

Uses and Limitations of Observations, Data, Forecasts, and Other Projections in Decision Support for Selected Sectors and Regions

Draft Report

U.S. Climate Change Science Program,
Synthesis and Assessment Product 5.1

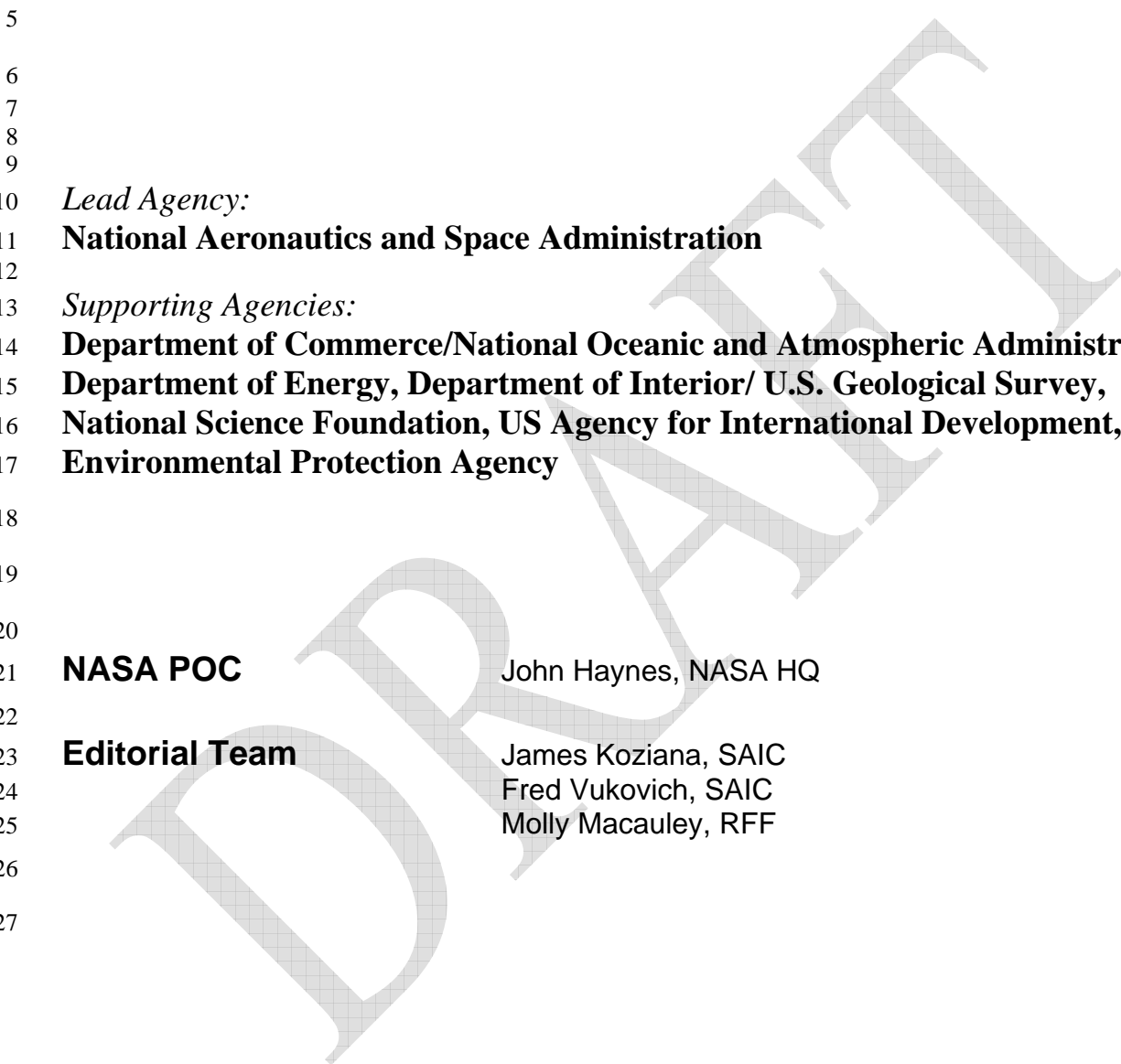
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National Aeronautics and Space Administration

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1 **Uses and Limitations of Observations, Data,**
2 **Forecasts, and Other Projections in Decision**
3 **Support for Selected Sectors and Regions**
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10 *Lead Agency:*
11 **National Aeronautics and Space Administration**

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13 *Supporting Agencies:*
14 **Department of Commerce/National Oceanic and Atmospheric Administration,**
15 **Department of Energy, Department of Interior/ U.S. Geological Survey,**
16 **National Science Foundation, US Agency for International Development,**
17 **Environmental Protection Agency**

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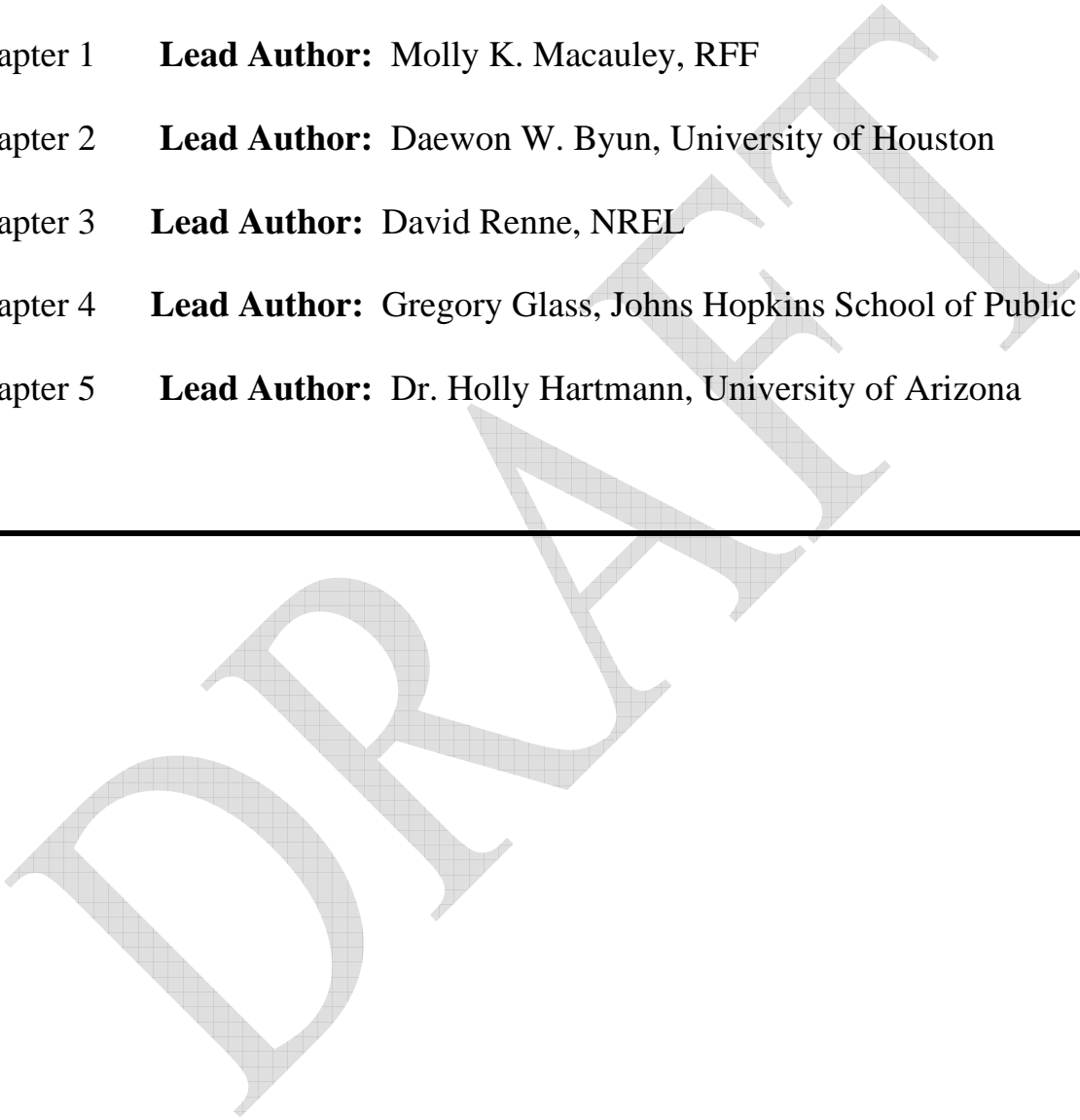
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1 **“Uses and Limitations of Observations, Data, Forecasts, and Other Projections**
2 **in Decision Support for Selected Sectors and Regions”**

3
4 **(Climate Change Science Program, Synthesis and Assessment Product [SAP] 5.1)**

5
6 **Executive Summary**

7
8 Earth information—the diagnostics of Earth’s climate, water, air, land, and other dynamic processes—is essential for
9 our understanding of humankind’s relationship to our natural resources and our environment. Earth information can
10 inform our scientific knowledge, our approach to resource and environmental management and regulation, and our
11 stewardship of the planet for future generations. New data sources, new ancillary and complementary technologies in
12 hardware and software, and ever-increasing modeling and analysis capabilities characterize the current and prospective
13 states of Earth science and are a harbinger of its promise. A host of Earth science data products is enabling a revolution
14 in our ability to understand climate and its anthropogenic and natural variations. Crucial to this relationship, however, is
15 understanding and improving the integration of Earth science information in the activities that support decisions
16 underlying national priorities: ranging from homeland security and public health to air quality and natural resource
17 management.

18
19 Also crucial is the role of Earth information in improving our understanding of the processes and effects of climate as it
20 influences or is influenced by actions taken in response to national priorities. Global change observations, data,
21 forecasts, and projections are integral to informing climate science.

22
23 The Synthesis and Assessment Product (SAP), “Uses and Limitations of Observations, Data, Forecasts, and Other
24 Projections in Decision Support for Selected Sectors and Regions” (SAP 5.1), examines the current and prospective
25 contributions of Earth science information in decision support activities and their relationship to climate change science.
26 The SAP contains a characterization and catalog of observational capabilities in a selective set of decision support
27 activities. It also contains a description of the challenges and promise of these capabilities and discusses the interaction
28 between users and producers of information (including the role, measurement, and communication of uncertainty and
29 confidence levels associated with decision support outcomes and their related climate implications).

30
31 **Decision Support Tools and Systems**

32 In 2002, the National Aeronautics and Space Administration (NASA) formulated a conceptual framework in the form of
33 a flow chart (Figure ES-1) to characterize the link between Earth science data and their potential contribution to
34 resource management and public policy. The framework begins with Earth observations, including measurements made
35 *in situ* and from airborne and space-based instruments. These data are inputs into Earth system models that simulate the
36 dynamic processes of land, the atmosphere, and the oceans. These models lead in turn to predictions and forecasts to
37 inform decision support tools (DSTs).

38
39 In this framework, DSTs are typically computer-based models assessing such phenomena as resource supply, the status
40 of real-time events (e.g., forest fires and flooding), or relationships among environmental conditions and other scientific
41 metrics (i.e., water-borne disease vectors and epidemiological data). These tools use data, concepts of relations among
42 data, and analysis functions to allow analysts to build relationships—including spatial, temporal, and process-based—
43 among different types of data, merge layers of data, generate model outcomes, and make predictions or forecasts.
44 Decision support tools are an element of the broader decision making context or Decision Support System (DSS). DSSs
45 include not just computer tools but the institutional, managerial, financial, and other constraints involved in the
46 decision-making process.

47
48 The outcomes in these decision frameworks are intended to enhance our ability to manage resources (management of
49 public lands and measurements for air quality and other environmental regulatory compliance) and evaluate policy
50 alternatives (as promulgated in legislation or regulatory directives) affecting local, state, regional, national, or even
51 international actions. To be exact, for a variety of reasons, many decisions are not based on data or models. In some
52 cases, formal modeling is not appropriate, timely, or feasible for all decisions. But among decisions that are influenced
53 by this information, the flow chart (Figure ES-1) characterizes a systematic approach for science to be connected to
54 decision processes.

1 For purposes of providing an organizational framework, the CCSP provides additional description of decision support:

2
3 In the context of activities within the CCSP framework, decision-support resources, systems, and
4 activities are climate-related products or processes that directly inform or advise stakeholders in order
5 to help them make decisions. These products or processes include analyses and assessments,
6 interdisciplinary research, analytical methods (including scenarios and alternative analysis
7 methodologies), model and data product development, communication, and operational services that
8 provide timely and useful information to decision makers, including policymakers, resource
9 managers, planners, government officials, and other stakeholders. (*“Our Changing Planet,” CCSP*
10 *FY2007, Chapter 7, p. 155*).

11 **Our Approach**

12 Our approach to this SAP has involved two overall tasks. The first task defines and describes an illustrative set of DSTs
13 in areas selected from a number of areas deemed nationally important by NASA and also included in societal benefit
14 areas identified by the intergovernmental Group on Earth Observations (GEO) in leading an international effort to build
15 a Global Earth Observation System of Systems (GOESS) (see Tables ES-1 and ES-2).
16

17
18
19 The areas we have chosen as our case studies are air quality, agricultural efficiency, energy management, water
20 management, and public health. As required by the *SAP 5.1 Prospectus*, in the case studies we:

- 21
- 22 • explain the observational capabilities that are currently or potentially used in these tools;
- 23 • identify the agencies and organizations responsible for their development, operation, and maintenance;
- 24 • characterize the nature of interaction between users and producers of information in delivering accessing and
25 assimilating information;
- 26 • discuss sources of uncertainty associated with observational capabilities and the decision tools and how they
27 are conveyed in decision support context and to decision makers; and
- 28 • describe relationships between the decision systems and global change information, such as whether the tools
29 at present contribute or in the future could contribute to climate-related predictions or forecasts.
30

31 Because our purpose in this first task is to offer case studies by way of illustration rather than a comprehensive
32 treatment of all DSTs in all national applications, in our second task we have taken steps to catalog other DSTs which
33 use or may use, or which could contribute to, forecasts and projections of climate and global change. The catalog is a
34 first step toward an ever-expanding inventory of existing and emerging DSTs. The catalog will be maintained on-line
35 for community input, expansion, and updating to provide a focal point for information about the status of DSTs and
36 how to access them.
37

38 The information in this report is largely from published literature and interviews with the sponsors and stakeholders of
39 the decision processes, as well as publications by and interviews with the producers of the scientific information used in
40 the tools.
41

42 **Our Case Studies**

43 We characterize the following DSTs:

- 44 1. The Production Estimate and Crop Assessment Division and its Crop Condition Data Retrieval and Evaluation
45 (PECAD/CADRE) system of the US Department of Agriculture, Foreign Agricultural Service (FAS).
46 PECAD/CADRE is the world’s most extensive and longest running (over two decades) operational user of
47 remote sensing for evaluation of worldwide agricultural productivity.
- 48 2. The Community Multiscale Air Quality (CMAQ) modeling system of the US Environmental Protection
49 Agency (EPA). CMAQ is a widely used, US continental/regional/urban-scale air quality decision support tool.

3. The Hybrid Optimization Model for Electric Renewables (HOMER), a micropower optimization model of the US Department of Energy's National Renewable Energy Laboratory (NREL). HOMER is used around the world to optimize deployment of renewable energy technologies.
4. Decision Support System to Prevent Lyme Disease (DDSPL) of the US Centers for Disease Control and Prevention (CDC) and Yale University. DDSPL seeks to prevent the spread of the most common vector-borne disease, Lyme disease, of which there are tens of thousands of cases annually in the US
5. RiverWare, developed by the University of Colorado-Boulder's Center for Advanced Decision Support for Water and Environmental Systems (CADSWES) in collaboration with the Bureau of Reclamation, Tennessee Valley Authority, and the Army Corps of Engineers. RiverWare is a hydrologic or river basin modeling system that integrates features of reservoir systems, such as recreation, navigation, flood control, water quality, and water supply, in a basin management tool with power system economics to provide basin managers and electric utilities a method of planning, forecasting, and scheduling reservoir operations.

Taken together, these DSTs demonstrate a rich variety of applications of observations, data, forecasts, and other predictions. In four of our studies, agricultural efficiency, air quality, water management, and energy management, the DSTs have become well established as a basis for public policy decision making. In the case of public health, our lead author points out reasons why direct applications of Earth observations to public health have tended to lag behind these other applications and thus is a relatively new application area. He also reminds us that management of air quality, agriculture, water, and energy—in and of themselves—have implications for the quality of public health. The DST he selects is a new, emerging tool intended to assist in prevention of the spread of infectious disease.

Our selection also varies in the geographic breadth of application, illustrating how users of these tools tailor them to relevant regions of analysis and how, in some cases, the geographic coverage of the tools carries over to their requirements for observations. For instance, PECAD/CADRE is used for worldwide study of agricultural productivity and has data requirements of wide geographic scope, HOMER can be used for renewable energy optimization throughout the world, and DDSPL focuses on the eastern, upper Midwest, and West Coast portions of the US. CMAQ is used to predict air quality for the contiguous US as well as regions and urban locales. RiverWare provides basin managers and electric utilities a method of planning, forecasting, and scheduling reservoir operations.

With the exception of DDSPL, none of the DSTs we considered for potential selection, nor those we discuss in this report, have to date made extensive use of climate change information and predictions or have been used to study the effect of a changing climate. However, in all cases, the developers and users of these DSTs fully recognize their applicability to climate change science. In the discussion of the five DSTs presented in this SAP, the authors describe how climate data and/or predictions might be used in these DSTs so that long-range decisions and planning might be accomplished, provided that good quality information and predictions can be ascertained.

Overview of the Chapters

In the Introduction we provide the rationale for the SAP and a brief overview of the chapters that follow. In the chapters that follow the Introduction, we describe the DST and its data sources, highlight potential uses as well as limits of the DSTs, note sources of uncertainty in using the tools, and finally, discuss the link between the DST and climate change and variability. After our summary, we offer general observations about similarities and differences among the studies.

Agricultural Efficiency: The Production Estimate and Crop Assessment Division (PECAD) of the US Department of Agriculture's Foreign Agricultural Service (FAS) uses remote sensing data for evaluation of worldwide agricultural productivity. PECAD supports the FAS mission to collect and analyze global crop intelligence information and provide periodic estimates used to inform official USDA forecasts for the agricultural market, including farmers; agribusiness; commodity traders and researchers; and federal, state, and local agencies. PECAD is often referred to as PECAD/CADRE with one of its major automated components known as the Crop Condition Data Retrieval and Evaluation (CADRE) geospatial database management system. Of all the DSTs we consider in this report, CADRE has the oldest pedigree as the operational outcome of two early, experimental earth observation projects during the 1970s and 1980s: the Large Area Crop Inventory Experiment (LACIE) and the Agriculture and Resources Inventory Surveys through Aerospace Remote Sensing (AgRISTARS).

Sources of data for CADRE include a large number of weather and other Earth observations from US, European, Japanese, and commercial systems. PECAD combines these data with crop models, a variety of GIS tools, and a large

1 amount of contextual information, including official government reports, trade and news sources, and on-the-ground
2 reports from a global network of embassy attaches and regional analysts.
3

4 Potential future developments in PECAD/CADRE could include space-based observations of atmospheric carbon
5 dioxide (CO₂) measurements and measurement of global sea surface salinity to improve understanding of the links
6 between the water cycle, climate, and oceans. Other opportunities for enhancing PECAD/CADRE include
7 improvements in predictive modeling capabilities in weather and climate.
8

9 One of the largest technology gaps in meeting PECAD requirements is the practice of designing Earth observation
10 systems for research rather than operational use, limiting the ability of PECAD/CADRE to rely on data sources from
11 non-operational systems. PECAD analysts require input data that are collected over long time periods, implying use of
12 operational systems that ensure continuous data streams and that minimize vulnerability to component failure through
13 redundancy.
14

15 Sources of uncertainty can arise at each stage of analysis, from the accuracy of data inputs to the assumptions in
16 modeling. PECAD operators have been able to benchmark, validate, verify, and then selectively incorporate additional
17 data sources and automated decision tools by way of detailed engineering reviews. Another aspect of resolving
18 uncertainty in PECAD is the extensive use of a convergence methodology to assimilate information from regional field
19 analysts and other experts. This convergence of evidence analysis seeks to reconcile various independent data sources to
20 achieve a level of agreement to minimize estimate error.
21

22 The relationship between climate and agriculture is complex, as agriculture is influenced not only by a changing
23 climate, but agricultural practices themselves are a contributory to climate change (e.g., in affecting land use and
24 influencing carbon fluxes). At present, PECAD is not directly used to address these dimensions of the climate-
25 agriculture interaction. However, many of the data inputs for PECAD are climate-related, thereby enabling PECAD to
26 inform understanding of agriculture as a “recipient” of climate-induced changes. For instance, observing spatial and
27 geographic trends in the output measures from PECAD can contribute to understanding how the agricultural sector is
28 responding to a changing climate. Likewise, trends in PECAD’s measures of the composition and production of crops
29 could shed light on the agricultural sector as a “contributor” to climate change (for instance, in terms of greenhouse gas
30 emissions or changes in soil that may affect the potential for agricultural soil carbon sequestration). The results
31 produced by PECAD may also be influenced by climate-induced changes in land use. In addition, the influences may
32 work in the other direction. The changes in the results overtime may be a barometer of land use changes such as
33 conversion from food production to biomass fuel production.
34

35 **Air Quality:** The EPA CMAQ modeling system has been designed to approach air quality by including state-of-the-
36 science capabilities for modeling tropospheric ozone, fine particles, toxics, acid deposition, and visibility degradation.
37 CMAQ is used to guide the development of air quality regulations and standards and to create state implementation
38 plans for managing air emissions. CMAQ also can be used to evaluate longer-term as well as short-term transport from
39 localized sources and to perform simulations using downscaled regional climate from global climate change scenarios.
40

41 The CMAQ modeling system contains three types of modeling components: a meteorological modeling system for the
42 description of atmospheric states and motions, emission models for man-made and natural emissions that are injected
43 into the atmosphere, and a chemistry-transport modeling system for simulation of the chemical transformation and fate.
44 Inputs for CMAQ, and their associated regional meteorological model, mesoscale model version 5 (MM5), can include,
45 but are not limited to, the comprehensive output from a general circulation model, anthropogenic and biogenic
46 emissions, description of wildland fires, land use and demographic changes, and meteorological and atmospheric
47 chemical species measurements by *in-situ* and remote sensing platforms, including satellites and aircraft.
48

49 CMAQ can be used to study questions such as: How will present and future emission changes affect attainment of air
50 quality standards? Will present and future emissions and/or climate/meteorological changes affect the frequency and
51 magnitudes of high pollution events? How will land use changes due to urbanization and global warming affect air
52 quality? How does long-range air pollution from other regions affect US air quality? How will changes in the long-
53 range transport due to the climate change affect air quality? How does wildland fire affect air quality and will climate
54 change affect wildland fire and subsequently air quality? How sensitive are the air quality predictions to changes in both
55 anthropogenic and biogenic emissions?
56

1 **Energy Management:** HOMER is a micropower optimization model of the US Department of Energy's NREL.
2 HOMER is able to calculate emission reductions enabled by replacing diesel-generating systems with renewable energy
3 systems in a micro-grid or grid-connected configuration. HOMER helps the user design grid-connected and off-grid
4 renewable energy systems by performing a wide range of design scenarios. HOMER can be used to address questions
5 such as: Which technologies are most cost-effective? What happens to the economics if the project's costs or loads
6 change? Is the renewable energy resource adequate for the different technologies being considered to meet the load?
7 HOMER does this by finding the least-cost combination of components that meet electrical and thermal loads.
8

9 The Earth observation information serving as input to HOMER is centered on wind and solar resource assessments
10 derived from a variety of sources. Wind data include surface and upper air station data, satellite-derived ocean and ship
11 wind data, and digital terrain and land cover data. Solar resource data include surface cloud, radiation, aerosol optical
12 depth, and digital terrain and land cover data from both *in-situ* and remote sensing sources.
13

14 All of the input data for HOMER can have a level of uncertainty attached to them. HOMER allows the user to perform
15 sensitivity tests on one or more variables and has graphical capabilities to display these results to inform decision
16 makers. As a general rule, the error in estimating the performance of a renewable energy system over a year is roughly
17 linear to the error in the input resource data.
18

19 One of the largest challenges in HOMER is the absence of direct or *in-situ* solar and wind resource measurements at
20 specific locations to which HOMER is applied. In addition, in many cases, values are not based on direct measurement
21 at all but are approximations based on the use of algorithms to convert a signal into the parameter of interest as is the
22 case with most satellite-derived data products. For example, satellite-derived ocean wind data are not based on direct
23 observation of the wind speed above the ocean surface but are derived from an algorithm that infers wind speed based
24 on wave height observations. Observations of aerosol optical depths (for which considerable research is underway) can
25 be complicated by irregular land-surface features that places limitations on the application of algorithms for satellite-
26 derived measures.
27

28 For renewable energy resource mapping, improved observations of key weather parameters (for instance, wind speed
29 and direction at various heights above the ground, particularly at the hub height of wind energy turbine systems, and
30 over the open oceans at higher and higher spatial resolutions, and improved ways of differentiating snow cover and
31 bright reflecting surfaces from clouds) will be of value to the renewable energy community. New, more accurate
32 methods of related parameters, such as aerosol optical depth, would also improve the resource data.
33

34 The relationship between HOMER and global change information is largely by way of the dependence of renewable
35 energy resource input measurements on weather and local climate conditions. Although HOMER was not designed to
36 be a climate-related management decision-making tool, by optimizing the mix of hybrid renewable energy technologies
37 for meeting load conditions, HOMER can enables users to respond to climate change and variability in their energy
38 management decisions. HOMER could be used to evaluate how renewable energy systems can be used cost-effectively
39 to displace fossil-fuel-based systems.
40

41 **Public Health:** The DDSPL is operated by the US CDC and Yale University to address questions related to the likely
42 distribution of Lyme disease east of the 100th meridian, where most cases occur. Lyme disease is the most common
43 vector-borne disease in the US, with tens of thousands of cases annually. Most human cases occur in the Eastern and
44 upper Midwest portions of the US, although there is a secondary focus along the West Coast. Vector-borne diseases are
45 those in which parasites are transmitted among people or from wildlife to people by insects or arthropods (as vectors,
46 they do not themselves cause disease). The black-legged tick is typically the carrier of the bacteria causing Lyme
47 disease.
48

49 Early demonstrations during the 1980s showed the utility of Earth observations for identifying locations and times that
50 vector-borne diseases were likely to occur, but growth of applications has been comparatively slow. Earth observing
51 instruments have not been designed to monitor disease risk; rather, data gathered from these platforms are "scavenged"
52 for public health risk assessment. DDSPL uses satellite data and derived products, such as land cover together with
53 meteorological data and census data, to characterize statistical predictors of the presence of black-legged ticks. The
54 model is validated by field surveys. The DDSPL is thus a means of setting priorities for the likely geographic extent of
55 the vector; the tool does not at present characterize the risk of disease in the human population.
56

1 Future use of DDSPL partly depends on whether the goal of disease prevention or the goal of treatment drives public
2 health policy decisions. In addition, studies have shown that communication to the public about the risk in regions with
3 Lyme disease often fails to reduce the likelihood of infection. The role of improved Earth science data is unclear in
4 terms of improving the performance of DDSPL because at present the system has a level of accuracy deemed “highly
5 satisfactory.” Future use may instead require a model of sociological/behavioral influences among the population.

6
7 Standard statistical models and in-field validation are used to assess the uncertainty in decision making with DDSPL.
8 The accuracy of clinical diagnoses also influences the ultimate usefulness of DDSPL as an indicator tool to characterize
9 the geographic extent of the vectors.

10
11 The DDSPL is one of the few public health DSTs that has explicitly evaluated the effects of climate variability. Using
12 outputs of a Canadian climate change model, study has shown that with warming global mean temperatures predicted
13 by the year 2050 to 2080 the geographic range of the tick vector will decrease at first, with reduced presence in the
14 southern boundary, and then expand into Canada and the central region of North America where it now absent. The
15 range also moves away from population concentrations.

16
17 **Water Management:** RiverWare was developed and is maintained by CADSWES in collaboration with the Bureau of
18 Reclamation, Tennessee Valley Authority, and the Army Corps of Engineers. It is a river basin modeling system that
19 integrates features of reservoir systems, such as recreation, navigation, flood control, water quality, and water supply in
20 a basin management tool, with power system economics to provide basin managers and electric utilities a method of
21 planning, forecasting, and scheduling reservoir operations. RiverWare uses an object-oriented software engineering
22 approach in model development. The object oriented software-modeling strategy allows computational methods for new
23 processes, additional controllers for providing new solution algorithms, and additional objects for modeling new
24 features to be added easily to the modeling system. RiverWare is data intensive in that a specific river/reservoir system
25 and its operating policies must be characterized by the data supplied to the model. This allows the models to be
26 modified as new features are added to the river/reservoir system and/or new operating policies are introduced. The
27 data-intensive feature allows the model to be used for water management in most river basins.

28
29 Riverware is menu driven through a graphical user interface (GUI). The basin topology is developed through the
30 selection of a reservoir, reach, confluence, and other necessary objects and by entering the data associated with each
31 object manually or through importing files. Utilities within RiverWare provide a means to automatically execute many
32 simulations, to access data from external sources, and to export model results. Users also define operating policies
33 through the GUI as system constraints or rules for achieving system management goals (e.g., related to flood control,
34 water supplies, water quality, navigation, recreation, and power generation). The direct use of Earth observations in
35 RiverWare is limited. Unlike traditional hydrologic models that track the transformation of precipitation (e.g., rain and
36 snow) into soil moisture and streamflow, RiverWare uses supplies of water to the system as input data. These data are
37 derived from a hydrologic model where direct use of earth observations can be and have been made. Application of
38 RiverWare is limited by the specific implementation defined by the user and by the quality of the input data. It has
39 tremendous flexibility in the kinds of data it can use, but long records of data are required to overcome the issue of data
40 non-stationarity.

41
42 The specific application of RiverWare in the context of mid- or long-range planning for a specific river basin will reflect
43 whether decisions may rely on global change information. For mid-range planning of reservoir operations,
44 characterization and projections of interannual and decadal-scale climate variability (e.g., monitoring, understanding,
45 and predicting interannual climate phenomena such as the El Nino-Southern Oscillation) are important. For long-term
46 planning, global warming has moved from the realm of speculation to general acceptance. The impacts of global
47 warming on water resources, and their implications for management, have been a major focus in the assessments of
48 climate change. The estimates of potential impacts of climate change on precipitation have been inconclusive, leading to
49 increasing uncertainty about the reliability of future water supplies.

50 51 **General Observations**

52 Application of all of the DSTs involves a variety of input data types, all of which have some degree of uncertainty in
53 terms of their accuracy. The amount of uncertainty associated with resource data can depend heavily on how the data
54 are obtained. Quality *in-situ* measurements of wind and solar data suitable for application in HOMER can have
55 uncertainties of less than $\pm 3\%$ of true value; however, when estimation methods are required, such as the use of Earth
56 observations, modeling, and empirical techniques, uncertainties can be as much as $\pm 10\%$ or more. The DSTs address

1 uncertainty by allowing users to perform sensitivity tests on variables. With the exception of HOMER, a significant
2 amount of additional traditional on-the-ground reports are a critical component. In the case of PECAD/CADRE,
3 uncertainty is resolved in part by extensive use of a convergence methodology to assimilate information from regional
4 field analysts and other experts. This brings a large amount of additional information to PECAD/CADRE forecasts, well
5 beyond the automated outputs of DSTs. In RiverWare, streamflow and other hydrologic variables respond to
6 atmospheric factors such as precipitation, and obtaining quality precipitation estimates is a formidable challenge,
7 especially in the western US where orographic effects produce large spatial variability and where there is a scarcity of
8 real-time precipitation observations and poor radar coverage.

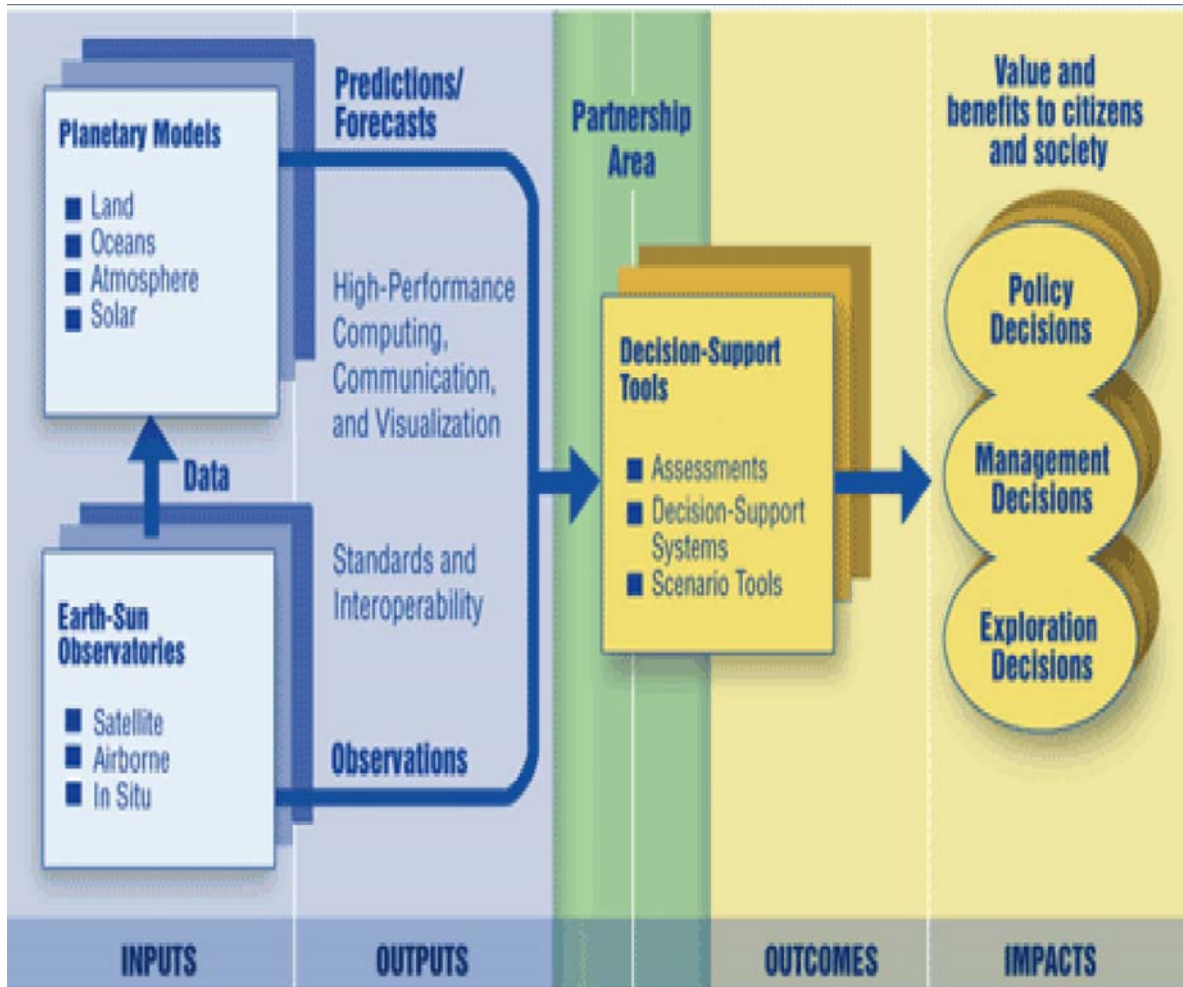
9
10 In terms of their current or prospective use of climate change predictions or forecasts as DST *inputs*, or the
11 contributions of DST *outputs* to understanding, monitoring, and responding to a changing climate, the status is mixed.
12 DDSPL is one of the few public health decision support tools that has explicitly an evaluation of the potential impact of
13 climate change scenarios on an infectious disease system. None of the other DSTs at present is directly integrated with
14 climate change measurements, but all of them can and may in the future take this step. PECAD/CADRE's assessment of
15 global agricultural production will certainly be influenced by reliable observations and forecasts of climate change and
16 variability as model inputs, just as the response of the agricultural sector to a changing climate will feedback into
17 PECAD/CADRE production estimates. HOMER's renewable energy optimization calculations will be directly affected
18 by climate-related changes in renewable energy resource supplies and will enhance our ability to adapt to climate-
19 induced changes in energy management and forecasting. Air quality will definitely be affected by global climate
20 change. The ability of CMAQ to predict those affects is conditional on acquiring accurate predictions of the
21 meteorology under the climate change conditions that will take place in the US and accurate emission scenarios for the
22 future. Given these inputs to CMAQ, reliable predictions of the air quality and their subsequent health affects can be
23 ascertained. It was noted that there is great difficulty in integrating climate change information into RiverWare and
24 other such water management models. The multiplicity of scenarios and vague attribution of their probability for
25 occurrence, which depends on feedback among social, economic, political, technological, and physical processes,
26 complicates conceptual integration of climate change impacts assessment results in a practical water management
27 context. Furthermore, the century timescales of climate change exceed typical planning and infrastructure design
28 horizons in water management.

29
30 **Audience and Intended Use**

31 The *CCSP SAP 5.1 Prospectus* describes the audience and intended use of this report:

32
33 This synthesis and assessment report is designed to serve decision makers and stakeholder
34 communities interested in using global change information resources in policy, planning, and other
35 practical uses. The goal is to provide useful information on climate change research products that
36 have the capacity to inform decision processes. The report will also be valuable to the climate change
37 science community because it will indicate types of information generated through the processes of
38 observation and research that are particularly valuable for decision support. In addition, the report will
39 be useful for shaping the future development and evaluation of decision-support activities, particularly
40 with regard to improving the interactions with users and potential users.

41
42 There are a number of national and international programs focusing on the use of Earth observations
43 and related prediction capacity to inform decision support tools (see Table ES-3, "Related National
44 and International Activities"). These programs both inform and are informed by the CCSP and are
45 recognized in the development of this product. (*CCSP Synthesis and Assessment Product 5.1,*
46 *Prospectus for "Uses and Limitations of Observations, Data, Forecasts, and Other Projections in*
47 *Decision Support for Selected Sectors and Regions," 28 February 2006)*



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Figure ES-1: The flow of information associated with decision support in the context of variability and change in climate and related systems (Source: CCSP Product 5.1 Prospectus, Appendix D).

1 Table ES-1: List of NASA National Applications Areas (*Appendix B, CCSP SAP 5.1 Prospectus*).

2

Nationally Important Applications	Nationally Important Applications
Agricultural Efficiency	Ecological Forecasting
Air Quality	Energy Management
Aviation	Homeland Security
Carbon Management	Invasive Species
Coastal Management	Public Health
Disaster Management	Water Management

3

4

5 Table ES-2. Societal benefit areas identified by the Group on Earth Observations (GEO) for the Global Earth
6 Observations System of Systems (GEOSS) (http://www.earthobservations.org/about/about_GEO.html) (accessed May
7 2007)

8

9

GEOSS Socio-Benefit Area Keywords	GEOSS Socio-Benefit Area Descriptions
Health	Understanding environmental factors affecting human health and well-being
Disasters	Reducing loss of life and property from natural and human-induced disasters
Forecasts	Improving weather information, forecasting, and warning
Energy	Improving management of energy resources
Water	Improving water resource management through better understanding of the water cycle
Climate	Understanding, assessing, predicting, mitigating, and adapting to climate variability and change
Agriculture	Supporting sustainable agriculture and combating desertification
Ecology	Improving the management and protection of terrestrial, coastal, and marine ecosystems

10

11

12 Table ES-3. References to Related National and International Activities (*Source: Appendix C, CCSP SAP 5.1*
13 *Prospectus*)

14

Priority	National	International
Climate Change	Climate Change Science Program and Climate Change Technology Program	Intergovernmental Panel on Climate Change and World Climate Research Programme
Global Earth Observations	National Science and Technology Council Committee on Environment and Natural Resources Subcommittee The United States Group on Earth Observations (USGEO)	Group on Earth Observations (GEO)
Weather	U.S. Weather Research Program (USWRP)	World Meteorological Organization
Natural Hazards	NSTC CENR Subcommittee on Disaster Reduction	International Strategy for Disaster Reduction
Sustainability	NSTC CENR Subcommittee on Ecosystems	World Summit on Sustainable Development
E-Government	Geospatial One-Stop and the Federal Geographic Data	World Summit on the Information Society

1
2 **“Uses and Limitations of Observations, Data, Forecasts, and Other Projections**
3 **in Decision Support for Selected Sectors and Regions”**

4
5 **(Climate Change Science Program, Synthesis and Assessment Product [SAP] 5.1)**
6

7
8 **Introduction**
9

10 This Synthesis and Assessment Product (SAP), “Uses and Limitations of Observations, Data, Forecasts, and Other
11 Projections in Decision Support for Selected Sectors and Regions” (SAP 5.1), examines the current and prospective
12 contribution of Earth science information/data in decision support activities and their relationship to climate change
13 science. The SAP contains a characterization and catalog of observational capabilities in an illustrative set of decision
14 support activities. It also contains a description of the challenges and promises of these capabilities and discusses the
15 interaction between users and producers of information, including the role, measurement, and communication of
16 uncertainty and confidence levels associated with decision support outcomes and their related climate implications.
17

18 The organizing basis for the chapters in this SAP is the decision support tools (DST), which are typically computer-
19 based models assessing such phenomena as resource supply, the status of real-time events (e.g., , forest fires and
20 flooding), or relationships among environmental conditions and other scientific metrics (for instance, water-borne
21 disease vectors, and epidemiological data). These tools use data, concepts of relations among data, and analysis
22 functions to allow analysts to build relationships—including spatial, temporal, and process-based—among different
23 types of data, merge layers of data, generate model outcomes, and make predictions or forecasts. DSTs are an element
24 of the broader decision-making context, the decision support system (DSS). DSSs include not just computer tools but
25 also the institutional, managerial, financial, and other constraints involved in decision making.
26

27 Our approach to this SAP is to define and describe an illustrative set of DSTs in areas selected from topics deemed
28 nationally important and included in societal benefit areas identified by the intergovernmental Group on Earth
29 Observations in leading an international effort to build a Global Earth Observation System of Systems. The areas we
30 have chosen as our focus are air quality, agricultural efficiency, energy management, water management, and public
31 health. The DSTs we characterize are:

- 32 1. The Production Estimate and Crop Assessment Division and its Crop Condition Data Retrieval and Evaluation
33 system (PECAD/CADRE) of the US Department of Agriculture, Foreign Agricultural Service (FAS).
34 PECAD/CADRE is the world’s most extensive and longest running (over two decades) operational user of
35 remote sensing for evaluation of worldwide agricultural productivity.
- 36 2. The Community Multiscale Air Quality (CMAQ) modeling system of the US Environmental Protection
37 Agency (EPA). CMAQ is a widely used, US continental/regional/urban-scale air quality decision support tool.
- 38 3. The Hybrid Optimization Model for Electric Renewables (HOMER), a micropower optimization model of the
39 US Department of Energy’s National Renewable Energy Laboratory (NREL). HOMER is used around the
40 world to optimize deployment of renewable energy technologies.
- 41 4. The Decision Support System to Prevent Lyme Disease (DDSPL) of the US Centers for Disease Control and
42 Prevention (CDC) and Yale University. DDSPL seeks to prevent the spread of the most common vector-borne
43 disease, Lyme disease, of which there are tens of thousands of reported cases annually in the United States.
- 44 5. RiverWare, developed by the University of Colorado-Boulder’s Center for Advanced Decision Support for
45 Water and Environmental Systems (CADSWES) in collaboration with the Bureau of Reclamation, Tennessee
46 Valley Authority, and the Army Corps of Engineers, is a hydrologic or river basin modeling system that
47 integrates features of reservoir systems, such as recreation, navigation, flood control, water quality, and water
48 supply, in a basin management tool with power system economics to provide basin managers and electric
49 utilities a method of planning, forecasting, and scheduling reservoir operations.
50

51 Taken together, these DSTs demonstrate a rich variety of applications of observations, data, forecasts, and other
52 predictions. In four of our studies—agricultural efficiency, air quality, water management, and energy management—

1 the DSTs have become well established as a basis for public policy decision making. In the case of public health, our
2 lead author points out reasons why direct applications of Earth observations to public health have tended to lag behind
3 these other applications and thus is a relatively new applications area. He also reminds us that management of air
4 quality, agriculture, water, and energy—in and of themselves—have implications for the quality of public health. The
5 DST selected for public health is a new and emerging tool intended to assist in prevention of the spread of infectious
6 disease.

7
8 With the exception of DDSPL, none of the DSTs we considered for potential selection, nor those we discuss in this
9 report, have to date made extensive use of climate change information or been used to study the effect of a changing
10 climate. However, in all cases, the developers and users of these DSTs fully recognize their applicability to climate
11 change science. In the discussion of the five DSTs presented in this SAP, the authors describe how reliable climate data
12 and/or predictions might be used in these DSTs so that long-range decisions and planning might be accomplished.

DRAFT

Chapter 1

Decision Support for Agricultural Efficiency

Lead Author: Molly K. Macauley

1. Introduction

The efficiency of agriculture has been one of the most daunting challenges confronting mankind in its need to manage natural resources within the constraints of weather, climate, and other environmental conditions. Defined as maximizing output per unit of input, agricultural efficiency reflects a complex relationship among factors of production (including seed, soil, human, and physical capital) and the exogenous influence of nature (such as temperature, sunlight, weather, and climate). The interaction of agricultural activity with the environment creates another source of interdependence, (e.g., the effect on soil and water from applications of pesticides, fungicides, and fertilizer). Agricultural production has long been a large component of international trade and of strategic interest as an indicator of the health and security of nations.

The relationship between climate change and agriculture is complex. A changing climate can influence agricultural practices (e.g., climate-induced changes in patterns of rainfall could lead to changes in these practices). Agriculture is not only influenced by a changing climate, but agricultural practices themselves are a contributory factor through emissions of greenhouse gases and influences on fluxes of carbon through photosynthesis and respiration. In short, agriculture is both a contributor to and a recipient of the effects of a changing climate (Rosenzweig, 2003; National Assessment Synthesis Team, 2004).

The use of Earth observations by the agricultural sector has a long history. The Large Area Crop Inventory Experiment (LACIE), jointly sponsored by the US National Aeronautics and Space Administration (NASA), the US Department of Agriculture (USDA), and the National Oceanic and Atmospheric Administration (NOAA) conducted from 1974 to 1978 demonstrated the potential for satellite observations to make accurate, extensive, and repeated surveys for global crop forecasts. LACIE used observations from the Landsat series of multi-spectral scanners on sun-synchronous satellites. The Agriculture and Resources Inventory Surveys through Aerospace Remote Sensing (AgRISTARS) followed LACIE and extended the use of satellite observations to include early warning of production changes, inventory and assessment of renewable resources, and other activities (Congressional Research Service, 1983; National Research Council, 2007; Kaupp *et al.*, 2005). Today these data are used by agencies of the federal government, commodity trading companies, farmers, relief agencies, other governments, and essentially anyone with an interest in crop production at a global scale.

An approach, among others, to increasing agricultural efficiency is to expand and enhance uses of Earth observation data for (1) policy and resource management decision support, (2) monitoring and measuring climate change affects, and (3) providing policy and resource climate change decision support. The foremost example of the application of Earth observations in agriculture is found in the USDA's crop-monitoring decision-support system, the Production Estimates and Crop Assessment Division (PECAD) of the USDA's Foreign Agricultural Service (FAS). (Reorganization at USDA finds the PECAD functionality, but not the name, residing within the USDA's FAS as part of the Office of Global Analysis, Impact Analysis Division, International Production Assessment [USDA/FAS/OGA/IAD/IPA]). PECAD is now the world's most extensive and longest running (over two decades) operational user of remote sensing data for evaluation of worldwide agricultural productivity (NASA, 2001). A Description of the PECAD decision-support system, its functionality, its analysis style, how it deals with making decisions under uncertainty, and its future uses form the basis of this chapter.

2. Description of PECAD

The USDA/FAS uses PECAD to analyze global agricultural production and crop conditions affecting planting, harvesting, marketing, commodity export and pricing, drought monitoring, and food assistance. Access to and uses of PECAD are largely by the federal government, rather than state and local governments, as a means of assessing regions of interest in global agricultural production.

PECAD uses satellite data, worldwide weather data, and agricultural models in conjunction with FAS overseas post reports, foreign government official reports, and agency travel observations to support decision making. FAS also works closely with the USDA Farm Service Agency and the Risk Management Agency to provide early warning and critical analysis of major crop events in the US. (FAS OnLine Crop Assessment at

1 http://www.fas.usda.gov/pecad2/crop_assmnt.html, accessed April 2007). FAS seeks to promote the security and
2 stability of the US food supply, improve foreign market access for U.S. agricultural products, provide reports on world
3 food security, and advise the US government on international food aid requirements. FAS bears the primary
4 responsibility for USDA's overseas activities: market development, international trade agreements and negotiations, and
5 the collection and analysis of statistics and market information. FAS also administers USDA's export credit guarantee
6 and food aid programs.

7 PECAD's Crop Condition Data Retrieval and Evaluation (CADRE) database management system, the
8 operational outcome of the LACIE and AgRISTARs projects, was one of the first geographic information systems (GIS)
9 designed specifically for global agricultural monitoring (Reynolds, 2001). CADRE is used to maintain a large satellite
10 imagery archive to permit comparative interpretation of incoming imagery with that of past weeks or years. The
11 database contains multi-source weather data and other environmental data that are incorporated as inputs for models to
12 estimate parameters such as soil moisture, crop stage, and yield. These models also indicate the presence and severity of
13 plant stress or injury. The information from these technologies is used by PECAD to produce, in conjunction with the
14 World Agricultural Outlook Board, official USDA foreign crop production estimates. (FAS OnLine Crop Assessment at
15 http://www.fas.usda.gov/pecad2/crop_assmnt.html, accessed April 2007)

16 Figure 1-1 (Kaupp *et al.*, 2005, p. 5) illustrates the global data sources and decision support tools for PECAD.
17 The left-hand portion of the figure shows sources of data for the CADRE geospatial DBMS. These inputs include
18 station data from the World Meteorological Organization and coarse resolution data from Meteosat, Scanning
19 Multichannel Microwave Radiometer (SSMR), and Geostationary Satellite (GOES). Meteosat, operated by the
20 European Organization for the Exploitation of Meteorological Satellites (EUMETSAT), provides visible and infrared,
21 weather-oriented imaging. The SSMR and its successor, the Special Sensor Microwave/Imager (SSM/I), are microwave
22 radiometric instruments in the US Air Force Defense Meteorological Satellite Program. Additional weather data come
23 from the US GOES program.

24 Medium resolution satellite data include Advanced Very High Resolution Radiometer (AVHRR)/NOAA,
25 Spot-Vegetation, and Terra/Aqua MODIS. AVHRR/NOAA, operated by NOAA, provides cloud cover and land, water,
26 and sea surface temperatures at approximately 1-km spatial resolution. The Systeme Pour L'Observation de la Terre
27 (SPOT) supplies commercial optical Earth imagery at resolutions from 2.5 to 20 meters (m); SPOT-Vegetation is a
28 sensor providing daily coverage at 1 km resolution. The NASA Moderate Resolution Imaging Spectroradiometers
29 (MODIS) on the Terra and Aqua satellites, part of the US Earth Observation System, show rapid biological and
30 meteorological changes at 250 to 1,000 m spatial resolution every two days. NASA's Global Inventory Modeling and
31 Mapping Studies (NASA/GIMMS) group processes data acquired from SPOT and Terra/Aqua MODIS.
32 NASA/GIMMS provides PECAD with cross-calibrated global time series of Normalized Difference Vegetation Index
33 maps from AVHRR and SPOT-Vegetation. Moderate-resolution Earth observation data are also used from the US
34 Landsat program.

35 Sources of high resolution and radar altimeter satellite data include SPOT, IKONOS, Poseidon, and Jason.
36 IKONOS is a commercial Earth imaging satellite providing spatial resolution of 1 and 4 m. Data from Poseidon and its
37 successor, Jason, provide lake and reservoir surface elevation estimates. Poseidon, part of the TOPEX/Poseidon
38 mission, and Jason-1, a follow-on mission, are joint ventures between NASA and the Centre National d'Etudes
39 Spatiales (CNES) using radar altimeters to map ocean surface topography (including sea surface height, wave height,
40 and wind speed above the ocean). These data enable analysts to assess drought or high water-level conditions within
41 some of the world's largest lakes and reservoirs to predict effects on downstream irrigation potential and inform
42 production capacity estimates (Birkett and Doorn, 2004; Kanarek, 2005). The assimilation of these data into PECAD is
43 described in detail in a recent systems engineering report (NASA, 2004b).

44 PECAD combines the satellite and climate data, crop models (along the bottom portion of the figure), a variety
45 of GIS tools, and a large amount of contextual information, including official government reports, trade and new
46 sources, and on-the-ground reports from a global network of embassy attaches and regional analysts. The integration
47 and analysis is attained by "convergence of evidence analysis" (Kaupp *et al.*, 2005). This convergence methodology
48 seeks to reconcile various independent data sources to achieve a level of agreement to minimize estimate error (NASA,
49 2004a).

50 The crop assessment products indicated along the right-hand side of the PECAD architecture in figure 1-1
51 represent the periodic global estimates used to inform official USDA forecasts. These products are provided to the
52 agricultural market, including farmers; agribusiness; commodity traders and researchers; and federal, state, and local
53 agencies. In addition to CADRE, other automated components include two features providing additional types of
54 information. The FAS Crop Explorer (middle of diagram) is a feature on the FAS Web site since 2002 (Kanarek, 2005).
55 Crop Explorer offers near-real-time global crop condition information based on satellite imagery and weather data from
56 the CADRE database and NASA/GIMMS. Thematic maps of major crop growing regions show vegetation health,

1 precipitation, temperature, and soil moisture. Time-series charts show growing season data for agro-meteorological
2 zones. For major agriculture regions, Crop Explorer provides crop calendars and crop areas. Through Archive Explorer,
3 PECAD provides access to an archive of moderate- to high-resolution data, allowing USDA users (access is controlled
4 by user name and password) to search an image database.

6 **3. Potential Future Use and Limits**

7 The most recent enhancements to PECAD/CADRE have included the integration and evaluation of MODIS,
8 Topex/Poseidon, and Jason-1 products (NASA, 2006a). Figure 1-2 summarizes the Earth system models, Earth
9 observations data, and the CADRE DBMS and characterizes their outputs. Several planned Earth observations missions
10 anticipated when this image was prepared (indicated in italics) show how PECAD/CADRE could incorporate new
11 opportunities, including those with additional land, atmosphere, and ocean observations. These would include space-
12 based observations of atmospheric carbon dioxide (CO₂) from the Orbiting Carbon Observatory (OCO) and
13 measurement of global sea surface salinity (Aquarius) to improve understanding of the links between the water cycle,
14 climate, and the ocean. Other opportunities for enhancing PECAD/CADRE could include improvements in predictive
15 modeling capabilities in weather and climate (National Aeronautics and Space Administration, 2006a).

16 In a recent evaluation report for PECAD, NASA has acknowledged that one of the largest technology gaps in
17 meeting PECAD requirements is the design of NASA systems for limited duration research purposes rather than for
18 long-term operational uses (NASA, 2004a). PECAD analysts require long-term continuity for inputs, implying the use
19 of operational systems that ensure continuous data streams over time and that minimize vulnerability to component
20 failure through redundancy. The report also emphasizes that PECAD requires systems that deliver real-time or near-
21 real-time data. Many NASA missions have traded timeliness for experimental research or improvements in other
22 properties of the information delivered. Additionally, the report identifies several potential Earth science data streams
23 that have not yet been addressed, including water balance, the radiation budget (including solar and long wave radiation
24 flux), and elevation, and expresses concern about the potential continuity gap between Landsat 7 and the Landsat Data
25 Continuity Mission.

26 A 2006 workshop convened at the United Nations Food and Agriculture Organization (FAO) by the Integrated
27 Global Observations of Land (IGOL) team identified priorities for agricultural monitoring during the next 5 to 10 years
28 as part of the emerging GEOSS. In summary, the meeting called for several initiatives including the following (United
29 Nations Food and Agriculture Organization, 2006):

- 30 (1) the need for an international initiative to fill the data gap created by the malfunction of Landsat 7;
- 31 (2) a system to collect cloud-free, high resolution (10 to 20 m) visible, near-infrared, and shortwave infrared
32 observations at 5 to 10-day intervals;
- 33 (3) workshops on global agricultural data coordination and on integrating satellite and *in situ* observations;
- 34 (4) an inventory and evaluation of existing agro-meteorological data sets to identify gaps in terrestrial networks, the
35 availability of data, and validation and quality control in order to offer specific recommendations to the World
36 Meteorological Organization to improve its database;
- 37 (5) funding to support digitizing, archiving, and dissemination of baseline data; and
- 38 (6) an international workshop within the GEOSS framework to develop a strategy for “community of practice” for
39 improved global agricultural monitoring.

40 A recent study by the National Research Council (NRC) of the use of land remote sensing expressed additional
41 concerns about present limits on the usefulness of Earth observations in agricultural assessment) (National Research
42 Council, 2007). These include data integration, communication of results, and capacity to use and interpret data.
43 Specifically, the NRC identified these concerns:

- 44 (1) inadequate integration of spatial data with socioeconomic data (locations and vulnerabilities of human populations
45 and access to infrastructure) to provide information that is effective in generating response strategies to disasters or
46 other factors influencing access to food or impairing agricultural productivity;
- 47 (2) a lack of communication between remote sensing mission planners, scientists and decision makers to ascertain what
48 types of information enable the most effective food resource management; and
- 49 (3) shortcomings in the acquisition, archiving, and access to long-term environmental data and development of capacity
50 to interpret these data, including maintaining continuity of satellite coverage over extended time frames, providing
51 access to affordable data, and improving capacity to interpret data.

53 **4. Uncertainty**

54 Two aspects of PECAD provide means of validation and verification of crop assessments. One is the maturity
55 of PECAD as a decision support system. Over the years, it has been able to benchmark, validate, verify, and then
56 selectively incorporate additional data sources and automated decision tools. An example of the systems engineering

1 review associated with a decision to incorporate Poseidon and Jason data, for example, is offered in a detailed NASA
2 study (NASA, 2004b).

3 Another example demonstrates how data product accuracy, delivery, and coverage are tested through
4 validation and verification during the process of assimilating new data sources, as well as to ascertain the extent to
5 which different data sources corroborate model outputs (Kaupp *et al.*, 2005). Essential considerations included
6 enhanced repeatability of results, increased accuracy, and increased throughput speed.

7 Another significant aspect of resolving uncertainty in PECAD is its extensive use of a convergence
8 methodology to assimilate information from regional field analysts and other experts. PECAD seeks to provide accurate
9 and timely estimates of production, yet must accommodate physical and biological influences (e.g., weather or pests),
10 the fluctuations in agricultural markets, and developments in public policy impacting the agricultural sector (Kaupp *et al.*,
11 2005). The methodology brings a large amount of additional information to the PECAD forecasts, well beyond the
12 automated outputs of the decision support tools. This extensive additional analysis may not fully correct for, but
13 certainly mitigates, the uncertainty inherent in the data and modeling at the early stages. Figure 1-3, a simplified
14 version of Figure 1-1, shows the step represented by the analyses that take place during this convergence of information
15 in relation to the outputs obtained from the decision support tools and their data inputs. Figure 1-4 further describes the
16 nature of information included in the convergence methodology in addition to the outputs of the data and automated
17 decision support tools. Official reports, news reports, field travel, and attaché reports are additional inputs at this stage.
18 The process is described as one in which, “while individual analysts reach their conclusions in different ways, giving
19 different weight to various inputs, analysts join experts from the USDA’s Economic Research Service and National
20 Agricultural Statistics Service once a month in a ‘lock-up.’ In this setting, the convergence of evidence approach is fully
21 realized as analysts join together in committee formed by (agricultural) commodity. Final commodity production
22 estimates are achieved by committee consensus” (NASA, 2004a, p. 4).

23 The convergence methodology is at the heart of analysis and the final step prior to official world agricultural
24 production estimates and suggests that uncertainty inherent in data and automated models at earlier stages of the
25 analysis are “scrubbed” in a broader context at this final stage.

26 27 **5. Global change information and PECAD**

28 The relationship between climate and agriculture is complex. Agriculture is not only influenced by a changing
29 climate, but agricultural practices themselves are a contributory factor through emissions of greenhouse gases and
30 influences on fluxes of carbon through photosynthesis and respiration. In short, agriculture is both a contributor to and a
31 recipient of the effects of a changing climate (Rosenzweig, 2003).

32 At present, PECAD is not directly used to address these dimensions of the climate-agriculture interaction.
33 However, many of the data inputs for PECAD are climate-related, thereby enabling PECAD to inform understanding of
34 agriculture as a “recipient” of climate-induced changes in temperature, precipitation, soil moisture, and other variables.
35 If reliable climate change prediction of temperature, precipitation, soil moisture, and other necessary variables become
36 available, then these variables can be used as input to PECAD and the results may be used to provide long-range
37 planning of agricultural practices. In addition, spatial and geographic trends in the output measures from PECAD have
38 the potential to contribute to understanding of how the agricultural sector is responding to a changing climate.

39 The output measures of PECAD also can serve to inform understanding of agriculture as a “contributor” to
40 climate changes. For example, observing trends in PECAD’s measures of production and composition of crops can shed
41 light on the contribution of the agriculture sector to agricultural soil carbon sequestration.

42 *The effects of a changing climate on agricultural efficiency as measured by PECAD:*

43
44
45 PECAD relies on several data sources for agro-meteorological phenomena that affect crop production and the quality of
46 agricultural commodities. These include data that are influenced by climate (e.g., precipitation, temperatures, snow
47 depth, and soil moisture). The productivity measures from PECAD (yield multiplied by area) are also influenced by
48 climate-induced changes in these data.

49 In addition, the productivity measures of PECAD can be indirectly but significantly affected by possible
50 climate-induced changes in land use. Examples of such changes include the reallocation of land from food production to
51 biomass fuel production or from food production to forestry cultivation as a means of carbon sequestration. In all of
52 these cases, Earth observations can contribute to understanding climate-related effects on agricultural efficiency
53 (National Research Council, 2007). Much of the research to integrate Earth observations into climate and agriculture
54 decision support tools is relatively recent; for example, in FY05, NASA, and USDA began climate simulations using
55 GISS GCM ocean temperature data and also completed fieldwork for verification and validation of a climate-based crop
56 yield model (NASA, 2006b). The UN FAO has begun to coordinate similar research on integrating Earth observations

1 and decision support systems to study possible effects of changing climate on food production and distribution (e.g., see
2 United Nations Food and Agriculture Organization, no date).

3

4 *The effects of agricultural practices and efficiency on climate:*

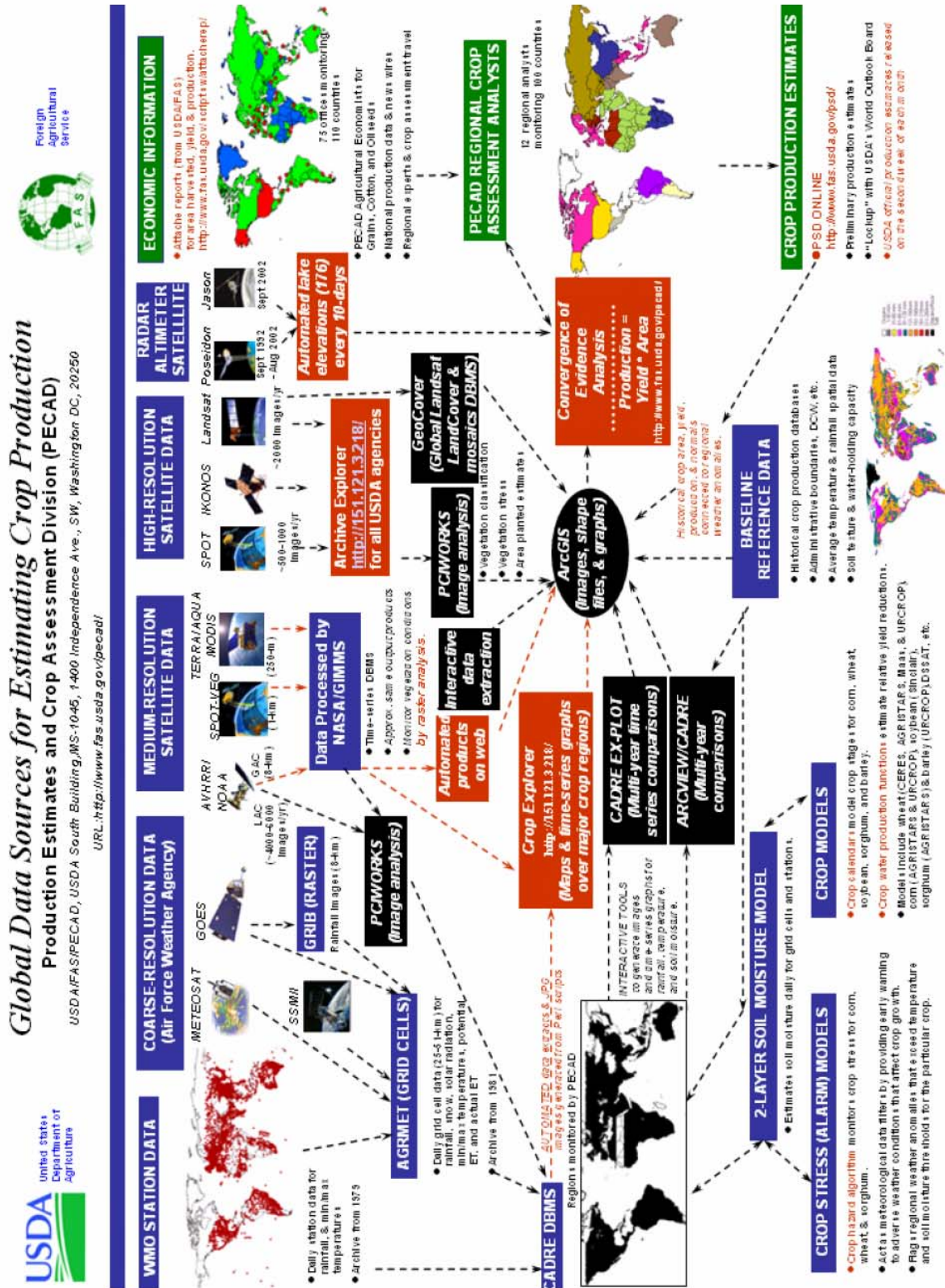
5

6 The crop assessments and estimates from PECAD, by revealing changes in agricultural practices, could play a role as
7 early indicators to inform forecasting future agricultural-induced effects on climate. The Agricultural Research Service
8 within USDA and NASA have undertaken research using Earth observation data to study scale-dependent Earth—
9 atmosphere interactions, suggesting that significant changes in regional land use or agricultural practices could affect
10 local and regional climate (NASA, 2001).

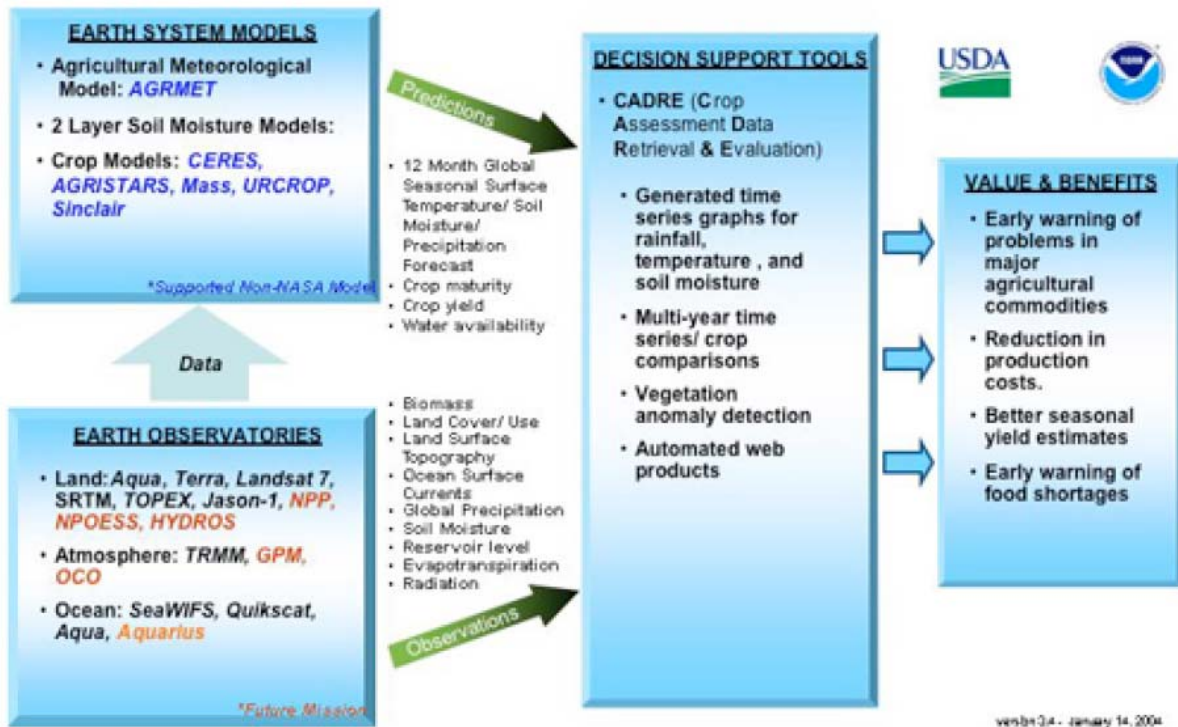
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1 **Figure 1-1: The PECAD Decision Support System: Data Sources and Decision Support Tools** (Source:
 2 Kaupp and coauthors, 2005, p. 5).
 3

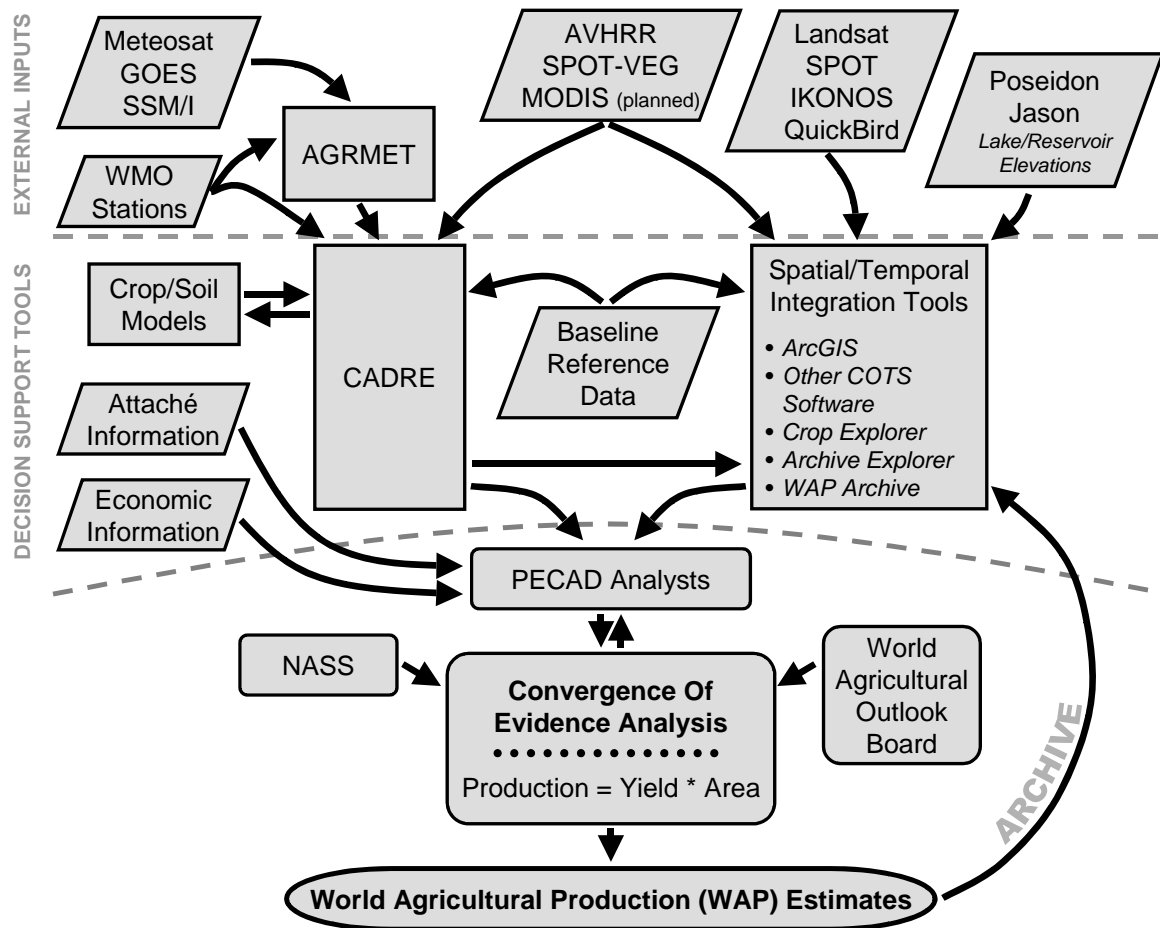


1 **Figure 1-2. The PECAD Decision Support System: Earth System Models, Earth Observations, Decision**
 2 **Support Tools, and Outputs** (Source: National Aeronautics and Space Administration, 2006a, p. 32).



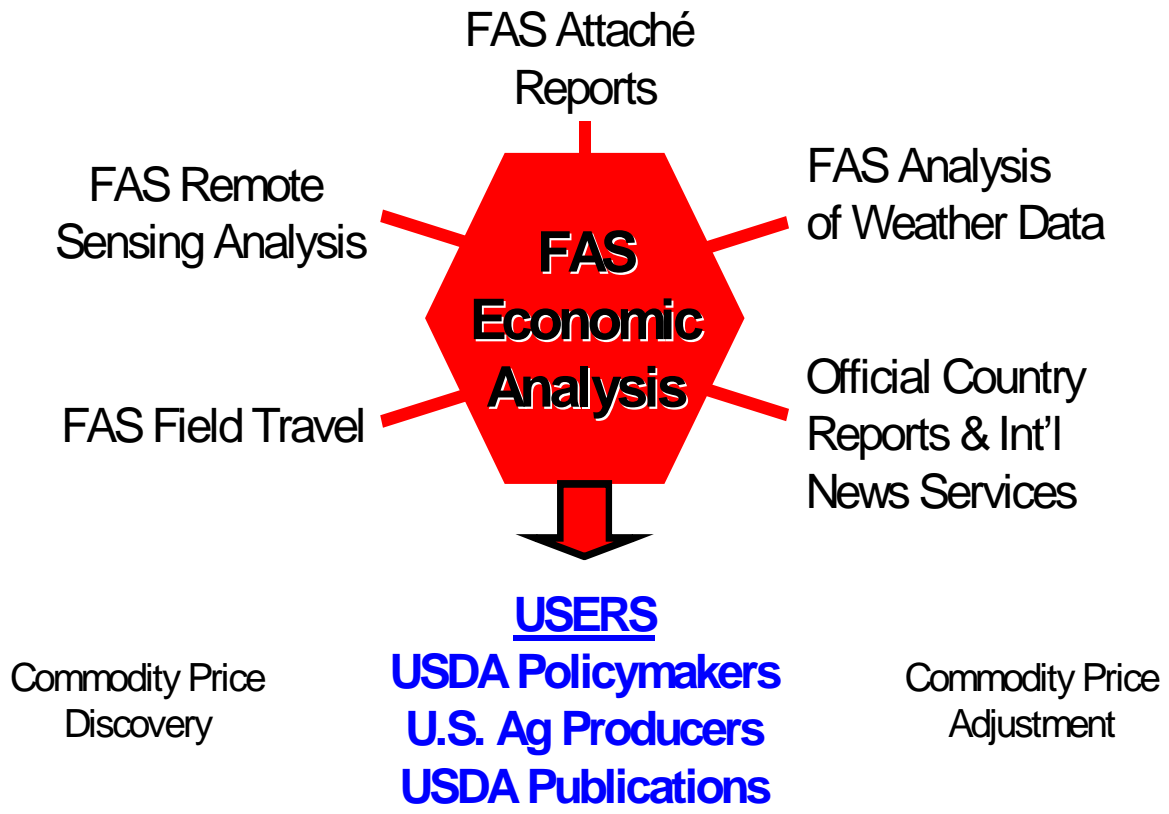
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Figure 1-3: The PECAD Decision Support System: The Role of Convergence of Evidence Analysis (Source: National Aeronautics and Space Administration, 2004a, p. 8).



From: http://www.fas.usda.gov/pecad/remote/overview/frame_OV.htm

1 **Figure 1-4: The PECAD Decision Support System: Information Sources for the Convergence of Evidence**
 2 **Analysis** (Source: National Aeronautics and Space Administration, 2004a, p. 5).

Chapter 2

Decision Support for Air Quality

(Use of CMAQ as a Decision Support Tool for Air Quality to Climate Change)

Lead Author: Daewon W. Byun

1. Introduction

Our ability to understand and forecast the quality of the air we breathe, as well as our ability to understand the science of chemical and physical atmospheric interactions, is at the heart of models of air quality. The quality of air is affected by and has implications for the topics presented in our other chapters. Air quality is affected by energy management and agricultural practices, for instance, and is a major factor in public health. Models of air quality also provide a means of evaluating the effectiveness of air pollution and emission control policies and regulations.

While numerous studies examine the potential impact of climate change on forests and vegetation, agriculture, water resources, and human health (examples are found in Brown *et al.*, 2004; Mearns, 2003; Leung and Wigmosta 1999; Kalkstein and Valimont 1987), attempts to project the response of air quality to changes in global and regional climates have long been hampered by the absence of proper tools that can transcend the different spatial and temporal scales involved in climate predictions and air quality assessment and by the uncertainties in climate change predictions and associated air quality changes.

One of the popular modeling tools to study air quality as a whole, including tropospheric ozone, fine particles, toxics, acid deposition, and visibility degradation is the US Environmental Protection Agency's (EPA) Community Multiscale Air Quality (CMAQ) modeling system. CMAQ has as its primary objectives to (1) improve the ability of environmental managers to evaluate the impact of air quality management practices for multiple pollutants at multiple scales, (2) enhance scientific ability to understand and model chemical and physical atmospheric interactions (<http://www.epa.gov/asmdnerl/CMAQ/>), and (3) guide the development of air quality regulations and standards and to create state implementation plans. It has been also used to evaluate longer-term pollutant climatology as well as short-term transport from localized sources, and it can be used to perform simulations using downscaled regional climate from global climate change scenarios listed in IPCC (2000). Various observations from the ground and from *in-situ*, aircrafts, and satellite platforms can be used at almost at every step of the processing of this Decision Support System (DSS) for air quality.

Although there are significant effects of long-range transport, most of the serious air pollution problems are caused by meteorological as well as chemical processes and their changes at regional and local areas, at scales much smaller than those resolved by global climate models (GCM), which are typically applied at a resolution of several hundred kilometers. Current-day regional climate simulations, which typically employ horizontal resolutions of 30 to 60 km, are insufficient to resolve small-scale processes that are important for regional air quality, including low-level jets, land-sea breezes, local wind shears, and urban heat island effects (Leung *et al.*, 2006). In addition, climate simulations place enormous demands on computer storage. As a result, most climate simulations only archive a limited set of meteorological variables, the time interval for the archive is usually 6 to 24 hours (e.g., Liang *et al.*, 2006), and some critical information required for air quality modeling is missing.

The interaction and feedback between climate and air chemistry is another issue. Climate and air quality are linked through atmospheric chemical, radiative, and dynamic processes at multiple scales. For instance, aerosols in the atmosphere may modify atmospheric energy fluxes by attenuating, scattering, and absorbing solar and infrared radiation, and may also modify cloud formation by altering the growth and droplet size distribution in the clouds. The changes in energy fluxes and cloud fields may, in turn, alter the concentration and distribution of aerosols and other chemical species. Although a few attempts have been made to address these issues, our understanding of climate change is based largely on modeling studies that have neglected these feedback mechanisms.

The impact of climate change on air emissions is also of concern. Changes in temperature, precipitation, soil moisture patterns, and clouds associated with global warming may directly alter emissions, including biogenic emissions (e.g., isoprene and terpenes). Isoprene, an important natural precursor of ozone, is emitted mainly by deciduous tree species. Emission rates are dependent on the availability of solar radiation in visual range and are highly temperature sensitive. Emissions of terpenes (semi-volatile organic species) may induce formation of secondary organic aerosols. The accompanying changes in the soil moisture, atmospheric stability, and flow patterns complicate these effects, and it is difficult to predict whether climatic change will eventually lead to increased degradation of air quality.

1 This chapter discusses how CMAQ is used as the DSS for studying climate change impact on air quality addressing
2 the focus areas required by the *SAP 5.1 Prospectus*: (1) observational capabilities used in the DSS, (2) agencies and
3 organizations responsible, (3) characterization of interactions between users and the DSS information producers, (4)
4 sources of uncertainties with observation and the decision support tools, and (5) description of the relation between the
5 DSS and climate change information.

6 7 8 **2. Description of CMAQ**

9 The US EPA CMAQ modeling system (Byun and Ching, 1999; Byun and Schere, 2006) has the capability to
10 evaluate relationships between emitted precursor species and ozone at urban/regional scales (Appendix W to Part 51 of
11 40CFR: Guideline on Air Quality Models in “<http://www.epa.gov/fedrgstr/EPA-AIR/1995/August/Day-09/pr-912.html>”). CMAQ uses state-of-the-science techniques for simulating all atmospheric and land processes that affect the
12 transport, transformation, and deposition of atmospheric pollutants. The primary modeling components in the CMAQ
13 modeling system include (1) a meteorological modeling system (e.g., The Fifth-Generation NCAR/Penn State
14 Mesoscale Model, MM5) or a Regional Climate Model (RCM) for the description of atmospheric states and motions,
15 (2) inventories of man-made and natural emissions of precursors that are injected into the atmosphere, and (3) the
16 CMAQ Chemistry Transport Modeling (CTM) system for the simulation of the chemical transformation and fate of the
17 emissions. The model can operate on a large range of time scales from minutes to days to weeks as well as on numerous
18 spatial (geographic) scales ranging from local to regional to continental.

19 The base CMAQ system is maintained by the U.S. EPA. The Center for Environmental Modeling for Policy
20 Development (CEMPD), University of North Carolina at Chapel Hill (UNC), is contracted to establish a Community
21 Modeling and Analysis System (CMAS) (<http://www.cmascenter.org/>) for supporting community-based air quality
22 modeling. CMAS helps development, application, and analysis of environmental models and helps distribution of the
23 DSS and related tools to the modeling community. The model performance has been evaluated for various applications
24 (e.g., Zhang *et al.*, 2006; Eder *et al.*, 2006; Tong and Mauzerall, 2006; Yu *et al.*, 2007). Table 2-1 lists Earth
25 observations (of all types-remote sensing and *in situ*) presently used in the CMAQ DSS.

26 Within this overall DSS structure as shown in Table 2-1, CMAQ is an emission-based, three-dimensional (3-D) air
27 quality model that does not utilize daily observational data directly for the model simulations. The databases utilized in
28 the system represent typical surface conditions, and demographic distributions. An example is the EPA’s Biogenic
29 Emissions Land Use Database, version 3 (BELD3) database (<http://www.epa.gov/ttn/chief/emch/biogenic/>) that
30 contains land use and land cover as well as the demographic and socioeconomic information. At present the initial
31 conditions are not specified using observed data even for those species routinely measured as part of the controlled
32 criteria species listed in the National Clean Air Act and its Amendments (CAAA) in an urban area using a dense
33 measurement network. This is because of the difficulty in specifying the multi-species conditions that satisfy chemical
34 balance in the system, which is subject to the diurnal evolution of radiative conditions and of the atmospheric boundary
35 layer as well as temporal changes in the emissions that reflect constantly changing human activities.

36 The main output of the CMAQ and its DSS is the concentration and deposition amount of atmospheric trace gases
37 and particulates at the grid resolution of the model, usually at 36 km for the continental United States (CONUS)
38 domain, and 12 km or 4 km for regional or urban scale domains. The end users of the DSS want information on the
39 major scientific uncertainties and our ability to resolve them subject to the information on socioeconomic context and
40 impacts. They seek information on the implications at the national, regional, and local scales and on the baseline and
41 future air quality conditions subject to climate change to assess the effectiveness of current and planned environmental
42 policies. Local air quality managers would want to know if the DSS could help assess methods of attaining current and
43 future ambient air quality standards and evaluate opportunities to mitigate the climate change impacts. Decision makers
44 would ask modelers to simulate the air quality in the future for a few plausible variations in the model inputs that
45 represent plausible climate scenarios of regional implications. Through sensitivity simulations of the DSS with
46 different assumptions on the meteorological and emissions inputs, the effectiveness of such policies and uncertainties in
47 the system can be studied. The results can be also compared with the historic air quality observations with similar
48 ambient conditions to validate predictions of the DSS.

49 50 51 **3. Potential Future Uses and Limits**

52 Although one of the major strengths of CMAQ is its reliance on the first principles of physics and chemistry, a few
53 modeling components, such as cloud processes, fine scale turbulence, radiative processes, etc., rely on
54 parameterizations or phenomenological concepts to represent intricate and less-well known atmospheric processes. The
55 present limitations in science parameterizations and modeling difficulties will continuously be improved as new
56 understanding of these phenomena are obtained through various measurements and model evaluation/verification. The

1 development of the chemical mechanism, Carbon Bond 05 (CB05), which recently replaced CB-4 is a case in point.
2 The reliability of the CMAQ simulation result is subject to quality of the emission inputs, both at the global and
3 regional scales, which depend heavily on socio-economic conditions. Because such estimates are obtained using
4 projection models in relevant socio-economic disciplinary areas, their accuracy must be scrutinized when used for the
5 decision-making process. The CMAQ DSS users/operators may not always have domain expertise to discern the
6 validity of such results.

7 CMAQ needs to have the ability to utilize available observations to specify more accurately the critical model
8 inputs, although they have been chosen based on best available information and experience currently. A data assimilation
9 approach may be used to improve the system performance at different processing steps.

10
11 Table 2-1. Input data used for operating the CMAQ-based DSS.

12 <<footnotes: PNNL, UIUC, NCEP, EPA, USGS, NASA>>

13 PNNL: Pacific Northwest National Laboratory

14 UIUC: University of Illinois at Urbana-Champaign

15 NCEP: National Center for Environmental Prediction

16 EPA: Environmental Protection Agency

17 USGS: US Geological Survey

18 NASA: National Aeronautics and Space Agency

19
20 For example, research has been undertaken to use satellite remote sensing data products together with high-
21 resolution land use and land cover (LULC) data to improve the land-surface parameterizations and boundary layer
22 schemes in the RCMs (e.g., Pour-Biazar *et al.*, 2007). Active research in chemical data assimilation (e.g.,
23 Constantinescu *et al.*, 2007a and b) is currently conducted with models such as STEM-II (Carmichael *et al.*, 1991) and
24 Goddard Earth Observing System (GEOS)-Chem (Bey *et al.*, 2001), which utilize both *in situ* and satellite observations
25 (e.g., Sandu *et al.*, 2005; Kopacz *et al.*, 2007; Fu *et al.*, 2007). Because of the coarse spatial and temporal resolutions of
26 the satellite data collected in the 1960s through the 1980s, and gas measurements through the launch of EOS Aura in
27 2004, most research in this area has been performed with global chemistry-transport models. As the horizontal
28 footprints of modern satellite instruments reach the resolution suitable for regional air quality modeling, these data can
29 be used to evaluate and then improve the bottom-up emissions inputs in the regional air quality models. However, they
30 do not provide required vertical information. The exception is occultation instruments, but these do not measure low
31 enough in altitude for air quality applications. *In-situ* and remote sensing measurements from ground and aircraft
32 platforms could be used to augment the satellite data in these data assimilation experiments.

33 Utilization of the column-integrated satellite measurements in a high-resolution 3-D grid model like CMAQ poses
34 serious challenges in distributing the pollutants vertically and separating those within and above the atmospheric
35 boundary layer. Because similar problems exist for the retrieval of meteorological profiles of moisture and temperature,
36 experiences in including these can be adapted for a few well-behaved chemical species. A data assimilation tool can be
37 used to improve the initial and boundary conditions using various *in situ* and satellite measurements of atmospheric
38 constituents. At present, however, an operational assimilation system for CMAQ is not yet available, although prototype
39 assimilation codes have recently been generated (Hakami, *et al.*, 2007; Zhang *et al.*, 2007). Should these data
40 assimilation tools become part of the DSS, various conventional and new satellite products, including Tropospheric
41 Emission Spectrometer (TES) ozone profiles, Geostationary Operational Environmental Satellites (GOES) hourly total
42 ozone column (GhTOC) data, Ozone Monitoring Instrument (OMI) total ozone column (TOC), The Cloud-Aerosol
43 Lidar and Infrared Pathfinder Satellite Observation (CALIPSO) (<http://www-calipso.larc.nasa.gov/>) attenuated
44 backscatter profiles, and OMI aerosol optical thickness (AOT) data can be utilized to improve the urban-to-regional
45 scale air quality predictions.

46 Because of the critical role of the RCM as the driver of CMAQ in climate change studies, RCM results for the long-
47 term simulations must be verified thoroughly. To date, evaluation of the RCM has been performed for the air quality
48 related operations only for relatively short simulation periods. For example, the simulated surface temperature, pressure,
49 and wind speed must be compared to surface observations to determine how well the model captures the mean land-
50 ocean temperature and pressure gradients, the mean sea breeze wind speeds, the average inland penetration of sea
51 breeze, the urban heat island effect, and the seasonal variations of these features. Comparisons with rawinsonde
52 soundings and atmospheric profiler data would determine how well the model reproduces the averaged characteristics of
53 the afternoon mixed layer heights and of the early morning temperature inversion, as well as the speed and the vertical
54 wind shears of the low-level jets. In addition to these mesoscale phenomena, changes in other factors can also alter the
55 air pollution patterns in the future and need to be carefully examined. These factors include the diurnal maximum,

1 minimum, and mean temperature; cloud cover; thunderstorm frequency; surface precipitation and soil moisture patterns;
2 and boundary layer growth and nocturnal inversion strength.

3 In global model applications, it has been demonstrated that satellite measured biomass burning emissions data are
4 necessary to enhance model predictability (e.g., Duncan *et al.*, 2003; Hoelzemann, *et al.*, 2004). Duncan *et al.* (2003)
5 presented a methodology for estimating the seasonal and interannual variation of biomass burning, designed for use in
6 global chemical transport models using fire-count data from the Along Track Scanning Radiometer (ATSR) and the
7 Advanced Very High Resolution Radiometer (AVHRR) World Fire Atlases. The Total Ozone Mapping Spectrometer
8 (TOMS) Aerosol Index (AI) data product was used as a surrogate to estimate interannual variability in biomass burning.
9 Also Spracklen *et al.* (2007) showed that the wildfire contribution to the interannual variability of organic carbon
10 aerosol can be studied using the area-burned data and ecosystem specific fuel loading data. A similar fire emissions
11 data set at the regional scales could be developed for use in a study of climate impact on air quality. For retrospective
12 application, a method similar to that used by the National Oceanic and Atmospheric Administration's (NOAA) Hazard
13 Mapping System (HMS) for Fire and Smoke (<http://www.ssd.noaa.gov/PS/FIRE/hms.html>) may be used to produce a
14 long-term regional scale fire emissions inventory for climate impact analysis.

15 16 **4. Uncertainty**

17 The CMAQ modeling system as currently operated has several sources of uncertainty in addition to those
18 associated with some of the limits described in the previous section. In particular, when CMAQ is used to study the
19 effects of climate change and air quality, improvements in several areas are necessary to reduce uncertainty. First, the
20 regional air quality models employ limited modeling domains and, as such, they are ignorant of air pollution events
21 outside the domains unless proper dynamic boundary conditions are provided. Second, because the pollutant transport
22 and chemical reactions are fundamentally affected by the meteorological conditions, improving both the global climate,
23 regional climate models, and the downscaling methods by evaluating and verifying physical algorithms that have been
24 implemented with observations as necessary in order to improve the system's overall performance. Third, the basic
25 model inputs, including land use/vegetation cover descriptions and emissions inputs must be improved. Fourth, the
26 model representativeness issues, including grid resolution problems, compensating errors among the model components,
27 and incommensurability of the model results compared with the dimensionality of the measurements (i.e., inherent
28 differences in the modeled outputs that represent volume and time averaged quantities to the point or path-integrated
29 measurements), as discussed in Russell and Dennis (2000) and NARSTO (2000), need to be addressed. These factors
30 are the principal cause of simulation/prediction errors.

31 Although the models incorporated in this DSS are first-principle based environmental models, they have difficulties
32 in representing forcing terms in the system, in particular, the influence of the earth's surface, long-range transport, and
33 uncertainties in the model inputs such as daily emissions changes due to anthropogenic and natural events. There is
34 ample opportunity to reduce some uncertainties associated with CMAQ through model evaluation and verification using
35 current and future meteorological and atmospheric chemistry observations. Satellite data products assimilated in the
36 global chemical transport models (GCTM) could provide better dynamic lateral boundary conditions for the regional air
37 quality modeling (e.g., Al-Saddi, *et al.*, 2005). Additional opportunities to reduce the model uncertainty include
38 comparison of model results with observed data at different resolutions, quantification of effects of initial and boundary
39 conditions and chemical mechanisms, application of CMAQ to estimate the uncertainty of input emissions data, and
40 ensemble modeling (using a large pool of simulations among a variety of models) as a means to estimate model
41 uncertainty.

42 A limitation in CMAQ applications, and therefore a source of uncertainty, has been the establishment of initial
43 conditions. The default initial conditions and lateral boundary conditions in CMAQ are provided under the assumption
44 that after spin-up of the model, they no longer play a role, and in time, surface emissions govern the air quality found in
45 the lower troposphere. Song *et al.* (2007) showed that the effects of the lateral boundary conditions differ for different
46 latitudes and altitudes, as well as seasons. In the future, dynamic boundary conditions can be provided by fully
47 integrating the GCTMs as part of the system. Several research groups are actively working on this, but the simulation
48 results are not yet available in open literature. A scientific cooperative forum, the Task Force on Hemispheric Transport
49 of Air Pollution (<http://www.htap.org/index.htm>), is endeavoring to bring together the national and international
50 research efforts at the regional, hemispheric, and global scales to develop a better understanding of air pollution
51 transport in the Northern Hemisphere. This task force is currently preparing its 2007 Interim Report addressing various
52 long-range transport of air pollutant issues (http://www.htap.org/activities/2007_Interim_Report.htm). Although the
53 effort does not directly address climate change issues, many of findings and tools used are very relevant to
54 meteorological and chemical downscaling issues.

1 Ultimately, CMAQ should consider all the uncertainties in the inputs. The system's response may be directly
2 related to the model configuration and algorithms (e.g., structures, resolutions, and chemical and transport algorithms),
3 compensating errors, and the incommensurability of modeling nature, as suggested by Russell and Dennis (2000).

5 **5. Global Change Information and CMAQ**

6 CMAQ could be used to help answer several questions about the relationship between air quality and climate
7 change. For instance:

- 8
- 9 1) How will global warming affect air quality in a region?
- 10 2) How will land use change due to climate, urbanization, or intentional management decisions affect air quality?
- 11 3) How much will climate change alter the frequency, seasonal distribution, and intensity of synoptic weather patterns
12 that influence pollution in a region?
- 13 4) How sensitive are air quality simulations to uncertainty in wildfire projections and to potential land management
14 scenarios?
- 15 5) How might the contribution of the local production and long-range transport of pollutants differ due to different
16 climate change scenarios?
- 17 6) Will future emissions scenarios or climate changes affect the frequency and magnitude of high pollution events?

18 To provide answers to these questions, CMAQ will rely heavily on climate-change-related information. In addition
19 to the influence of greenhouse gases and global warming, other forcing functions include population growth, land use
20 changes, new emission controls being implemented, and new energy sources to be available to replace the existing high-
21 carbon sources. Different scenarios can be chosen either to study potential impacts or to estimate the range of
22 uncertainties of the predictions. The two upstream climate models, GCMs and RCMs, generate the climate change data
23 that drive a GCTM and CMAQ. Both the GCMs and RCMs are expected to represent future climate change conditions
24 while simulating historic climate conditions that can be verified with comprehensive datasets such as the NCEP
25 Reanalysis data provided by the NOAA/OAR/ESRL PSD, Boulder, CO, from their Web site,
26 <http://www.cdc.noaa.gov/cdc/data.ncep.reanalysis.html> The meteorology simulated by the climate models represents
27 conditions in future year scenarios, reflecting changing atmospheric conditions. Furthermore, emissions inputs used for
28 the GCTM and CMAQ must reflect the natural changes and/or anthropogenic developments related to climate change
29 and other factors (e.g., population growth and geographical population shifts due to climate change).

30 In recent years, the EPA Science to Achieve Results (STAR) program has funded several projects on the possible
31 effects of climate change on air quality and on ecosystems. A majority of these projects have adopted CMAQ as the
32 base study tool. Figure 2-1 provides a general schematic of the potential structure of a CMAQ-based climate change
33 DSS. The figure shows potential uses of CMAQ for climate study; most climate-related CMAQ applications are not yet
34 configured as fully as indicated in the figure.

35 The projects linking CMAQ and climate study have used upstream models and downstream tools, including those
36 identified in Table 2-1. Related projects that use regional air quality models other than CMAQ are also listed. For the
37 GCMs, NCAR Community Climate Model (CCM) (Kiehl *et al.*, 1996), NASA Goddard Institute for Space Studies
38 (GISS) model (e.g., Hansen *et al.*, 2005), and NOAA Geophysical Fluid Dynamics Laboratory (GFDL) CM2 (Delworth
39 *et al.*, 2006) are the most popular global models for providing meteorological inputs representing climate change events.
40 A recent description for the GISS model can be found in Schmidt *et al.* (2006) (<http://www.giss.nasa.gov/tools/>) and for
41 the CCM in Kiehl *et al.* (1996) (<http://www.cgd.ucar.edu/cms/ccm3/>). A newer version of the CCM was released on
42 May 17, 2002 with a new name—the Community Atmosphere Model (CAM) ([http://www.cesm.ucar.edu/models/atm-
44 cam](http://www.cesm.ucar.edu/models/atm-
43 cam)). The model is described in Hurrell *et al.* (2006).

45 Table 2-2. An illustrative example of the potential uses of the models and upstream and downstream tools for a
46 CMAQ-based Climate Change Impact Decision Support System.

47 <footnote: WRF-ARW, WRF-NMM, SLEUTH>>

48

49 As shown in Table 2-2, for climate change studies, CMAQ is linked with upstream models such as a global climate
50 model (GCM), a global tropospheric chemistry model (GTCM), and a regional climate model (RCM) to provide
51 emissions sensitivity analysis, source apportionment, and data assimilation to assist policy and management decision-
52 making activities, including health impact analysis. Certain EPA STAR projects (Hogrefe *et al.*, 2004 and 2005;
53 Knowlton *et al.*, 2004; Civerolo *et al.*, 2007) have utilized the CMAQ-based DSS to assess whether climate change

1 would influence the effectiveness of current and future air pollution policy decisions subject to the potential changes in
2 local and regional meteorological conditions.

3 Other EPA STAR projects employ global climate change information from a GCM. For example, Tagaris *et al.*
4 (2007) and Liao *et al.* (2007) use the results of GCM simulation with the well-mixed greenhouse gases—CO₂, CH₄,
5 N₂O, and halocarbons—updated yearly from observations for 1950 to 2000 (Hansen *et al.*, 2002) and for 2000 to 2052
6 following the A1B SRES scenario from the Intergovernmental Panel on Climate Change (IPCC 2001). The simulation
7 used ozone and aerosol concentrations in the radiative scheme fixed at present-day climatological value provided in
8 Mickley, *et al.* (2004).
9

10 To resolve the meteorological features affecting air pollution transport and transformation at a regional scale, the
11 coarse scale meteorological data representing the climate change effects derived from a GCM are downscaled using an
12 RCM. An RCM is often based on a limited-domain regional mesoscale model, such as MM5, the Regional
13 Atmospheric Modeling System (RAMS), Eta, and WRF/ARW or WRF/NMM. An alternative method for constructing
14 regional scale climate change data is through a statistical downscaling, which evaluates observed spatial and temporal
15 relationships between large-scale (predictors) and local (predictands) climate variables over a specified training period
16 and domain (Spak *et al.*, 2007). Because of the need to use a meteorological driver that satisfies constraints of dynamic
17 consistency (i.e., mass and momentum conservations) for regional scale air quality modeling (e.g., Byun, 1999 a and b),
18 the CMAQ modeling system relies exclusively on the dynamic downscaling method.

19 Regional chemistry/transport models, like CMAQ, are better suited for regional air quality simulations than a
20 GCTM because of the acute air pollution problems that are managed and controlled through policy decisions at specific
21 geographic locations. Difficulty in prescribing proper boundary conditions (BC), especially in the upper troposphere, is
22 one of the deficiencies of CMAQ simulations of air quality (e.g., Tarasick *et al.*, 2007; Tang *et al.*, 2007). Therefore,
23 one of the main roles of the global CTM is to provide proper dynamic boundary conditions for CMAQ to represent
24 temporal variation of chemical conditions that might be affected by the long-range transport of pollution (e.g., particle
25 from large-scale biomass burnings) from outside the regional domain boundaries (Holloway, *et al.*, 2002; In *et al.*,
26 2007). The contemporary EPA funded projects on climate change impact on air quality mainly use two 3-D GCTM
27 models: the NASA/Harvard GEOS-Chem (Bey *et al.*, 2001) and the National Center for Atmospheric Research (NCAR)
28 Model of Ozone and Related Chemical Tracers (MOZART) (Brasseur *et al.*, 1998; Horowitz *et al.*, 2003).

29 The GEOS-Chem model (<http://www-as.harvard.edu/chemistry/trop>) is a global model for predicting tropospheric
30 composition. The model was originally driven by the assimilated meteorological observation data from the GEOS of the
31 NASA Global Modeling and Assimilation Office (GMAO). GEOS-Chem has been used as community assessment
32 models for NASA Global Model Initiative, climate change studies with the NASA/GISS GCM, chemical data
33 assimilation of tropospheric gaseous and aerosol species at NASA GMAO, and regulatory models for air pollution, in
34 particular providing long-range transport information for regional air quality models. Long-term retrospective studies
35 are possible with the GEOS data, which are available from 1985 to present at horizontal resolution of 2 degrees
36 (latitude) by 2.5 degrees (longitude) until the end of 1999 and 1 degree by 1 degree afterward. For climate studies, the
37 NASA GISS GCM meteorological outputs are used instead. Emission inventories include a satellite-based inventory of
38 fire emissions (Duncan *et al.*, 2003) with expanded capability for daily temporal resolution (Heald *et al.*, 2003) and the
39 National Emissions Inventory for 1999 (NEI 1999) for the US with monthly updates in order to achieve adequate
40 consistency with the CMAQ fields at the GEOS-Chem/CMAQ interface.

41 MOZART (<http://gctm.acd.ucar.edu/mozart/models/m3/index.shtml>) is built on the framework of the Model of
42 Atmospheric Transport and Chemistry (MATCH) that can be driven with various meteorological inputs and at different
43 resolutions such as meteorological reanalysis data from the National Centers for Environmental Prediction (NCEP),
44 NASA GMAO, and the European Centre for Medium-Range Weather Forecasts (ECMWF). For climate change
45 applications, meteorological inputs from the NCAR CCM3 are used. MOZART includes a detailed chemistry scheme
46 for tropospheric ozone, nitrogen oxides, and hydrocarbon chemistry, semi-Lagrangian transport scheme, dry and wet
47 removal processes, and emissions inputs. Emission inputs include sources from fossil fuel combustion, biofuel and
48 biomass burning, biogenic and soil emissions, and oceanic emissions. The surface emissions of NO_x, CO, and NMHCs
49 are based on the inventories described in Horowitz *et al.* (2003), aircraft emissions based on Friedl (1997), and lightning
50 NO_x emissions that are distributed at the location of convective clouds.

51 GCTMs are applied to investigate numerous tropospheric chemistry issues, involving gases – CO, CH₄, OH, NO_x,
52 HCHO, and isoprene– and inorganic (sulfates and nitrates) and organic (elemental carbons, organic carbons)
53 particulates. Various *in situ*, aircraft, and satellite-based measurements are used to provide the necessary inputs, to
54 verify the science process algorithms, and to perform general model evaluations. They include vertical profiles from
55 aircraft observations as compiled by Emmons *et al.* (2000), multiyear analysis of ozonesonde data (Logan, 1999), and
56 those available at the Community Data Web site managed by the NCAR Earth and Sun Systems Laboratory (ESSL)

1 Atmospheric Chemistry Division (ACD); and multiyear surface observations of CO reanalysis (Novelli *et al.*, 2003).
2 Current and previous atmospheric measurement campaigns are listed in Web pages by NOAA Earth Systems Research
3 Laboratory (ESRL), <http://www.esrl.noaa.gov/>; NASA, Tropospheric Integrated Chemistry Data Center, <http://www-air.larc.nasa.gov/>; and NCAR ESSL (Earth and Sun Systems Laboratory) Atmospheric Chemistry Division (ACD)
4 Community Data, <http://www.acd.ucar.edu/Data/>. These observations are used to set boundary conditions for the slow
5 reacting species, including CH₄, N₂O, and CFCs, and to evaluate other modeled species, including CO, NO_x, PAN,
6 HNO₃, HCHO, acetone, H₂O₂, and non-methane hydrocarbons. In addition, several satellite measurements of CO, NO₂,
7 and HCHO from the Global Ozone Monitoring Experiment (GOME), The Scanning Imaging Absorption SpectroMeter
8 for Atmospheric CHartographY (SCIAMACHY), and OMI instruments have been used extensively to verify the
9 emissions inputs and performance of the GCTM.
10

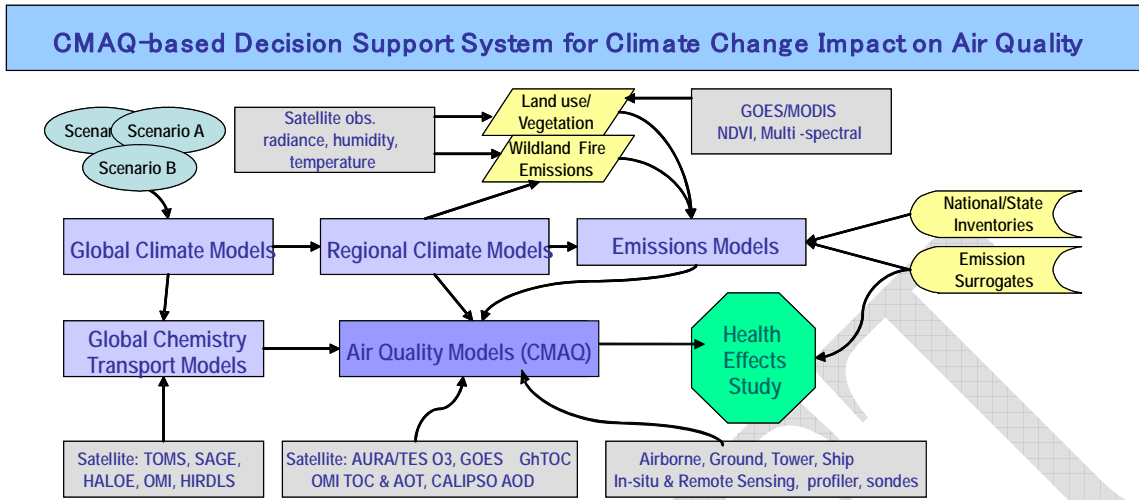
11 The grid resolutions used in the studies discussed above are much coarser than those used in the air quality models
12 for studying emission control policy issues, such as evaluating state implementation plans (SIP). SIP modeling
13 typically utilizes over 20 vertical layers at around 4-km horizontal grid spacing to reduce uncertainties in the model
14 predictions near the ground and around high-emission source areas including urban and industrial centers. Although
15 Civerolo *et al.*, (2007) applied CMAQ at a higher resolution; the duration of the CMAQ simulation was far too short a
16 time scale to evaluate the regional climate impacts in detail.

17 One of the additional key limitations of using the CMAQ for climate change studies is that the linkages between
18 climate and air quality and from the global scale to regional scale models are only one-way (i.e., no feedback). Jacob
19 and Gilliland (2005) stated that one-way assessment of the global change scenarios would be less useful for projection
20 of air pollutant emissions because the evolution of regional air quality policies were not accounted for in these
21 storylines. Also, to represent the interactions between atmospheric chemistry and meteorology, such as radiation and
22 cloud/precipitation microphysics, particulates and heterogeneous chemistry, a two-way linkage must be established
23 between the meteorology and chemistry models. An on-line modeling approach as implemented in WRF-chem is an
24 example of such a linkage, but still there is a need to develop a link between the global and regional scales. A multi-
25 resolution modeling system such as demonstrated by Jacobson (2001 a, b) might be necessary to address the true
26 linkage between air pollution forcing and climate change and to provide the urban-to-global connection.

27 In addition, there would be significant benefits to linking other multimedia models describing subsoil conditions,
28 vegetation dynamics, hydrological processes, and ocean dynamics, including the physical/chemical interactions between
29 the ocean micro-sub layer and atmospheric boundary layer to an air quality model. To generate such a mega model
30 under one computer coding structure would require handling of extremely different state variables in each multimedia
31 model with substantially different data. Furthermore, interactions among the multimedia models need multidirectional
32 data inputs, quality assurance checkpoints, and the decision-support entries. A more generalized on-line and two-way
33 data exchange tools currently being developed under the Earth System Modeling Framework (ESMF)
34 (<http://www.esmf.ucar.edu/>) may be a viable option.

35 Observations not only represent the real changes in the climate but also provide a fundamental database to verify
36 various modeling components in the DSS. The meteorological reanalysis data are available both in regional and global
37 scales, but similar atmospheric chemistry database for air quality is lacking. An ozone database from ozonesonde
38 system and other *in situ* measurements are useful for global scale studies. But for regional air quality studies, the
39 availability of such measurements representing urban and local conditions in long-term is limited. Satellite or other
40 remote sensing platform observations may provide additional data sources to build an atmospheric chemistry reanalysis
41 database at global and regional scales, but these observations are mainly limited to ozone and aerosols. Such chemical
42 reanalysis database can be utilized to study long-term air quality trends; to evaluate science process components in the
43 air quality models, emissions, and other model inputs and configurations; and to improve model predictions through
44 data assimilation approaches.

1



2
3 Figure 2-1. Configuration of CMAQ-based Decision Support System for climate change impact study

1 Table 2-1. Input data used for operating the CMAQ-based DSS.

Data Set	Type of Information	Source	Usage
Regional climate model output	Simulation results from a regional climate model (RCM) used as a driver for CMAQ modeling; processed through meteorology-chemistry interface processor (MCIP)	RCM modeling team; PNNL, UIUC, NCEP, EPA, and universities	Regional climate characterization, driver data for air quality simulations, and emissions processing
Land use, land cover, subsoil category, and topography data; topography for meteorological modeling	Describes land surface conditions and vegetation distribution for surface exchange processes	Various sources from USGS, NASA, NCEP EPA, states, etc.	Usually the data are associated with RCM's land surface module; need to be consistent with vegetation information, such as BELD3 if possible
Biogenic emissions land use database version 3 (BELD3)	Land use and biomass data and vegetation/tree species fractions	EPA	Processing of biogenic emissions; used to provide activity data for county-based emission estimates; now also used for land surface modeling in RCM
Air emissions inventories: national emissions inventories (NEI) and state/special inventories; often called as "bottom-up" inventories	Amount and type of pollutants into the atmosphere. Includes: - Chemical or physical identity of pollutants - Geographic area covered - Institutional entities - Time period over which the emissions are estimated - Types of activities that cause emissions	EPA, regional program organizations (RPO), states and local government, and foreign governments	Preparation of model-ready emission inputs; perform speciation for the chemical mechanism used; used to evaluate "top-down" emissions (i.e., from inversion of satellite observations through air chemistry models)
Chemical species initial and boundary conditions	Clean species concentration profiles initial input and boundary conditions used for CMAQ simulations; originally from observations from clean background locations	EPA (fixed profiles), GEOS-Chem (Harvard & Univ. Houston), MOZART (NCAR); dynamic concentrations with diurnal variations (daily, monthly or seasonal)	CMAQ simulations; fixed profiles are used for outer domains where no significant emissions sources are located
AQS/AIRNow	Near real-time (AIRNow) and archived datasets (AQS) for ozone, PM, and some toxics species	Joint partnership between EPA and state and local air quality agencies	Measurement data used for model evaluations; report and communicate national air quality conditions for

2

1 Table 2-2. An illustrative example of the potential uses of the models and upstream and downstream tools for a
 2 CMAQ-based Climate Change Impact Decision Support System.

Component	Functions	Model Name: Owner	Users
Global climate models (GCM)	Performs climate change simulations over the globe for different SRES climate scenarios. Typical resolution for a long-term (50 year) simulation is at 4° x 5° latitude and longitude	Community Climate Model (CCM): NCAR Goddard Institute for Space Studies (GISS) GCM: NASA CM2: Geophysical Fluid Dynamics Laboratory (GFDL) of NOAA	Climate research institutes, universities, and government institutions
Global chemistry transport models (GCTM)	Computes global scale chemical states in the atmosphere; uses same resolution as GCM	GEOS-Chem: NASA, Harvard University MOZART: NCAR (ESSL/Atmospheric Chemistry Division)	Global chemistry research organizations, universities, and government institutions
Regional climate models (RCM)	Simulates regional scale climate and meteorological conditions downscaling the GCM output; for US application ~36 km resolution used	MM5-based: NCAR, PNNL, UIUC, and others; the weather research and forecasting (WRF) model - advanced research WRF (WRF-ARW) core based: NCAR, UIUC Eta-based: NCEP (before June, 2006) The WRF- nonhydrostatic mesoscale model (WRF-NMM) core based: NCEP (after June, 2006)	Regional climate research groups, universities, and government institutions
Regional air quality models (AQM)	Performs air quality simulations at regional and urban scales at the same resolution as the RCM	Community multiscale air quality (CMAQ): EPA Comprehensive air quality model with extensions (CAMx): Environment WRF-Chem: NOAA/NCAR STEM-II: University of Iowa	Regional, state, and local air quality organizations; universities; private industries; and consulting companies
Downstream tools for decision support	Performs additional computations to help decision support, such as sensitivity and source apportionment studies, exposure studies	CMAQ/DDM: GIT CMAQ/4Dvar: CalTech/VT/UH Stochastic human exposure and dose simulation (SHEDS): EPA Total risk integrated methodology (TRIM): EPA	Universities and consulting companies
Upstream tools for representing climate change impacts on input data	Performs additional computations to generate model inputs that affect simulations	Land surface models SLEUTH: USGS, UC Santa Barbara (captures urban patterns) CLM (community land model): NCAR (used for RCM and biogenic emission estimates after growth)	Universities and consulting companies

3

Chapter 3

Decision Support System for Assessing Hybrid Renewable Energy Systems

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1. Introduction

The national application area addressed in this chapter is the deployment of renewable energy technologies. Renewable energy technologies are being used around the world to meet local energy loads, to supplement grid-wind electricity supply, to perform mechanical work such as water pumping, to provide fuels for transportation, to provide hot water for buildings, and to support heating and cooling requirements for building energy design. Numerous organizations and research institutions around the world have developed a variety of decision-support tools to address how these technologies might perform in a most cost-effective manner to address specific applications. This chapter will focus on one specific tool, known as the Micropower Optimization Model, Hybrid Optimization Model for Electric Renewables (HOMER), that has been under consistent development and improvement at the US Department of Energy's National Renewable Energy Laboratory and is used extensively around the world.

HOMER relies heavily on knowledge of the renewable energy resource available to the technologies being analyzed. Renewable energy resources, particularly for solar and wind technologies, are highly dependent on weather and climate phenomena, and are also driven by local microclimatic processes. Given the absence of a sufficiently dense ground network of reliable solar and wind observations, we must rely on validated numerical models, empirical knowledge of microscale weather characteristics, and collateral (indirect) observations derived from Earth observations, such as reanalysis data and satellite-borne remote sensors, to develop reliable knowledge of the geospatial characteristics and extent of these resources. Thus, the Decision Support System (DSS) described in this chapter includes HOMER as an end-use application and is described in the context of the renewable energy resource information required as input, as well as some intermediate steps that can be taken to organize these data, using Geographic Information Systems (GIS) software, to facilitate the application of HOMER.

2a. Description of the HOMER DSS

The HOMER DSS described in this chapter consists of three main components: (1) the renewable energy resource information required to estimate technology performance and operational characteristics, (2) (optional) organization of the resource data into a GIS framework so that the data can be easily imported into the decision support tool, and (3) NREL's Micropower Optimization Model known as HOMER, which ingests the renewable resource data for determining the optimal mix of power technologies for meeting specified load conditions at specified locations. This section describes each of these components separately. Although climate-based Earth observational data are primarily relevant only to the first component, some related Earth observation information could also be associated with the second and even the third component. Furthermore, it will be apparent that the first component is of major importance in the successful use of the HOMER DSS.

Although HOMER handles a number of power technologies, we will focus our attention in this chapter on solar and wind technologies and the resources required to run these technologies.

Solar and Wind Resource Assessments

The first component of the HOMER DSS is properly formatted, reliable renewable energy resource data. The significant data requirements for this component are time-dependent measurements of wind and solar resources, as well as Earth observational data and data from numerical models, to provide the necessary spatial information for these resources, which can vary significantly over relatively small distances due to local microclimatic effects. Because of this natural variability, it is necessary to examine these energy resources geospatially in order to determine optimal siting of renewable energy technologies; alternatively, if a renewable energy technology is sited at a specific site in order to meet

1 a nearby load requirement (such as a solar home system), it is necessary to know what the resource availability is at that
2 location, since microclimatic variability may make even nearby data sources irrelevant.

3
4 Examples of the products derived from the methodologies described below can be found for many areas around the
5 world. One significant project that has recently been completed is the Solar and Wind Energy Resource Assessment
6 (SWERA) Project, which provided high-resolution wind and solar resource maps for 13 countries around the world.
7 SWERA was a project funded by the Global Environment Facility and was cost-shared by several technical
8 organizations around the world: NREL; the State University of New York at Albany, the NASA's Langley Research
9 Center, and the USGS/EROS Data Center in the U.S.; Riso National Laboratory in Denmark; the German Aerospace
10 Institute (DLR); the Energy Resources Institute (New Delhi, India); and the Brazilian Spatial Institute (INPE) in Sao
11 Jose dos Campos, Brazil. The United Nations Environment Programmer (UNEP) managed the project. Besides the
12 solar and wind resource maps and underlying data sets, a variety of other relevant data products came out of this
13 program. All of the final products and data can be found on the SWERA archive, hosted at the UNEP/GRID site,
14 collocated with the USGS/EROS data center in Sioux Falls, South Dakota (<http://swera.unep.net>).

15
16 For wind resource assessments, NREL's approach, known as Wind Resource Assessment Mapping System (WRAMS)
17 relies on mesoscale numerical models such as MM5 or Weather Research and Forecasting (WRF), which can provide
18 simulations of near-surface wind flow characteristics in complex terrain or where sharp temperature gradients might
19 exist (such as land-sea contrasts). Typically, these numerical models use available weather data, such as the National
20 Climatic Data Center's Integrated Surface Hourly (ISH) data network and National Center for Atmospheric Research-
21 National Centers for Environmental Protection (NCAR-NCEP) reanalysis data as inputs. In coastal areas or island
22 situations NREL's wind resource mapping also relies heavily on SeaWinds data from the Quikscat satellite to obtain
23 near-shore and near-island wind resources. WRAMS also relies on Global Land Cover Characterization (GLCC) 1-km
24 and Regional Gap Analysis Program (ReGAP) 200-m land cover data, as well as Moderate Resolution Imaging
25 Spectroradiometer (MODIS) data from the Aqua and Terra Earth Observation System satellites, to obtain information
26 such as percent of tree cover and other land use information. This information is used not only to determine roughness
27 lengths in the numerical mesoscale models but also to screen sites suitable for both wind and solar development in the
28 second component of the HOMER DSS.

29
30 The numerical models are typically run at a 2.5-km resolution. However, wind resource information is often reported at
31 the highest resolution at which a digital elevation model (DEM) can provide. Globally this has traditionally been 1-km
32 resolution; however, in some cases in the US 400-m DEM data are available. Furthermore, the Shuttle Radar Topology
33 Mission has now been able to provide users with a
34 90-m DEM for much of the world. Thus, additional steps are needed beyond the 2.5-km resolution model output to
35 depict wind resources at the higher resolutions offered by these DEM's. This can be accomplished by using a
36 secondary high-resolution mesoscale model, empirical methods, or both. For example, with NREL's WRAMS
37 methodology, GISD-based empirical modeling tools have been developed to modify results from the numerical models
38 that appear to have provided unreliable results in complex-terrain areas.

39
40 The numerical models generally provide outputs at multiple levels above the ground. The WRAMS methodology
41 provides values at a single specified height above the ground, nominally 50 m, or near the hub-height of modern-day
42 large wind turbines (although with the recent advent of larger and larger wind turbines, hub heights are approaching 100
43 m, so this standard height designation is changing). Where measured data are used to assess wind resources, a simple
44 "power law" relationship is used to extrapolate the measured data to the desired height (Elliott *et al.*, 1987), i.e.

$$45 \quad V_R/V_a = (Z_R/Z_a)^\alpha \quad (1)$$

46
47
48 where α , the power law coefficient, is normally assumed to be 1/7, V_R is the wind speed at reference height Z_R
49 (nominally, 50 m), and V_a is the wind speed at the measurement height Z_a .

50
51 The output of the WRAMS methodology is typically a value of wind power density at every grid-cell representative of
52 an annual average (in order to produce monthly values, the procedure outlined above would have to be repeated for each
53 month of the year). For mapping purposes, a classification scheme has been set up that relates a "wind power class" to
54 a range of wind power densities. The classification scheme ranges from 1 to >7, and applies to a specific height above
55 ground. Normally, for grid-connected applications, a wind power class of 4 or above is best, while for small wind
56 turbine applications where machines can operate in lower wind speeds, wind power class of 3 or above is suitable. Of

1 course, the wind maps are not intended to identify sites at which large wind turbines can be installed, but rather are
2 intended to provide information to developers on where they might most effectively install wind measurement systems
3 for further site assessment. The maps also provide a useful tool for policy makers to obtain reliable estimates on the
4 total wind energy potential for a region.

5
6 Other well-known approaches besides NREL's WRAMS methodology are also used to produce large-area wind
7 resource mapping. For example, Riso National Laboratory calculates wind speeds within 200 m above the Earth's
8 surface using the Karlsruhe Atmospheric Mesoscale Model (KAMM). Although KAMM also uses NCEP/NCAR
9 reanalysis data, the model is based on large-scale geostrophic winds, and simulations are performed for classes of
10 different geostrophic wind. The classes are weighted with their frequency to obtain statistics for the simulated winds.
11 The results can then be treated as similar to real observations to make wind atlas files for the Wind Atlas Analysis and
12 Application Program (WASP), which are employed to predict local winds at a much higher resolution than KAMM can
13 provide. WASP calculations are based on wind data measured or simulated at specific locations and includes a complex
14 terrain flow model, a roughness change model, and a model for sheltering obstacles. More on WASP can be found at
15 <http://www.wasp.dk/>.

16
17 Due to the scarcity of high-quality, ground-based solar resource measurements, large-area solar resource assessments in
18 the US have historically relied on the analysis of surface National Weather Service cloud cover observations. These
19 observations are far more ubiquitous than solar measurements, and allowed NREL to develop a 1961 to 1990 National
20 Solar Radiation Database for 239 surface sites. However, more recently in the US more and more reliance has been
21 placed on GOES visible channel data to obtain surface reflectance information that can be used to derive high-resolution
22 (~10-km) site-time specific solar resource data (see for example Perez, *et al.*, 2002). In fact, this approach has become
23 commonplace in Europe, using Meteosat data. And the NASA Langley Research Center has recently completed a 20-
24 year worldwide 100-km resolution Surface Solar Energy Data set derived from International Satellite Cloud
25 Climatology Project data, which is derived from data collected by all of the Earth's geostationary and polar orbiting
26 satellites (<http://eosweb.larc.nasa.gov/sse>).

27
28 The use of satellite imagery for estimating surface solar resource characteristics over large areas has been studied for
29 some years, and Renné *et al.* (1999) published a summary of approaches developed around the world. These satellite-
30 derived assessments require good knowledge of the aerosol optical depth over time and space, which can be obtained in
31 part from MODIS and Advanced Very High Resolution Radiometer (AVHRR) data from polar orbiting environmental
32 satellites. The assessments provide information both on Global Horizontal Irradiance (GHI), which is useful for
33 estimating resources available to flat plate collectors such as photovoltaic panels or solar water heating systems, and
34 Direct Normal Irradiance (DNI), which is needed for determining the resources available to solar concentrators that
35 track the sun.

36
37 Besides NREL and NASA, other organizations perform similar types of high-resolution solar resource data sets. For
38 example, the German Space Agency (DLR) has been applying similar methods to Meteosat data for developing solar
39 resource maps and data for Europe and northern Africa. DLR was also involved in the SWERA project and applied
40 their methodologies to several SWERA countries.

41 42 43 Geospatial Toolkit

44
45 Recently, NREL has begun to format the solar and wind resource information into GIS software-compatible formats,
46 and has incorporated this information, along with other geospatial data relevant to renewable energy development, into
47 a Geospatial Toolkit (GsT). The GsT is a stand-alone, downloadable, and executable software package that allows the
48 user to overlay the wind and solar data with other geospatial data sets available for the region, such as transmission
49 lines, transportation corridors, population (load) centers, locations of power plant facilities and substations, land use and
50 land form data, terrain data, etc. Not only can the user overlay various data sets of their choosing, there are also simple
51 queries built into the toolkit, such as the amount of "windy" land (e.g. Class 3 and above) available within a distance of
52 10-km of all transmission lines (minus specified exclusion areas, such as protected lands). The GsT developed at NREL
53 makes use of the Environmental Science and Research Institute's (ESRI) Map Objects software, although other
54 platforms, including on-line, Web-based platforms, could also be used.

1 In a sense, the GsT is a DSS, since it allows the user to manipulate resource information with other critical data relevant
2 to the deployment of renewable energy technologies to assist decision makers in identifying and conducting preliminary
3 assessments of possible sites for installing these systems and supporting renewable energy policy decisions. However,
4 up to now NREL has only prepared GsT's for a few locations: the countries of Sri Lanka, Afghanistan, and Pakistan;
5 Hebei Province in China; the state of Oaxaca in Mexico; and the state of Nevada in the US. By the time of publication
6 of this chapter, additional toolkits may also be available. As with the resource data, all toolkits developed by NREL are
7 available for download from NREL's Web site. Those toolkits developed under the SWERA project are also available
8 from the SWERA Web site.

9 10 HOMER: NREL's Micropower Optimization Model

11
12 The primary decision support tool that makes up the DSS being described here is HOMER, NREL's Micropower
13 Optimization Model. HOMER is a computer model that simplifies the task of evaluating design options for both off-
14 grid and grid-connected power systems for remote, stand-alone, and distributed generation applications. HOMER's
15 optimization and sensitivity analysis algorithms allow the user to evaluate the economic and technical feasibility of a
16 large number of technology options and to account for variation in technology costs and energy resource availability.
17 HOMER can also address system component sizing and the adequacy of the available renewable energy resource.
18 HOMER models both conventional and renewable energy technologies:

19 **Power sources:**

- 20 • solar photovoltaic
- 21 • wind turbine
- 22 • run-of-river hydropower
- 23 • Generator: diesel, gasoline, biogas, alternative and custom fuels, co-fired
- 24 • electric utility grid
- 25 • microturbine
- 26 • fuel cell

27 **Storage:**

- 28 • battery bank
- 29 • hydrogen

30 **Loads:**

- 31 • daily profiles with seasonal variation
- 32 • deferrable (e.g., water pumping and refrigeration)
- 33 • thermal (e.g., space heating and crop drying)
- 34 • efficiency measures

35
36 In order to find the least cost combination of components that meet electrical and thermal loads, HOMER simulates
37 thousands of system configurations, optimizes for lifecycle costs, and generates results of sensitivity analyses on most
38 inputs. HOMER simulates the operation of each technology being examined by making energy balance calculations for
39 each of the 8,760 hours in a year. For each hour, HOMER compares the electric and thermal load in the hour to the
40 energy that the system can supply in that hour. For systems that include batteries or fuel-powered generators, HOMER
41 also decides for each hour how to operate the generators and whether to charge or discharge the batteries. If the system
42 meets the loads for the entire year, HOMER estimates the lifecycle cost of the system, accounting for the capital,
43 replacement, operation and maintenance, and fuel and interest costs. The user can obtain screen views of hourly energy
44 flows for each component as well as annual costs and performance summaries.

45
46 This and other information about HOMER are available on NREL's Web site: <http://www.nrel.gov/homer/>. The Web
47 site also provides extensive examples of how HOMER is used around the world to evaluate optimized hybrid renewable
48 power systems to meet load requirements in remote villages. Figure 1 shows a typical example of an output graphic
49 available from HOMER.

50
51 In order to accomplish these tasks, HOMER requires information on the hourly renewable energy resources available to
52 the technologies being studied. However, typically hour-by-hour wind and solar data are not available for most sites.
53 Thus, the user is requested to provide monthly or average information on solar and wind resources; HOMER then uses
54 an internal weather generator to provide the best estimate of a simulated hour-by-hour data set, taking into consideration
55 diurnal variability if the user can provide an indication of what this should be. However, these approximations

1 represent a source of uncertainty in the model. For those locations where a GsT is available, the GsT offers a
2 mechanism for the user to easily ingest data from the toolkit into HOMER for the specific location of interest. However,
3 since the toolkit contains only monthly solar and wind data, the limitations described above still apply. More
4 information on the weather generator can be found in the HOMER Help files.
5

6 The HOMER developers have implemented various methods to facilitate access to reliable resource data that provide
7 some of the input for simulations. For example, a direct link with the NASA SSE data site enables the user to download
8 monthly and annual solar data from any location on Earth. The 100-km resolution NASA data have become a
9 benchmark of solar resource information, due to the high quality of the modeling capability used to generate the data,
10 the fact that the SSE is validated against numerous ground stations, and the fact that it is global in scope and now covers
11 a 20-year period. However, the data set is still limited by a somewhat coarse resolution and no validation in areas where
12 ground data do not exist. The procedures used to generate the SSE also have problems where land-ocean interfaces
13 occur, and in snow-covered areas.
14

15 Linking HOMER to higher-resolution regional solar data sets would likely improve these uncertainties somewhat, but in
16 general these data sets are also limited to monthly and seasonal values. However, since these methods rely on
17 geostationary satellite data that provide frequent imagery of the Earth's surface, an opportunity exists to produce hourly
18 time series data for up to several years at a 10-km resolution. This option will require significant data storage and
19 retrieval capabilities on a server, but such a possibility now exists for future assessments.
20

21 Wind data available to HOMER is also generally limited to annual and at best monthly values. The standard HOMER
22 interface allows the user to also designate a Weibull "k" value if this information is available. The Weibull k is a
23 statistical means of defining the frequency distribution of the long-term hourly wind speeds at a location; this value can
24 vary substantially depending on local terrain and microclimatic conditions. HOMER also has a provision for the user to
25 designate the diurnal range of wind speeds and the timing when maximum and minimum winds occur. This
26 information then provides improved simulation of the hour-by-hour wind values. The difficulty is that there may be
27 applications where even these statistical values are not known to the user and are not available from the standard wind
28 resource maps produced for a region, but this limitation may not be critical and requires further study to determine the
29 impact on model output uncertainties.
30

31 2b. Access to the HOMER DSS 32

33 HOMER was originally developed and has always been maintained by the National Renewable Energy Laboratory.
34 The model can be downloaded free of charge from NREL's Web site at <http://www.nrel.gov/homer/default.asp>. The
35 user is required to register, and registration must be updated every six months. The Web site also contains a variety of
36 guides for getting started and using the software.
37

38 Resource information required as input to HOMER is generally freely available at the Web sites of the institutions
39 developing the data. These institutions also generally maintain and continuously update the data. For example,
40 renewable energy resource information can be found in several places on NREL's Web site, such as <http://redc.nrel.gov>
41 or www.nrel.gov/GIS. NASA solar energy data, which can be easily input to HOMER, is available at
42 <http://eosweb.larc.nasa.gov/sse>. In fact, there is a specific feature built into HOMER that automatically accesses and
43 inputs the SSE data for the specific location that the model is analyzing. Wind and solar resource data for the 13
44 SWERA countries can be found at <http://unep.swera.net>. This Web site is currently undergoing expansion and
45 upgrading by the USGS/EROS Data Center in Sioux Falls, SD, and will eventually become a major clearing house for
46 resource data from around the world in formats that can be readily ingested into tools such as HOMER.
47

48 2c. Definition of HOMER information requirements 49

50 The ideal input data format to HOMER is an hourly time series of wind and solar resource data covering a complete
51 year (8,760 values). In addition, the wind data should be representative of the wind turbine hub height that is being
52 analyzed within HOMER. Unfortunately data sets such as these are seldom available at the specific locations for which
53 HOMER is being applied. More typically, the HOMER user will have to identify input data sets from resource maps
54 (even within the GsT, the resource data are based on what is incorporated into the map, which, in the case of wind, may
55 represent only a single annual value). Because monthly and annual mean data are more typically available, HOMER
56 has been designed to take monthly mean wind speeds (in m/s) and monthly mean solar resource values (in kw-h/m²-

1 day). In the case of wind, HOMER also allows for the specification of other statistical parameters related to wind speed
2 distributions and diurnal characteristics. Furthermore, if the wind data available for input to HOMER do not represent
3 the same height above the ground as the wind turbine’s hub height being analyzed, HOMER has internal algorithms to
4 adjust for this. The user must specify the height above the ground for which the data represent, and a power law
5 conversion adjusts the wind speed value to the hub height of the specific wind turbine being analyzed. HOMER then
6 utilizes an internal weather generator that takes the input information and creates an hour-by-hour data profile
7 representing a one-year data file. Then, HOMER calculates turbine energy output by converting each hourly value to
8 the energy production of the machine using the manufacturer’s turbine power curve.
9

10 Besides the mean monthly wind speeds, the statistical parameters required by HOMER to generate the hourly data sets
11 include the following:
12

- 13 • The altitude above sea level (to adjust for air density, since turbine performance is typically rated at sea level);
- 14 • The Weibull k value, which typically ranges from 1.5 to 2.5, depending on terrain type;
- 15 • An auto-correlation factor, which is a measure of how strongly the wind speed in 1 hour depends (on average)
16 on the wind speed in the previous hour (these values typically range from 0.85 to 0.90);
- 17 • A diurnal pattern strength, which is a measure of how strongly the wind speed depends on the time of day
18 (values are typically 0.0 to 0.4); and
- 19 • The hour of the peak wind speed (over land areas this is typically 1400 to 1600 local time)
20

21 In the US as elsewhere, wind resource maps often depict the resource in terms of wind power density, in units of watts-
22 m⁻² rather than in wind speeds. In this case, the wind power density must be converted back to a mean wind speed. The
23 relationship between wind power density (P) and wind speed (v) is given as follows:
24

$$25 \quad P = \frac{1}{2}\rho \sum_i v_i^3, \quad (2)$$

26
27 where ρ is the density of the air and i is the individual hourly wind observation. Since the frequency distribution of
28 wind speed over the period of a year or so follows a Weibull distribution shape, the wind power density can be
29 converted back to a wind speed if the “k” factor in the Weibull distribution is known, as well as the height above sea
30 level of the site (to determine the air density).
31

32 2d. Access to and use of the HOMER DSS among the federal, state, and local levels 33

34 Because of the easy access to HOMER and to the related resource assessment data products, the HOMER DSS is freely
35 available to all government and private entities in the US and worldwide. Thousands of users from all economic sectors
36 are using HOMER to evaluate renewable energy technology applications, particularly for off-grid use.
37

38 2e. Variation of the HOMER DSS by geographic region or characteristic 39

40 A key feature of HOMER is the evaluation of specific renewable energy technologies and related energy systems for
41 different regions and for different applications. The HOMER model contains information on renewable energy
42 technology characteristics; however, these characteristics, such as power curves of difference wind turbine models,
43 generator fuel curves, and other factors are not affected by location. Because of the location-specific dependency of
44 resource data, use of data that is not representative of the specific region of analysis will introduce additional
45 uncertainties in the model results. Thus, the user should evaluate the accuracy and relevancy of any default information
46 that is built into HOMER, or any resource data chosen as input to HOMER before completing the final analyses.
47

48 3. Observations used by the HOMER DSS now and of potential use in the future 49

50 This section focuses on the Earth observations (of all types, from remote sensing and *in situ*) used or of potential use in
51 the HOMER DSS.
52

53 3a. Kinds of observations being used 54

1 In the previous section we provided a description of the renewable energy resource assessment related to solar and wind
2 technologies that are required as input to HOMER when these technologies are being modeled. As noted in that section,
3 developing this resource information requires the use of a variety of Earth observations. In this section we list out these
4 observations for each resource category, as well as other types of observations relevant to the HOMER DSS.

5 6 Wind Resources

7
8 The ideal observational platform for obtaining reliable wind resource data to be input into HOMER would be calibrated
9 wind speed measurements from a meteorological tower installed at the location of interest. These measurements should
10 be obtained at the hub height of the wind turbine being modeled, should be of sufficient sampling frequency to provide
11 hourly measurements, and should be of sufficient quality and duration to result in at least one full year of continuous
12 measurements. Although measurements of this quality are typically necessary at project sites where significant
13 investments in large grid-connected wind turbines are anticipated, and where a decision has already been made to
14 implement a large-scale project, it is extremely rare that this level of observation is available for most HOMER
15 applications, where the user is examining potential applications for proposed projects. Thus, some indirect means to
16 establish wind characteristics at a proposed site, such as extrapolating wind resource measurements available from a
17 nearby location or developing a wind resource map such as described in Section 2, is required. The major global data
18 sets typically used by NREL for wind resource assessment are summarized in table 1.

19
20 More discussion on some of these data sets is provided below.

21 22 Surface Station Data

23
24 In the US, as well as in most other countries, the main source of routine surface wind observations would be
25 observations from nearby national weather stations, such as those routinely maintained to support aircraft operations at
26 airports. These data can be made available to the user from the National Climatic Data Center (NCDC) in the form of
27 the Integrated Surface Hourly (ISH) data set. This database is composed of worldwide surface weather observations
28 from about 20,000 stations, collected and stored from sources such as the Automated Weather Network (AWN), the
29 Global Telecommunications System (GTS), the Automated Surface Observing System (ASOS), and data keyed from
30 paper forms (see, http://gcmd.nasa.gov/records/GCMD_C00532.html).

31 32 Satellite-Derived Ocean Wind Data

33
34 Ocean wind data can be obtained from the SeaWinds Scatterometer (see <http://manati.orbit.nesdis.noaa.gov/quikscat/>)
35 mounted aboard NASA's Quick Scatterometer (QuickSCAT) satellite. QuickSCAT was launched on June 19, 1999 in a
36 sun-synchronous polar orbit. A longer-term ocean winds data set is available from the Special Sensor
37 Microwave/Imager (SSM/I) data products as part of NASA's Pathfinder Program. The SSM/I geophysical dataset
38 consists of data derived from observations collected by SSM/I sensors carried onboard the series of Defense
39 Meteorological Satellite Program (DMSP) polar orbiting satellites (see
40 http://www.ssmi.com/ssmi/ssmi_description.html#ssmi). An example of how more recent QuickScat data were used in
41 support of a wind resource assessment in Pakistan is provided in figure 2 (see also
42 http://www.nrel.gov/applying_technologies/applying_technologies_pakistan.html; click under "Monthly maps of
43 satellite-derived wind speed estimates at 10-m above the surface for the Arabian Sea" at the Wind Resources section).
44 Airborne or space borne Synthetic Aperture Radar systems can also provide information on ocean wind data, although
45 these data are not commonly used for this purpose in the US, since Scatterometer data products are more readily and
46 freely available.

47 48 Reanalysis Upper Air Data

49
50 The US reanalysis data set was first made available in 1996 to provide gridded global upper air and vertical profiles of
51 wind data derived from 1,800 radiosonde and pilot balloon observations stations (Kalnay, *et al.* 1997). The reanalysis
52 data were prepared by NCAR-NCEP and can be found at <http://www.cdc.noaa.gov/cdc/reanalysis/>. An early analysis of
53 the data set (Schwartz, George, and Elliott, 1999) showed that for wind resource assessments the dataset was a
54 promising tool for gaining a more complete understanding of vertical wind profiles around the world but that
55 discrepancies with actual radiosonde observations still existed. Since that time, continuous improvements have been

1 made to the NCAR-NCEP dataset, and it is has become an ever-increasingly important data source for contributing to
2 reliable wind resource mapping activities.

3 4 Digital Terrain Data

5
6 Digital Elevation Models (DEM) have been accessed from the USGS/EROS data center. These models consist of a
7 raster grid of regularly spaced elevation values that have been derived primarily from the USGS topographic map series.
8 The USGS no longer offers DEMs, and for the US these can now be accessed from the National Elevation Dataset
9 (<http://ned.usgs.gov/>). The Shuttle Radar Topographic Mission (SRTM) offers much higher resolution terrain data sets,
10 which are now beginning to be used in some wind mapping exercises. These are also being distributed by USGS/EROS
11 under agreement with NASA (<http://srtm.usgs.gov/>).

12 13 Digital Land Cover Data

14
15 Land cover data are used to estimate roughness length parameters required for the mesoscale meteorological models
16 used in the wind mapping process. Data from the Global Land Cover Characterization dataset provide this information
17 at a 1-km resolution (see <http://edcsns17.cr.usgs.gov/glcc/background.html>). The Moderate Imaging Spectroradiometer
18 (MODIS) is used to obtain global percent tree cover values at a spatial resolution of 0.5 km (Hansen, *et al.*, 2003).
19 Existing natural vegetation is also being mapped at a 200-m resolution as part of the USGS Regional Gap Analysis
20 program. Gap analysis is a scientific method for identifying the degree to which native animal species and natural
21 communities are represented in our present-day mix of conservation lands (Jennings and Scott, 1997).

22 23 Solar Resources

24
25 As with wind, the ideal solar resource data set for incorporation into HOMER would be data derived from a quality,
26 calibrated surface solar measurement system consisting of a pyranometer and a pyrliometer that can provide a
27 continuous stream of hourly data for at least one year. Such data are seldom available at the site for which HOMER is
28 being applied. Although interpolation to nearby surface radiometer data sets can be accomplished with reasonable
29 reliability, we usually resort to an estimation scheme to derive an *in-situ* data set. The solar resource assessments that
30 NREL and others undertake make use of several different observational datasets, such as ground-based cloud cover
31 measurements, satellite-derived cloud cover measurements, or the use of the visible channel from satellite imagery data.
32 The major global data sets used for solar resource assessments are summarized in table 2.

33
34 More discussion on some of these data products is described below.

35 36 World Radiation Data Center

37
38 Since the early 1960s the World Radiation Data Center, located at the Main Geophysical Institute in St. Petersburg,
39 Russia, has served as a clearinghouse for worldwide solar radiation measurements collected at national weather stations.
40 The WRDC is under the auspices of the World Meteorological Organization. A Web-based data set was developed by
41 NREL in collaboration with the WRDC and can be accessed at <http://wrdc-mgo.nrel.gov/>. This data archive covers the
42 period 1964 to 1993. For more recent data, the user should go directly to the WRDC home page at
43 <http://wrdc.mgo.rssi.ru/>.

44 45 Aerosol Optical Depths (AOD)

46
47 After clouds, atmospheric aerosols have the greatest impact on the distribution and characteristics of solar resources at
48 the Earth's surface. However, routine *in-situ* observations of this parameter have only recently begun. Consequently, a
49 variety of surface-based and satellite-based observations are used to derive the best information possible of the temporal
50 and spatial characteristics of the atmospheric AOD. The most prominent of the surface data sets is the AERONET
51 (<http://aeronet.gsfc.nasa.gov/>), a network of automated multiwavelength sun photometers located around the world.
52 This network also has links to other networks, where the data may be less reliable. AERONET data can be used to
53 provide ground-truth data for different satellite sensors that have been launched on a variety of sun-synchronous
54 orbiting platforms since the 1980s, such as the Total Ozone Mapping Spectrometer (TOMS), the Advanced Very High
55 Resolution Radiometer (AVHRR), the Moderate Resolution Imaging Spectroradiometer (MODIS), and the Multi-Angle
56 Imaging Spectroradiometer (MISR), the latter two mounted on NASA's Terra satellite. As noted by Gueymard (2003)

1 determination of AOD from satellite observations is still subject to inaccuracies, particularly over land areas, due to a
2 variety of problems such as insufficient cloud screening or interference with highly reflective surfaces. The Global
3 Aerosol Climatology Project (GACP), established in 1998 as part of the NASA Radiation Sciences Program and the
4 Global Energy and Water Experiment (GEWEX), has as its main objectives to analyze satellite radiance measurements
5 and field observations in order to infer the global distribution of aerosols, their properties, and their seasonal and
6 interannual variations and to perform advanced global and regional modeling studies of the aerosol formation,
7 processing, and transport (<http://gacp.giss.nasa.gov/>).

8 Other sources of aerosol optical depth data include the Global Ozone Chemistry Aerosol Transport (GOCART) model
9 (<http://code916.gsfc.nasa.gov/People/Chin/gocartinfo.html>) which is derived from a chemical transport model. An
10 older dataset, the Global Aerosol Dataset (GADS), which can be found at [http://www.lrz-](http://www.lrz-muenchen.de/~uh234an/www/radaer/gads.html)
11 [muenchen.de/~uh234an/www/radaer/gads.html](http://www.lrz-muenchen.de/~uh234an/www/radaer/gads.html), is a theoretical data set providing aerosol properties averaged in space
12 and time on a 5⁰ x 5⁰ grid. (Koepke, *et al.*, 1997).

13 Other Renewable Energy Resources

14 Although the scope of this chapter focuses on wind and solar energy resources, it is evident that many of the Earth
15 observation data sets listed above can apply to other renewable energy resources as well. For example, hydropower
16 resources can be determined by analysis of high resolution DEM data, along with knowledge of the rainfall amounts
17 over specific watersheds and the land use characteristics of these watersheds. Biomass resource assessments can be
18 enhanced through use of MODIS data as well as other weather-related data, and through evaluation of MODIS and
19 AVHRR data to determine the Normalized Vegetation Index (NVI).

20 3b. Limitations on the usefulness of observations

21
22 In the absence of direct solar and wind resource measurements at the location for which HOMER is being applied, the
23 observations described in Section 3a, when used in the wind and solar resource mapping techniques described in
24 Section 2, will together provide useful approximations of the data required as input to HOMER. However, the
25 observations all have limitations in that they do not explicitly provide direct observation of the data value required for
26 the mapping techniques but only approximations based on the use of algorithms to convert a signal into the parameter of
27 interest. These limitations for some of these data sets can be summarized here:

28
29 Surface Station Data: These are generally not available at the specific locations at which HOMER would be applied, so
30 interpolation is required. Furthermore, they generally do not have actual solar measurements, but rather proxies for
31 these measurements (i.e., cloud cover). The wind data are generally collected at 10 m above the ground or less, and the
32 anemometer may not be in a well-exposed condition. When the station observations are derived from human
33 observations, they represent samples of a few minutes duration every 1 or 3 hours; therefore, many of the observations
34 are missing. For those stations that have switched from human observations to Automated Surface Observation Stations
35 (ASOS), the means of observation have changed significantly from the human observations, representing a
36 discontinuity in long-term records. Occasionally, the location of the station is changed without changing the station ID
37 number, which can also cause a discontinuity in observations. Similarly, equipment changes can cause a discontinuity in
38 observations

39
40 Satellite-Derived Ocean Wind Data: These data are not based on direct observation of the wind speed at
41 10 m above the ocean surface, but rather from an algorithm that infers wind speeds based on the wave height
42 observations provided by the scatterometers or Synthetic Aperture Radar

43
44 Satellite-Derived Cloud Cover and Solar Radiation Data: These data sets are derived from observations of the
45 reflectance of the solar radiation from the Earth-atmosphere system. Although it could be argued that this method does
46 provide a direct observation of clouds, the solar radiation values are determined from an algorithm that converts
47 knowledge of the reflectance observation, the incoming solar radiation at the top of the atmosphere, and the
48 transmissivity characteristics of the atmosphere to develop estimates of solar radiation.

49
50 Aerosol Optical Depth: Considerable research is underway to improve the algorithms used to convert multi-spectral
51 imagery of the Earth's surface to aerosol optical depth. The satellite-derived methods have additional shortcomings

1 over land surfaces, where irregular land-surface features make application of the algorithms complicated and uncertain.

2 3 4 3c. Reliability of the observations

5
6 For those observations that provide inputs to the solar and wind resource data, their reliability can vary from parameter
7 to parameter. Generally all of the observations used to produce data values required for solar and wind assessments
8 have undergone rigorous testing, evaluation, and validation. This research has been undertaken by a variety of
9 institutions, including the institutions gathering the observations (e.g., NASA and NOAA) as well as the institutions
10 incorporating the observations into resource mapping techniques (e.g., NREL). Many of the satellite-derived
11 observations of critical parameters will be less reliable than *in-situ* observations; however, satellite-derived observations
12 must still be used due to the scarcity of *in-situ* measurement stations.

13 14 3d. What kinds of observations could be useful in the near future

15
16 All of the observations currently available will continue to be of critical value in the near future. For renewable energy
17 resource mapping, improved observations of key weather parameters (wind speed and direction at various heights above
18 the ground and over the open oceans at higher and higher spatial resolutions, improved ways of differentiating snow
19 cover and bright reflecting surfaces from clouds, etc.) will always be of value to the renewable energy community.
20 New, more accurate methods of related parameters such as aerosol optical depth would result in improvements in the
21 resource data. All of these steps will lead to improvements in the quality of outputs from renewable energy decision
22 support tools such as HOMER.

23 24 4. Uncertainty

25
26 Application of the HOMER DSS involves a variety of input data types, all of which can have a level of uncertainty
27 attached to them. HOMER addresses uncertainties by allowing the user to perform sensitivity analyses for any
28 particular input variable or combination of variables. HOMER repeats its optimization process for each value of that
29 variable and provides displays to allow the user to see how results are affected. An input variable for which the user has
30 specified multiple values is called a sensitivity variable, and users can define as many of these variables as they wish.
31 In HOMER, a “one-dimensional” sensitivity analysis is done if there is a single sensitivity variable, such as the mean
32 monthly wind speed. If there are two or more sensitivity variables, the sensitivity analysis is “two” or “multi-
33 dimensional.” HOMER has powerful graphical capabilities to allow the user to examine the results of sensitivity
34 analyses of two or more dimensions. This is important for the decision maker, who must factor in the uncertainties of
35 input variables in order to make a final judgment on the outputs of the model.

36
37 The amount of uncertainty associated with resource data is largely dependent on how the data are obtained and on the
38 nature of the analysis being undertaken. For some types of analyses, very rough estimates of the wind resource would
39 be sufficient; for others, detailed hourly average data based on surface measurements would be necessary. Quality *in-*
40 *situ* measurements of wind and solar data in formats suitable for renewable energy applications over a sufficient period
41 of time (one year or more) can have uncertainties of less than $\pm 3\%$ of the true value. However, when estimation
42 methods are required, such as the use of Earth observations and modeling and empirical techniques, uncertainties can be
43 as much as $\pm 10\%$ or more. These uncertainties are highest for shorter-term data sets, and are lower when annual
44 average values are being used, since throughout the year errors in the estimation methods have a tendency to
45 compensate among the individual values.

46
47 Based on wind turbine and solar technology operating characteristics, it is possible that the error in estimating a
48 renewable energy system performance over a year is roughly linear to the error in the input resource data. For example,
49 for wind energy systems, even though the power of the wind available to a wind turbine is a function of the cube of the
50 wind speed, it turns out that the turbine operating characteristics, where turbines typically do not provide any power at
51 all until a certain threshold speed is reached, and then the power output increases linearly with wind speed until the
52 winds are so high that the turbine must shut down. This results in an annual turbine power output that is roughly linear
53 to the mean annual wind speed for certain mean wind speed rangers. This would mean that, in some cases, an
54 uncertainty in the annual wind or solar resource of $\pm 10\%$ results in an uncertainty of expected renewable energy
55 technology output of approximately $\pm 10\%$.

1
2 **5. Global change information and the HOMER DSS**
3

4 This section expands the discussion of the HOMER DSS to include the relationship of HOMER and its input data
5 requirements with global change information
6

7 5a. Reliance of HOMER DSS global change information
8

9 As shown in the previous section, a number of observations that provide information on global change are also used in
10 either direct or indirect ways as input to HOMER. These observations related primarily to the renewable energy
11 resource information that is required for HOMER applications. Renewable energy system performance is highly
12 dependent on the local energy resources available to the technologies. The extent and characteristics of these resources
13 is driven by weather and local climate conditions, which happens to be the primary area in which Earth observational
14 systems monitoring climate change are addressing. Thus, as users seek access to observations to support renewable
15 energy resource assessments, they will invariably be seeking certain global change observational data.
16

17 Specifically, users will be seeking global change data related to atmospheric properties that support the assessment of
18 solar and wind energy resources, such as wind and solar data, and atmospheric parameters important for estimating
19 these data. For example, major data sets used in solar and wind energy assessments include long-term reanalysis data,
20 climatological surface weather observations, and a variety of satellite observations from both active and passive
21 onboard remote sensors.
22

23 Key factors in affecting the choice of these observational data are their relevance to conducting reliable solar and wind
24 energy resource assessment, their ease of access, and low or no cost to the user. The extensive list of observational data
25 being used in the assessment of renewable energy resources represents strong leveraging of major, taxpayer-supported
26 observational programs that are geared primarily for global change assessment.
27

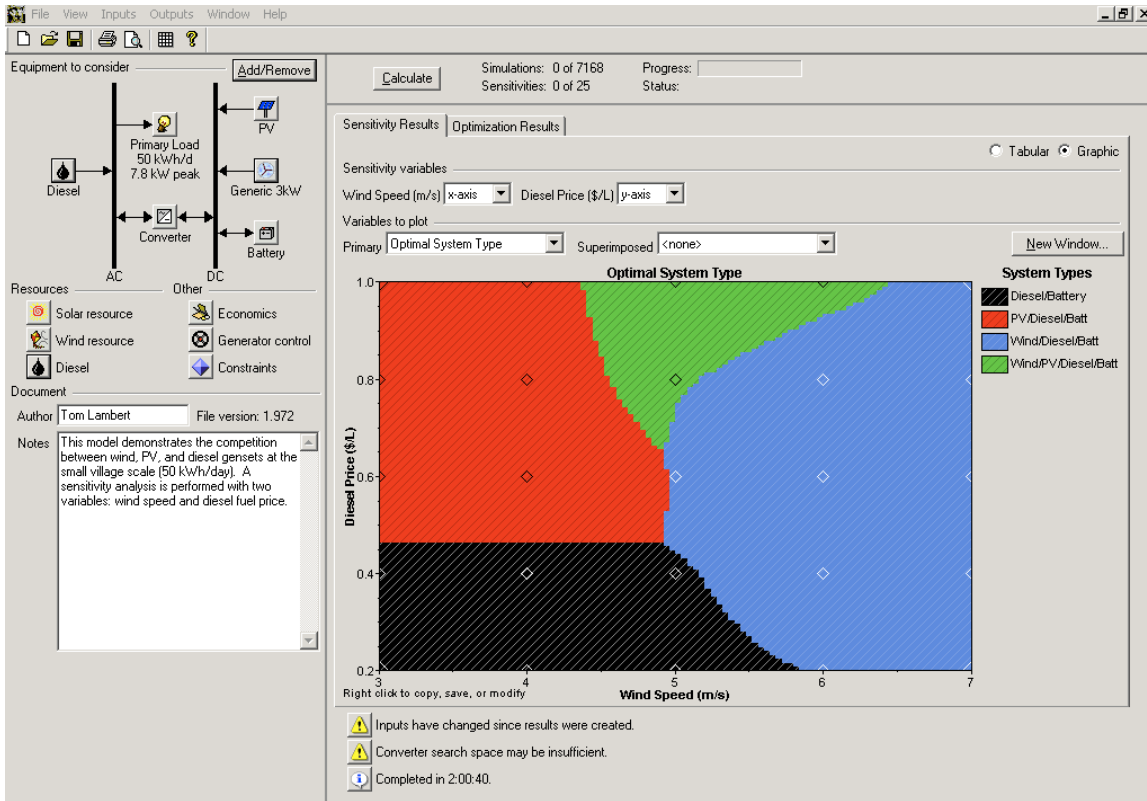
28 There is also an important consideration regarding the potential influence of long-term climate change on the renewable
29 energy resources that are used as input into HOMER. Through the Intergovernmental Panel on Climate Change there
30 has been a significant improvement in the reliability and spatial resolution of General Circulation Models (GCM) used
31 to estimate the impacts of greenhouse gas emissions on climate change. As weather patterns change under changing
32 climate conditions, wind and solar energy resources at a specific location can also change over time. The GCM results
33 indicate that these renewable energy resources can be measurably different 50 to 100 years from now than today in
34 specific locations and regions. These changes may have a noticeable impact on the results of HOMER simulations in
35 the future; however, significant uncertainties exist in GCM results. Until these uncertainties are reduced sufficiently,
36 implementation of GCM results will produce unreliable HOMER simulations.
37

38 5b. How the HOMER DSS can support climate-related management decision-making among US government agencies
39

40 Although HOMER was not intentionally designed to be a climate-related management decision-making tool, the
41 HOMER DSS has attributes that can support these decisions. For example, as we explore mechanisms for mitigating
42 the growth of carbon emissions in the atmosphere, the HOMER DSS can be deployed to evaluate how renewable energy
43 systems can be used cost-effectively to displace energy systems dependent on fossil fuels. Clearly, the science results
44 and global change data and information products coming out of our reanalysis and satellite-borne programs are of
45 critical importance to HOMER for supporting this decision-making process. Given that the pertinent observational data
46 sets have been developed primarily by federal agencies, these data sets tend to be freely available or available at a
47 relatively small cost, given the costs involved in making the observations in the first place. However, as we have noted
48 in previous sections, the use of global change observations as input to the resource assessment data required by
49 HOMER is not the optimal choice of data; ideally, *in-situ* (site-specific) measurements of wind and solar data relevant
50 to the technologies being analyzed would be the most useful and accurate data to have for HOMER, if they were
51 available.
52

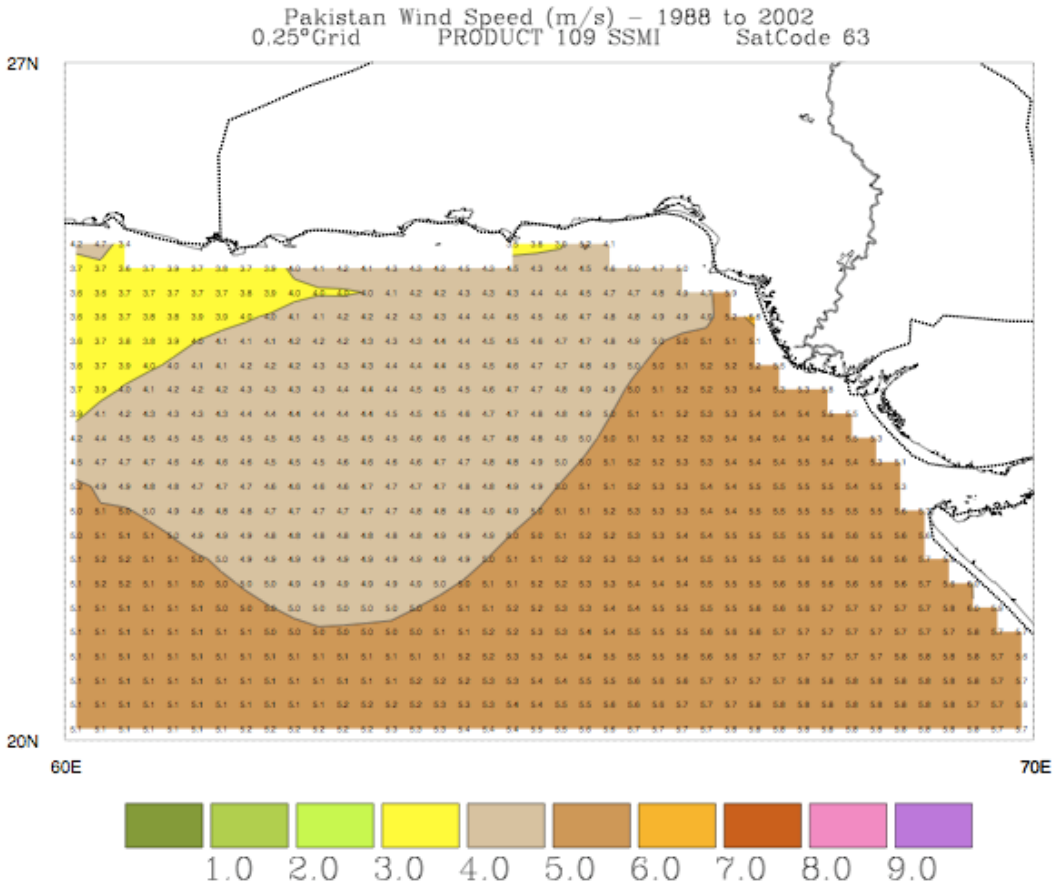
53 Figure 3-1: Example of HOMER output graphic. The column on the left provides a diagram showing the load
54 characteristics and the types of equipment considered to meet the load. The optimal system design graphic shows the
55 range within specified diesel fuel prices and wind energy resources for which various system types are most economical
56 (e.g., a wind/diesel/battery system becomes the most optimal configuration to meet the load requirement for wind
speeds greater than 5 m/s and fuel costs at 0.45 to 0.75\$/l.

1



2
3

1 Figure 3-2. Example of ocean wind resource assessment output for the offshore regions of Pakistan. These data were
 2 derived from the SeaWinds scatterometer aboard NASA's QuickSCAT satellite. The assessment provides estimated
 3 mean annual wind speeds at 10-m above the ocean surface, averaged over the period 1988 to 2002.
 4
 5



6

1 Table 3-1: Major Global Data Sets Used by NREL for Wind Resource Assessment

2

Data Set	Type of Information	Source	Period of Record
Surface station data	Surface observations from more than 20,000 stations worldwide	NOAA/NCDC	Variable up to 2006
Upper air station data	Rawinsonde and pibal observations at 1,800 stations	NCAR	1973–2005
Satellite-derived ocean wind data	Wind speeds at 10 m above the ocean surface gridded to 0.25 ^o	NASA/JPL	1988–2006
Marine climatic atlas of the world	Gridded (1.0 ^o) statistics of historical ship wind observations	NOAA/NCDC	1854–1969
Reanalysis upper air data	Model-derived gridded (~200-km) upper air data	NCAR-NCEP	1958–2005
Global upper air climatic atlas	Model-derived gridded (2.5 ^o) upper air statistics	NOAA/NCDC	1980–1991
Digital geographic data	Political, hydrograph, etc.	ESRI	N/A
Digital terrain data	Elevation at 1-km spatial resolution	USGS/EROS	N/A
Digital land cover data	Land use/cover and tree cover density at 0.5-km resolution	NASA/USGS	N/A

3

1 Table 3-2: Major global data sets used for solar resource assessments
 2
 3

Data Set	Type of Information	Source	Period of Record
Surface station data	Surface cloud observations from more than 20,000 stations worldwide	NOAA/NCDC	Variable up to 2006
World Radiation Data Center	Surface radiation observations from over 1,000 stations worldwide	WRDC, St. Petersburg	1964–1993
Satellite imagers	Imagery from the visible channel of geostationary weather satellites, 1-km resolution	NASA/NOAA	1997– present
International Satellite Cloud Climatology Project	Used in the 1 ⁰ global surface solar energy meteorological data set	NASA/SSE	1983–2003
AERONET	Observations of aerosol optical depth from around the world	NASA/Goddard	Variable depending on station
GACP	Aerosol optical depths (generally over oceans) at 1 ⁰ x 1 ⁰ from AVHRR data	NASA	1981–2005
MODIS, MISR, TOMS	Aerosol optical depth	NASA	Variable since 1980s
GOCART	Aerosol optical depth for turbid areas	NASA	March 30–May 3, 2001
GADS	Aerosol optical depth derived from theoretical calculations and proxies		Compilation of Measurements & Models
Digital geographic data	Political, hydrography, etc.	ESRI	N/A
Digital terrain data	Elevation at 1-km spatial resolution	USGS/EROS	N/A
Digital land cover data	Land use/cover and tree cover density at 0.5-km resolution	NASA/USGS	N/A

4

Chapter 4

Decision Support for Public Health

Lead Author: Gregory E. Glass

1. Introduction

Public health is an approach to protect and improve the health of community members by preventive medicine, health education, control of communicable diseases, application of sanitary measures, and monitoring of environmental hazards (Lilienfeld and Lilienfeld 1980). This overall task is achieved by assessing and monitoring populations at risk to identify health problems and establishing priorities, to formulate policies to solve identified problems and to ensure populations have access to appropriate care, including health promotion, disease prevention, and evaluation of care. During the past century, the notable public health achievements as identified by the US Centers for Disease Control and Prevention (CDC) include vaccinations and treatments against infectious diseases, injury prevention strategies, reduced occupational exposures to toxins, improved food and water safety, decreases in childhood and maternal mortality, and safer water sources. Thus, many of the key issues related to public health are incorporated in previous chapters in this report, though they may not be characterized as public health. Regardless, public health may represent a key factor in problem solving under climate change situations. Many of the anticipated public health consequences of climate change are due to the influences of temperature and precipitation patterns, as well as land cover with consequences for the affected human communities. For example, changes in the availability of food resources and the quality of drinking water are anticipated to directly affect nutritional status, the spread of communicable infectious agents, and the impacts of poor air quality on vulnerable populations and in extreme situations the creation of “environmental refugees,” i.e. individuals displaced by serious environmental changes such as rising sea levels, desertification, dried up aquifers, weather-induced flooding and other climatic changes (Huntingford *et al.*, 2007).

Because public health is an important outcome component of decision support tools (DST) involving air quality, water management, energy management and agricultural efficiency issues, it was decided to focus on a unique public health aspect of DST/DSS by examining infectious disease systems. Infectious diseases remain a significant burden to populations both globally, as well as within the US. Some of these, such as syphilis and measles involve a relatively simple dynamic of the human host population and the parasite—be it a virus, bacterium, or other micro-organism. These diseases, therefore, tend to be influenced by social behavior and the ability to provide resources and of health education to significantly alter human behavior. However, other disease systems include additional species for their successful transmission—either wildlife species that maintain the micro-organism (zoonoses) or there are insect or arthropod vectors that serve to transmit the parasites either among people or from the wildlife to people (vector-borne diseases).

Some of the most significant diseases globally are vector-borne or zoonotic diseases. Examples include malaria and dengue. In addition, many newly recognized (i.e., emerging) diseases either are zoonoses, such as SARS, or appear to have been derived from zoonoses that became established in human populations (e.g., HIV). Changes in rates of contact between component populations of these disease systems alter the rates of infectious disease (Glass 2007). Many of these changes come about through activities involving the movement of human populations into areas where these pathogen systems normally occur or they can occur because people introduce materials with infectious agents into areas where they were not known previously (Gubler *et al.* 2001). The introduction of West Nile virus from its endemic area in Africa, the Middle East, and Eastern Europe into North America and its subsequent spread across the continent is a recent example. The impacts of the virus on wildlife, human, and agricultural production are an excellent example of the economic consequence of such emergent disease systems.

More recently, attention has focused on the potential impact that climate change could have on infectious disease systems, especially those with vector or zoonotic components (e.g., Gubler *et al.*, 2001). Alterations in climate could impact the abundances or interactions of vector and reservoir populations, or the way in which human populations interact with them (Gubler, 2004). In addition, there is speculation that

1 climate change will alter the locations where disease systems are established, shifting the human population
2 that is at risk from these infectious diseases (e.g., Brownstein *et al.*, 2005a; Fox, 2007)

3 Unlike many of the other applications in this report where Earth observations and modeling are of
4 growing importance, the use of Earth observations by the public health community has been sporadic and
5 incomplete. Although early demonstrations showed their utility for identifying locations and times that vector-
6 borne diseases were likely to occur (e.g., Linthicum *et al.*, 1987; Beck *et al.*, 1997), growth of their application
7 has been comparatively slow. Details of the barriers to implementation include the need to “scavenge” data
8 from Earth observation platforms, as none of these are designed for monitoring disease risk. This is not an
9 insurmountable problem and in fact, only few applications for Earth observations have dedicated sensors.
10 However, disease monitoring requires a long history of recorded data to provide information concerning the
11 changes in population distribution and the environmental conditions associated with outbreaks of disease.
12 Detailed spectral and spatial data need to be of sufficient resolution and the frequency of observations must be
13 high enough to enable identification of changing conditions (Glass 2007). As a consequence, many DSTs
14 undergoing development have substantial integration of Earth observations but lack an end-to-end public
15 health outcome, particularly when focusing on infectious diseases. Therefore, the Decision Support System to
16 Prevent Lyme Disease (DDSPL) supported by the CDC and Yale University was selected to demonstrate the
17 potential utility of these systems within the context of climate change science. Lyme disease is a vector-borne,
18 zoonotic bacterial disease. In the US it is caused by the spirochete, *Borrelia burgdorferi*, and it is the most
19 common vector-borne disease with tens of thousands of reported cases annually (Piesman and Gern 2004).
20 Most human cases occur in the Eastern and upper Mid-West portions of the US, although there is a secondary
21 focus along the West Coast of the country. In the primary focus, the black-legged tick (or deer tick), of the
22 genus *Ixodes*, is most often found infected with *B. burgdorferi*.

24 25 **2. Description of DDSPL**

26 The diverse ways in which Lyme disease presents itself in different people has made it a public health
27 challenge to ensure that proper priorities are established, to formulate policies to solve the problem, and to
28 ensure that populations have access to appropriate care. The CDC uses DDSPL to address questions related to
29 the likely distribution of Lyme disease east of the 100th meridian, where most cases occur (Brownstein *et al.*,
30 2003). This is done by identifying the likely geographic distribution of the primary tick vector (the black-
31 legged) tick in this region. DDSPL uses field reports of the known distribution of collected tick vectors, as
32 well as sites with repeated sampling without ticks as the outcome space. DDSPL uses satellite data, and
33 derived products such as land cover characteristics, and census boundary files and meteorological data files to
34 identify the best statistical predictor of the presence of black-legged ticks within the region. Land cover is
35 derived from multi-date Landsat TM imagery and 10-m panchromatic imagery.

36 DDSPL combines the satellite and climate data with the field survey data of *Ixodes* ticks sampled at
37 locally sampled sites throughout the region (Brownstein *et al.*, 2003) or from rates of reported cases of Lyme
38 disease (Brownstein *et al.*, 2005b) in spatially explicit statistical models to generate assessment products of the
39 distribution of the tick vector or human disease risk, respectively. These models are validated by field surveys
40 in additional areas and the sensitivity and specificity of the results determined (figure 4-1). Thus, the DDSPL
41 is primarily a DST for prioritizing the likely geographic extent of the primary vector of Lyme disease in this
42 region (figures 4-1 and 4-2). It currently stops short of characterizing the risk of disease in the human
43 population but is intended to delimit the area within which Lyme disease (and other diseases caused by
44 additional pathogens carried by the ticks) might occur (Figure 4-2). Researchers at Yale University are
45 responsible for developing and validating appropriate analytical methods to develop interpretations that can
46 deal with many of the challenges of spatially structured data, as well as the acquisition of Earth science data
47 that are used for model DDSPL predictions. The distinction between the presence/abundance of the tick vector
48 and actual human risk relies on the effects of human population abundance and behavioral heterogeneity (e.g.,
49 work or recreational activity) that can alter the contact rate between the tick vector and susceptible humans.
50 However, such detailed human studies (especially behavioral heterogeneity) are typically not available
51 (Malouin *et al.*, 2003). In Brownstein *et al.* (2005b) analysis, they found that although the entomological risk
52 (the abundance of infected ticks) increased with landscape fragmentation, the human incidence of Lyme
53 disease decreased, thus indicating there is a complex relationship between the landscape, the population of
54 ticks, and the human response resulting in the health outcome.

1 **3. Potential Future Use and Limits**

2 Future use of DDSPL depends to a great extent on public health policy decisions exterior to the DST. The
3 perspective of the role that Lyme disease prevention rather than treatment of diseased individuals will play is a
4 key aspect of the importance that DDSPL will experience. For example, studies have shown that even in Lyme
5 disease endemic regions, risk communication often fails to reduce the likelihood of infection (Malouin, *et al.*,
6 2003). In principle, policy makers may decide that it is more cost effective to provide improved treatment
7 modalities rather than investing in educational programs that fail to reduce disease burden. Alternatively, the
8 development of vaccines is time consuming, costly, and may have additional risks of unacceptable side effects
9 that affect the likelihood that this would be a policy choice. Thus, depending on policy decisions and the
10 effects of alternative interventions, the DDSPL might be used to forecast risk areas for educational
11 interventions, to inform health care providers in making diagnoses, or to plan mass vaccination campaigns.

12 Currently, the removal of the licensed Lyme disease vaccine from the general public has eliminated this as
13 a strategy to reduce the disease burden. The apparent lack of impact of targeted education also makes this a
14 less likely strategy. Thus, the extent to which treatment modalities rather than prevention of infection will drive
15 the public health response in the near future will play a major role in the use of DDSPL. However, even if the
16 decision is made to focus on treatment of potentially infected individuals, DDSPL may still be useful by
17 identifying regions where disease risk may be low, helping health care workers to focus clinical diagnoses on
18 alternate causes.

19 Presuming that the DST continues to be used, the need for alternative/improved Earth science data to
20 clarify environmental data for DDSPL such as land cover, temperature, and moisture regimes is currently
21 uncertain. The present system reports a sensitivity of 88 percent and specificity of 89 percent—generally
22 considered a highly satisfactory result. Sensitivity and specificity are considered the two primary measures of a
23 method’s validity in public health analyses. Sensitivity in the DDSPL model refers to the expected proportion
24 of times (88 percent) that ticks would be found when field surveys were conducted at sites that the DDSPL
25 predicted they should occur. Specificity refers to the proportion of times (89 percent) that a survey would not
26 be able to find ticks at sites where the DDSPL excluded them from occurring. These two measures provide an
27 estimate of the “confidence” the user can have in the DST prediction (Selvin 1991). These analyses extended
28 geographically from the East Coast to the 100th meridian and were validated by field sampling for the presence
29 of *Ixodes* ticks at sites throughout the region.

30 Typically, patterns of weather regimes appear to have a greater impact on distribution than more
31 detailed information on land cover patterns. However, some studies indicate that fragmentation of forest cover
32 and landscape distribution at fairly fine spatial resolution can substantially alter patterns of human disease risk
33 (Brownstein *et al.*, 2005b). These results also suggest that human incidence of disease may, in some areas of
34 high transmission, be decoupled from the model constructed for vector abundance, reemphasizing the
35 distinction between a key component (the vector) and actual human risk. When coupled with the stated
36 accuracy of the DDSPL in identifying vector distribution, this would suggest that future efforts will probably
37 require an additional model structure that includes sociological/behavioral factors of the human population that
38 puts it at varying degrees of risk. An additional limit of the DDSPL is that it does not explicitly incorporate
39 human health outcomes in its analyses. In part, this reflects a public health infrastructure issue that limits
40 detailed information on the distribution of human disease to (typically) local and state health agencies. For
41 example, confidentiality of health records, including detailed locational data, such as home addresses, are often
42 shielded in the absence of explicit permission. This makes establishing the relationship between monitored
43 environmental conditions and human health outcomes difficult. One solution is to aggregate data to some
44 jurisdictional level. However, this produces the well know “ecological fallacy” in establishing relationships
45 between environmental factors and health outcomes (Selvin 1991). With appropriate planning or the
46 movement of the technology into local public health agencies, these challenges could be overcome. Some
47 localized data (e.g., Brownstein *et al.*, 2005b) of human health outcomes have been used to evaluate the utility
48 of DDSPL and indicate that there is good potential for the DSS to provide important information on local risk
49 factors.

50
51
52 **4. Uncertainty**

53 Uncertainty in decision making from DDSPL is based on the results of statistical analyses in which
54 standard statistical models with spatially explicit components, such as autologistic intercepts of logistic
55 models, are used to account for spatial autocorrelation in outcomes. The statistical analyses are well-supported

1 theoretically. Typical calibration approaches involve model construction followed by in-field validation.
2 Accuracy of classification is then assessed in a sensitivity-specificity paradigm.

3 However, little attention is paid in the current model to assessing uncertainty in the environmental data
4 obtained from remotely sensed (or even *in situ*) monitors of the environment. For example, most of the
5 derivative data, such as land cover, may change with population growth and development. In addition, the use
6 of average environmental conditions provide an approximate characterization of local edaphic conditions that
7 may affect the abundance of the tick vectors.

8 Whether these are the primary sources of “error” in the sensitivity and specificity results (although these
9 are considered excellent results) of the DDSPL is not addressed and is an area the public health applications
10 need to consider in future applications. Alternatively, there are biological reasons for the errors in the model,
11 including the interaction of climatic factors and tick activity that may be responsible for sites predicted to have
12 ticks that were not found to have them. To resolve some of the biological/environmental issues, validation is
13 ongoing.

14 There also are a number of public health issues that affect the certainty of the DDSPL (and any DST)
15 that are extrinsic to the system or tool. Accuracy in clinical diagnoses (both false positives and negatives), as
16 well as reporting accuracy can affect the evaluation of the tool’s utility. Currently, this is an issue of serious
17 contention and forms part of the rationale for focusing on accurately identifying the distribution of the primary
18 tick vector, as an integral step in delimiting the distribution of the disease and evaluating needs for the
19 community.

20 21 **5. Global Change Information and DDSPL**

22 The relationship between climate and public health outcomes is complex. It is affected both by the
23 direction and strength of the relationship between climatic variability and the component populations that make
24 up a disease system, as well as the human response to changes in disease risk (Gubler 2004).

25 The DDSPL is one of the few public health DSTs that has explicitly evaluated the potential impact of
26 climate change scenarios on this infectious disease system. Assuming that evolutionary responses of the black-
27 legged tick, *B. burgdoferi* and the reservoir zoonotic species remains little changed under rapid climate change,
28 Brownstein *et al.*, (2005a) evaluated anticipated changes in the distribution and extent of disease risk.

29 This analysis used the basic climate-land cover suitability model developed for DDSPL and selected the
30 Canadian Global Coupled Model (CGCM1) under two historically forced integrations. The first with a 1
31 percent per year increase in greenhouse gas emissions and the second with greenhouse gas and sulfate aerosol
32 changes, resulted in a 4.9 and 3.8° Celsius increase in global mean temperature by the year 2080. Near (2020),
33 mid (2050) and farpoint (2080) outcomes were evaluated (Figure 4-3). The choice of CGCM1 was based on
34 the Intergovernmental Panel on Climate Change criteria for vintage, resolution, and validity (Brownstein *et al.*,
35 2005a).

36 Extrapolation of the analyses suggest that the tick vector will experience a significant range expansion
37 into Canada but will also experience a likely loss of habitat range in the current southern portion of its range
38 (figure 4-3). This loss of range is thought to be due to impact of increased temperatures causing decreased
39 survival in ticks when they are off their feeding hosts. It also is anticipated that its range will shift in the central
40 region of North America – where it is currently absent. When coupled with the anticipated continued human
41 movement to more southern portions of the country, the numbers of human cases are expected to show an
42 overall small decrease.

43 These long-range forecasts disguise a more dynamic process with ranges initially decreasing during near
44 and mid-term timeframes. This range reduction is later reversed in the long-term producing the overall pattern
45 described by the authors. The impact in range distribution also produces an overall decrease in human disease
46 risk as suitable areas move from areas of primary human concentration to areas that are anticipated to be less
47 well populated.

48 Thus, DSS similar to those developed for Lyme disease have the potential for providing both near- and
49 far-term forecasts of potential infectious disease risk that are so important for public health planning. In
50 addition, detailed studies (e.g. Brownstein *et al.*, 2005b) provide public health agencies with important
51 information on drivers of human risk that have been difficult to obtain by other means. As a consequence,
52 DSS using remotely sensed data sources either in part or whole have the potential to significantly improve the
53 health of communities.

54 The primary challenges for the Earth science community involve understanding the needs of the public
55 health community for the appropriate data at the appropriate spatial, temporal, and spectral scales. This will
56 involve understanding a historically entrenched set of methodologies for interpreting health data and

1 establishing causal relationships between inputs (environmental data) and outputs (health outcomes). In
2 addition, there is the challenge of performing these tasks in the presence of limited resources for a community
3 that has little cultural understanding of both the strengths and limitations of the data derived from these
4 sources.

DRAFT

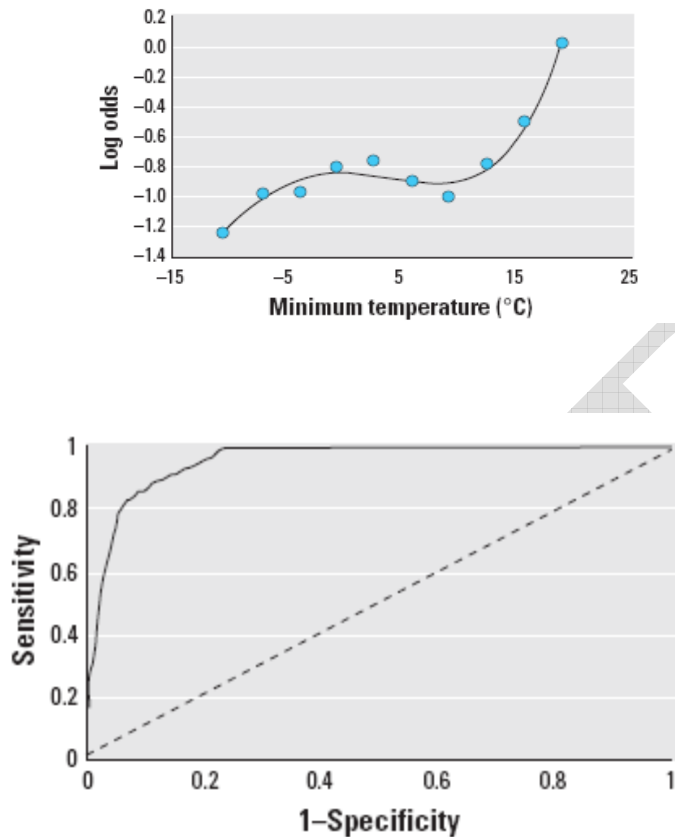


Figure 4-1. Relationship between the occurrence of black-legged tick presence at a site and minimum temperature (top) and evaluation of model (bottom). From Brownstein et al. 2003 Env. Hlth Perspect. **Top Panel:** Log odds plot for relationship between *I. Scapularis* population maintenance and minimum temperature (T). Minimum temperature showed a strong positive association with odds of an established *I. Scapularis* population. According to goodness of fit testing, the relationship was fit best by a fourth order polynomial regression ($R^2 = 0.97$) $\text{Log odds} = 0.0000067^4 + 0.00027^3 - 0.0027T^2 + 0.0002T - 0.8412$. **Bottom Panel:** ROC Plot describing the accuracy of the auto logistic model. This method graphs sensitivity versus 1-specificity over all possible cutoff probabilities. The AUC is a measure of overall fit, where 0.5 {a 1:1 line} indicates a chance performance {dashed line}. The plot for the auto logistic model significantly outperformed the chance model with an accuracy of 0.95 ($p < 0.00005$).

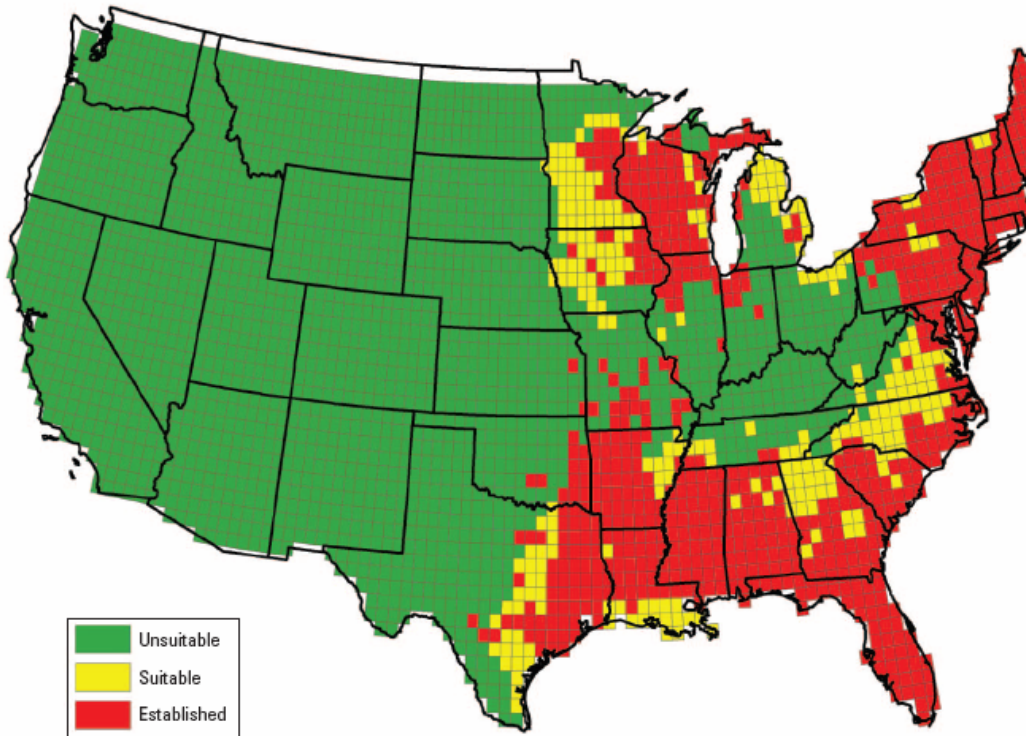


Figure 4-2. Forecast geographic distribution of the black-legged tick vector east of the 100th meridian in the United States for DSSPL. From Brownstein et al (2003) *Envr. Hlth. Perspect.* 2a. New distribution map for *I. Scapularis* in the United States. To determine whether a given cell can support *I. Scapularis* populations, a probability cutoff point for habitat suitability from the auto logistic model was assessed by sensitivity analysis. A threshold of 21% probability of establishment was selected, giving a sensitivity of 97% and a specificity of 86%. This cutoff was used to reclassify the reported distribution map {Dennis et al. 1998}. The auto logistic model defined 81% of the reported locations {n=427} as established and 14% of the absent areas {n=2,327} as suitable. All other reported and absent areas were considered unsuitable. All areas previously defined as established maintained the same classification.

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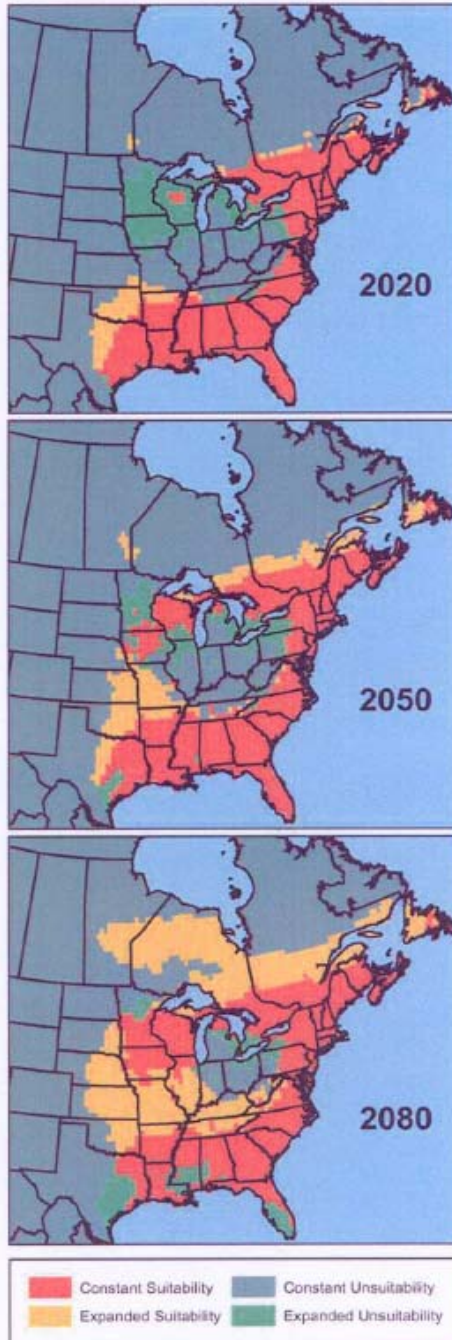


Figure 4-3. Forecast change in black-legged tick distribution in Eastern and Central North America under climate change scenarios using DSSPL. From Brownstein et al (2005a) EcoHealth

1

Chapter 5

Decision Support for Water Resources Management

Lead Author: Holly C. Hartmann

1. Introduction

Water resource managers have long been incorporating information related to climate in their decisions. The tremendous, regionally ubiquitous, investments in infrastructure to reduce flooding (e.g., levees and reservoirs) or assure reliable water supplies (e.g., reservoirs, groundwater development, irrigation systems, water allocation, and transfer agreements) reflect societal goals to mitigate the impacts of climate variability at multiple time and space scales. As the financial, political, social, and environmental costs of infrastructure options have become less tractable, water management institutions have undergone comprehensive reform, shifting their focus to optimizing operations of existing projects and managing increasingly diverse, and often conflicting, demands on the services provided by water resources (Bureau of Reclamation [BOR], 1992; Beard, 1993; Congressional Budget Office, 1997; Stakhiv, 2003; National Research Council [NRC], 2004). Governments have also made substantial investments to improve climate information and understanding over the past decades through satellites, *in situ* measuring networks, supercomputers, and research programs. National and international programs have explicitly identified as an important objective ensuring that improved data products, conceptual models, and predictions are useful to the water resources management community (Endreny et al., 2003; Lawford et al., 2005). Although exact accounting is difficult, potential values associated with appropriate use of accurate hydrometeorologic predictions generally range from the millions to the billions of dollars (e.g., National Hydrologic Warning Council, 2002). There are also non-monetary values associated with more efficient, equitable, and environmentally sustainable decisions related to water resources.

Droughts, floods, and increasing demands on available water supplies continue to create concern, and even crises, for water resources management. Many communities have faced multiple hydrologic events that were earlier thought to have low probabilities of occurrence (e.g., NRC, 1995), and long-term shifts in streamflows have been observed (Lettenmaier et al., 1994; Lins and Slack, 1999; Douglas et al., 2000), leading to questions about the relative impacts of shifts in river hydraulics, land use, and climate conditions.

Until the last two decades, climate was viewed largely as a collection of random processes, and this paradigm informed much of the water resource management practices developed over the past 50 years that persist today. However, climate is now recognized as a chaotic process, shifting among distinct regimes with statistically significant differences in average conditions and variability (Hansen et al., 1997). As instrumental records have grown longer and extremely long time-series of paleoclimatological indicators have been developed (Ekwurzal, 2005), they increasingly belie one of the fundamental assumptions behind most extant water resources management—stationarity. Stationary time series have time-invariant statistical characteristics (e.g., mean or variance), meaning that different parts of the historical record can be considered equally likely. Within the limits posed by sampling, statistics computed from stationary time series can be used to define a probability distribution that will also then faithfully represent expectations for the future (Salas, 1993).

Further, prospects for climate change due to global warming have moved from the realm of speculation to general acceptance (Intergovernmental Panel on Climate Change [IPCC] 1990, 1995a, 2001a, 2007). The potential impacts of climate on water resources, and their implications for management, have been central topics of concern in climate change assessments (e.g., EPA, 1989; IPCC, 1995b, 2001b; National Assessment Synthesis Team, 2000; Gleick and Adams, 2000; Barnett *et al.*, 2004). These studies are becoming increasingly confident in their conclusions that the future portends statistically significant changes in hydroclimatic averages and variability.

There has been persistent and broad disappointment in the extent to which improvements in hydroclimatic science from large-scale research programs have affected resource management practices in general (Pielke, 1995, 2001; NRC, 1998a, 1999a) and water resource management in particular (NRC, 1998b, 1999b,c). For example, seasonal climate outlooks have been slow to be entered into the water management decision processes, even though they have improved greatly over the past 20 years (Hartmann et al., 2002a, 2003). Water managers have been even more resistant to incorporating notions of hydrologic non-stationarity in general and climate change in particular in decision processes. Until recently, hydrologic analysis techniques have been seen as generally sufficient (e.g., Matalas, 1997; Lins and Stakhiv, 1998), especially in the context of slow policy and institutional evolution (Stakhiv, 2003). However, an inescapable message for the water resource management community is the inappropriateness of the stationarity assumption in the face of climate change.

1 Several ongoing efforts are leading the way forward to establish more effective ways of incorporating climate
2 understanding and earth observations into water resources management (Pulwarty, 2002; Office of Global Programs,
3 2004; NASA, 2005). While diverse in their details, these efforts seek to link hydroclimatological variability, analytical
4 and predictive technologies, and water management decisions within an end-to-end context extending from
5 observational data through large-scale analyses and predictions, uncertainty evaluation, impacts assessment,
6 applications, and evaluations of applications (e.g., Young, 1995; Miles et al., 2000). Some end-to-end efforts focus on
7 cultivating information and management networks; designing processes for recurrent interaction among research,
8 operational product generation, management, and constituent communities; and developing adaptive strategies for
9 accommodating climate variability, uncertainty, and change. Other end-to-end efforts focus on the development of
10 decision support tools (DST) that embody unique resource management circumstances to enable formal and more
11 objective linkages between meteorological, hydrologic, and institutional processes. Typically, end-to-end DST
12 applications are developed for organizations making decisions with high-impact (e.g., state or national agencies) or
13 high-economic value (e.g., hydropower production) and that possess the technical and managerial abilities to efficiently
14 exploit research advances (e.g., Georgakakos et al, 1998, 2004, 2005; Georgakakos, 2006). If linked to socioeconomic
15 models incorporating detailed information about the choices open to decision-makers and their tolerance for risk, these
16 end-to-end tools could also enable explicit assessment of the impacts of scientific and technological research advances.

17 This chapter describes a river management DST, RiverWare, which facilitates coordinated efforts among the
18 research, operational product generation, and water management communities. RiverWare emerged from an early and
19 sustained effort by several federal agencies to develop generic tools to support the assessment of water resources
20 management options in river basins with multiple reservoirs and multiple management objectives (Frevert et al., 2006).
21 RiverWare was selected for use as a case study because it has been used in a variety of settings, by multiple agencies,
22 over a longer period than many other water management DSTs. Furthermore, RiverWare can explicitly accommodate a
23 broad range of resource management concerns (e.g., flood control, recreation, navigation, water supply, water quality,
24 and power production). RiverWare can also consider perspectives ranging from day-to-day scheduling of operations to
25 long-range planning and can accommodate a variety of climate observations, forecasts, and even climate change
26 projections. RiverWare can incorporate hydrologic risk, whereby event consequences and their magnitudes are mediated
27 by their probability of occurrence, in strategic planning applications and design studies, which can offer a way forward
28 for decision makers reluctant to shift away from use of traditional, stationarity-based, statistical analysis of historical
29 data (Lee, 1999; Davis and Pangburn, 1999).

30 31 **2. Description of RiverWare**

32 RiverWare is a software framework used to develop detailed models of how water moves and is managed
33 throughout complex river basin systems. RiverWare applications include physical processes (e.g., streamflow, bank
34 storage, and solute transport), infrastructure (e.g., reservoirs, hydropower generating turbines, spillways, and diversion
35 connections), and policies (e.g., minimum instream flow requirements and trades between water users) (Zagona et al.,
36 2001, 2005). At a minimum, RiverWare applications require streamflow hydrographs as input for multiple locations
37 throughout a river system. While hydrographs can be generated within the DST, they can also be input from other
38 sources, with the latter approach being especially important in advanced end-to-end assessments. Detailed discussion of
39 the role of observations and considerations of global change using RiverWare are discussed in later sections. RiverWare
40 can be applied to address diverse water management concerns, including real-time operations, strategic planning for
41 seasonal to interannual variability in water supplies and demands, and examining impacts of hydrologic non-
42 stationarity. Because infrastructure, management rules, and policies can be easily changed, RiverWare also allows
43 examination of alternative options for achieving management objectives over short-, medium-, and long-term planning
44 horizons.

45 RiverWare was developed by the University of Colorado-Boulder's Center for Advanced Decision Support for
46 Water and Environmental Systems (CADSWES) in collaboration with the BOR, Tennessee Valley Authority, and the
47 Army Corps of Engineers (Frevert et al., 2006). CADSWES continues to develop and maintain the RiverWare software,
48 as well as offer training and support for RiverWare users (see <http://cadswes.colorado.edu>). According to CADSWES,
49 RiverWare is used by more than 75 federal and state agencies, private sector consultants, universities and research
50 institutes, and water districts, among others.

51 52 *Example Applications*

53 Consistent with the intent of its original design, the use of RiverWare varies widely, depending on the specific
54 application. An early application was its use for scheduling reservoir operations by the Tennessee Valley Authority
55 (Eshenbach et al., 2001). In that application, RiverWare was used to define the physical and economic characteristics of
56 the multi-reservoir system, including power production economics, to prioritize the policy goals that governed the

1 reservoir operations and to specify parameters for linear optimization of system objectives. In another application,
2 RiverWare was used to balance the competing priorities of minimum instream flows and consumptive water use in the
3 operation of the Flaming Gorge Reservoir in Colorado (Wheeler et al., 2002).

4 While day-to-day scheduling of reservoir operations is more a function of weather than climate, the use of
5 seasonal climate forecasts to optimize reservoir operations has long been a goal for water resources management.
6 RiverWare is being implemented for the Truckee-Carson River basin in Nevada to investigate the impact of
7 incorporating climate outlooks into an operational water management framework that prioritizes irrigation water
8 supplies, interbasin diversions, and fish habitat (Grantz et al., 2007). Another example application to the Truckee-
9 Carson River using a hypothetical operating policy indicated that fish populations could benefit from purchases of water
10 rights for reservoir releases to mitigate warm summer stream temperatures resulting from low flows and high air
11 temperatures (Neumann et al., 2006).

12 RiverWare has also been used to evaluate politically charged management strategies, including water transfers
13 proposed in California's Quantification Settlement Agreement and the BOR's Inadvertant Overrun Policy, maintaining
14 instream flows sufficient to restore biodiversity in the Colorado River delta, and conserving riparian habitat while
15 accommodating future water and power development in the BOR Multiple Species Conservation Program (Wheeler et
16 al., 2002). RiverWare also played a key role in negotiations by seven western states concerning how the Colorado River
17 should be managed and the river flow should be distributed among the states during times of drought. The BOR
18 implemented a special version of the RiverWare model of the Colorado River and its many reservoirs, diversions, and
19 watersheds (Jerla, 2005). The model was used to provide support to the Basin States Modeling Work Group Committee
20 over an 18-month period, as they assessed different operational strategies under different hydrologic scenarios,
21 including extreme drought (U.S. Department of Interior, 2007).

22 *Implementation*

23 RiverWare requirements are multi-dimensional. A specific river system and its infrastructure operating policies
24 are defined by data files supplied to RiverWare. This allows incorporation of new basin features (e.g., reservoirs),
25 operating policies, and hydroclimatic conditions without users having to write software code. Utilities within RiverWare
26 enable users to automatically execute many simulations, including accessing external data or exporting results of model
27 runs. Users can also write new modules that CADSWES can integrate into RiverWare for use in other applications. For
28 example, in an application for the Pecos River in New Mexico, engineers developed new methods and software code for
29 realistic downstream routing of summer monsoon-related flood waves (Boroughs and Zagona, 2002). RiverWare is
30 implemented for use on Windows or Unix Solaris systems, as described in the requirements document
31 (<http://cadswes.colorado.edu/PDF/RiverWare/RecommendedMinimumSystemsRequirements.pdf>). An extensive
32 manual is also available (<http://cadswes.colorado.edu/PDF/RiverWare/documentation/>).

33 RiverWare applications can be implemented by any group that can pay for access, both in terms of finances
34 and educational effort. Development of RiverWare applications requires a site license from CADSWES. Significant
35 investment is required to learn to use RiverWare as well. CADSWES offers two 3-day RiverWare training courses, an
36 initial class covering general simulation modeling, managing scenarios, and incorporating policy options through rule-
37 based simulation, and a second class covering rule-based simulation in more detail, creating basin policies, and
38 examining water policy options. Costs for the original license, annual renewals, technical support, and training require
39 several thousand dollars. The costs of licensing and learning RiverWare mean that small communities and civic groups
40 are unlikely to implement their own applications for assessing water management options. Rather, large agencies with
41 technical staff or the financial means to fund university research or consultants are the most frequent users of
42 RiverWare. The agencies then mediate the access of stakeholders to assessments of water management options through
43 traditional public processes (e.g., U.S. Department of Interior, 2007). Conflicts may arise in having academic research
44 groups conduct analyses funded by stakeholder groups, with inherent tensions between the open publication of research
45 required by academia and the limited access to results required by strategic negotiations among interest groups.

46 **3. Current and Future Use of Observations**

47 The specific combination of observations used by a RiverWare application depends on both the decision
48 context and the use of other models and DSTs to provide input to RiverWare that more comprehensively or accurately
49 describes the character, conditions, and response of the river basin system. Figure 1 illustrates the information flow
50 linking observations, RiverWare, other models and DSTs, and water management decisions; it shows that RiverWare
51 has tremendous flexibility in the kinds of observations that could be useful in hydrologic modeling and river system
52 assessment and management. The types of observations that may ultimately feed into RiverWare applications also
53 depend on the timescale of the situation.

54 A detailed discussion of the role of satellite observations in RiverWare applications and selected input models
55 and DSTs (e.g., the BOR's ET Toolbox and Precipitation Runoff Modeling System [PRMS]) is given by the
56

1 “Evaluation Report for AWARDS ET Toolbox and RiverWare Decision Support Tools” (Hydrological Sciences
2 Branch, 2007). Briefly, RiverWare can use a combination of observations from multiple sources, including satellites,
3 products derived from land-atmosphere or hydrologic models, and combinations of both. Satellite observations can
4 assist models in estimating evapotranspiration, precipitation, snow water equivalent, soil moisture, groundwater storage
5 and aquifer volumes, reservoir storage, and water quality, among other variables. Measurements from sensors aboard a
6 variety of satellites are being considered for their usefulness within DST contexts and their impacts on reducing water
7 management uncertainty, including the MODIS (Moderate Resolution Imaging Spectroradiometer) sensor aboard the
8 Earth Observing System (EOS) Terra and Aqua satellites, Landsat TM data, Advanced Spaceborne Thermal Emission
9 and Reflection Radiometer (ASTER), Shuttle Radar Topography Mission (SRTM), Advanced Microwave Scanning
10 Radiometer–EOS (AMSR-E), Gravity Recovery and Climate Experiment (GRACE), CloudSat, and Tropical Rainfall
11 Mapping Mission (TRMM), among others. Future and planned satellites with hydrologically relevant sensors and
12 measurements include the Global Precipitation Mission (GPM), and the National Polar-Orbiting Operational
13 Environmental Satellite (NPOESS). Use of these observations can be enhanced by assimilating them into land surface
14 models to produce spatially-distributed estimates of snowpack, soil moisture, evapotranspiration, energy fluxes, and
15 runoff, which then provide inputs to RiverWare to base a more comprehensive assessment of river basin conditions. The
16 land surface models include the Community Land Model (CLM), Mosaic, Noah, and VIC, among others, supported by
17 NASA’s Land Data Assimilation System (LDAS) and Land Information System (LIS) (NASA, 2006a).

18 NASA has several pilot projects specifically focused on assessing the impact of satellite observations in a
19 variety of hydrologic models and DSTs as they feed into RiverWare applications (NASA, 2005, 2006b, 2007). For
20 example, one project is comparing Terra and Aqua MODIS snow cover products for the Yakima-Columbia River basins
21 with land-based snow telemetry measurements, testing their use for LIS simulations that also use the North American
22 LDAS, connecting assimilated snow data with the Modular Modeling System (MMS) Precipitation-Runoff Modeling
23 System (PRMS), and then supplying the simulated runoff as inputs to RiverWare. Another project on the Rio Grande
24 River basin is assessing MODIS and Landsat data to improve evapotranspiration estimates generated by the BOR DST,
25 the Agricultural Water Resources Decision Support (AWARDS) ET Toolbox, which then provides water demand time
26 series to RiverWare. While application of specific hydrologic models and observations depend on the specific
27 RiverWare application, significant processing of both model and observations are required and can be resource
28 intensive (e.g., calibration and aggregation/disaggregation).

29 Operational scheduling of reservoir releases depend on orders of water from downstream users (e.g., irrigation
30 districts) that are largely affected by day-to-day weather conditions as well as seasonally varying demands. In these
31 cases, the important observations are the near real-time estimates of conditions within the river basin system (e.g., soil
32 moisture or infiltration capacity), which affect the transformation of precipitation into runoff into the river system,
33 relative to constraints on system operation (e.g., reservoir storage levels or water temperatures at specific river
34 locations). Prospective meteorological impacts are buffered by those placing the water orders or adjusting operations
35 when the system is near some constraint (e.g., flood flows when reservoir levels are near peak storage capacity). In
36 these situations, the important observations are recent extreme precipitation events and their location, which may be
37 provided, separately or in some combination, by *in situ* monitoring networks, radar, or satellites.

38 For mid-range applications, such as strategic planning for operations over the next season or year, outlooks of
39 total seasonal water supplies are routinely used in making commitments for water deliveries, determining industrial and
40 agricultural water allocation, and carrying out reservoir operations. In these applications, it is also important for water
41 managers to keep track of the current state of the watershed. Such observations are often used as input to one of the
42 many independent hydrologic models that can provide input to a specific RiverWare application. In these situations, the
43 important observations are those that provide boundary or forcing conditions for the independent hydrologic models,
44 including snowpack moisture storage, soil moisture, precipitation (intensity, duration, and spatial distribution), air
45 temperature, humidity, winds, and other meteorological conditions.

46 For long-term planning and design applications, future meteorological uncertainty has a larger impact on
47 outcomes than recent conditions based on observations; institutional change at multi-decadal time scales may have even
48 greater impact. In these applications, accurate representation of anticipated natural hydroclimatological variability is
49 important. In many western U.S. applications, observed streamflows are adjusted to remove the effects of reservoir
50 management, interbasin diversions, and water withdrawals. The adjusted flows, termed “naturalized flows.” may be
51 used as input to RiverWare applications to assess the impact of different management options. Use of naturalized flows
52 is fraught with problems. A central issue is poor monitoring of actual human impacts, especially withdrawals,
53 diversions, and return flows (e.g., from irrigation). Alternative approaches include the use of proxy streamflows (e.g.,
54 from paleoclimatological indicators) or output from hydrologic modeling studies (Hartmann, 2005). For example,
55 Tarboton (1995) developed hydrologic scenarios for severe sustained drought in the Colorado River basin based on

1 streamflows reconstructed from centuries of tree-ring records; the scenarios were used in an assessment of management
2 options using a precursor to the current RiverWare application to the Colorado River system.

3 The usefulness of the observations used within RiverWare depends on the specific implementation, as well as
4 the quality of the information itself. For example, one direct use of climate information for long-term planning includes
5 hydrologic and hydraulic routing of “design storms” of various magnitudes and likelihoods, with the storms based on
6 analyses of the available instrumental record (Urbanas and Roesner, 1993). However, those instrumental records have
7 often been too short to adequately express climate variability and resulting impacts, regardless of the specific DSTs
8 used to do the hydrologic or hydraulic routing. In short- and mid-range forecasting applications, the use of observations
9 is mediated by the hydrologic model or DST that transforms weather and climate into streamflows, evaporative water
10 demands, and other hydrologic processes. In these situations, from an operational perspective, the stream of
11 observational inputs must be dependable, without downtime or large data gaps, and data processing, model simulation,
12 and creation of forecast products must be fast and efficient. The usefulness of observations may be limited by other
13 issues as well. The water resources management milieu is complex and diverse, and climate influences are only one
14 factor among many affecting water management policies and practices. Factors limiting the use of observations or
15 subsequent hydrologic model input to RiverWare for actual water management include lack of familiarity with the
16 available information, disconnects between the specific information available (e.g., variables and spatiotemporal scales)
17 and their relevance to decision makers, skepticism about the quality and applicability of information, conservative
18 decision preferences due to accountability for poor consequences, and institutional impediments such as the inflexible
19 nature of many multi-jurisdictional water management agreements (Changnon, 1990; Kenney, 1995; Pulwarty and
20 Redmond, 1997; Pagano et al., 2001, 2002; Jacobs, 2002; Jacobs and Pulwarty, 2003; Rayner et al., 2005).

21 22 **4. Uncertainty**

23 The reliability of observations for driving hydrologic models that may provide input to RiverWare applications
24 is the subject of much ongoing research. The hydrologic models, because they incompletely describe the physical
25 relationships among important watershed components (e.g., vegetation processes that link the atmosphere and different
26 levels of soil and surface and groundwater interactions), are themselves the subject of much research to determine their
27 reliability. Streamflow and other hydrologic variables are intimately responsive to atmospheric factors, especially
28 precipitation, that drive a watershed’s behavior; however, errors in precipitation estimates are often amplified in the
29 hydrologic response (Oudin et al., 2006).

30 Obtaining quality precipitation estimates is a formidable challenge, especially in the western U.S. where
31 orographic effects produce large spatial variability and where there is a scarcity of real-time precipitation gage data and
32 radar beam blockage by mountains. In principal, outputs from atmospheric models can serve as surrogates for
33 observations, as well as providing forecasts of meteorological variables that can be used to drive hydrologic models.
34 One issue in integrating atmospheric model output into hydrologic models for small watersheds (<1000 km²) is that the
35 spatial resolution of atmospheric models is lower than the resolution of hydrologic models. For example, quantitative
36 precipitation forecasts (QPF) produced by some atmospheric models may cover several thousand square kilometers, but
37 the hydrologic models used for predicting daily streamflows require precipitation to be downscaled to precipitation
38 fields for watersheds covering only tens or hundreds of square kilometers. One approach to produce output consistent
39 with the needs of hydrologic models is to use nested atmospheric models, whereby outputs from large scale but coarse
40 resolution models are used as boundary conditions for models operating over smaller domains with higher resolution.
41 However, the error characteristics of atmospheric model products (e.g., bias in precipitation and air temperature) also
42 can have significant effects on subsequent streamflow forecasts. Bias corrections require knowledge of the
43 climatologies (i.e., long-term distributions) of both modeled and observed variables.

44 Although meteorological uncertainty may be high for the periods addressed by streamflow forecasts, accurate
45 estimates of the state of watershed conditions prior to the forecast period are important because they are used to
46 initialize hydrologic model states, with significant consequences for forecast results. However, watershed conditions
47 can be difficult to measure, especially when streamflow forecasts must be made quickly, as in the case of flash flood
48 forecasts. One option is to continuously update watershed states by running the hydrologic models continuously and by
49 using inputs from recent meteorological observations and/or atmospheric models. Regardless of the source of inputs,
50 Westrick et al. (2002) found it essential to obtain observational estimates of initial conditions to keep streamflow
51 forecasts realistic; storm-by-storm corrections of model biases determined over extended simulation periods were
52 insufficient. Recent experimental end-to-end forecasts of streamflow produced in a simulated operational setting (Wood
53 et al., 2001) highlighted the critical role of quality estimates of spring and summer soil moisture used to initialize
54 hydrologic model states for the eastern U.S.

55 Where streamflows may be largely comprised of snowmelt runoff, quality estimates of snow conditions are
56 important. The importance of reducing errors in the timing and magnitude of snowmelt runoff are especially acute in

1 regions where a large percentage of annual water supplies derive from snowmelt runoff, snowmelt impacts are highly
2 non-linear with increasing deviation from long-term average supplies, and reservoir storage is smaller than interannual
3 variation of water supplies. However, resources for on-site monitoring of snow conditions have diminished rather than
4 grown, relative to the increasing costs of errors in hydrologic forecasts (Davis and Pangburn, 1999). Research activities
5 of the NWS National Office of Hydrology Remote Sensing Center (NOHRSC) have long been directed at improving
6 estimates of snowpack conditions through aerial and satellite remote sensing (Carroll, 1985). However, the cost of aerial
7 flights prohibits routine use (T. Carroll, NOHRSC, personal communication, 1999), while satellite estimates have
8 qualitative limitations (e.g., not considering fractional snow coverage over large regions) and have not found broad use
9 operationally.

10 Multiple techniques exist to more accurately represent the uncertainty inherent in understanding and predicting
11 potential hydroclimatic variability. Stochastic hydrology techniques use various forms of autoregressive models to
12 generate multiple synthetic streamflow time series with statistical characteristics matching available observations. For
13 example, in estimating the risk of low flows for the Sacramento River Basin in California, the BOR (Frevert et al.,
14 1989) generated 20 one-thousand-year streamflow time series matching selected statistics of observed flows (adjusted to
15 compensate for water management impacts on natural flows); the non-exceedance probabilities of low flows were
16 computed by counting the occurrences of low flows within 1- through 10-year intervals for all 20 one-thousand-year
17 sequences. The U.S. Army Corps of Engineers (1992) used a similar approach to estimate flood magnitudes with return
18 periods exceeding 1,000 years, using Monte Carlo sampling from within the 95% confidence limits of a Log Pearson III
19 distribution developed by synthesizing multiple streamflow time series.

20 The ability to automatically execute many model runs within RiverWare, including accessing data from
21 external sources and exporting model results, facilitates using stochastic hydrology approaches for representing
22 uncertainty. For example, Carron et al. (2006) demonstrated RiverWare's capability to identify and quantify significant
23 sources of uncertainty in projecting river and reservoir conditions, using a first-order, second-moment (FOSM)
24 algorithm that is computationally more efficient than more traditional Monte Carlo approaches. The FOSM processes
25 uncertainties in inputs and models to provide estimates of uncertainty in model results that can be used directly within a
26 risk management decision framework. The case study presented by Carron et al. (2006) evaluated the uncertainties
27 associated with meeting goals for reservoir water levels beneficial for recovering endangered fish species within the
28 lower Colorado River.

29 With regard to RiverWare applications concerned with mid-range planning and use of hydrologic forecasts, at
30 the core of any forecasting system is the predictive model, whether a simple statistical relationship or a complex
31 dynamic numerical model. Advances in hydrologic modeling have been notable, especially those associated with the
32 proper identification of a model's parameters (e.g., Duan et al., 2002) and the development of models that consider the
33 spatially distributed characteristics of watersheds, rather than treating entire basins as a single point (Grayson and
34 Blöschl, 2000). Conceptual rainfall-runoff models offer some advantages over statistical techniques in support of long-
35 range planning for water resources management. These models represent, with varying levels of complexity, the
36 transformation of precipitation and other meteorological forcing variables (e.g., air temperature and humidity) to
37 watershed runoff and streamflow, including accounting for hydrologic storage conditions (e.g., snowpack, soil moisture,
38 and groundwater). These models can be used to assess the impacts and implications of various climate scenarios by
39 using historic meteorological time series as input, generating hydrologic time series, and then using those hydrologic
40 scenarios as input to RiverWare. This approach enables consideration of current landscape and river channel conditions,
41 which may be quite different than recorded in early instrumental records and which can dramatically alter a watershed's
42 hydrologic behavior (Vorosmarty et al., 2004). Furthermore, the use of multiple input time series, system
43 parameterizations, or multiple models, enables a probabilistic assessment of an ensemble of scenarios. The Hydrological
44 Ensemble Prediction Experiment (HEPEX) (Schaake et al., 2007) aims to address the unique challenges of expressing
45 uncertainty associated with ensemble forecasts for water resources management.

46 An additional concern for mid- and long-range planning is that, as instrumental records have grown longer,
47 they often show trends (e.g., Baldwin and Lall, 1999; Olsen et al., 1999; Andreadis and Lettenmaier, 2006) or persistent
48 regimes (i.e., periods characterized by distinctly different statistics) (e.g., Angel and Huff, 1995; Quinn, 1981, 2002),
49 with consequences for estimation of hydrologic risk (Olsen et al., 1998). Observed regimes and trends can have multiple
50 causes, including climatic changes, watershed and river transformations, and management impacts (e.g., irrigation
51 return flows and trans-basin water diversions). These issues enter into RiverWare applications directly through the use
52 of naturalized flows, which are notoriously unreliable. For example, in assessments of water management options on the
53 San Juan River in Colorado and New Mexico, the reliability of naturalized flows was considered to be affected by the
54 inconsistent accounting of consumptive uses between irrigation and non-irrigation data, use of reservoir evaporation
55 rates with no year-to-year variation, neglecting time lags in the accounting of return flows from irrigation to the river,

1 errors in river gage readings that underestimated flows in critical months, and the lack of documentation of diversions
2 that reduce river flows as well as subsequent adjustments to data used to compute naturalized flows.
3

4 **5. Global Change Information and RiverWare**

5 *Climate Variability*

6 Decision makers increasingly recognize that climate is an important source of uncertainty and potential
7 vulnerability in long-term planning for the sustainability of water resources (Hartmann, 2005). With the appropriate
8 investment in site licenses, training of personnel, implementation for a specific river system, and assessment efforts,
9 RiverWare is capable of supporting climate-related water resources management decisions by U.S. agencies. However,
10 technology alone is insufficient to resolve conflicts among competing water uses. Early in the development of
11 RiverWare, Reitsma et al. (1996) investigated its potential role as a DST within complex negotiations between
12 hydroelectric, agricultural, and flood control interests. Results indicated that while DSTs can help identify policies that
13 can satisfy specific management requirements and constraints, as well as expand the range of policy options considered,
14 they are of limited value in helping decision makers understand interactions within the river system. Furthermore, the
15 burdens of direct use by decision makers of a DST that embodies a complex system are significant; a more useful
16 approach is to have specialists support decision makers by making model runs and presenting the results in an iterative
17 manner. This is the approach used by the Bureau of Reclamation in the application of RiverWare to support interstate
18 negotiations concerning the sharing of Colorado River water supply shortages during times of drought (Jerla, 2005; U.S.
19 Department of Interior, 2007).

20 From the perspective of mid-range water management issues, the use of forecasts within RiverWare
21 applications constitutes an important pathway for supporting climate-related decision making. Each time a prediction is
22 made, science has an opportunity to address and communicate the strengths and limitations of current understanding.
23 Each time a decision is made, managers have an opportunity to confront their understanding of scientific information
24 and forecast products. Furthermore, each prediction and decision provides opportunities for interaction between
25 scientists and decision makers and for making clear the importance of investments in scientific research. Perceptions of
26 poor forecast quality are a significant barrier to more effective use of hydroclimatic forecasts (Changnon, 1990; Pagano
27 et al., 2001, 2002; Rayner et al., 2005); however, recent advances in modeling and predictive capabilities naturally lead
28 to speculation that hydroclimatic forecasts can be used to improve the operation of water resource systems.

29 Great strides have been made in monitoring, understanding, and predicting interannual climate phenomena
30 such as the El Nino-Southern Oscillation (ENSO). This improved understanding has resulted in long-lead (up to about a
31 year) climate forecast capabilities that can be exploited in streamflow forecasting. Techniques have been developed to
32 directly incorporate variable climate states into probabilistic streamflow forecast models based on linear discriminant
33 analysis (LDA) with various ENSO indicators, (e.g., the Southern Oscillation Index [SOI]) (Peichota and Dracup, 1999;
34 Peichota et al., 2001). Recent improved understanding of decadal-scale climate variability also has contributed to
35 improved interannual hydroclimatic forecast capabilities. For example, the Pacific Decadal Oscillation (PDO) (Mantua
36 et al., 1997) has been shown to modulate ENSO-related climate signals in the West. Experimental streamflow
37 forecasting systems for the Pacific Northwest have been developed based on long-range forecasts of both PDO and
38 ENSO (Hamlet and Lettenmaier, 1999). In the U.S., the Pacific Northwest, California, and the Southwest are strong
39 candidates for the use of long-lead forecasts because ENSO and PDO signals are particularly strong in these regions and
40 each region's water supplies are closely tied to accumulation of winter snowfall, amplifying the impacts of climatic
41 variability.

42 While many current water management decision processes use single-value deterministic approaches,
43 probabilistic forecasts enable quantitative estimation of the inevitable uncertainties associated with weather and climate
44 systems. From a decision maker's perspective, probabilistic forecasts are more informative because they explicitly
45 communicate uncertainty and are more useful because they can be directly incorporated into risk-based calculations.
46 Probabilistic forecasts of water supplies can be created by overlaying a single prediction with a normal distribution of
47 estimation error determined at the time of calibration of the forecast equations (Garen, 1992). However, to account for
48 future meteorological uncertainty, new developments have focused on ensembles, whereby multiple possible futures
49 (each termed an ensemble trace) are generated; statistical analysis of the ensemble distribution then provides the basis
50 for a probabilistic forecast.

51 Changnon (2000), Rayner et al. (2005), and Pagano et al. (2002) found that improved climate prediction
52 capabilities are initially incorporated into water management decisions informally, using subjective, ad hoc procedures
53 on the initiative of individual water managers. While improvised, those decisions are not necessarily insignificant. For
54 example, the Salt River Project, among the largest water management agencies in the Colorado River Basin and primary
55 supplier to the Phoenix metropolitan area, decided in August 1997 to substitute groundwater withdrawals with reservoir
56 releases, expecting increased surface runoff during a wet winter related to El Nino. With that decision, they risked

1 losses exceeding \$4 million in an attempt to realize benefits of \$1 million (Pagano et al., 2002). Because these informal
2 processes are based in part on confidence in the predictions, overconfidence in forecasts can be even more problematic
3 than lack of confidence, as a single incorrect forecast that provokes costly shifts in operations can devastate user
4 confidence in subsequent forecasts (e.g., Glantz, 1982).

5 The lack of verification of hydroclimatic forecasts is a significant barrier to their application in water
6 management, but it is not easy to resolve with traditional research efforts, because the level of acceptable skill varies
7 widely depending on the intended use (Hartmann et al., 2002a; Pagano et al., 2002). Information on forecast
8 performance has rarely been available to, and framed for, decision makers, although hydrologic forecasts are reviewed
9 annually by the issuing agencies in the U.S (Hartmann et al., 2002b). Hydrologic forecast verification is an expanding
10 area of research (Franz et al., 2003; Hartmann et al., 2003; Bradley et al., 2004; Pagano et al., 2004; Kruger et al., 2007),
11 but much work remains and could benefit from approaches developed within the meteorological community (Welles et
12 al., 2007). Because uncertainty exists in all phases of the forecast process, forecast systems designed to support risk-
13 based decision making need to explicitly quantify and communicate uncertainties from the entire forecast system and
14 from each component source, including model parameterization and initialization, meteorological forecast uncertainty at
15 the multiple spatial and temporal scales at which they are issued, adjustment of meteorological forecasts (e.g., through
16 downscaling) to make them usable for hydrologic models, implementation of ensemble techniques, and verification of
17 hydrologic forecasts.

18 19 *Climate Change*

20 From the perspective of long-range water management issues, the potential impacts of climate change on water
21 resources, and their implications for management, are central topics of concern. Estimates of prospective impacts of
22 climate change on precipitation have been mixed, leading, in many cases, to increasing uncertainty about the reliability
23 of future water supplies. However, where snow provides a large fraction of annual water supplies, prospective
24 temperature increases dominate hydrologic impacts, leading to stresses on water resources and increased hydrologic
25 risk. Higher temperatures effectively shift the timing of the release of water stored in the snowpack “reservoir” to earlier
26 in the year, reducing supplies in summer when demands are greatest, while also increasing the risk of floods due to rain-
27 on-snow events. While not using RiverWare, several river basin studies have assessed the risks of higher temperatures
28 on water supplies and management challenges. The near universal analytical approach has been one of sensitivity
29 analysis (Lettenmaier, 2003):

- 30 1) downscaling outputs from a dynamic general circulation model of the global land-atmosphere-ocean system to
31 generate regional- or local-scale meteorological time series over many decades,
- 32 2) using the meteorological time series as input to rainfall-runoff models to generate hydrologic time series,
- 33 3) using the hydrologic scenarios as input to water management models, and
- 34 4) assessing differences among baseline and change scenarios using a variety of metrics.

35 Early assessments of warming impacts on large river basins generally showed extant water management systems to
36 be effective for all but the most severe scenarios (Hamlet and Lettenmaier, 1999; Lettenmaier et al., 1999), with a
37 notable exception being the Great Lakes system where increased lake heat storage was tied to loss of ice cover,
38 increased winter lake evaporation, lower lake levels, and potential failure to meet Lake Ontario regulation objectives
39 under extant operating rules (Croley, 1990; Hartmann, 1990; Lee et al., 1994; Lee et al., 1997; Sousounis et al., 2000;
40 Lofgren et al., 2002).

41 Extensive detailed studies of the ability of existing reservoir systems and operational regulation rules to meet water
42 management goals under changed climates are fairly recent (e.g., Saunders and Lewis, 2003; Christensen, et. al, 2004;
43 Payne et. al, 2004; VanRheenan et. al, 2004; Maurer, 2007). However, there is a rapidly growing literature on broad
44 considerations of climate change in water resources management (Frederick et al., 1997; Gamble et al., 2003;
45 Lettenmaier, 2003; Loomis et al., 2003; Snover et al., 2003; Stakhiv, 2003; Ward et al., 2003; Vicuna et al., 2007).
46 Some (Matalas, 1997) that contend that existing approaches are sufficient for water resource management planning and
47 risk assessment because they contain safety factors; however, an inescapable message for the water resource
48 management community is the inappropriateness of the stationarity assumption in the face of climate change. While
49 precipitation changes may remain too uncertain for consideration in the near term, temperature increases are more
50 certain and can have strong hydrologic consequences.

51 Cognitively, climate change information is difficult to integrate into water resources management. First, within
52 the water resources engineering community, the stationarity assumption is a fundamental element of professional
53 training. Second, the century timescales of climate change exceed typical planning and infrastructure design horizons
54 and are remote from human experience. Third, even individuals trying to stay up-to-date can face confusion in
55 conceptually melding the burgeoning climate change impacts literature. Assessments are often repeated as general
56 circulation and hydrologic model formulations advance or as new models become available throughout the research

1 community. Furthermore, assessments can employ a variety of techniques for downscaling. Transposition techniques
2 (e.g., Croley et al., 1998) are more intuitive than the often mathematically complex statistical and dynamical
3 downscaling techniques (e.g., Clark et al., 1999; Westrick and Mass, 2001; Wood et al., 2002; Benestad, 2004).

4 GCMs and their downscaled corollaries provide one unique perspective on long-term trends related to global
5 change. Another unique perspective is provided by tree-ring reconstructions of paleo-streamflows, which, for example,
6 indicate that in the U.S. Southwest droughts over the past several hundred years have been more intense, regionally
7 extensive, and persistent than those reflected in the instrumental record (Woodhouse and Lukas, 2006). Decision makers
8 have expressed interest in combining the perspectives of paleoclimatological information and GCMs. While some
9 studies have linked instrumental records to paleoclimatological information (e.g., Prairie, 2006) and others with GCMs
10 (e.g., Christensen and Lettenmaier, 2006), few link all three (an exception is Smith et al., 2007).

11 Conceptual integration of climate change impacts assessment results in a practical water management context
12 is complicated by the multiplicity of scenarios and vague attribution of their prospects for occurrence, which depend so
13 strongly on feedbacks among social, economic, political, technological, and physical processes. For decision makers, a
14 critical issue concerns the extent to which the various scenarios reflect the actual uncertainty of the relevant risks versus
15 the uncertainty due to methodological approaches and biases in underlying models. The difficulties facing decision
16 makers in reconciling disparate climate change impact assessments are exemplified by the Upper Colorado River Basin,
17 where reductions in naturalized flow by the mid-21st century have been estimated to range from about 45% by Hoerling
18 and Eischeid (2007), 10 to 25% by Milly et al (2005), about 18% by Christensen et al. (2004), and about 6% by
19 Christensen and Lettenmaier (2006). Furthermore, using the difference between precipitation and evapotranspiration as
20 a proxy for runoff, Seager et al. (2007) suggest an “imminent transition to a more arid climate in southwestern North
21 America.”

22 However, in the face of circumstances nearing or exceeding the effectiveness of existing management
23 paradigms, individuals can become more cognizant of the need to consider climate change. In the U.S. Southwest, over
24 1999–2004, Lake Powell levels declined faster than previously considered in scenarios of extreme sustained drought
25 (e.g., Harding et al., 1995; Tarboton, 1995), from full to only 38% capacity in November 2004 (BOR, 2004). Resource
26 managers, policymakers, and the general public are now actively seeking scientific guidance in exploring how
27 management practices can be more responsive to the uncertainties associated with a changing climate.

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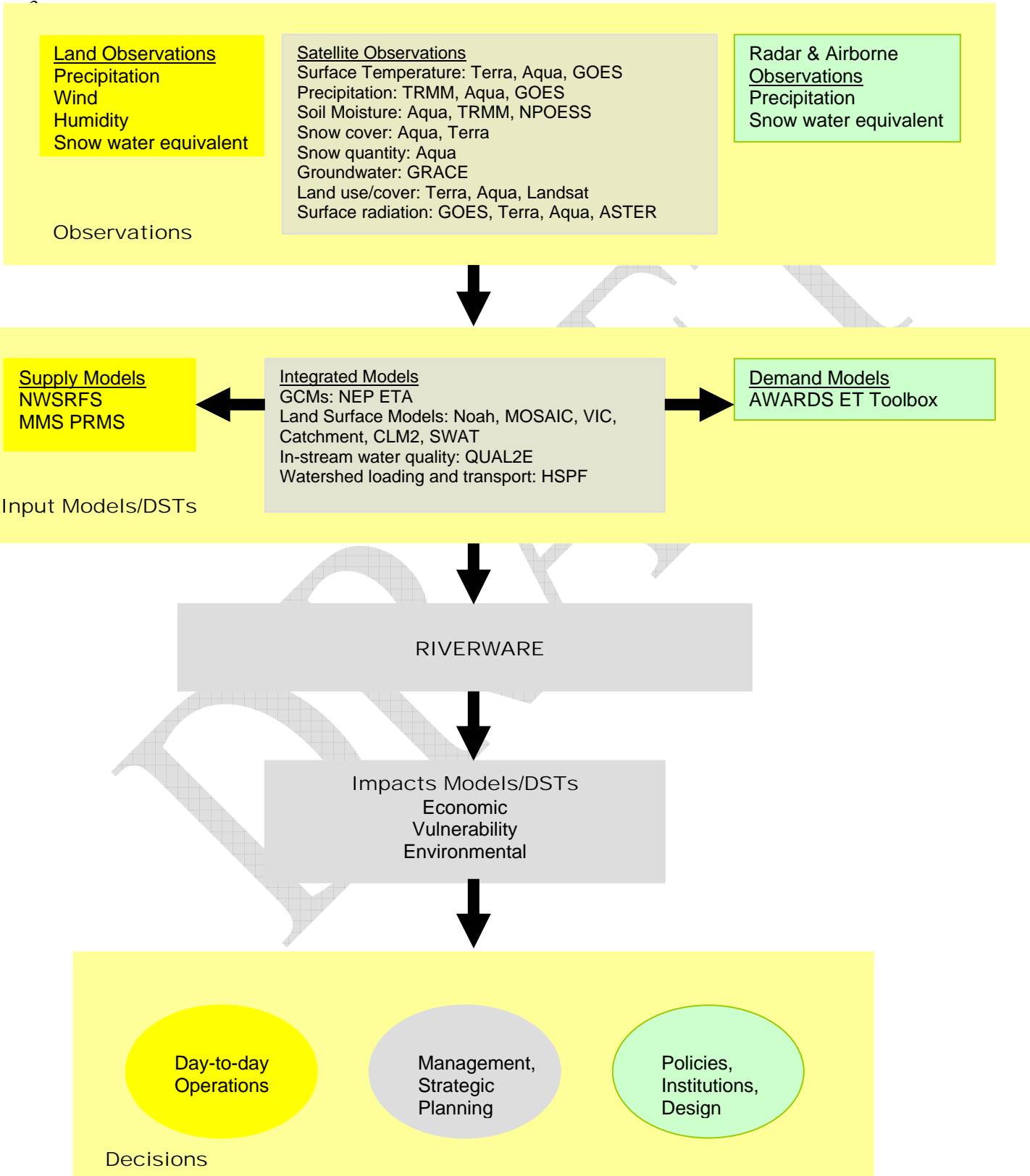


Figure 5-1: Illustration depicting the flow of information

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Appendix A References by Chapter

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APPENDIX B

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Appendix C Glossary, Acronyms, Symbols & Abbreviations

3-D	Three-dimensional
ACD	Atmospheric Chemistry Division
AERONET	Aerosol RObotic NETwork
AgRISTARS	Agriculture and Resources Inventory Surveys through Aerospace Remote Sensing
AI	Aerosol Index
AOD	Aerosol Optical Depths
ASOS	Automated Surface Observation Stations
ATSR	Along Track Scanning Radiometer
AVHRR	Advanced Very High Resolution Radiometer
AWN	Automated Weather Network
BC	Boundary Conditions
BELD3	Biogenic Emissions Land Use Database version 3
CAAA	Clean Air Act and its Amendments
CAM	Community Atmosphere Model
CAMx	Comprehensive Air quality Model with Extensions
CBv	Carbon Bond V
CCSP	Climate Change Science Program
CDC	Disease Control and Prevention
CEMPI	Center for Environmental Modeling for Policy Development
CENR	Committee on Environment and Natural Resources Research
CH₄	Methane
CM2	Climate Model 2
CMAQ	Community Multiscale Air Quality
CMAS	Community Modeling and Analysis System
CNES	Centre National d'Etudes Spatiales
CO₂	Carbon Dioxide
CONUS	Continental United States
CTM	Chemistry Transport Modeling
DDSPL	Decision Support System to Prevent Lyme disease
DEM	Digital Elevation Models
DG	Distributed generation
DLR	German Aerospace Center (DLR) (German: Deutsches Zentrum für Luft- und Raumfahrt e.V.)
DMSP	Defense Meteorological Satellite Program
DSSs	Decision Support Systems
DSTs	Decision Support Tools
ECMWF	European Centre for Medium-Range Weather Forecasts
EPA	Environmental Protection Agency
ESMP	Earth System Modeling Framework
ESRI	Environmental Science and Research Institute
ESRL	Earth Systems Research Laboratory
ESSL	Earth and Sun Systems Laboratory
EUMETSAT	European Organization for the Exploitation of Meteorological Satellites
FAS	Foreign Agricultural Service

GACP	Global Aerosol Climatology Project
GADS	Global Aerosol Dataset
GCM	Global Climate Model
GCTM	Global Chemistry Transport Models
GEO	Group on Earth Observations
GEOS	Goddard Earth Observing System
GEWEX	Global Energy and Water Experiment
GFDL	Geophysical Fluid Dynamics Laboratory
GhTOC	HourlyTotal Ozone Column
GIS	geographic information system
GISS	Goddard Institute for Space Studies
GLCC	Global Land Cover Characterization
GMAO	Global Modeling and Assimilation Office
GOCAT	Global Ozone Chemistry Aerosol Transport
GOES	Geostationary Environmental Operational Satellite
GOME	Global Ozone Monitoring Experiment
GsT	Geospatial Toolkit
GTCM	Global Tropospheric Chemistry Model
GTS	Global Telecommunications System
HMS	Hazard Mapping System
HOMER	Hybrid Optimization Model for Electric Renewables
IGOL	Integrated Global Observations of Land
INPE	Brazilian Spatial Institute
IPCC	Intergovernmental Panel on Climate Change
ISH	Integrated Surface Hourly
KAMM	Karlsruhe Atmospheric Mesoscale Model
kw	Kilowatt
h	Hour
m	Meter
LACIE	Large Area Crop Inventory Experiment
LULC	Land Use and Land Cover
MATCH	Model of Atmospheric Transport and Chemistry
MCIP	Meteorology-Chemistry Interface Processor
MIST	Multi-Angle Imaging Spectroradiometer
MM5	Mesoscale Model Version 5
MODIS	Moderate Resolution Imaging Spectroradiometer
MOZART	Model of Ozone and Related Chemical Tracers
N2O	Nitrous oxide
NASA	National Aeronautics and Space Administration
JPL	Jet Propulsion Laboratory
SSE	Surface meteorology and Solar Energy
USGS	US Geological Survey
NCAR	National Center for Atmospheric Research
NCAR- NCEP	National Center for Atmospheric Research-National Centers for Environmental Protection
NCDC	National Climatic Data Center
NCEP	National Centers for Environmental Prediction
NOAA	National Oceanic and Atmospheric Administration
NRC	National Research Council
NREL	National Renewable Energy Laboratory
NSTC	National Science and Technology Council

OCO	Orbiting Carbon Observatory
OMI	Ozone Monitoring Instrument
AOT	aerosol optical thickness
TOC	Total Ozone Content
P	Wind Power Density
PECAD	Production Estimate and Crop Assessment Division
CADRE	Crop Condition Data Retrieval and Evaluation system
PNNL	Pacific Northwest National Laboratory
PV	Photovoltaic
RCM	Regional Climate Model
ReGAP	Regional Gap Analysis Program
RPOs	Regional Program Organizations
SAP	Synthesis and Assessment Product
SHEDS	Stochastic Human Exposure and Dose Simulation
SIP	State Implementation Plans
SPOT	Systeme Pour L'Observation de la Terre
SRTM	Shuttle Radar Topographic Mission
SSE	Surface meteorology and Solar Energy
SSM/I	Special Sensor Microwave/Imager
SSMR	Scanning Multichannel Microwave Radiometer
STAR	Science to Achieve Results
SWERA	Solar and Wind Energy Resource Assessment
TES	Tropospheric Emission Spectrometer
TOMS	Total Ozone Mapping Spectrometer
TOMS	Total Ozone Mapping Spectrometer
TRI,	Total Risk Integrated Methodology
U.S.	United States
UIUC	Unknown Sent email to Daewon
UNC	University of North Carolina at Chapel Hill
UNEP	United Nations Environment Programme
USDA	Department of Agriculture
EROS	Earth Resources Observation Systems
USWRP	United States Weather Research Program
V	Wind Speed
WAsP	Wind Atlas Analysis and Application Program
WRAMS	Wind Resource Assessment Mapping System
WRDC	World Radiation Data Centre
WRF	Weather Research and Forecasting

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