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Monitoring and Modeling Environmental Change in Protected Areas: Integration of Focal Species Populations and Remote Sensing[*]

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21.1 Introduction

Humans have created protected areas (PAs) over the past millennia for a multitude of reasons. The establishment of Yellowstone National Park in 1872 by the United States Congress ushered in the modern era of governmental

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protection of natural areas that catalyzed a global movement (IUCN, 2008; Heinen, 2007). Today, approximately 13% of terrestrial and 1% of marine environments are designated as protected and a tremendous variety of monitoring programs and conservation planning efforts are underway (e.g., UNEP the United Nations Environment Programme http://www.unep.org/; see also http://www.wdpa.org/). Despite these conservation achievements, species' population declines, biodiversity loss, extinctions, system degradation, pathogen spread, and state change events are occurring at unprecedented rates (Hoffmann et al., 2010; Pereira et al., 2010). These effects are augmented by continued changes in land-use, alongside the direct, indirect, and interactive effects of climate change and disruption. It is clear that designation and monitoring of PAs are necessary but insufficient in providing the needed levels of support to effectively maintain the attributes of ecosystem function and species preservation into the indefinite future (Sinclair et al., 1995).

Monitoring, when coupled with *modeling*, can provide a powerful basis for guiding management actions, while simultaneously advancing science through hypothesis testing and predictions. Modeling of ecosystem indicators informed by monitoring information such as that provided from remote sensing (RS) is essential for efficient, transparent, repeatable, and defensible decision-making in ecological systems. These decisions should include outcomes-based activities driving toward goals such as population recovery, critical habitat restoration, biodiversity increase, and improved ecosystem services. Models—whether narrative, conceptual, visual, ecological, or statistical—provide a common language for scientists and practitioners, permitting hypothesis testing about the mechanisms or drivers underlying the observed variation in data. Of particular importance is the idea that statistical models can be improved by careful attention to ecological concepts and mechanisms (Austin, 2002) with the goal of clarifying the "sometimes tenuous link between observed pattern and significant ecological process" (Gross et al., 2009).

Many PAs are centered on an explicit or implicit valuation of the species they support, and many monitoring and management programs are focused on species persistence, as both an ecological goal and as part of a set of legislated mandates. In this context, long-term species data sets are of unique value because they provide insight into the mechanisms that support the desired attributes of the PA systems. What would be the value of Yellowstone National Park without its iconic charismatic megafauna? Leaving the difficulties of shifting baselines aside (Baum and Myers, 2004), the intrinsic value of PAs is in part set by the unique and rare species and processes they encompass. For these reasons, we focus in this chapter on the role of long-term, legacy species data sets ("focal species" in the parlance of the U.S. Fish and Wildlife Service, hereafter FWS). What is their monitoring value, in a PA setting, in helping to elucidate the metrics of resilient, intact, and sustainable ecosystems? What are their limitations?

Practitioners such as agency biologists and managers commonly fund and conduct monitoring programs, while scientists seek access to the data that have been collected. This provides a common ground for collaboration and bridging of the gap between scientists and practitioners (Marris, 2007). Science and decision making should go hand in hand, because they both measure success by their ability to predict the consequences of actions (Pielke, 2003). Although monitoring of focal species, as well as other ecological indicators or vital signs, are the critical first steps needed for science-based decisions, it is often treated as an end unto itself. How do we explain their variation across space and over time? To what is it attributable? What are the anticipated long- and short-term outcomes from our management activities? At its best, ecological modeling provides answers to these questions by (1) exploratory and synthetic analysis of possible causes using explanatory variables, (2) investigating possible causes while testing hypotheses (diagnostic models), and (3) predicting consequences, for example, under future scenarios (prognostic models). Models serve the essential function of connecting cause and effect in otherwise intractably complex natural systems (Paola, 2011).

Arguably, ecological models are as powerful as the quality and relevance of the causal and explanatory variables ("covariates") included. In a sense, lack of explanatory covariates in predictive modeling is equivalent to conducting science without alternate hypotheses. Ecosystem indicators, whether process-based (e.g., productivity), pattern-based (e.g., land-use activities), or component-based (species populations) vary in space and time, yet a major limiting factor in comprehensive ecological models is lack of explanatory geospatial data. Although these geospatial data may exist, impediments to access by ecologists in PA contexts may include issues as varied as data formats, technical barriers to data integration (e.g., CPU time), validation issues, documentation issues, uniform standards and protocols accompanying RS data, increasing specialization of disciplines, cost, lack of requisite technical expertise, and time for dealing with all of the above complexities. These issues conspire against the ready, standardized integration of RS into ecological research for PA management.

Nonetheless, RS science is a universal tool for managers and researchers across many domains (Kennedy et al., 2009). The lack of standardized protocols, workflow architecture, guidelines, training, and software tools has led us into a baffling jungle of complexity. Our goal in this chapter is to take steps toward standardized yet flexible workflow architecture alongside a set of decision support (software) tools that can be modified as needed, all for integration of RS data into ecological applications for PA systems, in order to support an enhanced role for science at the decision-making table. In this chapter, we propose that RS data/data products coupled with user-friendly data exploration, data management, analyses and modeling tools, in an accessible common platform, can assist scientists and practitioners toward a better understanding of how environmental impacts affect species populations and the ecosystem services that sustain them. It is our intent to describe a science-based approach that makes the most out of existing data (i.e., legacy data) from monitoring programs and decision-support systems in and adjacent to PAs by analysis and modeling of focal species populations.

21.2 PAs and the Focal Species Concept

Focal species (legacy, sensitive, endangered, or otherwise noteworthy species) are often of substantial socioeconomic and ecological importance. Data from long-term monitoring programs related to focal species and their habitats (Figure 21.1) have the potential to provide invaluable insight into both stable and changing ecosystem function and, if addressed carefully, provide insight into cause and consequence of dynamic environmental impacts. In order to work with a focal species for monitoring and modeling, variation in space and time discloses environmental impacts at landscape scales and at both short and long timescales. Building empirically based diagnostic models and prognostic models (ecological forecasting) using focal species data (time-series, legacy data sets) and making use of the concept of benchmark ecosystems (see Section 21.4) may be the best approach to craft successful adaptation strategies that protect biodiversity and ecosystem

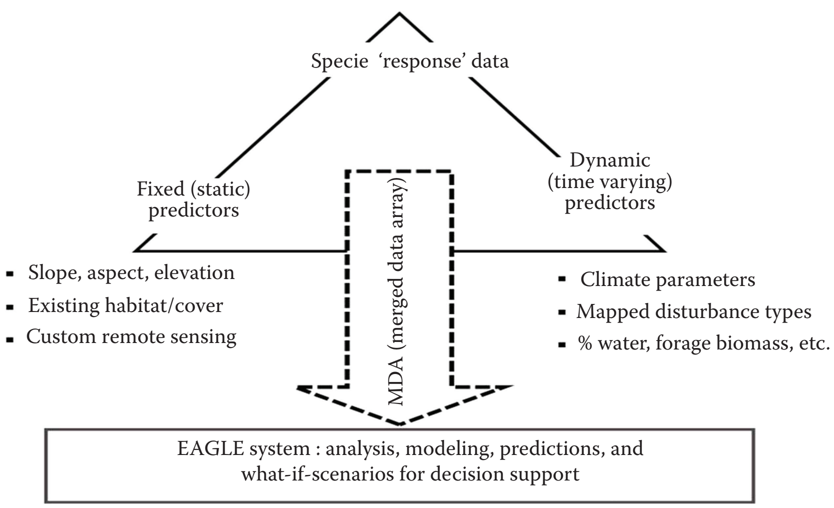


FIGURE 21.1
Schematic representation of the process of matching (1) fixed and (2) temporally dynamic geospatial covariates with spatio-temporal response data from legacy data sets to create a merged data array (MDA) for analysis and modeling in EAGLES (Ecosystem Assessment, Geospatial Analysis and Landscape Evaluation).

services for human value and those of nature in its own right and intrinsic value (Wiens, 2007).

Any number of species, vital rates, vital signs, or ecosystem indicators could have been chosen for our monitoring and modeling approach, for example, using annual NPP (net primary production) as in Crabtree et al. (2009). Here, we focus on species populations (legacy data) as ecosystem indicators to understand complex environmental impacts for three major reasons. First, "species" constitute the longest standing indicator within the ecological/wildlife/biological management professions. For example, the 55-year waterfowl monitoring program (Figure 21.1, for mallards) is believed to be the most extensive, comprehensive, long-term wildlife survey effort in the world. The concept of species as indicators, keystones, and umbrellas has been a dominant theme in ecology and conservation worldwide (Landres et al., 1988; Mills and Soule, 1993) and is still the focus of land management agencies in the United States (e.g., FWS). Second, and most importantly, the legacy of species as ecosystem indicators has created long-term, time-series data sets. These legacy data serve as continuously running experimental units responding to both natural and policy experiments. Because conducting randomized, replicated experiments at ecosystem and regional scales is rarely feasible, we can use these "quasi-experimental" approaches to study impacts on ecosystem structure and function (Hargrove and Pickering, 1992). Analysis of variability in legacy data sets may be our best means to understand the complex interactions of climate disruption with existing environmental impacts such as changing land-use and invasive spread. With modeling, we can detangle multicausal impacts and build the foundation of predictive models (ecological forecasting). These data have the potential to explain response to climate (multidecadal) and thus allow us to craft adaptation strategies to climate, both direct and indirect (e.g., disturbance), and their interaction with land-use activities.

The third reason for using focal species as indictors of ecosystem impacts is due to their link to human management systems and their socioeconomic importance. Focal species are often protected and managed by state and federal agencies and can bridge gaps between science and practitioners (biologists, conservationists, managers) on-the-ground (Anonymous, 2007). This becomes the key charge of those concerned with successful, long-term, adaptive management strategies for PAs—many of which are undergoing rapid environmental changes.

Figure 21.2 presents the essential function of our approach: matching variation in species legacy data to covariates (candidate hypotheses) across space and time to create a candidate model. Ideally, legacy data can be modeled with known, suspected, and causal spatially explicit and time-varying covariates. However, difficulties in obtaining the needed geospatial covariates to explain observed variation in response remain a prominent challenge for scientists and decision-makers. Forward-looking models (scenarios, forecasts, prognostic models, or projections) present even greater challenges due

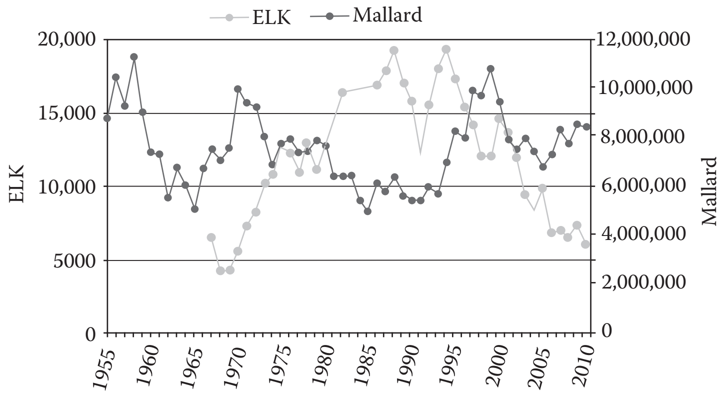


FIGURE 21.2
Legacy data on focal species populations are regularly collected by state and federal agency monitoring programs. Explaining their variation across space and time requires models that include geospatial explanatory variables that change over time. A multitude of these spatio-temporal variables have been recently provided by recent advances in RS technologies. Elk (*Cervus elaphus*) data are derived from winter aerial surveys across Yellowstone National Park's northern winter range. Mallard (*Anas platyrhynchos*) data are from the joint FWS/Canadian Wildlife Service annual aerial survey of breeding waterfowl.

to lack of stationarity, threshold phenomenon, interaction effects, and discontinuities. We submit that RS data, data products, and output from models that assimilate RS data constitute our best chance at creating the needed covariates required to construct accurate and realistic models of species populations that can be generalized across ecosystems.

21.3 Remote Sensing: Data Integration for Monitoring and Modeling

On-the-ground monitoring of PA ecosystems is expensive primarily due to the size and logistical constraints of national parks, designated wilderness, wildlife refuges, and other large PA ecosystems. However, recent advances in technology—primarily RS—provide new avenues for monitoring and modeling of large PA ecosystems at multiple spatial and temporal scales. Unlike traditional field plots and surveys, RS provides wall-to-wall coverage of geospatial products at unprecedented scales across landscapes, ecosystems, ecoregions, and the globe, revealing continuous empirical patterns of environmental variables in space and time. These patterns are crucial to uncovering cause and consequence in analyses and modeling of a wide variety of ecosystem indicators and vital signs. Of course, this view requires a belief that these observed patterns indicate a comprehensible system of control underlying the material under observation, and that these controls may be disclosed by rule-based (e.g., logic-based) approaches.

In the past, RS data seldom provided the information needed to fulfill the requirements (e.g., accuracy, scale) for the specific objectives of an investigation. Today, integration of data from multiple sources allows creation of previously unavailable geospatial data for monitoring and modeling. Remote sensors on satellites, airborne platforms, and a wide variety of ground-based instruments such as weather stations, sensor networks, and wildlife GPS collars are producing rich streams of environmental data about ecosystems and the species that inhabit them. Even satellite data can now be readily acquired at varying spatial (1 m to 1 km) and temporal (daily to annual) resolutions globally to track many environmental impacts such as land use, disturbance, and climate change. For example, recent deployment of MODIS (Moderate Resolution Imaging Spectroradiometer, http://modis.gsfc.nasa.gov/) sensors have systematically generated multiple ecological indicators available at many resolutions across the entire globe at no or low cost (Justice et al., 1998).

Based on the existing literature of optimal trade-space between spectral, spatial, and temporal resolutions, RS data can provide direct and accurate measurement of important environmental variables with both single and multiple sensors (i.e., fusion). And when direct and/or accurate measurement is not feasible, data integration and data assimilation models can provide direct, relative or by-proxy measurement of previously unavailable parameters of interest that can be validated. The TOPS (Terrestrial Observation and Prediction System) program (Nemani et al., 2009), for example, is a data integration system that uses data from multiple sources (airborne, spaceborne, and ground-based) to produce continuous, gridded variables for monitoring and modeling (see Nemani et al., this volume). Concurrent with this exponential growth of geospatial information is the parallel development of statistical and mathematical techniques, as well as the CPU (computer muscle) capacity to handle these enormous analytical tasks. It is now feasible to create analyses of multiple responses to multiple factors at even global scales (see Zhao and Running, 2010).

21.4 PAs and the Concept of Benchmark Ecosystems

Following the concept of a benchmark ("a standard for evaluation or measurement, a standard of reference"), we propose the concept of a *benchmark ecosystem*. A benchmark ecosystem is one in which all entities (*species*, *biotic components*, *abiotic/geophysical components*, *hydrological processes*, and other *ecological processes*, e.g., migration and predation) function within an integrated and potentially self-sustaining unit. Given the encroachment of threats on even the most remote ecological systems, the idea of a benchmark system represents an idealization. Yet even as an abstraction, the construct serves a heuristic and pragmatic role, forming the basis for evaluation and comparison (e.g., with other systems under restoration). In an era dominated by shifting ecological baselines, the benchmark ecosystem concept provides a set of reference standards for restoration, conservation, and related management activities. Without a specified suite of standards, of metrics, the entities and components of PAs will be increasingly vulnerable to the systemic degradation characteristic of expedience, as well as economic and societal pressures. The benchmark state is to some degree embodied in all PAs, and as such, justifies their creation, perpetuation, and legitimacy. An analogy, from human epidemiology, is the "well-normal" set of criteria for system values. Just as human physiological parameters fall within a defined specified *a priori* range of values for a healthy human body system, so too can the well-normal ranges of ecological systems be specified ("bench-marked"). Precedents already exist for many ecological parameters, such as minimum viable population standards for breeding vertebrate populations, and air and water quality standards. We are still short on the overall metrics conferring resilience and stability for the long term.

Benchmark ecosystems can then be used (1) to derive the well-normal attributes of a functioning ecosystem, (2) as a reference standard for restoration efforts, and (3) to provide an empirical testing ground for ecological research into the mechanisms driving sustainable systems and the focal species they contain. The relationship of this concept to PAs becomes one of quantitative and qualitative measurement and justification of the validity of the protection and restoration/conservation efforts. Is the wildlife refuge large enough to sustain its population and the processes that sustain them, such as staging for migration? As research moves forward hand-in-hand with management activities, the outcomes from proposed and forecast activities can be validated or rejected on the basis of the benchmarked goals in a quasi-experimental PA setting (Hargrove and Pickering, 1992).

The concept of a benchmark system can help bridge the gap between scientific measurement and actionable management goals, by finding the common agreement on outcomes-driven, prespecified activities. For example, the ecological process of herbivory (amenable to time-series analysis of RS measurement), is well-characterized in a functioning ecosystem, with published values for production, offtake, and patterns of occupancy by species of interest. The absence of this process then, is demonstrable as the process of species depletion occurs, and the restoration of this absent, yet well-characterized process, can be set as a specified goal. General reluctance among ecologists and managers to set hard targets for the maintenance, in perpetuity, of species and habitats, may be overcome by acceptance of standardized metrics of ecological function based on empirical standards.

In this intentional design, standardized RS data and data products serve an absolutely critical role. Given the current incompleteness of our ability to characterize, in a deterministic manner, those system attributes required for effective preservation, our best hope may be to attempt functional RS representations, which characterize, with appropriate resolution, and temporal repeat rates, then to store these characterizations as attribute sets of PAs. The novel application of *dynamic attribute mapping* as benchmark metrics is perhaps the most interesting application of RS in PA ecosystems in need of adaptive management and research strategies into our uncertain future.

As ecological insight improves, as we begin to understand the mechanisms driving the components that PAs were originally intended to preserve. As this characterization improves, we will be able to more formally set value ranges for functioning and sustainable ecosystem components, and, by extension, apply those to the restoration of other systems. These challenges are directly related to those metrics needed in the developing theory of long-term system health and resilience (Holling, 1973).

As PA monitoring techniques become increasingly powerful, standardizing the metrics of management outcomes in a systems framework becomes an increasingly important objective. PAs exist because they embody ideals of content and condition such as the charismatic panda bear (*Ailuropoda melanoleuca*), the historic legacy of bison (*Bison bison*), and ecological processes like migration and natural disturbance regimes that humans decide to perpetuate. PAs are created, set aside, and managed with the implicit justification of maintaining specific components and functions whose presence originally caused the PA set-aside in the first place, with recognition of their intrinsic worth. Yet managers and scientists still lack clear standards of how to measure success.

In a sense, then, benchmark ecosystems, the best of the remaining PAs globally, offer researchers a "Rosetta Stone" for decoding system attributes which we will need to actively protect, even as we struggle with a still foggy comprehension of what constitutes an intact ecosystem, we can decode the architecture of attributes of those systems, in order to accomplish the mandates of the Endangered Species Act, as well as the more profound ethical obligations that underlie that Act.

21.5 Augmenting Decision Support Systems: Workflow Architecture and Tools as Unifying Elements

Recent efforts within the US Department of Interior (DOI) provide a case-study opportunity to narrow the gap between research and applications, by bridge building from the side of practitioners. Recently, the National Park Service (NPS) began a nationwide Inventory and Monitoring program (Fancy et al., 2009). The FWS has begun a similar Inventory and Monitoring Program for the national Refuge system. At the same time, the FWS and its federal partner, the U.S. Geological Survey (USGS) formed a National Ecological

Assessment Team to reevaluate how the FWS makes trust resource management decisions, encompassing fish, wildlife, and plants as well as the habitats necessary to sustain them. The team developed a Strategic Habitat Conservation (SHC) framework (NEAT, 2006; http://www.fws.gov/science/doc/SHCTechnicalHandbook.pdf), which was adopted formally in October 2006. This framework became the conceptual basis for the creation of Landscape Conservation Cooperatives or LCC program (http://www.fws.gov/science/shc/lcc.html) and is intended to provide funding to enact the SHC through partnerships that link science and conservation delivery. The LCC effort is being led by the FWS, an agency with a long and profound history of PA management and conservation of biodiversity. The FWS, whose responsibilities include protecting threatened and endangered species, maintaining migratory wildlife populations, and managing national wildlife refuges, has an urgent need to understand how environmental change affects species populations as well as the habitats and ecological functions that support them. In order to achieve these goals, an integrated systems approach or architecture of methods and tools will be required. It must be both consistent enough to be reproducible and defensible, and flexible enough to operate in a variety of contexts. From a modeling standpoint, the ability to census the attributes at landscape to regional scales, through the use of RS technologies, confers that single most necessary tool in unraveling cause and consequence.

21.6 EAGLES: Workflow Architecture and Tools for Scientists and Practitioners

Below, we describe an initial series of linked Decision Support Tools (DSTs) organized as an adaptable, unifying workflow architecture, collectively referred to as EAGLES (*E*cosystem *A*ssessment, *G*eospatial analysis, and *L*andscape *E*valuation *S*ystem). The goal of EAGLES is to lower the barrier of entry to allow scientists and practitioners the ability to understand the cause and consequence of environmental change using focal species (legacy) data as key ecosystem indicators. It stresses the use of *common* data sources (e.g., standardized libraries of RS data products), standardized protocols, and a set of transparent, robust, defensible analysis techniques across jurisdictional and ecological boundaries to provide site-specific, actionable outcomes.

Because species legacy data sets vary with regard to management objectives, spatial and temporal extent, data drop-out in space and time and sampling design, we focused the development of EAGLES to be flexible and user-friendly. We understand the tension between a workflow that is general enough to be applicable across a broad array of data types, yet specific enough to be useful, and emphasize the need for clear set of approaches, providing a road map for practitioners arriving at management decisions that are well-supported by science and common data standards. Thus, EAGLES is a prototype framework for modeling, using a variety of tools for integrating species legacy data (response) and geospatial covariates (explanatory variables), in a variety of forms, within a standardized and documentable workflow for decision-making.

EAGLES was developed through grants awarded from NASA (Ecological Forecasting Program—Award no. NNX08AO58G) and the FWS to the authors in order to enhance existing agency DSSs, in this case the SHC and subsequent LCC program within the Department of Interior (DOI). The project's overriding goal was to integrate RS data into species habitat and demography models. Its three main objectives follow the three sequential segments of the EAGLES acronym: (1) *assess* the ecological conditions of focal region or *ecosystem* where climate and other related environmental drivers are having significant impacts, (2) conduct *geospatial analysis* of focal species populations responding to these impacts, and (3) use these statistical (diagnostic) models to create forecasts (prognostic models) of land cover change and future climate, hence, *landscape evaluations*.

EAGLES's linked software tools (Table 21.2) operate in a user-friendly software environment, allowing user control of data processing, analysis, and predictive modeling capabilities. The work flow components of EAGLES within a generic DSS are presented in Figure 21.3. End-users access tools through multiple pathways of data processing, beginning with matching species data sets with RS data/data products (data products include modeled products such as forage quality). The end-to-end nature of the work flow—from data input to visualization, analysis and forecasting of species populations—is intended to provide a platform for flexible yet repeatable analytical pathways. For the remainder of this chapter, we highlight the major processing components and tools within the EAGLES architecture (Figure 21.3) and provide focal species and covariate examples from the legacy data sets accessed through our partnership with FWS and from NASA data/data products. We also provide some general guidelines to covariate selection criteria.

EAGLES tools were designed for a personal computer (PC) platform, including accessing and sharing large data sets on the internet to support a community of users involved in advanced data acquisition, management and manipulations, exploration, data integration, data mining, analysis and modeling, visualization, and other computing and information processing services. The ArcGIS (ESRI, 2009) software interface is chosen because this is the most widely employed and available platform across city, county, state, federal, and international levels. The Data Exploration Toolset (DET) and models were developed primarily in the open-source, statistical software "R" (R Development Core Team, 2009) by Zuur et al. (2010), subsequently translated into ArcGIS user interface, to lower the barrier for end-users (specifically the steep learning curve for command line interface). Both R and

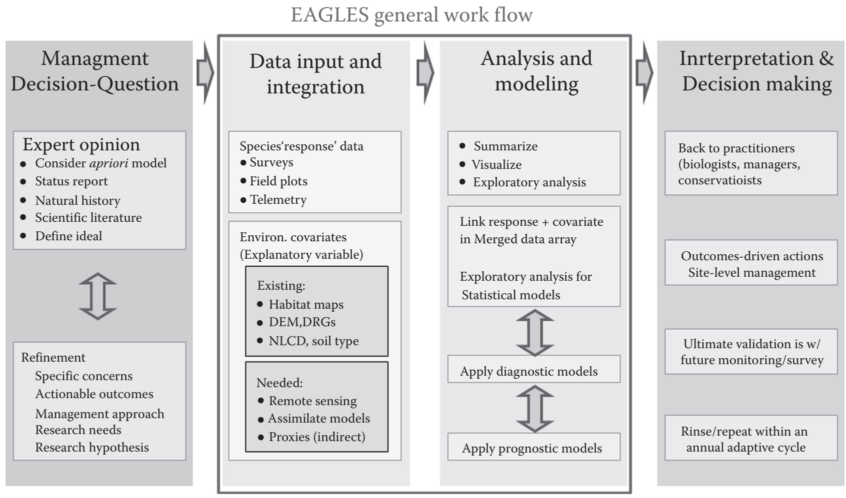


FIGURE 21.3
The EAGLES (Ecosystem Assessment, Geospatial analysis, and Landscape Evalution System) workflow schematic diagram. EAGLES is a workflow architecture that includes both tools (software based) and workflow to allow modeling of species legacy data sets to address management and conservation decision making. It is flexible and provides multiple workflow pathways based on the specifics of the species response data and management question(s). The general idea is to provide a systematic yet flexible architecture for integration of species data with geospatial covariates, most of which are derived from NASA data, data products, and ecosystem models that assimilate sensor data. As the degree of complexity in statistical analyses and RS data increases, the need for a set of standardized techniques and common data protocols becomes more essential, if we are to support repeatable, transparent methods for ecological modeling.

ArcGIS are in widespread use among government, NGOs, and in the private sector. The documented underlying code arrays are available to the expert user community, which may include ecological statisticians, academics, and scientists interested in continuing code development.

21.6.1 Outside and Inside EAGLES

We also designed EAGLES with the explicit intent of augmenting existing agency and organizational DSSs. Because EAGLES provides a variety of tools (Table 21.1) for decision-makers it is not a DSS, but is rather a framework populated with DSTs to enhance existing DSS structures. Thus, columns 1 and 4 in Figure 21.3 exist outside EAGLES but are essential activities in order to achieve decision-making. They depict how practitioners might interact with EAGLES given a species legacy data set. At the outset, a specific set of questions need to be defined in order to extract necessary information from a legacy data set that leads to a science-based management action. As is the goal of any science application, outcomes-driven questions must initiate

TABLE 21.1

List of EAGLES Tools

Tool	Platform	Code	Readiness
Remote Sensing (RS) data WIKI http://geospatialdatawiki.wikidot.com/	Internet	Web application	Online
www.ClimateScape.net	Internet	Web application	Online
Data integration and assimilation models for covariates (CASA, TOPS, NCEP, etc.); there are many that will be listed in RS WIKI	Various	Application specific	Beta
Remote Sensing Classification techniques, for example, percent surface water from MODIS	Various	In publications	Beta
COASTER: data extraction, visualization (www.COASTERdata.net)	Internet	C#	Online (beta)
Data Exploration Tools (DET)	ArcMap	R w/in Arc interface	Beta
Animal-habitat Models (RSPF)	ArcMap	R w/in Arc interface	Beta
GLM, MHRA, others for animal habitat	ArcMap	R w/documentation	Prototype
SWAP tool nonclimate scenarios	ArcMap	Various	Prototype
FcModelBuilder for Future Climate scenarios	Various	Python	Beta

from the decision-makers. They will eventually interpret the results of model analyses before proceeding to site-level actions (column 4, Figure 21.3). Thus, EAGLES provides the intermediate decision support tools needed in an iterative process starting with the management or decision concern and ending with site-level action (e.g., habitat restoration, harvest levels, land-use activities).

21.6.2 EAGLES Workflow

We envision that experts/managers convene either informally or formally, using for example, new Structured Decision Making (Lyons et al., 2008) procedures in order to develop a basic understanding of the factors affecting their focal species and/or its habitat. Species recovery plans serve as excellent examples of extant information that can form the basis for *a priori* model structures. Another important objective of this process is to develop the required set of covariates. After a list of candidate covariates is assembled, the user will be able to integrate these into the modeled structure. Given the ideal situation, EAGLES end-users will also be faced with two data input and integration tasks: (1) bias correction and data drop-out issues in the legacy response data (which is beyond the scope of this chapter), and (2) accessing the needed covariates and matching them to the response data.

21.6.3 Covariate Selection Criteria

With rapid technological advances, another gap is being created between method and underlying theory. As RS technologies accelerate delivering new data products, the underlying theory of covariate selection is still catching up. Ecologists are waiting for theoretical and statistical frameworks that can help guide the complex and rapidly expanding world of RS data and RS-modeled products. Indeed, covariate selection for ecological modeling is both an art and a science (Weins, 2002). Little guidance exists for ecologists charged with building diagnostic and prognostic models for focal species populations that requires a cadre of needed covariates that may or may not vary adequately in space and time.

In an ideal world, the covariates should reflect a minimum and sufficient set of known factors that affect species response. Whether the statistical theory underlying the modeling effort relies on information-theoretic approaches and *a priori* model selection, or involves other approaches, we are after a clear-minded, interpretable approach to understanding cause and effect—regardless of the RS inputs, PA status, and inferential techniques. In our view, building an ecological model with RS data and data products may be greatly facilitated by access to standardized, documented, accessible, and cost-controlled geospatial layers (see Reichmann et al., 2011 for a more formal exposition of these structures and their importance). As a modest beginning, we have started this process by building a variety of web-based tools to access these data sources (rows 1–3, Table 21.1) (see GeoSpatial data wiki at http://geospatialdatawiki.wikidot.com/, which lists RS data for ecological applications).

All ecological models are to some extent *incomplete*, and this incompleteness can sometimes be characterized by overall goodness-of-fit, expert knowledge, visually plotting the predictions on the landscape, hypothesis testing, and most importantly, independent validation. A *deficient* model, however, is one that proceeds without inclusion of *known and expected* causal covariates, or at least, interpretable proxies of these covariates. And this violation of scientific principle is in addition to the perennial problem of creating the needed covariates when they usually do not exist or are too costly to acquire. Below, we provide initial guidelines and suggested solutions to this conundrum as well as the overall problem of covariate selection. At this point in a hypothetical EAGLES workflow, we assume we have identified the ideal situation, independent of availability or cost, that is, a full list of causal or mechanistic covariates based upon the discovery process described above. However, given their sensitivity and fundamental role in the scientific method, careful consideration must be given to the selection of covariates prior to preliminary analysis and final modeling. There is surprisingly little attention provided in the published literature (but see Scott et al., 2002). Too often we gather what is easily available without further consideration of either creating the needed covariate or selection of a proxy that is interpretable.

21.6.3.1 Scale

Issues of scale present fundamental challenges for all ecological data. These challenges are further compounded by the interpretation and classification of the abstractions of rasters, pixels, and postings. Most spatial ecological data are inherently continuous in nature, but we discretize them in space, time, and often, level of organization. Scale determination can be made based on prior research grounded in empirical biology, and is often determined by spatio-temporal resolution available in covariate sets as well. Based on research, natural history, field observation and intuition, scale of covariates can be selected from the perspective of the species of study. When in doubt, select several scales and use and then use, for example, metrics like log-likelihood values in model selection approaches (Burnham and Anderson, 2002) to arrive at a one or a reduced set.

Measurement error in the response data should also be used. For example, error polygons for radio telemetry locations set the lower limit on analytical resolution for species studied with telemetry. It is also important to keep in mind the inherent level of spatial and temporal heterogeneity of the covariate of interest, for example, 30 m snow-water-equivalent (SWE) measurements may vary little over a 1 km distance. Continuous observations are recommended over categorical classifications of the same covariate, for example, percent cover of sagebrush captures a more meaningful aspect of selection criteria for a given species compared to a multinomial category that may or may not include sagebrush presence. Finally, selection of temporal resolution is very challenging. Consider not only scale but "critical windows" or seasonality given the life-history strategy for your species of interest. Species response to specific events (e.g., previous disturbance) and cumulative lags are common, for example, peak phytomass production responding to precipitation in both the current spring and previous year (Potter et al., 2007).

21.6.3.2 Collinearity

Collinearity can be considered from both biological and statistical points of view. Rigorous and clear-minded approaches to data exploration tools (DET) and diagnostics before, during, and after the modeling process (e.g., see Zuur et al., 2010) give the best outcomes for deconstructing the relevance of collinearity metrics in the data under investigations. There are accepted statistical criteria for collinearity, but ecological insights can be of equal or greater importance. This is troublesome because two correlated covariates are often ecologically related to one another from the perspective of the species of interest. For example, assume prey availability, shrub cover, and southern aspects are all significantly correlated and ecologically related covariates. Are bobcats, for example, selecting for one, two, or all three? Also, because many approaches offer only loose guidelines with respect to collinearity in model selection procedures, we strongly suggest the using our data exploration toolset (DET) which is patterned after Zuur et al. (2010).

21.6.3.3 Proxies and Interpretation

Owing to the cost and/or unavailability of important covariates, we are often left with selection of proxy covariates that can be difficult to interpret. Because proxy covariates exist as abstractions on a gradient ranging from gross approximations to specific causal agents, caution must be taken when interpreting model results. The strong relationship between level of proxy and ability to interpret model results, can lead to erroneous conclusions. For example, annual plant production may serve as an interpretable proxy for herbivores responding to forage biomass but not forage quality. Finally, any suspected proxy can be further examined with field validation and field observation efforts. In a sense, a proxy relationship can be thought of as a hypothetical relationship, and is therefore one that should be tested and validated.

21.7 Final Covariate Selection and Creation

Owing to the information needs of a particular focal species data set, it is very likely that some important covariates will have to be created or existing proxies interpreted. We provide just four examples (Figure 21.4a–d) of the many covariates one might need in order to build predictive models and test hypotheses. These examples underscore the vast potential that RS data holds in providing covariates, ranging from free or low-cost to high-cost solutions, for ecological modeling. In our experience, temporally dynamic covariates are most often those in critically short supply.

The most time-consuming step we have experienced in the analysis of focal species data is in data integration techniques (column 2, Figure 21.3) and in creating covariates for modeling and further analysis. This vast subject lies beyond the scope of this chapter. There are many early and developed utilities that are moving rapidly in the right direction to remedy this shortfall. TOPS (see chapter in this volume) serves as an excellent example of a data integration system useful for creation of many covariates. We also refer the reader to http://geospatialdatawiki.wikidot.com/ and www.climatescape.net as examples of both a source and portal to examine further links and techniques to discover and then access covariates or proxy measures. Table 21.2 gives examples of recently created covariates using data integration techniques, in particular, using data from space-borne, airborne, and ground sensor networks to create previously unavailable geospatial covariate layers at various temporal resolutions.

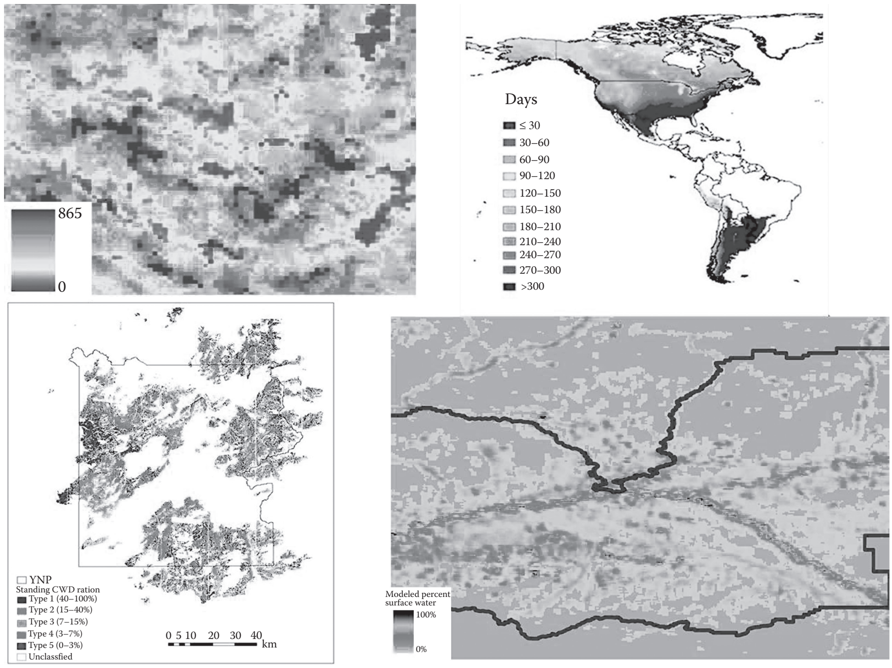


FIGURE 21.4
Four different geospatial covariates created to avoid "deficient" models which lead to erroneous conclusions and poor inference. Percent surface water (PSW) at Yukon Flats National Wildlife Refuge, Alaska (lower right). Lesser scaup (*Aythya affinis*) breeding pairs were measured in response to the intra- and inter-annual variability of PSW. The number of frost-free days (Kim et al. 2010) across North America were used to estimate changes in the timing and duration of the growing season for analysis of migratory waterfowl (upper right). These data were generated using merged SSMR and SSM/I data and can be retrieved at (http://freezethaw.ntsg.umt.edu). We created classification maps of coarse woody debris biomass in the areas burned in the great fires of 1988 in Yellowstone National Park (YNP) using AIRSAR and AVIRIS data (Huang et al., 2009). The proportion of standing vs. downed CWD was also estimated (lower left) using these procedures. Inclusion of the CWD data into the CASA ecosystem model resulted in large portions of YNP switching from a carbon sink to a carbon source. CASA_Express, an ArcGIS version of CASA was used to generate estimates of annual forage production (biomass available to ungulates) using MODIS EVI data (upper left). These data were then used in spatio-temporal models to predict seasonal movements of elk (*Cervus elaphus*) and bison (*Bison bison*) in and out of YNP (Geremia et al., 2011).

21.8 Ecosystem Assessment and Diagnosis

Once the needed covariates have been identified and created they can be accessed and manipulated using a recently developed software tool called the *C*ustomized *O*nline *A*ggregation & *S*ummarization *T*ool for *E*nvironmental *R*asters or COASTER (www.COASTERdata.com). This tool has two major

TABLE 21.2

A List of the Available Geospatial Data Products we Considered for Use in the Analysis of Focal Species Populations in the Northern Rockies Ecoregion

NASA Data Product (Variables and Covariates)	Frequency	Period	Resolution
Terrestrial Observation and Prediction System			
Evapotranspiration (TOPS ET)	Daily	1950–Present	1 km
Solar radiation (TOPS SRAD)	Daily	1950–Present	1 km
Snow water equivalent (TOPS SWE)	Daily	1950–Present	1 km
Temperature (min/max) (TOPS MIN, MAX	Daily	1950–Present	1 km
Precipitation (TOPS PRCP)	Daily	1950–Present	1 km
Snow temperature (TOPS SNWTMP)	Daily	1950–Present	1 km
Vapor Pressure Deficit (TOPS VPD)	Daily	1950–Present	1 km
Gross primary productivity (TOPS GPP)	8-Day	2000–Present	1 km
*Soil cover (% sand, %silt, %clay, hydro, root depth	Static	Recent	1 km
Snow Extent	16-day	2000–Present	1 km
Landcover (IGBP & UMD)	Static	Single Years	1 km
EVI and NDVI – Vegetation indices	8-Day	2000–Present	1 km
FPAR – Photosynthetic Active Radiation	8-Day	2000–Present	1 km
LAI – Leaf Area Index	8-Day	2000–Present	1 km
CASA_Express Wetlands version			
NPP, Net primary productivity	W,M,A	'84/'00–Present	250 m/30 m
***Soil Moisture—3 layers to root depth**	W,M,A	'84/'00–Present	250 m/30 m
***PET, Potential Evapotranspiration**	W,M,A	'84/'00–Present	250 m/30 m
***Herbaceous (Foliar) Biomass Production**	M,A	'84/'00–Present	250 m/30 m
***SWE, Snow Water Equivalent**	D,W,M	'84/'00–Present	250 m/30 m
***Snowmelt Rate**	W,M	'84/'00–Present	250 m/30 m
***Water Temperature in Rivers and Lakes**	W,M	'84/'00–Present	250 m/30 m
Growing Season Length (in days)	Annual	'84/'00–Present	250 m/30 m
Drought—User Specified and Probabilistic	Annual	'84/'00–Present	250 m/30 m
Disturbance Classes (MODIS derived)			
Urban Expansion	Annual	2001–Present	250 m
*Agriculture Expansion—New Irrigated Cropland	Annual	2001–Present	250 m
*Agriculture Expansion—CRP for two years or more	Annual	2001–Present	250 m
***Wetland Conversion to cropland**	Annual	2001–Present	250 m
***Wetland Loss (drained or dried out)**	Annual	2001–Present	250 m
***Wetland Expansion**	Annual	2001–Present	250 m
Fires (nonforest)	Annual	2001–Present	250 m
Fires (forested)	Annual	2001–Present	250 m
Insect kill (forested)	Annual	2001–Present	250 m
Logging (forested)	Annual	2001–Present	250 m

TABLE 21.2 (continued)

A List of the Available Geospatial Data Products we Considered for Use in the Analysis of Focal Species Populations in the Northern Rockies Ecoregion

NASA Data Product (Variables and Covariates)	Frequency	Period	Resolution
Other Remote Sensing Products			
***Percent Cover of Shrubs, Herbacious, Soil**	Static	Recent	30 m
***PSW, Percent Surface Water**	8-Day	2000–Present	1 km
Freeze–Thaw Parameters (Frozen/Thawed/Trans.)	Daily	1979–Present	25 km

Temporal resolution, temporal extent, and spatial resolution must all be carefully considered in the selection and interpretation steps of modeling efforts in EAGLES. D = Daily, W = Weekly, M = Monthly, and A = Annual. We placed a large emphasis on those products related to water and wetlands (in bold) due to the strong relationship between water and biodiversity. Products marked with an asterisk had to be validated in select locations prior to their use in predictive modeling.

functions within EAGLES: (1) data discovery and (2) data access. COASTER allows end-users to identify and extract desired subsets of RS covariates from archived geospatial databases (~1 TB and larger). These typically reside on servers and supercomputers. The subsetted covariates are accessed via COASTER, then posted to an ftp site for input into the EAGLES environment for further analysis (column 3, Figure 21.3; see http://coasterdata.net/Examples.aspx for examples). Second, it allows end-users to conduct ecosystem and vulnerability assessments through use of basic functions that summarize, threshold, and compare covariates across space and time. Additional functions allow the creation of visualization models to assess, for example, how key climate metrics are driving changes in plant productivity. Most simply, this can be done through creation of trend maps and anomaly detection. Figure 21.5 provides a trend map of climate anomalies for the Northern Rockies region created in COASTER. The combination of functions within COASTER provides desktop capability for characterization of ecosystem condition, function, pattern, and process in a specific area of interest, for example, a refuge or a management region. It can also be used to create new covariates needed for further analysis of species legacy data. At a more streamlined level, end-users may arrive at a sufficient level of decision support directly within the COASTER suite of utilities (data visualization and change detection, trend, threshold, and anomaly metrics) and elect not to proceed further in the EAGLES framework.

The conversion of input data types into a standardized protocol is accomplished with the software tools that reside in the EAGLES workflow architecture. These functions are programmed to be compatible with, or are already included in, the ArcGIS environment. They can also be further modified by expert users. These include resampling, interpolation, simulation modeling, statistical correction of bias, and calibration/validation of the final mapped products. Two components occur outside the workflow, (1) datum and

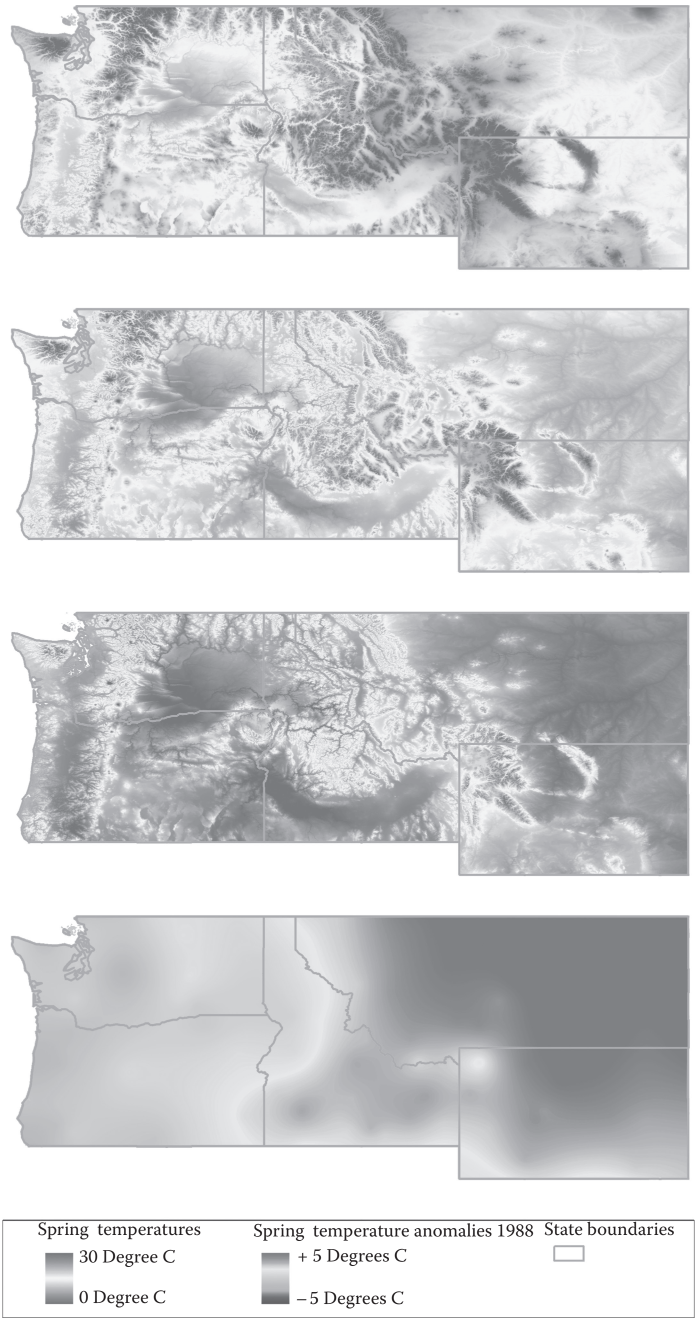


FIGURE 21.5
These maps illustrate some of the functionality available within the COASTER system. To create these maps, gridded, daily maximum temperature datasets from March 21st through June

scaling integration and (2) creation of unique or nonstandard RS products, for example, geospatial covariates specific to analysis and predictive modeling of a given focal species. These unique RS products may be essential for successful modeling efforts. For example, in order to support a waterfowl model from annual counts of breeding pairs, we created a fractional surface water product (see Figure 21.4b) from MODIS that produces estimates every eight days (Weiss and Crabtree, submitted). This RS product met an identified critical need suggested by a federal agency practitioner working group focused on waterfowl and shorebird populations.

21.9 Statistical Analysis and Modeling

Figure 21.6 provides an example of our Data Exploration Toolset or DET (Zuur et al., 2010) as applied to analysis of pronghorn (*Antilocapra americana*) data in Yellowstone National Park, WY. The utility of data exploration before, during, and after modeling cannot be overstated. Data exploration serves a vital role in testing assumptions (e.g., about the distribution of the data, the relative contributions of extreme values, and the presence of underlying patterns that may require more thought). As the sophistication of RS data inputs increases, the investigation of unexpected patterning of relationships within and among covariates becomes increasingly important. Making use of a readily available and standardized toolbox for investigation the patterning of dependent and independent variables has proven to be of great utility.

After data exploration procedures, end-users are now ready for diagnostic analysis using various statistical models. For this, we created a conceptual and practical framework for analysis of species populations and their habitats called Risk-Reward Spatial Capacity (RRSC) models. These are a progressive series of spatially explicit species population models that can be diagnostic and/or predictive. Historically, species–environment models (e.g., Scott et al., 2002) focus on desirable habitat conditions, leaving out important risk or hazard conditions and their impacts on vital rates (Wittmer et al.,

FIGURE 21.5 (continued)
21st were summarized for each year and for all years from 1955 to 2009. The top three maps show (from top to bottom) the minimum, mean, and maximum average springtime temperatures for the Pacific Northwest. These graphs are conceptually similar to the normal high, record high, and record low values typically provided within weather reports on the local news. However, instead of the conditions for a single day the maps show conditions summarized for all days within spring. The lower map, in contrast, shows how conditions in the spring of a single year (1988) differ from normal conditions. This map was created by subtracting the average springtime high temperature (i.e., the second map) from the springtime temperatures summarized for 1988, which was one of the warmest years on record in the United States.

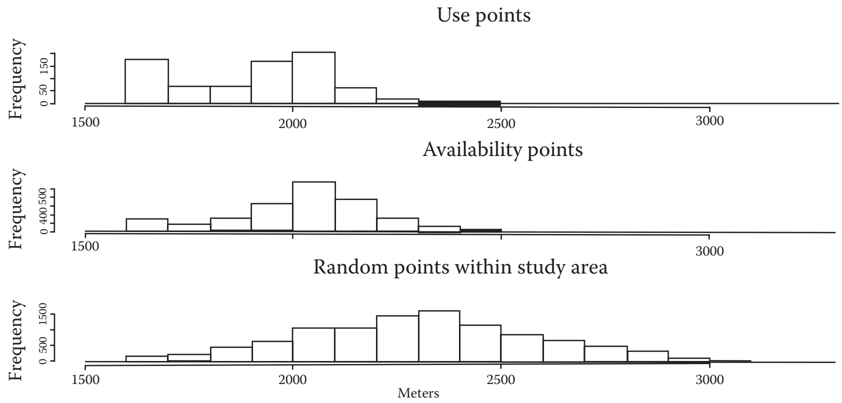


FIGURE 21.6
Example of the utilization function in the EAGLES Data Exploration Toolset (DET). The summer 2008 relocations presented in Figure 21.7 (purple spears) are summarized above as a three-panel frequency histogram for the covariate "elevation." The top displays the actual response data or "use points"; the middle displays a random sample of points within a 1 km buffer area around the response use points and; the bottom panel displays a random sample of points within the study area (user-defined region of interest for model inference) (n = 10,000 random points).

2007). It is clear that inclusion of spatial information on hazards such as predation risk can expose sublethal effects on species distributions and vital rates. Similarly, in the temporal domain, extreme weather and disturbance events, which can often be characterized as single-event hazards, are essential to integrate into species modeling efforts and can have long-lasting impacts on populations.

The RRSC framework provides a logical progression of legacy data set analysis starting with basic coarse-scale species distribution models (SDMs) to identify and delineate critical habitat components. Next, fine-scale habitat selection models that include temporally dynamic information, either implicitly (time for space substitution) or explicitly (time-varying model structure) can be constructed. Both SDMs and habitat selection models can then be used to identify and filter out important covariate structures prior to demographic analysis and modeling (vital rates and abundance as related, ultimately, to fitness). Species must survive environmental risks and then utilize resource (habitat and prey/forage) to successfully reproduce and increase fitness. Species abundance at a given time is essentially the result of survival (loss) and reproduction (gain).

As a first RRSC model within EAGLES, we developed an ArcGIS tool for analysis of species location data using a recent modification of a widely used technique called Resource Selection Functions or RSF (Manly et al., 2002). This falls under a more general category referred to as resource selection analysis, hence our RRSC-RSA tool. This type of RSF model is described in

Lele and Keim (2006) and Lele (2009), and provides a probabilistic approach to identifying regions and resources/risks that are used more/less than expected. These approaches are robust and are additionally appealing because they create empirical response plots and probabilistic maps (resource selection surfaces) across the study area of interest. These are particularly useful for threshold delineation, for example, for explicating the patterning of animal response data against each covariate (e.g., polar bear, *Ursus maritimus*, vs. sea ice density). Originally developed in R, we have translated this approach into an ArcGIS platform, and have developed numerous diagnostics and interactive decision-points for end-users, providing a transparent, repeatable process or "white-box" approach. We have also developed and documented a suite of RRSC modeling approaches (e.g., GLM, GLM with spatial autocorrelation, and GAMs) for habitat and demographic analysis in R and are in the process of translating them into the ArcGIS environment.

Figure 21.7 provides a visualization of how a merged data array (MDA) is created from the legacy and covariate data sets and then input into a habitat model for diagnostic analysis and final model output. These and related functions and tools are available as ArcGIS plug-ins. Again, the specifics of the data sets will dictate the specific processing chain or pathways through EAGLES. The original or modified MDA can also be run through other pathways and various statistical models to explore further relationships and test hypotheses. The output of the RSPF analysis is shown at the bottom of Figure 21.7 as a predicted probability surface within the region-of-interest or sampling universe (bottom of Figure 21.6). This probability surface was used to estimate a species distribution, delineate critical habitat, identify critical habitat components, and provided a probabilistic resource selection/avoidance surface with measures of uncertainty per pixel. Table 21.3 provides results of the pronghorn RSPF model. Many other diagnostics are provided as well as intermediate steps and decision points that guide the end-user through the statistical analysis.

Once a diagnostic model has been developed, we have developed other tools to create prognostic models and explore "what-if" scenarios. One tool ingests and manipulates downscaled future climate scenarios and another allows end-users to apply RRSC models to different areas or under different habitat scenarios such as habitat restoration, development, and disturbance events (fire, drought, snow-hardening events, and a variety of land-use activities). The "SWAP tool" is an ArcGIS utility that allows the end-user to modify a covariate value in an existing model structure, holding all else constant, and examining resultant changes in modeled output. For example, an existing diagnostic model structure (Figure 21.7) created the output in Table 21.3. The SWAP tool allows the end-user to simulate (or forecast) a new covariate (or a new range of values for an existing covariate, e.g., increase biomass, 50% increase in precipitation, new road as in Figure 21.8) by swapping out the previous covariate value with the new one. The predictive model structure and coefficients stay the same while only the new covariate values—new or

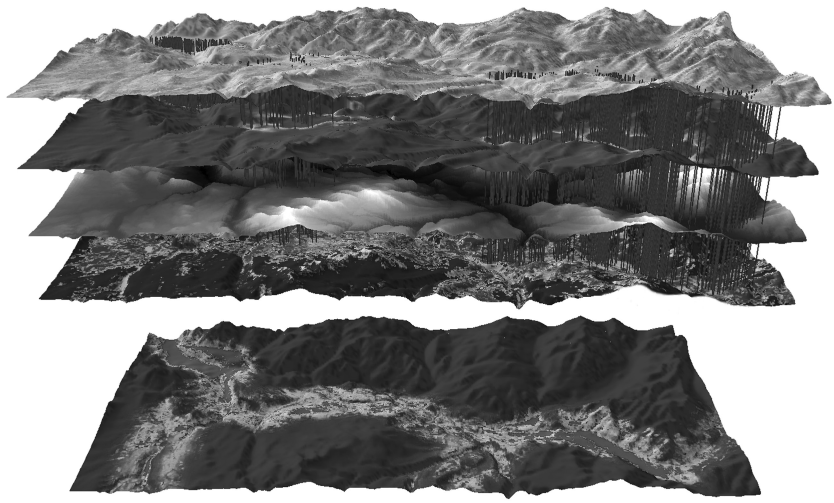


FIGURE 21.7
(**See color insert.**) Visualization of co-registered GIS layers generated using various data integration procedures in EAGLES, a set of decision-support tools integrated into ESRI's ArcGIS environment. Four geospatial data layers, generated for resource selection analysis (RSPF, Lele and Keim, 2006) of pronghorn summer habitat selection, are (from top to bottom): (a) forage biomass created by the CASA model assimilating MODIS EVI data (Potter, 2007), (b) coyote utilization created from kernel density smoothing (cite) of relocations of radio-marked adults, (c) elevation and aspect from a USGS 30 m DEM, and (d) a remotely sensed classification map of forest (dark green) and sagebrush (light green) using PALSAR and Landsat ETM data. The locations of radio-tracked pronghorn adults (response data used in the RSPF model) are indicated as coregistered purple "spears." The bottom layer is the resource selection probability surface generated by the EAGLES RSPF model tool where "warmer" temperature colors indicate higher probability of use (ranging from selected to avoided habitat areas) by pronghorn during the summer.

future scenarios—are inserted and the model re-run. The original diagnostic model was modified to create a "what-if" scenario by adding a road (Figure 21.8). It was then re-run to create prognostic model output that predicts how pronghorn would respond as well as how critical habitat may be functionally removed or improved.

The Future Climate Tool or FcModelBuilder (listed in Table 21.1) is a similar tool that ingests and manipulates downscaled future climate scenarios (IPCC, AR4, etc.) and another allows end-users to apply RRSC models to different areas or under different habitat scenarios such as habitat restoration, development, and disturbance events (fire, drought, snow-hardening events, and a variety of land-use activities). Through a disciplined, documented, and transparent diagnostic modeling processes, end-users can then utilize these tools to build prognostic models to effectively support scenario construction guiding site-level actionable outcomes. Such ecological forecasting (Clark, 1999) is an emerging subdiscipline in ecology that has many unsolved

TABLE 21.3

Model Results for the Pronghorn Example Depicted in Figure 21.7

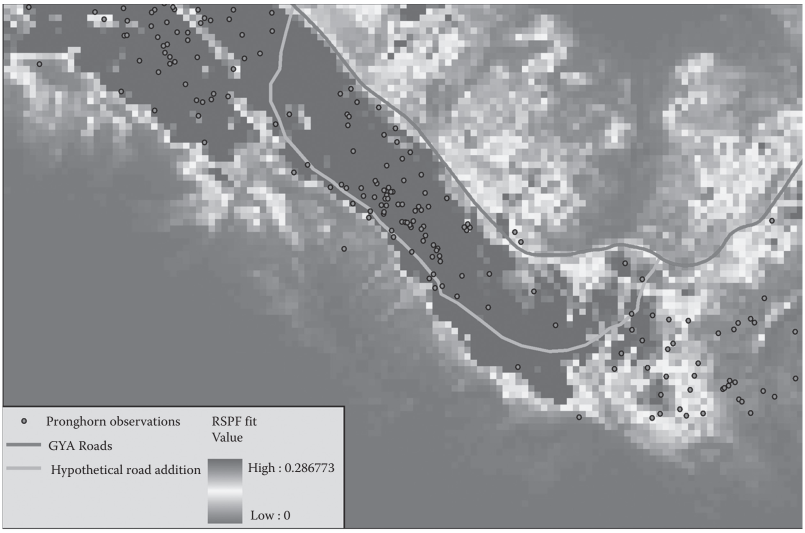
Parameter	*t*-Value	*p*-Value	v-i-f
(Intercept)	–2.76	5.92E–03	NA
Distance to road (+)	3.59	3.52E–04	1.8
Distance to road ^2 (-)	–6.98	6.51E–12	1.3
Coyote (+)	4.64	4.11E–06	1.4
Elevation (–)	–5.91	5.19E–09	2.6
Forage (+)	2.51	1.23E–02	2.8
June NPP (–)	–2.15	3.19E–02	2.3
% Sage (–)	–3.1	2.01E–03	1.5
% Forest (–)	–3.45	5.92E–04	3.5
% Herbaceous (+)	2.45	1.45E–02	2.4
Slope (–)	–4.68	3.40E–06	1.4
Wolf (–)	–8.35	3.29E–16	1.1

The VIF, variance inflation factor, is a measure of multicollinearity among the independent variables, that is, it gives a measure of correlation.

issues, not the least of which is how one independently validates such future forecasts for conservation action. Making sense of the chaotic and disarticulated array of old and emerging issues involved in future predictions and decision-making (issues of scale, components, instrumentation, algorithm function, information about uncertainty and assumptions, and statistical issues) (see Fulton, 2010) can be helped by beginning with a standardized, highly documented, and inter-comparable common set of inputs and methods (e.g., Hijmans et al., 2005) as we have outlined in this chapter.

21.10 Conclusions

Maintaining resilient plant and animal communities within managed PA ecosystems is becoming a daunting challenge. Yet PAs often have internal monitoring programs in place that produce legacy data sets as well as national and global monitoring efforts producing vast streams of environmental data (ground-, air-, and space-borne sensors). We contend that the analysis and modeling of these “merged” data sets provide our best hope for crafting successful adaptation strategies to environmental change agents, especially those being complicated by climate disruption. The generalized modeling approach—from narrative, conceptual models to visual, spatially explicit population models—provided by EAGLES allows a solution to these challenges as well as a bridge between science and decision-makers. Conservation of species and the ecosystem processes that support them will



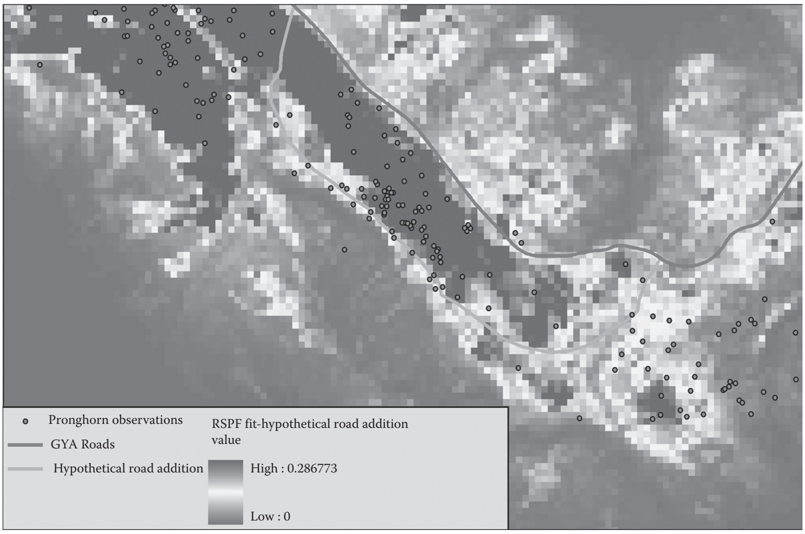


FIGURE 21.8
A portion of the original RSPF model output (bottom layer of Figure 21.7) indicating the resource selection function for pronghorn in Yellowstone National Park (left). The SWAP was used to create an additional road shown in orange. The new prognostic RSPF model output for pronghorn (right) indicates that pronghorn are excluded from portions of their original selected habitats. These types of What-if-Scenario (WIS) will provide practitioners with important decision support to guide site-level action plans, restoration efforts, and understand the environmental impacts from climate disruptions, invasive species, changing land-use, and disturbance regimes.

require a more effective set of programmatic linkages (e.g., DSTs), narrowing the gap between scientists (researchers and academics) who are forging ahead with new methodologies, and the end-user practitioners (biologists, managers, conservationists) who require straightforward, cost-effective tools in order to make informed and defensible decisions based on diagnostic and predictive modeling. Casting and comparing these activities against the concepts and metrics of "benchmark ecosystems" will provide yet another set of powerful adaptive management techniques leading to resilient species and ecosystems.

The modeling approaches we describe are not new. But lowering the barrier of entry for users as they approach an increasingly complex analytical environment seems useful. Among various factors limiting the development and use of predictive landscape models, the lack of access to known, causal covariates may be the most problematic. This leads to "deficient" models that are the antithesis of the scientific principles: predictive models that exclude explanatory variables are equivalent to conducting science without explanatory alternate hypotheses. It is unfortunate that many needed explanatory covariates simply do not exist or are too expensive to acquire. However, with the advent of many new RS sensors, data products (e.g., free MODIS data products), and assimilation models that ingest RS data, we can now create direct or proxy measures of those needed covariates. For example, Geremia et al. (2011, accepted) derived annual estimates of above-ground forage biomass and weekly snow-water-equivalents from sensor-assimilation models. Those two factors were crucial in predicting winter bison (*Bison bison*) movements outside of Yellowstone National Park, a famous benchmark ecosystem.

While new information and technology is emerging at unprecedented rates, environmental impacts on species populations are in a state of flux due to the cumulative impacts of human activities on landscapes. Invasive spread, pathogen outbreaks, land-use activities, and especially climate disruption and its associated impacts—severe drought, reduced stream flow, increased wildfire frequency, extended growing season, and extreme weather events—are increasing, and in some cases accelerating. These changes are outpacing management and conservation actions. In particular, the increase in frequency and severity of climate-mediated impacts (e.g., record drought in the Northern Rockies) are now occurring at larger, landscape to regional scales. This combined with unpredictability and unexpected interactions are rendering traditional management strategies ineffective at sustaining ecological function, resiliency, and viable species populations.

As a solution to this uncertain future, we have described the EAGLES framework and provided example of DSTs, important geospatial covariates, ecosystem assessment tools, and initial RRSC species population models for analysis of focal species. It will allow agencies like the FWS (and the new LCC program) the ability to examine what–if scenarios guiding outcomes-driven, on-the-ground actions to recover or maintain populations. Restoration in response to disturbance, acquisition of additional habitat, and regulation of risk factors such as hunting and predation are examples of such outcomes-driven actions. These necessitate the need for models that are spatially explicit because decision-makers regulate land-use activities or conduct habitat management at the site level (e.g., forest stand, allotment, and refuge scales). At the same time, multiple impacts are occurring at unpredictable, multiple temporal scales from periodic oscillations (e.g., ENSO), planned disturbance events, and daily extreme weather events. Thus, spatially explicit models also need to incorporate such temporally dynamic information. In this highly uncertain spatiotemporal frame it seems imperative to adhere to standardized, transparent, and defensible processes in arriving at science-based management decisions, so that we are able to systematically track, measure, and evaluate outcomes, such as species persistence, as clearly as possible.

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