

Terrestrial Observation and Prediction System (TOPS): Developing ecological nowcasts and forecasts by integrating surface, satellite and climate data with simulation models.

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Abstract

Ecological Forecasting, predicting the effects of changes in the physical, chemical, and biological environments on ecosystem state and activity, is an emerging field with significant socio-economic implications. Though the concepts behind and expectations for ecological forecasting are clear, progress towards producing consistent, reliable, and objective forecasts has been slow. Lack of infrastructure for integrating a variety of modeling tools, information technologies, and ground and satellite data sets that could serve the diverse needs of eco-hydrological community has been one key impediment. Here, we describe our efforts at such an integrated system called the

Terrestrial Observation and Prediction System (TOPS). TOPS is a data and modeling software system designed to seamlessly integrate data from satellite, aircraft, and ground sensors with weather/climate and application models to expeditiously produce operational nowcasts and forecasts of ecological conditions. TOPS has been operating at a variety of spatial scales, ranging from individual vineyard blocks in California, and predicting weekly irrigation requirements, to global scale producing regular monthly assessments of global vegetation net primary production.

Introduction

The latest generation of NASA Earth Observing System (EOS) satellites has brought a new dimension to monitoring the living part of the Earth system – the biosphere. EOS data can now measure weekly global productivity of plants and ocean chlorophyll and related biophysical factors, such as changes to land cover and to the rate of snowmelt. However, a greater economic benefit would be realized by forecasting biospheric conditions (Clark et al., 2001). Such predictive ability would provide an advanced decision-making tool to be used in the mitigation of natural hazards or in the exploitation of economically advantageous trends. Imagine if it were possible to accurately predict shortfalls or bumper crops, epidemics of vector-borne diseases such as malaria and West Nile virus, or wildfire danger as much as 3 to 6 months in advance. Such a predictive tool would allow improved preparation and logistical efficiencies.

Forecasting provides decision-makers with insight into the future status of ecosystems and allows for the evaluation of the *status quo* as well as alternatives or preparatory actions that could be taken in anticipation of future conditions. Whether preparing for the summer fire season or for spring floods, knowledge of the magnitude and direction of future conditions can save time, money, and valuable resources. Space- and ground-based observations have significantly improved the ability to monitor natural resources and to identify potential changes, but these observations can describe current conditions only. This information is useful, but many resource managers often need to make decisions months in advance for the coming season. Recent advances in climate

forecasting have elicited strong interest in a variety of economic sectors: agriculture (Cane et al., 1994), health (Thomson et al., 2005) and water resources (Wood et al., 2001). The climate forecasting capabilities of coupled ocean-atmosphere global circulation models (GCMs) have steadily improved over the past decade (Zebiak 2003). Given observed anomalies in sea-surface temperatures (SSTs) from satellite data, GCMs are now able to forecast general climatic conditions, including temperature and precipitation trends, 6 to 12 months into the future with reasonable accuracy (Goddard et al., 2001; Robertson et al., 2004).

While such climatic forecasts alone are useful, the advances in ecosystem modeling allow specific exploration of the direct impacts of these future climate trends on the ecosystem. One day predictions made in March might accurately forecast whether Montana's July winter wheat harvest will be greater or less than normal, and whether the growing season will be early or late.

One of the key problems in adapting climate forecasts to natural ecosystems is the "memory" that these systems carry from one season to the next. For example, soil moisture levels, plant seed banks, and fire fuel build-up are all affected by cumulative ecosystem processes that occur over many seasons or years. Simulation models are often the best tools to carry forward information about this spatio-temporal memory. The ability of models to describe and to predict ecosystem behavior has advanced dramatically over the last two decades, driven by major improvements in process-level understanding, climate mapping, computing technology, and the availability of a wide range of satellite- and ground-based sensors (Waring and Running 1998). In this chapter, we summarize the efforts of the Ecological Forecasting Group at NASA Ames Research Center over the past six years to integrate advances in these areas and develop an operational ecological forecasting system.

Background of Ecological Forecasting

Ecological Forecasting (EF) predicts the effects of changes in the physical, chemical, and biological environments on ecosystem state and activity (Clark et al.,

2001). EF is pursued with a variety of tools and techniques in different communities. For example, for community ecologists EF commonly includes methods for describing or predicting the ecological niche for various species. Much of invasive species forecasting falls in this area, where a set of conditions associated with the presence/absence of a species is derived and then these empirical relations are used to predict the occurrence or potential for occurrence of that species within a landscape. Similarly, bio-geographers use EF to predict species/community compositions in response to changes in long-term climate or geo-chemical conditions. Climate change and carbon cycling research falls in this category of predicting the state and/or functioning of ecosystems over long-lead times of decades to centuries. In contrast, the eco-hydrological community uses EF as a way of extending weather/climate predictions, with lead times ranging from days to months, for use in operational decision-making. Examples include forecasts of frost damage, flood/streamflow, crop yield, and pest/disease outbreaks. Though such forecasts are age-old among practitioners of various trades, there has been much subjectivity in the decision-making process that is hard to quantify and pass on to later generations. Providing an operational forecasting capability brings a new level of complexity to creating, verifying, and distributing information that is worth acting upon.

Components of ecological forecasting for eco-hydrological applications

Increasing interest in ecological forecasting is evident from several recent applications ranging from streamflows (Wood et al., 2001), crop yields (Cane et al., 1994) and human health (Thompson et al., 2006). These attempts tend to focus on specific watersheds or a geographic location with a very specific application; therefore they do not deal with EF as a broad theme associated with certain tools and technologies. Our past heritage in eco-hydrology and NASA's strengths in global observations and technology led us to focus on the development of a general data and modeling system that allows to produce operational nowcasts and forecasts relevant for many in the eco-hydrological community. Here we briefly review the important components that make our approach to EF possible, extensible, and economically viable.

Ecosystem Models: As in numerical weather prediction, models form the basis for EF. These models range in complexity, computational requirements, and in the representation of the spatio-temporal details of a given process or system. For example, biogeochemical cycling models are often complex and versatile in the sense that the basic ingredients that they simulate (carbon, water, nutrient cycling) form the core information for a variety of biospheric activities of economic value. For example, changes in carbon cycling expressed as net primary production (NPP) can be a key indicator of crop yields, forage production or production of board feet of wood. These models use the Soil-Plant-Atmosphere continuum concept to estimate various water (evaporation, transpiration, stream flows, and soil water), carbon (net photosynthesis, plant growth) and nutrient flux (uptake and mineralization) processes. They are adapted for all major biomes exploiting their unique eco-physiological principles such as drought resistance, cold tolerance, etc. (e.g. BIOME-BGC, Waring and Running 1998; CASA, Potter et al., 2003). The models are initialized with ground-based soil physical properties and satellite-based vegetation information (type and density of plants). Following the initialization process, daily weather conditions (max/min temperatures, solar radiation, humidity, and rainfall) are used to drive various ecosystem processes (e.g., soil moisture, transpiration, evaporation, photosynthesis, and snowmelt) that can be translated into drought, crop yields, NPP, and water yield estimates. We currently use a diagnostic (with satellite data input) version of BGC to produce nowcasts and a prognostic (without satellite data inputs) version of BIOME-BGC to produce forecasts of carbon and water related fluxes.

Extensive discussion on types of ecosystem models and their relevant applications can be found in Waring and Running (1998) and Canham et al., (1997).

Microclimate mapping from surface weather observations: Access to reliable weather data is a pre-requisite for ecosystem modeling. The availability of weather observations has been a key obstacle in the development of real-time EF systems. Historically, weather data was made available on tapes or CDs months after it was collected and corrected for errors. This time lag precluded real-time simulations, a precursor to developing forecasting capability. Through the World Wide Web, however, there are now thousands

of on-line weather stations providing real-time weather data. These real-time data include ground-based observations of max/min/dew temperature and wind speed, satellite-based solar radiation, and spatially continuous rainfall fields produced by weather agencies.

Another important advancement for EF is the ability to grid point observations onto the landscape at various spatial resolutions, as observations are rarely sufficient to represent the spatial variability. Models such as PRISM, DAYMET, and SOGS (Daly et al. 1994; Thornton et al. 1997; Jolly et al. 2004) ingest point surface observations, and use topography and other ancillary information to compute spatially continuous meteorological fields (temperature, humidity, solar radiation, and rainfall) that can be directly used in ecosystem modeling.

Weather/Climate Forecasts: There is considerable optimism among the climate community about our ability to forecast climate into the future (Trenberth 1996). This optimism stems from several recent advancements in climate modeling, such as improvements in GCMs that have allowed realistic reproduction of observed global climate (Roads et al. 1999), adaptation of new forecasting strategies, demonstration of the links between El Niño/Southern Oscillation (ENSO) and short-term climate, and the ability to forecast ENSO 12-18 months in advance. Barnett et al. (1994) showed that with the above improvements, GCMs could be used successfully to predict air temperature, precipitation, and solar radiation at extended lead times over many parts of the world. Research as well as operational agencies that currently produce and disseminate climate forecasts includes the NOAA's National Center for Environmental Prediction, Columbia University's International Research Institute, the Scripps Institute of Oceanography's Experimental Climate Prediction Center, and others.

Satellite remote sensing: A number of studies over the past two decades have shown the utility of satellite data for monitoring vegetation (type, density, and production), extent of flood damage, wildland fire detection, and monitoring snow and drought conditions. However, many of the products generated from satellite data have been experimental, and did not have a wide distribution among natural resource managers. Over the past five years, through NASA's EOS program, there have been substantial improvements in the

way satellite data is acquired, processed, converted to products, and delivered (Table 1). For example, weekly maps of leaf area index (LAI, area of leaves per unit ground area) and vegetation indices, key inputs for many ecosystem models, are being generated and distributed from the NASA/MODIS sensor. A number of other key land products such as NPP, fire occurrence, snow cover, and surface temperature are available globally at 1-km resolution every 8 days (Justice et al 1998; Myneni et al. 2002). Without this near-realtime observing capacity, systems such as TOPS would never have materialized.

Integrated modeling: Numerous studies over the past two decades addressed the logical steps for modeling land surface processes over various spatial scales, by integrating ecosystem models with satellite, climate data, and other ancillary information (Waring and Running 1998). One such attempt that many of us have been part of was the development of the Regional Hydro-Ecological Simulation System (RHESSys, Band et al. 1993; Nemani et al. 1993; Tague and Band 2004). RHESSys has been used in various studies for estimating soil moisture, stream flows, snow pack, and primary production (Waring and Running 1998). Much of the work using RHESSys has been retrospective, using past climate and satellite data, mainly to evaluate various issues related to the parameterization of key variables, scaling and determining the suitability of RHESSys outputs for use by resource managers (Waring and Running 1998). While this type of retrospective analysis is useful for long-term management decisions, only a real-time analysis can provide data necessary for dynamic decision making such as the assessment of fire risk. Our work has focused on the development of the Terrestrial Observation and Prediction System (TOPS) to provide this capability for real-time analysis, which is essential for forecasting ecological conditions desired by decision makers.

The Terrestrial Observation and Prediction System (TOPS)

TOPS is a data and modeling software system designed to seamlessly integrate data from satellite, aircraft, and ground sensors with weather/climate models and application models to expeditiously produce operational nowcasts and forecasts of ecological conditions (Figure 1). TOPS provides reliable data on current and predicted

ecosystem conditions through automation of the data retrieval, pre-processing, integration, and modeling steps, allowing TOPS data products to be used in an operational setting for a range of applications.

Implementation of TOPS over a region consists of first developing the parameterization scheme for the area of interest. Parameterization inputs include data on soils, topography, and satellite derived vegetation variables (land cover and LAI). Observational weather data, gridded from point data or downscaled from previously gridded data to the appropriate resolution, are then used to run a land surface model, such as BIOME-BGC (Waring and Running 1998; White et al. 2000). Finally, weather and climate forecasts are brought into the system as gridded fields and downscaled to the appropriate resolution to drive the land surface model and generate predictions of future ecosystem states.

Given the diversity of data sources, formats, and spatio-temporal resolutions, system automation is critical for the reliable delivery of data products for use in operational decision-making. TOPS has been engineered to automatically ingest various data fields required for model simulations (Figure 2). Ingested data go through a number of preprocessing filters in which each parameter is mapped to a list of attributes (e.g., source, resolution, and quality). This results in each data field being self-describing to TOPS component models such that any number of land surface models can be run without extensive manual interfacing. Similarly, the model outputs also pass through a specification interface, facilitating post-processing so that model outputs can be presented as actionable information, as opposed to just another stream of data. TOPS derives its flexibility and automation capability from two key software components: *JDAF* (*Java Distributed Application Framework*) and the ImageBot planner.

JDAF and IMAGEbot

The TOPS software is implemented using a flexible framework that enables fast and easy integration of new models and data streams into an automated system. The core components of this framework are *JDAF* (Java Distributed Application Framework) and

IMAGEbot. JDAF consists of a large set of data processing and image analysis algorithms that are deployed to pre-process and post-process inputs and outputs of the TOPS ecosystem models. When we want to process new data with our existing models, we re-use the JDAF algorithms to create intermediate datasets that adhere to the model's input specifications so that we can execute our models without having to alter the science implementation. Because the pre-processing itself can be a very complex process, involving for example data acquisition, mosaicking, reprojection, subsetting, scaling etc. We have developed a planner-based agent (*IMAGEbot*), which automatically generates the sequence of processing steps needed to perform the appropriate data transformations. In other words, JDAF provides all the processing components of the system and *IMAGEbot* determines how they fit together to achieve the desired goal, creates a plan, and executes it. This gives a great flexibility to the TOPS software and speeds-up significantly the integration of both datasets and models into new applications. Additionally, JDAF provides interface to the database system and to web services capabilities for seamless access to both data and services provided by TOPS.

As currently deployed within TOPS, JDAF and *ImageBot* perform two dynamic functions critical for the real-time monitoring, modeling and forecasting of ecosystem conditions: gridding of weather observations to create continuous fields of climatic parameters, and acquisition and processing of satellite data for initializing or verifying the models.

Climate Gridding

To produce gridded climate fields, the user specifies a geographic area of interest and the spatial resolution for the gridded fields. The *ImageBot* planner uses these specifications to create a data processing plan comprised of a series of requirements and corresponding actions. For example, *ImageBot* will identify the acquisition of topographic data as a requirement, evaluate the possible sources for this data from the data library, identify the required resolution, and create the set of actions required to obtain the data at the appropriate resolution. These actions are then passed to JDAF,

which fetches the data from the source, and reformats and reprojects the data to meet the user-specified requirements. Similarly, for meteorological data, ImageBot produces a list of weather networks available for the region, a list of variables available from each network, and the frequency of observations available from the network. From this information and the user-defined set of constraints, ImageBot again formulates a series of actions specifying which networks and what variables need to be retrieved and input to the database. After receiving these instructions, JDAF fetches the necessary data, checks for consistency against historical averages, fills-in missing values from additional sources, flags missing values, and finally interfaces these observations with the Surface Observation and Gridding System (SOGS, Jolly et al. 2004, Figure 3), a component layer within TOPS. SOGS is an operational climate-gridding system, and an improvement upon DAYMET (Thornton et al. 1997), that uses maximum, minimum, and dewpoint temperatures, in addition to rainfall, to create spatially continuous surfaces for air temperatures (e.g. Figure 4a), vapor pressure deficits, and incident radiation. The cross-validation statistics returned from SOGS allow ImageBot to decide if the user-specified requirements for accuracy have been achieved, or if alternative gridding methods need to be found.

Acquiring and Processing of Satellite Data

TOPS has access to a number of satellite data sets (Table 1), produced and processed by either NASA or NOAA. This access involves machine-to-machine, web-based ordering, and FTP pushes for routine data sets such as those from the NOAA Geostationary Operational Environmental Satellites (GOES). Similarly to the climate gridding process described in the previous section, ImageBot defines a set of actions pertaining to satellite data and products based on user-defined constraints and requirements. The requirements in this case may include, for example, obtaining LAI and snow cover data with the following constraints: a minimum resolution of 1km, a weekly time interval, and a specification to obtain the highest possible quality data available. From the data library, ImageBot creates a list of sites that provide LAI. ImageBot sends a

command to JDAF to fetch all of the metadata files relating to the LAI product to be evaluated and screened for quality. A list of ‘tiles’ (the 1200x1200km area used in MODIS processing) covering the geographic area of interest and meeting the quality criteria is prepared. A request is sent to the archival site (for example, the USGS Eros Data Center). When the order is ready for download, JDAF collects the order and updates the internal database. JDAF then initiates a series of actions on the tile data available locally, including the creation of mosaics, filling-in of missing values, regridding, and reprojection. An example of LAI output from this procedure is shown in Figure 4b.

In many cases, data available from the Distributed Active Archive Centers (DAACs) may be 2-8 days old. While this may not pose a significant problem for geophysical fields such as LAI that vary slowly, snow cover can change dramatically in a week. To deal with these situations, TOPS has the ability to ingest and use MODIS data from Direct Broadcast readouts available throughout the United States.

Interfacing new models in TOPS

Interfacing the pre-processed climate and satellite data with models is the next step in producing TOPS nowcasts and forecasts. In order to facilitate the integration of new models, TOPS provides a system for describing new models in terms of their inputs and their outputs. These descriptions include specifications for the format, resolution, variables, and temporal and spatial extent of model parameters. These descriptions are then embedded in the domain descriptions of the model using the DPADL language (Golden 2003). While this method still lacks robustness and is not fully automated, it enables TOPS to integrate new models into the system faster than the manual integration that would otherwise be required. To improve the automation of this process, we are currently designing an applications programming interface for model integration.

TOPS Nowcasts

On a daily basis, TOPS uses the technologies described above to produce a set of 30 variables including gridded climate, satellite-measured and modeled fields. For the current TOPS implementation for the State of California at 1km and the continental U.S at 8km, the data products that are most widely requested are gridded climatic data consisting of daily max/min temperatures, vapor pressure deficits, rainfall, and incident shortwave radiation (Figure 4a). Satellite products include daily GOES-based infra-red and visible reflectances and 8-day MODIS (Figure 4b) and other sensor products (Table 1). One key difference between TOPS satellite products and products from various DAACs is that TOPS pre-processes the data for immediate use. In addition to the meteorological data, TOPS provides ecosystem nowcasts for California including maps of soil moisture, snow cover and depth, gross and net primary production (e.g. Figure 4c), growing season dynamics (leaf on and leaf off), evapotranspiration, and streamflow.

TOPS Forecasts

TOPS currently produces two types of ecological forecasts: 1) model-based, where the model is run into the future, and 2) those based on historical associations. Model-based forecasts are either short-term (3-7 days), as in the case of vineyard irrigation, or experimental long-term (3 months) based on outputs from GCMs. In both cases, land surface states are continuously updated using satellite and ground-based observations. Forecasts based on historical associations include those derived from weather-phenology and weather-fire risk. For both applications, we developed empirical models that provided reasonable predictions of the parameter of interest, i.e., the start and end of the growing season, and relative fire risk. In each, we used a combination of climate data and spatially continuous historical satellite data to develop the predictive models (<https://ecocast.arc.nasa.gov>).

Verification & Validation

TOPS outputs are continuously compared against observed data to assess spatio-temporal biases and general model performance. In the case of snow pack dynamics, for example (Figure 5), we perform a three-way comparison among model-, observation-, and satellite-derived fields of snow cover expansion and contraction ($r=0.91$). Carbon-related variables such as gross and net primary production fields are tested against FLUXNET-derived data at selected locations representing a variety of landcover/climate combinations ($r=0.83$). Similarly, the SCAN network of soil moisture, USGS streamflow, and SNOTEL provide valuable data for verifying the hydrology predictions from TOPS.

TOPS Applications

TOPS Helping the California Wine Industry

The impetus for developing TOPS came from NASA's research in Napa Valley, California, which explored the relationship between climate and wine quality and the application of remote sensing and modeling in vineyard management. Analysis of long-term climate records and wine ratings showed that interannual variability in climate has a strong impact on the yearly \$30 billion California wine industry. Warmer SSTs observed from satellite along the California coast were found to help wine quality by modulating humidity, reducing frost frequency, and lengthening the growing season (Nemani et al. 2001). Because changes in regional SSTs persist for 6 to 12 months, predicting vintage quantity and quality from previous winter conditions appears to be possible (Nemani et al., 2001).

TOPS also helps vintners during the growing season as a real-time vineyard management tool. For example, satellite remote sensing data during the early growing season helps vineyard managers to locate areas for pruning so that an optimum canopy density is maintained. Similarly, LAI derived from satellite data is used in ecosystem process models to compute water use and irrigation requirements to maintain vines at given water stress levels. Research suggests that vines need to be maintained at moderate water stress to maximize fruit quality (Johnson et al., 2003). By integrating leaf area, soils data, daily weather, and weekly weather forecasts, TOPS can estimate spatially

varying water requirements within the vineyard so that managers can adjust water delivery from irrigation systems (Figure 6a). A number of Napa valley vintners presently participate in our experimental irrigation forecast program, helping us verify the utility of the forecasts, the packaging and delivery of information, and assess the economic value of the forecasts. Satellite imagery at the end of the growing season also helps growers in delineating regions of similar grape maturity and quality so that differential harvesting can be employed to optimize wine blending and quality (Johnson et al. 2003).

TOPS monitors global ecosystems

NPP, the net result of photosynthesis and respiration by plants, forms the basis for life on earth, and provides food, fiber and shelter for humanity. Continuous monitoring of NPP therefore is in our best interest (Running et al. 2004) as the biosphere responds to a variety of pressures from changing climate, atmospheric chemistry, agricultural and land use practices. Spatially continuous assessments of global NPP have been possible only in the past two decades with the availability of NOAA/AVHRR data. One such assessment spanning 1982 to 1999 showed significant increases in global NPP, attributed to a variety of changes in climatic conditions (Nemani et al. 2003). While good news, the underlying message of this study is that interannual and decadal changes in NPP can be dramatic and require regular monitoring (Milesi et al. 2005). Using TOPS, we extended our historical analysis of global NPP into global NPP nowcasts (Figure 6b). Every 8 days, TOPS brings together the latest MODIS data on land cover, LAI/FPAR, climate data from NCEP, regrid the data to 0.5 degree resolution, estimates NPP, and expresses the output as weekly/monthly anomalies from long-term normals. Because SSTs have a strong association with land surface climate (e.g. ENSO), we also produce maps of global SST anomalies. Animations of these anomalies provide information regarding the location, magnitude, and persistence of anomalies that need further exploration using high-resolution data sets. When a persistent anomaly is detected, TOPS can be tasked to perform a higher resolution model run for that region using the best possible data sets. An extended analysis of the anomaly helps us to understand whether the estimated NPP anomaly is related to changes in climate or land use (Hashimoto et al. 2004).

On-going applications of TOPS include nowcasting and forecasting of snow dynamics in the Columbia River Basin (Northwestern U.S.), mapping fire risk across the continental U.S., mapping NPP at 250m in protected areas such as U.S. National Parks, carbon and water management in urban ecosystems (Milesi et al.,2005) , and monitoring and forecasting mosquito abundance and outbreaks of West Nile virus in California. TOPS products are available in WMS format so these data can be accessed and visualized using NASA's WorldWind (<http://worldwind.arc.nasa.gov>) software system designed explicitly for educational purposes.

Summary

In the past, ecological forecasting has been largely anecdotal. Its transformation into a rigorous, scientific endeavor is now possible through the observing capacity of operational satellites, the speed and flexibility of the internet, the use of high-performance computing for complex modeling of living systems, and mining of large quantities of data in search of relations that could offer potential predictability. Unlike the case of weather and climate forecasting, EF can be as diverse as the number of weather-influenced phenomena. We hope our efforts at EF can provide the necessary guidance for future applications, since the basic infrastructure needed to enable ecological forecasts appears to be similar across different domains. Our experience with EF has been that producing the forecasts may be the easy part, convincing users and conveying the uncertainty associated with the forecasts has been a challenge. Much work is needed along these lines to realize the full potential of ecological forecasting.

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Figure Captions:

Figure 1. The Terrestrial Observation and Prediction System (TOPS) integrates a wide variety of data sources at various space and time resolutions to produce spatially and temporally consistent input data fields, upon which ecosystem models operate to produce ecological nowcasts and forecasts needed by natural resource managers.

Figure 2: TOPS data processing flowchart showing three key modules that perform data acquisition and pre-processing, data and model integration and decision support through analysis of model inputs and outputs. Application front-ends, predictive models, and data mining algorithms are modular and can be easily swapped out as needed. The modular architecture also allows for the concurrent use of multiple ecosystem models to generate forecasts for different parameters.

Figure 3: Flow diagram of the SOGS. Three main components that comprise the system are: data retrieval and storage, interpolation and output handling. Data retrieval is configured to automatically retrieve the most recent data available and insert those data into the SQL database. Interpolation methods are modular and allow maximum flexibility in implementing new routines as they become available. Outputs are generated on the prediction grid that is determined by the latitude, longitude, elevation and mask layers. Another key feature of the SOGS implementation is scenario generation where long-term normal station data can be perturbed according to climate model forecasts. Weather data from over 6000 stations distributed globally is ingested into TOPS database where it is gridded to a variety of resolutions, globally at 0.5 degree, continental U.S at 8km and at 1km over California.

Figure 4: Examples of TOPS nowcasts. a) Patterns of maximum air temperature over the conterminous U.S., produced using over 1400 stations on April, 27, 2004. b) MODIS-derived leaf area index after pre-processing through TOPS, and c) Model estimated gross primary production, the amount of photosynthate accumulated on April 27, 2004 over the conterminous U.S.

Figure 5: Testing TOPS products against satellite and network observations: a) TOPS snow cover against MODIS-derived snow cover, b) TOPS Evapotranspiration against FLUXNET observations at Harvard Forest, and c) TOPS Gross Primary Production shown against FLUXNET observations at a number of sites across the U.S.

Figure 6: a) Application of TOPS over Napa valley vineyards showing the recommended irrigation amounts to keep the vines at a stress level of -12 bars for the week of September 7, 2004. b) A global application of TOPS for monitoring and mapping net primary production anomalies over land and sea surface temperature anomalies over global oceans. NPP and SST anomalies for May 2005 are based on monthly means from 1981-2000.

Table 1: Data sources, derived products and their usage within TOPS

Data Source	Products	Usage
<i>Satellite data</i>		
MODIS – TERRA/AQUA (250/500/1000m)	Surface reflectances	Vegetation monitoring
	Land surface Temperature	Drought/Fire/Snow
	Leaf area index	Vegetation monitoring
	Snow cover	Hydrology
	Vegetation indices	Vegetation monitoring
	Fire	Burnt area/recovery
AVHRR (1000m)	Vegetation index	Vegetation monitoring
	Land surface temperature	Drought/Fire/snow
AMSR-E (25km)	Brightness temperature Surface soil moisture	Hydrology monitoring
Thematic Mapper (30m)	Reflectances, land cover maps	Vegetation monitoring
SSM/I (25km)	Brightness temperatures	Hydrology monitoring
ASTER (10-20m)	Reflectances, land surface temperature	Vegetation monitoring
SRTM (30-50m)	Topography	Drainage, climate mapping
<i>Ground observations</i>		
NWS (hourly)	Weather	Model inputs
SNOTEL (daily)	Weather, snow	Model inputs, validation
RAWS (hourly)	Weather	Model inputs
CIMMIS (hourly)	Weather, ETo	Model inputs
FLUXNET (fortnightly)	Weather, ET, GPP	Inputs, validation
SCAN (daily)	Soil moisture	Validation
USGS –Gauges (daily)	Streamflow	Validation
<i>Model results</i>		
NCEP (daily)	Global weather/climate forecasts	Model inputs
DAO (daily)	Global weather	Model inputs
ECPC (weekly)	Climate forecasts	Model inputs

Acronyms

AMSR-E	Advanced Microwave Scanning Radiometer-Earth Observing System
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
AVHRR	Advanced Very High Resolution Radiometer
BIOME-BGC	Biome-biogeochemistry
CIMIS	California Irrigation Management Information System
DAAC	Distributed Active Archive Center
DAO	Data Assimilation Office
ECPC	Experimental Climate Prediction Center
EF	Ecological Forecasting
ENSO	El Niño–Southern Oscillation
ET	Evapotranspiration
ET _o	Reference Evapotranspiration
FLUXNET	Network of eddy covariance towers
FPAR	Fraction of Photosynthetic Active Radiation
GCM	General Circulation Model
GOES	Geostationary Operational Environmental Satellites
GPP	Gross Primary Production
ImageBot	heuristic-search constraint-based planner
JDAF	Java-based Distributed Application Framework (executing plans and for interfacing with DAACs)
DAPDL	Data Processing Action Description Language
WMS	Web Map Server
LAI	
MODIS	MODerate resolution Imaging Spectro-radiometer
NCEP	National Center for Environmental Prediction
NOAA	National Oceanic and Atmospheric Administration
NPP	Net Primary Production
NWS	National Weather Service
RAWS	Remote Automated Weather Stations
RHESSys	Regional Hydro-Ecological Simulation System
SCAN	Soil Climate Analysis Network
SNOTEL	SNOWpack TELemetry network
SOGS	Surface Observation and Gridding System
SRTM	Shuttle Radar Topography Mission
SSM/I	Special Sensor Microwave Imager
SST	Sea surface temperature
TOPS	Terrestrial Observation and Prediction System
USFS	United States Forest Service
USGS	United States Geological Survey
XML	Extensible Markup Language

Terrestrial Observation and Prediction System

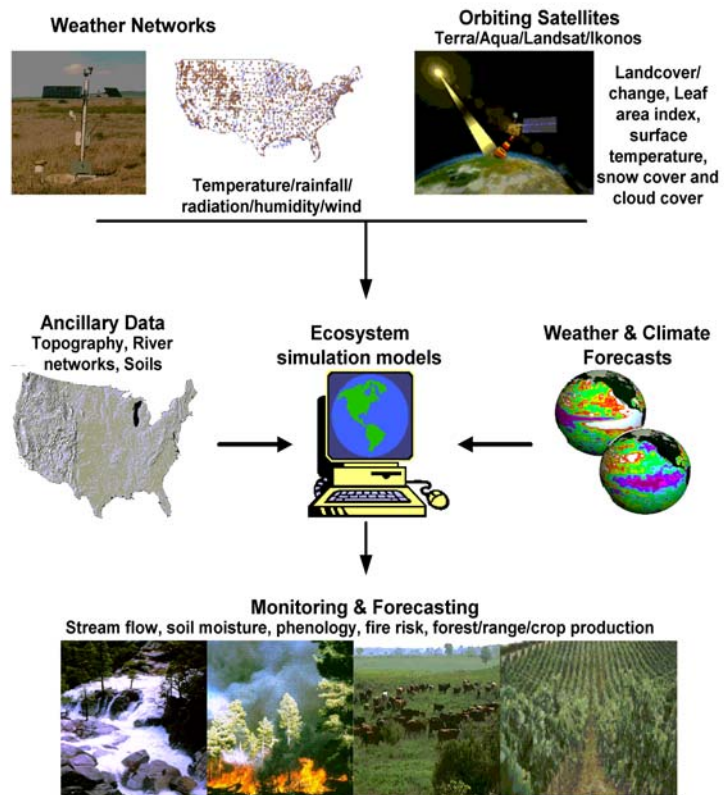


Figure 1:

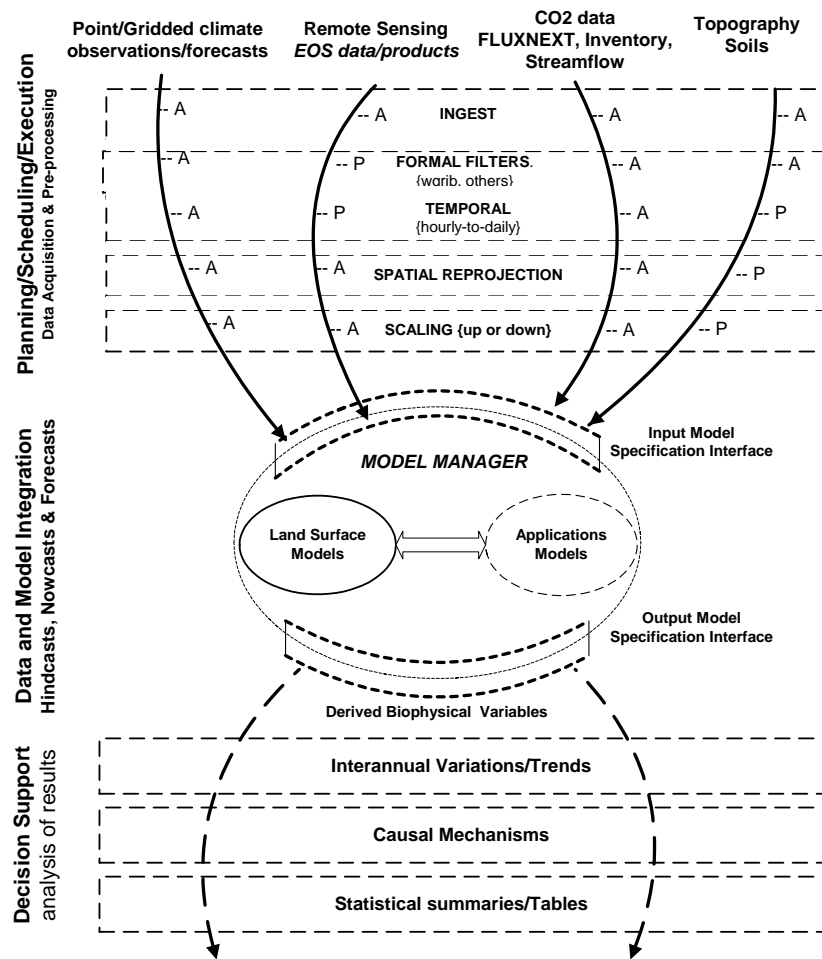


Figure 2:

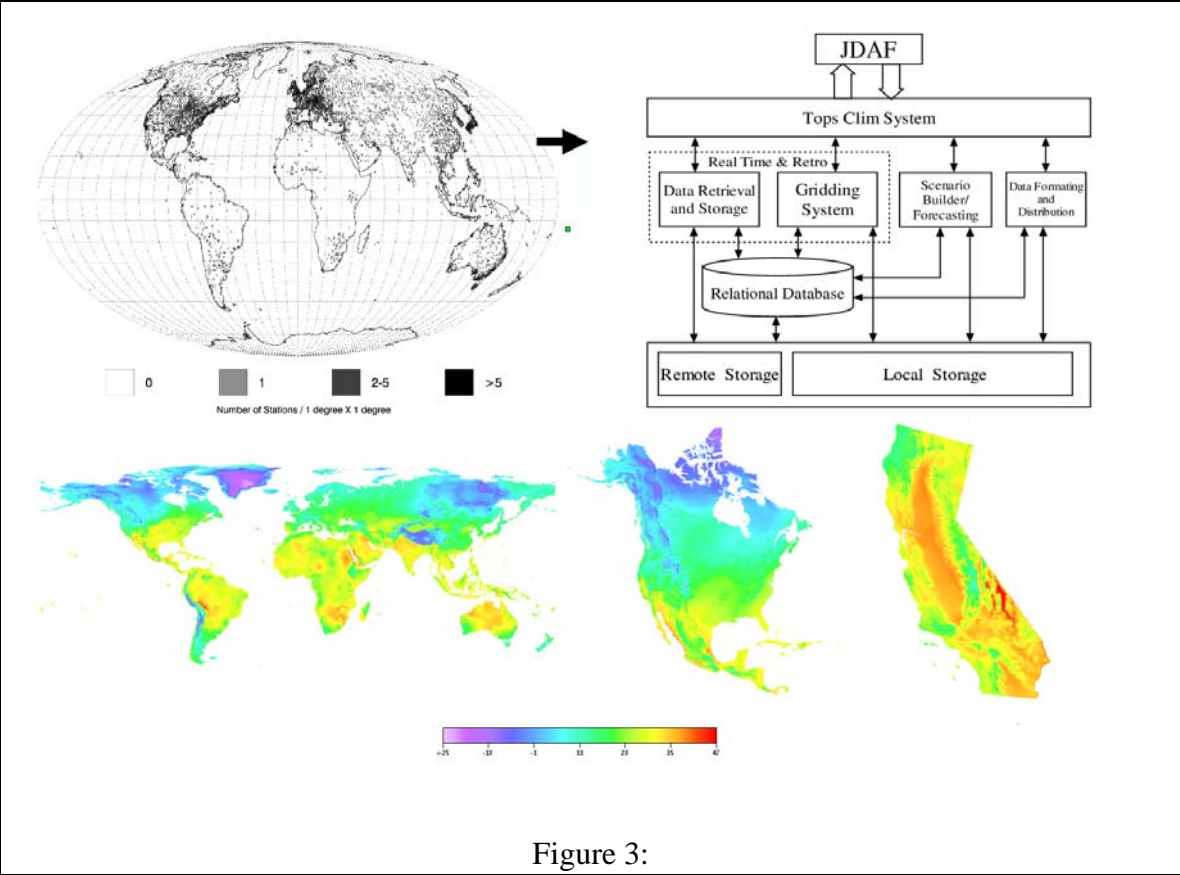
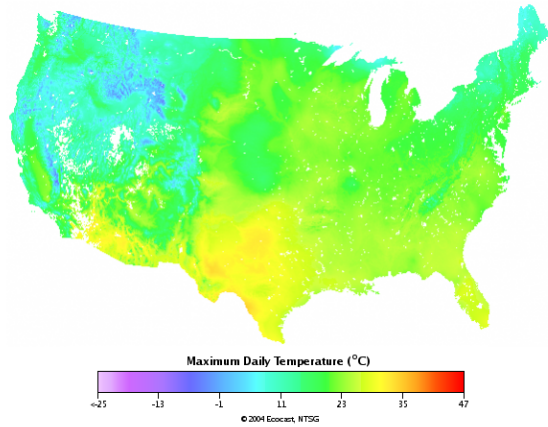


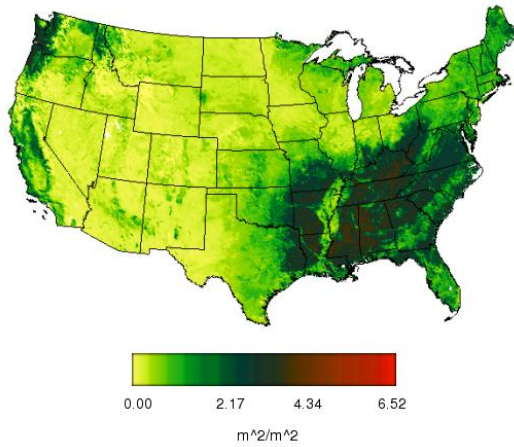
Figure 3:

Tmax Continental USA, April 27, 2003



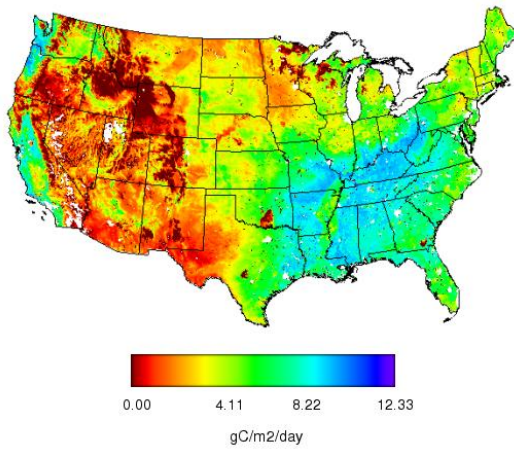
4a)

Leaf Area Index
USA - 8km
Apr 23, 2003 - Apr 30, 2003

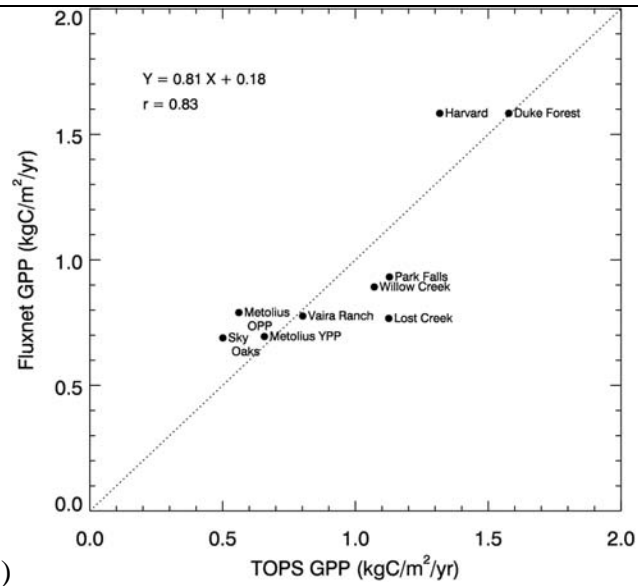
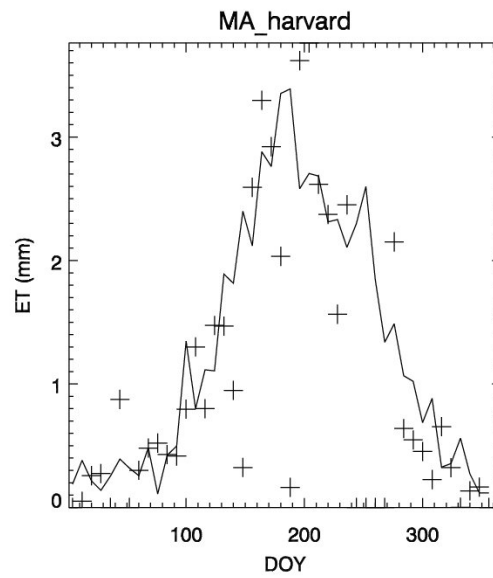
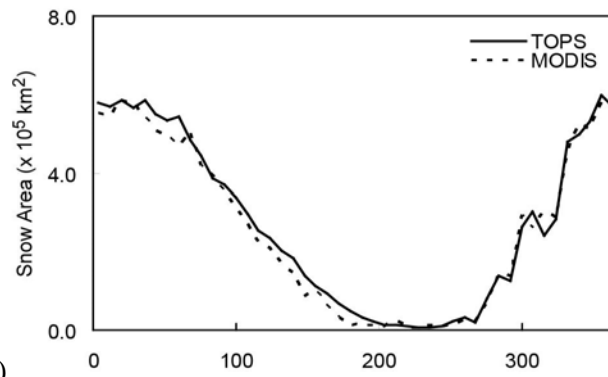


4b)

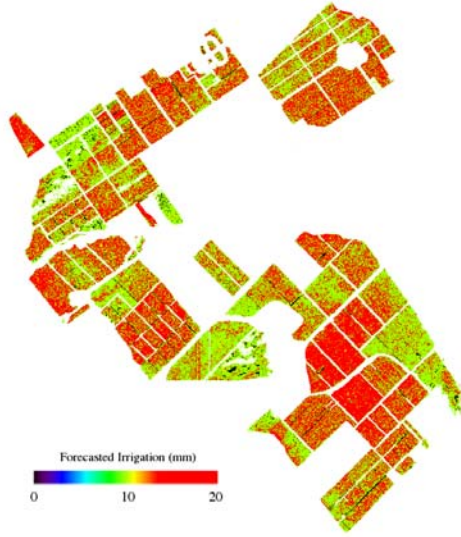
TOPS GPP
USA - 8km
Apr 27, 2003



4c)

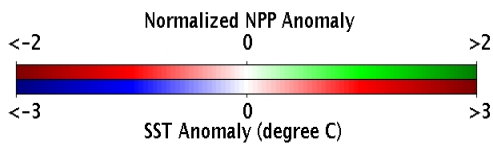
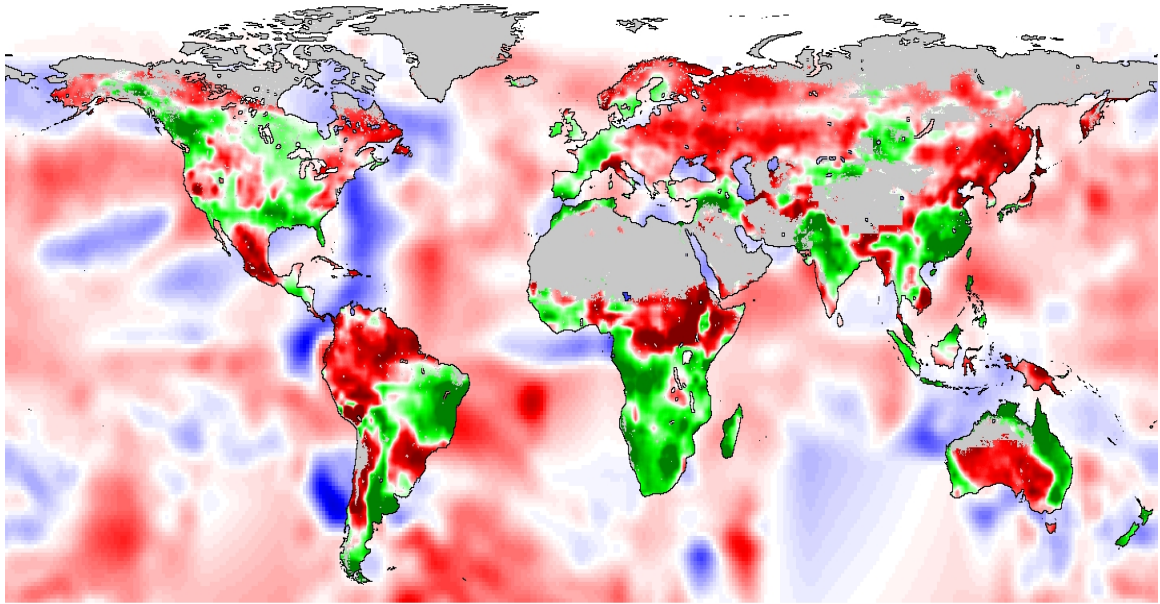


Forecasted Irrigation, September 7, 2005



6a)

Mapping changes in global net primary production near real-time depiction of the droughts in the Amazon and Horn of Africa, May 2005



6b)