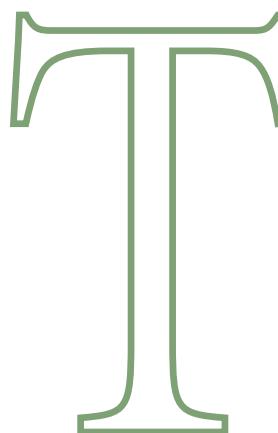


GEOSPATIAL DECISION SUPPORT FOR DROUGHT RISK MANAGEMENT

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Drought affects virtually all regions of the world and results in significant economic, social, and environmental impacts. The Federal Emergency Management Agency estimates annual drought-related losses in the U.S. at \$6–\$8 billion, which is more than any other natural hazard. Congress enacted the Agricultural Risk Protection Act of 2000 to encourage the U.S. Department of Agriculture (USDA) Risk Management Agency (RMA) and farmers to be more proactive in managing drought risk.



Through the NSF's Digital Government Program, the USDA RMA is working with the University of Nebraska-Lincoln Computer Science and Engineering Department, National Drought Mitigation Center (NDMC), and High Plains Regional Climate Center (HPRCC) to develop new geospatial decision-support tools to address agricultural drought hazards and identify regions of vulnerability in the management of drought risk. The goal of the National Agricultural Decision Support System (NADSS) research project is to develop a support system of geospatial analyses to enhance drought risk assessment and exposure analysis.

Drought risk management involves both expanding our ability to provide better early warning systems and creating more awareness of cropping systems and tillage practices that can reduce agricultural demand for water. The NDMC has made tremendous progress in raising awareness of drought and the ability of government and farmers to manage the risk associated with drought through the use of the Drought Monitor [6] and extension outreach services. However, the key to providing better early warning systems is improving our under-

standing of past historical events and the probability of drought in time and space.

The NADSS project has taken the first step in improving early warning systems by using drought indices to perform exposure analysis. A simple example of exposure analysis is shown in Figure 1. Daily precipitation and temperature data is collected from thousands of cooperative and automated weather stations around the U.S. and archived in regional climate centers. The NADSS project has automated drought index tools—such as the Standardized Precipitation Index [3], the Newhall Simulation Model [4], and the Palmer Drought Severity Index [5]—to automatically retrieve the climatic data from archived sites and iden-

tify drought regions of the U.S. (see nadss.unl.edu). Once vulnerable regions are identified, various geospatial databases are examined to evaluate the potential impact of a drought on the region.

Future tools will improve the spatial and temporal resolution of drought risk assessment and exposure analysis. For example, linking climatic variables to the farm plan will allow farmers to analyze the potential impact of an emerging drought on the crops in their fields as shown in Figure 2. Updating and automating known processes has been the key behind much of the project's early progress. While the contribution of these efforts to the scientific community has been substantial, the key to future progress lies in new computer science research.

New Research

Achieving the project's goal will require the discovery of patterns in drought indices, crop phenology and genetics, and soil characteristics. Unfortunately, traditional methods of pattern discovery have been slow and relatively ineffective due to the vast amounts of data in various databases maintained throughout the U.S., the spatial extent of the data, and the extended temporal lag between related events. Thus, new research investigates data mining and retrieval, constraint databases, spatial analysis, data interpolation, and visualization.

For example, we have developed two new data mining algorithms—Representative Episodal Association Rules [1] and Minimal Occurrences With Constraints and Time Lags [2]—that identify relationships between different types of episodes that may not overlap in time. These algorithms find the relationships between climatic and oceanic parameters. The relationships can then be used to predict target drought episodes and potential yield impact based on oceanic indices such as the Multivariate ENSO Index (MEI) [7]. The MEI is a new approach that combines the monthly El-Nino Southern Oscillation (ENSO) index with measurements of observed variables over the Equatorial Pacific that includes sea-level pressure, surface wind, sea-surface temperature, surface air temperature, and total cloudiness fraction of the sky. Negative MEI values are associated with La Nina (colder ocean temperatures in the Equatorial Pacific) conditions and positive MEI values are associated with El Nino

(warmer ocean temperatures in the Equatorial Pacific) conditions.

AN IMPORTANT aspect of this project is accessibility of the tools to researchers, government workers, and farmers. The natural avenue for accessing the tools is the Web. However, the traditional three-tier architecture of Web-based geographic information system (GIS) tools uses a proprietary (or at least nonstandard) interface to access these tools.

The decision-making process begins by combining and organizing data into pieces of information. These

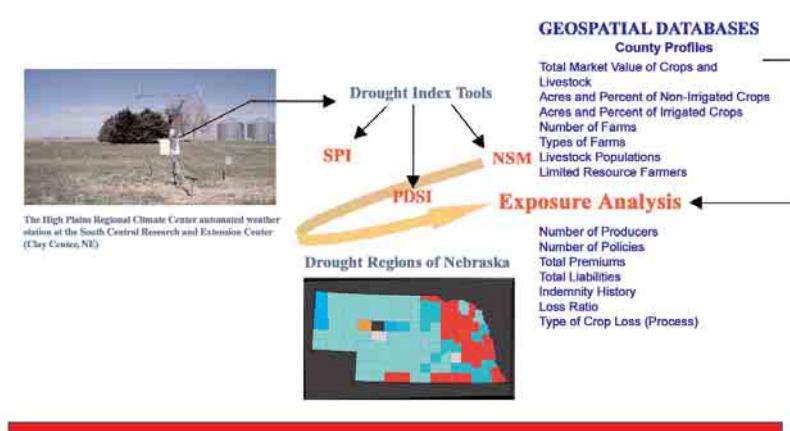


Figure 1.
The National Agricultural Decision Support System (NADSS) project combines data from weather stations and various geospatial databases to compute drought indices, risk assessment, and exposure analysis.

multiple pieces of information are then examined and combined to discover or create knowledge, which is the basis upon which a decision is made. High-order layers are able to make requests to nonadjacent, low-order layers. Each of the three lower layers (data, information, and knowledge) is associated with a cache for performance reasons. Strictly speaking, the cache is not needed, but we have found that for interactive distributed systems, building the cache into the architecture provides performance benefits that outweigh the complexity it brings (for example, cache coherency).

The *data layer* contains distributed spatial, constraint, and relational databases. This layer provides transparent access to either local or remote data without concern for data formats. The layer also provides a mechanism to encapsulate existing data interoperability solutions such as Common Object Request Broker Architecture (CORBA)-based or Distributed Component Object Model (DCOM)-based Open GIS Consortium objects, or data access via the Open Geographic Datastore Interface.

The *information layer* combines data and organizes it into information. It is organized around a collection of domain-specific servers that aggregate data into information. Examples of servers in this layer are data interpolation servers and map servers, which may be

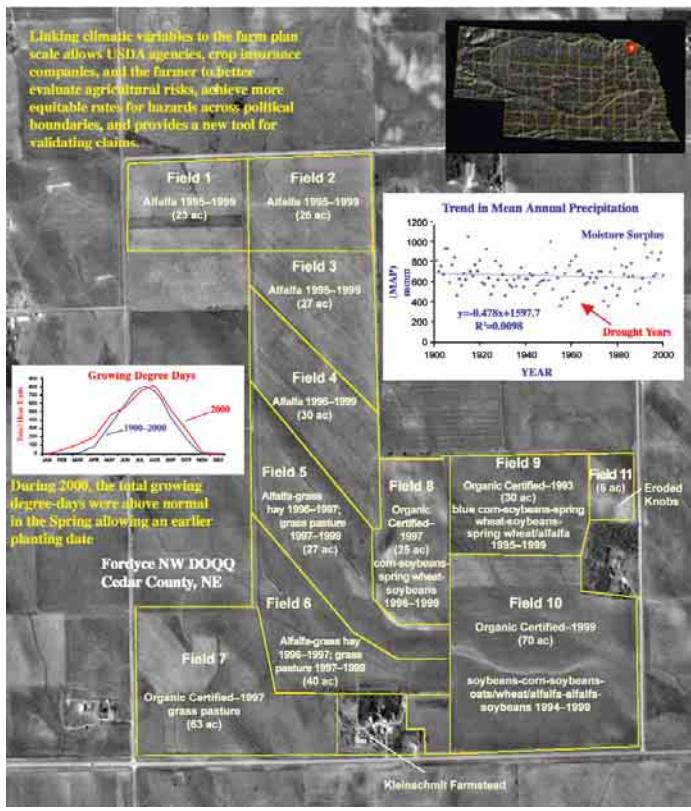


Figure 2. Future geospatial decision-support system tools will improve the spatial and temporal resolution of drought risk management.

we have developed drought index servers for our NADSS that process current and historical climate data from a weather station. The resulting index reflects how dry or wet a site is for a given period of time relative to its historical record. Thus the drought index is domain-specific information developed from climate data.

The *knowledge layer* builds on the information layer to create or discover knowledge. Servers that provide or discover domain-specific knowledge are implemented in the knowledge layer that incorporates several sequential data mining techniques. Simulation models and other knowledge analysis algorithms may also be used. The intent is that decision makers will interact with this layer, via the User Presentation interface to build and gather domain-specific knowledge.

The *presentation layer* provides the interface for the decision makers to interact with the GDSS. The user interface can take many forms. The simplest interface is developed using Web pages that interact with the lower layers via CGI requests. The goal of this architecture is that each layer can make requests to any of the lower-level layers using a standard open interface.

For example, an exposure analysis tool in the knowledge layer may request an interpolated drought index map layer for a given region from the information layer. If the data is not available (that is, has not been precomputed), the information layer will be able to retrieve the data from distributed spatial and relational databases making standard queries to the data layer to compute a response for the higher-level request.

Conclusion

The NADSS project is developing an integrated but distributed geospatial decision-support system for drought risk management. Users can monitor progress and interact with the system by visiting nadss.unl.edu. 

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This work supported, in part, by grants from the National Science Foundation (EIA-0091530) and the Nebraska Research Initiative.

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