather data were also resampled using a technique known as bootstrapping (Efron, 1993), creating a data set of 1,000 "synthetic" years of monthly data for each weather station and for each ENSO phase. These bootstrapped values were used to generate smooth probability density functions for the climate variables, which are used to produce the probability graphs displayed in *AgClimate*. Figure 1 shows the probability of occurrence for various ranges of rainfall for the month of January in Jackson County, Florida. The top graph shows the probabilities calculated by using all years of data available for the local meteorological station. It can be noticed that the probability for Jackson County receiving different amounts of rainfall in January vary from 2.0 percent for 1 inch or less to 15.1 percent for 3 to 4 inches. The question to be asked is: will the probabilities change if the year ahead is an El Niño, La Niña, or Neutral year? The bottom graph clearly indicates significant changes according to ENSO phases. It can be observed that the probability distribution for total rainfall during La Niña years shift towards lower rainfall amounts, about 25 percent for 3 to 4 inches of rainfall in January as compared to 7.8 percent during El Niño years. Conversely, the probabilities for greater amounts of rainfall are higher during El Niño years. Probability distributions for rainfall and minimum and maximum temperature are available in *AgClimate* at the county level.

Crop Modeling

A crop modeling effort was undertaken for selected commodities with the objective of providing the base line for evaluating crop production risk under alternative climate forecasts. The crops initially selected to be added to the system were peanut (*Arachis hypogaea* L.), tomato (*Lycopersicon esculentum* Mill.), and potato (*Solanum tuberosum* L.). The Decision Support Systems for Agrotechnology Transfer (DSSAT) suite of crop models was used for this effort. These models share a common input and output file format. The CSM-CROPGRO-Peanut (Hoogenboom et al., 1992; Boote et al. 1998; Jones et al., 2003), CROPGRO-Tomato (Scholberg, 1996), and SUBSTOR-Potato (Ritchie, 1995) crop models were used to simulate crop yield under different management scenarios using weather data from 1950-2004 for several counties in Georgia, Florida and Alabama. The DSSAT Version 4.0 (Hoogenboom et al., 2004) crop models are process based models that simulate crop growth and development and the plant and soil water, and nitrogen balances. The 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 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.

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 coun-

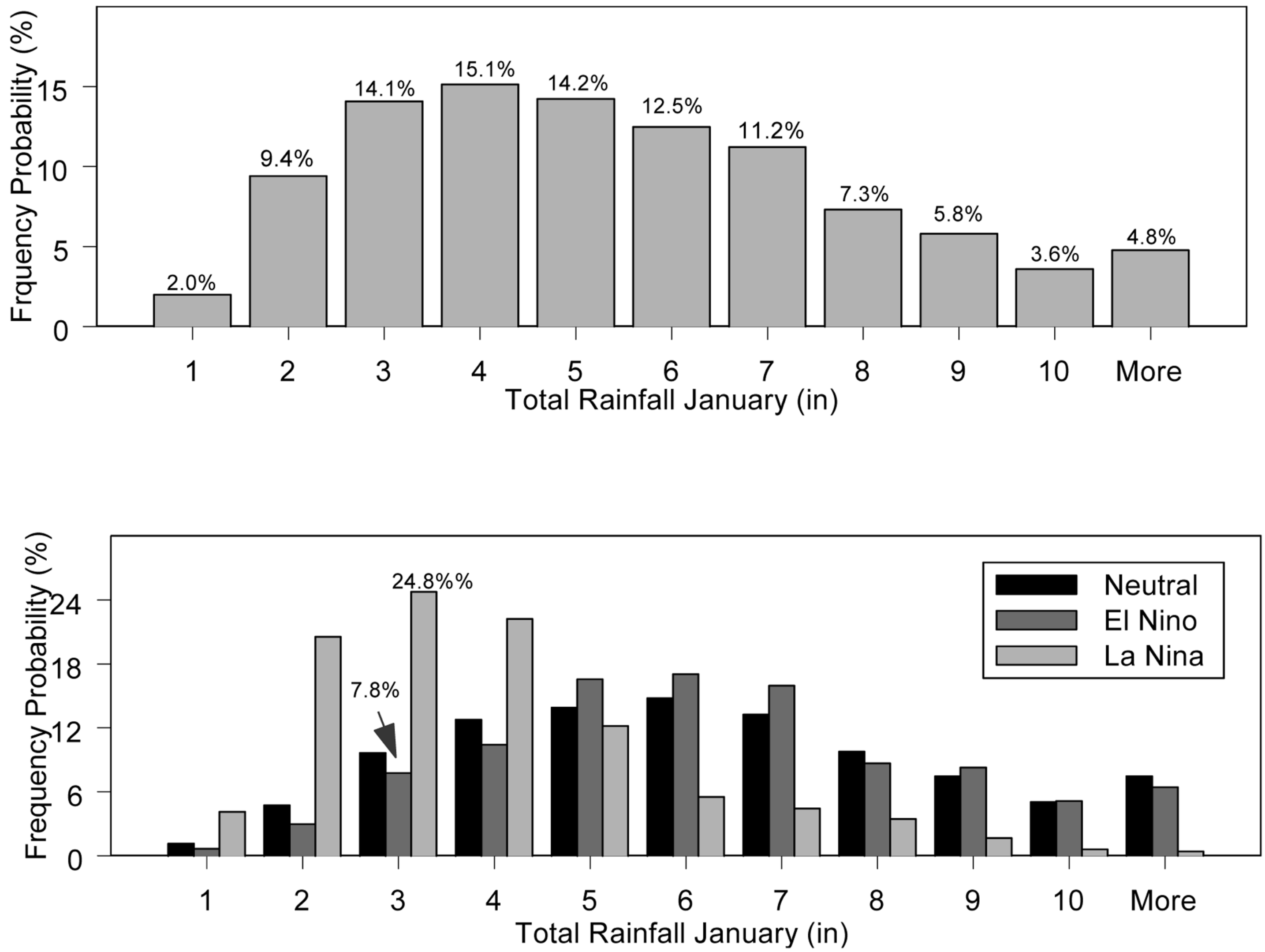

Figure 1. Probability distribution of total rainfall in January for all years (top) and Neutral, El Niño, and La Niña years (bottom) for Jackson County, Florida.

ties 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 chipping with high yield potential. Tomato simulations focused initially on the fresh market tomato crop produced in south Florida. The tomato cultivar Sunny was selected to represent the cultivars grown in South Florida.

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.

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 easily allow the expansion of the 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 its development. Although the *AgClimate* contents are added and maintained by SECC members, we realized that investing on a professionally designed system would increase the chances of its long term sustainability and success. SECC members can easily add menu items 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. Figure 2 shows the main AgClimate page. Its navigation menu includes the following items:

1. *AgClimate Tools*: (a) Climate Risk: Expected (probabilistic) and historical climate information (precipita-

tion and average min/max temperature) at the county level; (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 yet); (c) National, linking to the National Oceanic Atmospheric Administration (NOAA); and (d) International, linking to International Research Institute for Climate Prediction (IRI), (e) ENSO phase forecast, and (f) Hurricane forecasts.

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.

4. *Forestry*: The main product under the forestry section is a wildfire activity potential forecast that is based on the Keetch-Byram Drought Index (Byram and Keetch, 1988).

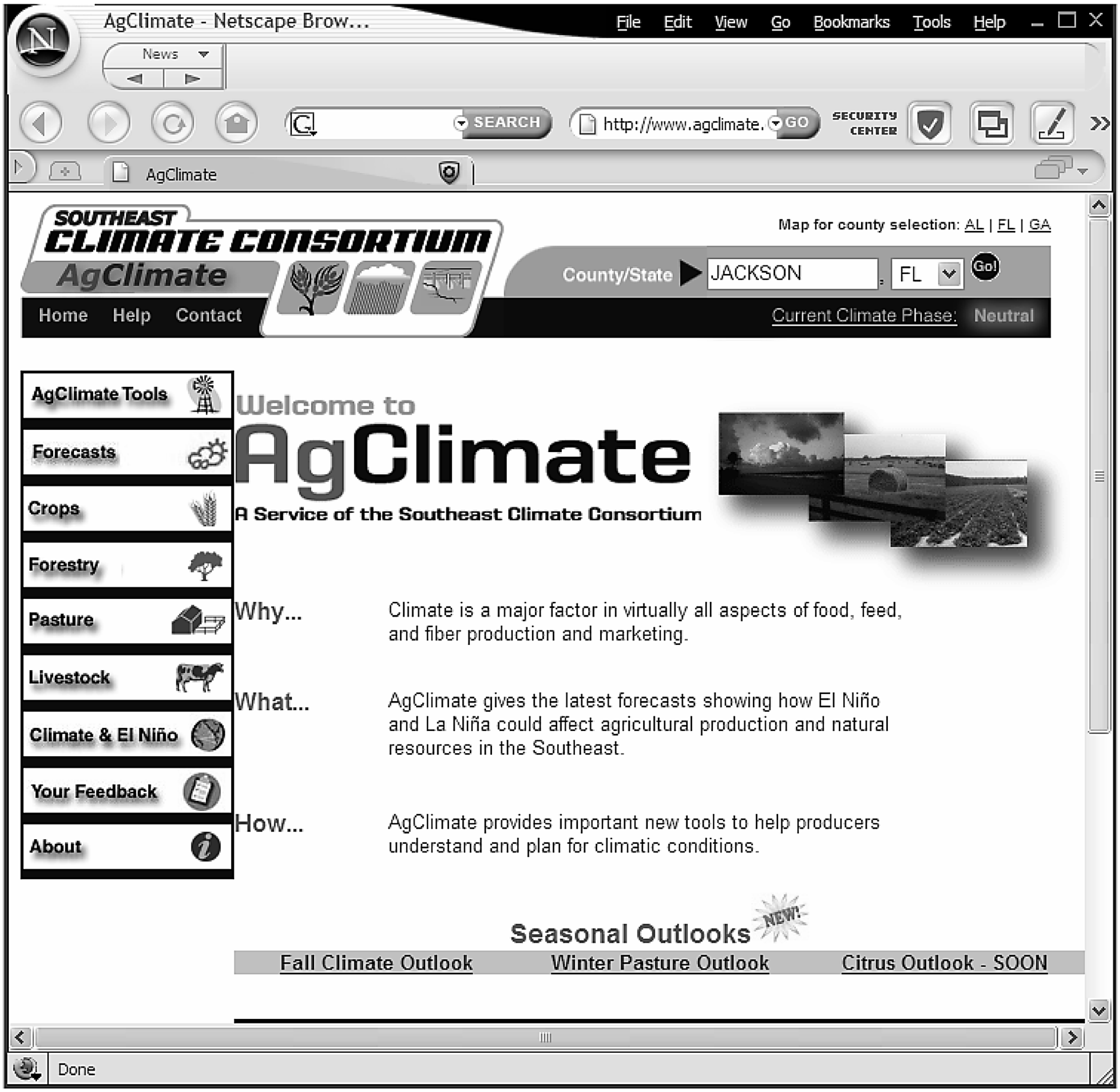

Figure 2. AgClimate main web page.

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 discussion 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 US, 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.

Conclusions

AgClimate was designed with participation from potential end users including agricultural farmers and Extension agents. It is intended to be user-friendly and interactive decision support system that translates seasonal climate forecasts into information that can help users make decisions under uncertainty in their operations. *AgClimate* is user friendly because its interfaces and tools were designed together with end users who continuously inputted feedback to improve visual as well as operational aspects. The tools embedded in *AgClimate* are interactive and site specific at the county level. 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 in the southeastern United States. 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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