converge to a clear limit in long enough series (*6*, *7*, *17*, *18*). Toward the other end of the range of conceivable behavior lies density-independent stochastic growth, the prime example of which is a random walk, for which the variance grows linearly with time (*7*, *13*). It seems (Fig. 2A) that the dynamics of animal populations, on the longest time scales available to us, lie somewhere between these two poles. These results show that population variability is not a single fixed quantity. The incorporation of some measure of variance increase into widely used measures of temporal variability (such as the coefficient of variation or the standard deviation of the logarithm of abundance) offers the possibility of substantially improving the understanding of ecological variability.

Often, the limiting factor while investigating ecological phenomena and in the development of theory to explain them has been the availability of suitable long-term data. As we have illustrated here, the GPDD now offers an unprecedented opportunity to undertake broad-scale comparative studies aimed at understanding the main features of population dynamics.

References and Notes

1. The GPDD can be accessed at http://www.cpb.bio.ic.ac.uk.
2. B. Kendall, J. Prendergast, O. Bjornstad. *Ecol. Lett.* **1**, 164 (1998).
3. S. Pimm, A. Redfearn, *Nature* **334**, 613 (1988).
4. J. Lawton, *Nature* **334**, 563 (1988).
5. S. Pimm, *The Balance of Nature? Ecological Issues in the Conservation of Species and Communities* (Univ. of Chicago Press, Chicago, IL, 1991).
6. B. MacArdle, K. Gaston, J. Lawton, *J. Anim. Ecol.* **59**, 439 (1990).
7. A. Ariño, S. Pimm, *Evol. Ecol.* **9**, 423 (1995).
8. W. Murdoch, *Ecology* **75**, 271 (1994).
9. H. Cyr, *Oikos* **79**, 54 (1996).
10. J. Halley, *Trends Ecol. Evol.* **11**, 33 (1996).
11. A. White, M. Begon, R. Bowers, *Nature* **381**, 198 (1996).
12. J. Steele, *Nature* **313**, 355 (1986).
13. J. Halley, W. Kunin, *Theor. Pop. Biol.* **56**, 215 (1999).
14. Methods for spectral and variance growth exponents are available as supplementary Web material on *Science* Online at www.sciencemag.org/cgi/content/full/293/5530/655/DC1.
15. R. Adler, R. Feldman, M. S. Taqqu, Eds., *A Practical Guide to Heavy Tails: Statistical Techniques for Analysing Heavy-tailed Distributions* (Birkhauser, Boston, 1997).
16. J. Halley, P. Inchausti, unpublished data.
17. R. May, in *Ecology and Evolution in Communities*, M. Cody, J. Diamond, Eds. (Princeton Univ. Press. Princeton, NJ, 1975), pp. 81–120.
18. T. Royama, *Analytical Population Dynamics* (Chapman & Hall, New York, 1992).

19. We thank S. Pimm for his comments on the manuscript. P.I. acknowledges the support of a TMR Marie Curie Fellowship from the European Commission. J.H. was supported by grant 97EL-6 from the General Secretariat for Research and Technology, Greece.

VIEWPOINT

Ecological Forecasts: An Emerging Imperative

James S. Clark,[1]* Steven R. Carpenter,[2] Mary Barber,[3] Scott Collins,[4] Andy Dobson,[5] Jonathan A. Foley,[6] David M. Lodge,[7] Mercedes Pascual,[8] Roger Pielke Jr.,[9] William Pizer,[10] Cathy Pringle,[11] Walter V. Reid,[12] Kenneth A. Rose,[13] Osvaldo Sala,[14] William H. Schlesinger,[15] Diana H. Wall,[16] David Wear[17]

Planning and decision-making can be improved by access to reliable forecasts of ecosystem state, ecosystem services, and natural capital. Availability of new data sets, together with progress in computation and statistics, will increase our ability to forecast ecosystem change. An agenda that would lead toward a capacity to produce, evaluate, and communicate forecasts of critical ecosystem services requires a process that engages scientists and decision-makers. Interdisciplinary linkages are necessary because of the climate and societal controls on ecosystems, the feedbacks involving social change, and the decision-making relevance of forecasts.

Scientists and policy-makers can agree that success in dealing with environmental change rests with a capacity to anticipate. Rapid change in climate and chemical cycles, depletion of the natural resources that support regional economies, proliferation of exotic species, spread of disease, and deterioration of air, waters, and soils pose unprecedented threats to human civilization. Continued food, fiber, and freshwater supplies and the maintenance of human health depend on our ability to anticipate and prepare for the uncertain future (*1*). Anticipating many of the environmental challenges of coming decades requires improved scientific understanding. An evolving science of ecological forecasting is beginning to emerge and could have an expanding role in policy and management.

An initiative in ecological forecasting must define the appropriate role of science in the decision-making process and the research that is required to develop the capability. Ecological forecasting is defined here as the process of predicting the state of ecosystems, ecosystem services, and natural capital, with fully specified uncertainties, and is contingent on explicit scenarios for climate, land use, human population, technologies, and economic activity. The spatial extent ranges from small plots to regions to continents to the globe. The time horizon can extend up to 50 years. The information content of a forecast is inversely proportional to forecast uncertainty (*2*). A wide confidence envelope indicates low information content. A scenario assumes changes in "possible future boundary conditions (e.g., emissions scenarios). . . . For the decision maker, scenarios provide an indication of possibilities, but not definitive probabilities" (*3*). Scenarios can be the basis for projections, which apply the tools of ecological forecasting to specific scenarios.

What Is Forecastable?

Accurate estimation and communication of information content will determine the success of an ecological forecasting initiative. "Forecastable" ecosystem attributes are ones for which uncertainty can be reduced to the point where a forecast reports a useful amount of information. Information content is affected by all sources of stochasticity.

[1]Department of Biology, Duke University, Durham, NC 27708 USA. [2]University of Wisconsin Center for Limnology, Madison, WI 53706, USA. [3]Ecological Society of America, 1707 H Street NW, Suite 400, Washington, DC 20006, USA. [4]Division of Biology, Kansas State University, Manhattan, KS 66506, USA. [5]Department of Ecology and Evolutionary Biology, Princeton University, Princeton, NJ 08544, USA. [6]Center for Sustainability and the Global Environment, University of Wisconsin, Madison, WI 53706, USA. [7]Department of Biological Sciences, University of Notre Dame, Notre Dame, IN 46556, USA. [8]Department of Ecology and Evolutionary Biology, University of Michigan, Ann Arbor, MI 48109, USA. [9]Environmental and Societal Impacts Group/National Center for Atmospheric Research, 3250 Mitchell Lane, Boulder, CO 80301, USA. [10]Resources for the Future, 1616 P Street NW, Washington, DC 20036, USA. [11]Department of Ecology, University of Georgia, Athens, GA 30602, USA. [12]Millennium Ecosystem Assessment, 731 North 79th Street, Seattle, WA 98103, USA. [13]Coastal Fisheries Institute and Department of Oceanography and Coastal Sciences, Louisiana State University, Baton Rouge, LA 70803, USA. [14]Department of Ecology, Faculty of Agronomy–IFEVA, University of Buenos Aires–CONICET, Buenos Aires 1417, Argentina. [15]Nicholas School of Environment and Earth Sciences, Duke University, Durham, NC 27708, USA. [16]Natural Resource Ecology Laboratory, Colorado State University, Fort Collins, CO 80523, USA. [17]United States Department of Agriculture Forest Service, Post Office Box 12254, Research Triangle Park, NC 27709, USA.

*To whom correspondence should be addressed. E-mail: jimclark@duke.edu

Low information content can result because drivers (and, thus, model structures) are uncertain, parameters are uncertain, and unknown human responses to ecosystem change (or to forecasts of ecosystem change) affect outcomes. Many sources of stochasticity are typically ignored in ecological models. When reported at all, prediction uncertainties are typically confined to estimation error (*4*, *5*), which is reduced by sampling and is often overwhelmed by other sources of uncertainty.

Most daunting is the "inherent" uncertainty that results from strong nonlinearities and stochasticity. For example, the inherent uncertainty involved in extinction risks leads ecologists to disagree on the value of predictions from population viability models (*6*). Extinction forecasts are highly sensitive to poorly constrained assumptions (*7*). Inherent uncertainty will always limit informative forecasts of spread velocity for invasive plants with high reproductive rates. Even precise knowledge of parameters that might be estimated, for example, through detailed study of long-distance dispersal, would do little to increase forecast information (*8*).

Large inherent uncertainty does not necessarily neutralize efforts to anticipate change. Forecasting will improve as ecologists identify the "slow" variables that forewarn of consequences years in advance. Whereas deterministic weather forecasts confront an approximate 2-week limit, probabilistic climate prediction makes use of the system memory represented by sea-surface temperatures. The limitations imposed on a deterministic weather forecast by nonlinearities may not defeat efforts to provide informative climate forecasts (*9*). There are many "slow variables" that constrain ecological processes (*10*). For example, successional change in forests is constrained by climate and soils. If these change slowly relative to tree life-spans, succession is predictable using physiology and competitive interactions among trees (*5*, *11*). Land-use change is determined by individual decisions that are influenced by a variety of uncertain needs and goals. Yet decade-scale land-cover change can be predictable based on overriding controls imposed by topography and distance to market centers (*12*).

Agricultural practices result from complex decisions, but slow variables can be the basis for useful projections. Projections of subsidies to global food production (irrigation, fertilizers, and transport and storage of crops) (*13*) can inform forecasts of downstream eutrophication in coastal fisheries and increases in atmospheric greenhouse gases (CH_4, CO_2, and N_2O) (*14*). Ecologists can forecast how environmental change affects carbon storage in agriculture, by production forestry, and in natural ecosystems. Nitrogen deposition leads to predictable changes in plant composition and reduced carbon storage potential in tallgrass prairie soils (*15*). Knowledge of fertilizer and irrigation effects on carbon storage in agroecosystems can be used to forecast how managed ecosystems will contribute to or stem the future rise of CO_2 in Earth's atmosphere (*16*).

Analysis of projections can help anticipate change, even where forecasts are uninformative. Although forecasts of population migration rates will typically have low information content, analysis shows that productive research will focus on factors affecting invasion potential, such as the mechanisms of long-distance dispersal and propagule production, as opposed to precise estimation of long-distance dispersal (*8*). Rates will remain uncertain, but we may improve our ability to predict introduced species that can successfully invade (*17*).

The developing capacity for prediction requires careful model evaluation, which can involve model selection, model averaging, or both. Model selection methods are routinely used in ecological applications. Because the models themselves are often uncertain, ecological forecasting may eventually rely more heavily on model averaging. Techniques for model evaluation developed in econometrics, finance, and meteorology make use of hind casting (*18*), including the ability to identify turning points and events (*12*).

Failing to accommodate the important sources of stochasticity makes for a forecast that contains less information than it purports (confidence intervals are misleadingly narrow). In the case of western North America's Northern Spotted Owl (*Strix occidentalis*), confidence intervals on population growth rates became basis for policy (*19*). Ecological models typically ignore variability among individuals, which is large and has impact on population growth and decline. New computational approaches represented by hierarchical models accommodate multiple stochastic elements (*20*) and can be used to estimate the uncertainty in growth of populations having variability among individuals (*21*). New applications of these recent techniques are used in weather and climate models (*22*), but they are not exploited by ecologists. Inevitable failures that result from forecast uncertainties that are unrealistic would eventually erode confidence (*9*).

Data from Experiments and Monitoring

Technical construction of forecasts requires initiatives to develop new or augment existing data networks and to support experimental research. Experimental and observational data that extend to landscapes or regions are a foundation for forecasting capability. Large experiments are critical, because landscape processes are often unpredictable from fine-grained studies (*23*, *24*). The feedbacks from vegetation to climate become important only when the spatial extent of a study exceeds a critical threshold. Factorial, whole-ecosystem experiments with CO_2, temperature, moisture, and nutrients may be the only way to determine forest responses to global change (*25*). For example, free-air CO_2 enrichment (FACE) studies show that the water stress expected from studies of individual plants may not be realized in an intact stand (*26*).

Data networks can provide a baseline for forecasting. Missing variables, low resolution, inadequate duration, temporal and spatial gaps, and declining coverage are pervasive limitations. Due to abandonment of precipitation, stream-height, and discharge gauges, the capacity to forecast droughts and floods was greater 30 years ago than it is today. Countries with the poorest hydrological networks (e.g., sub-Saharan Africa, arid regions of the former Soviet Union) have the most pressing water needs (*27*). The problem is not restricted to developing and transitional economies. There is an average density of one stream gauge per 1024 km^2 in the lower 48 states of the United States (*28*). Since 1971 there has been a 22% decline in gauging stations that record flow on small U.S. rivers. Sustained monitoring is needed that can dovetail with forecasts in an adaptive feedback design.

The ability to anticipate exotic invasions would benefit from historic records of species introductions and their vectors (e.g., ship traffic). Where eventual colonization seems inevitable, forecasts may guide mitigative actions. Disease forecasting can also require extensive spatial and temporal data, such as those used to inform intervention for foot-and-mouth disease (*29*). Prediction of childhood epidemics depends on long records of births and vaccinations (*30*). Cholera and malaria predictions require climate data, which determine growth and/or spread of pathogens and vectors (*31*).

Developing technologies do not fully compensate for sparse data, but they promise to facilitate forecasting. Hydrologic forecasting and remote sensing, together with geophysical tomography, can provide high-resolution coverage of precipitation and the effects of dams and irrigation (*32*). Biogeochemical cycles, hydrology, and biodiversity forecasts require land inventory and census data (*33*) in combination with satellite-based data (*34*). Satellites could be used to monitor habitat loss, a predictor of extinction risk.

Satellite data could be used to develop global scenarios for disease spread in response to environmental degradation and climate change (*35*). Prevalence of hantavirus pulmonary syndrome (HPS), a viral disease characterized by acute respiratory distress that has a high death rate, depends on the infection rates of its host, the common deer mouse (*Peromyscus maniculatus*) (*36*). The 1993 HPS outbreak in the Southwest United States was attributed to unusual weather of 1991–1992 that was quantified from Landsat Thematic Mapper satellite imagery. A model developed for the 1993 outbreak, which followed an El Niño year, provided accurate predictions for the 1995 non–El Niño year. Likewise, surveillance networks could improve understanding of climate constraints on malaria and its vectors (*37*, *38*) and of climate events that forewarn of cholera risk (*31*).

Forecasts in Decision-Making

A 1981 report (*39*) predicting that the Eurasian zebra mussel (*Dreissena polymorpha*) would become established in North America gained the attention of neither policy-makers nor the general public. Zebra mussels were discovered 5 years later and soon spread throughout the upper Midwest. In the Great Lakes alone, annual mitigation costs to industry of $20 to $100 million (*38*) will continue into the foreseeable future. Unquantified, noncommercial costs include losses of biodiversity, such as the extirpation of native clams (*40*), and shifts in ecosystem energy flows and productivity (*41*). No regulatory actions can be traced to the 1981 prediction. The invasion itself prompted a flurry of reactive legislation, culminating in the Nonindigenous Aquatic Nuisance Prevention and Control Act of 1990.

The zebra mussel experience highlights issues concerning the state of environmental science and its place in planning for global change. A developing capacity for prediction has not yet been integrated as part of a comprehensive prediction process (*9*, *42*). Missed opportunities to engage ecological understanding have become a source for growing concern. The zebra mussel experience illustrates that the $138 billion spent annually on control of nonindigenous species (NIS) (*43*) can be blamed, in part, on failure to communicate. Forecasts based solely on scientific objectives have little impact on policy (*44*) because there is no stakeholder (*9*). Climate change forecasts developed under the Intergovernmental Panel on Climate Change have been influential, in part, because they respond to a request from governments. Priorities for ecological forecasting must come from dialogue that ensures active participation by policy-makers, managers, and the general public.

Some experience suggests that a proactive approach holds promise. Chlorofluorocarbon use has declined, in part, due to the Montreal Protocol, which was drafted in response to scenarios for ozone-depleting chemicals in the atmosphere. Scenarios helped propel the ban of DDT and the Kyoto discussions on greenhouse gasses. Policy-makers can respond to research that is motivated by management or conservation interests. For example, population studies, together with 30-year discharge records, were used by the Puerto Rican Aqueduct and Sewage Authority to develop a system for water withdrawal from streams to meet human demands while minimizing the loss of migrating freshwater shrimp (*45*).

Ecologists should increasingly consider their own role in the decision-making process. "Bet-hedging" uncertainty may involve choosing policies that are relatively insensitive to uncertainty, that increase the ability of ecosystems to provide services even if a surprise occurs, or both. Ecologists can help develop options. For example, maintaining local species diversity and heterogeneity of land cover may stabilize regional primary production despite uncertain changes in climate. Limnologists have shown that optimal nutrient loadings to lakes decrease if the information content of ecological forecasts is taken into account (*46*). Ecologists have found correctives for eutrophication that offer managers a number of options.

In situations where uncertainties are large and impossible to quantify, information content is necessarily low and decisions can be complex. Rarely can policies direct an outcome. Instead, they are often designed to affect outcomes by influencing choices made by vast numbers of people. The effects can extend beyond their intended targets and even have countervailing impacts. For example, restrictions on tree harvest in one region can lead to intensified harvesting elsewhere, as trade offsets local scarcity. Thus, environmental restrictions can lead to export of environmental hazard from one jurisdiction to another.

When reaction to anticipated change is possible, it is appropriate to explore scenarios that are as consistent as possible with current scientific understanding but are not predictions (*47*, *48*). Scenarios can embrace ambiguous and uncontrollable drivers, such as climate or globalization of markets, and nonlinear and unpredictable dynamics, such as the reflexive responses of people. Scenarios provide insight into drivers of change, implications of current trajectories, and options for action. Alternative policies can be considered in light of contrasting scenarios and to compare their robustness to possible futures.

Ecologists may provide decision-makers with information as part of an integrated perspective of vulnerability to extreme events and their potential consequences. For example, the tragic human toll of Hurricane Mitch in Central America was exacerbated by degradation due to overexploitation of fuels and construction materials. Ecologists could have foreseen that the floods of Hurricane Floyd would release hog waste into North Carolina rivers and sounds. Ecological forecasting may target the vulnerabilities that decision-makers must consider, if not the events themselves.

Next Steps

Linking science with decision-making will depend on scientific accuracy and effective communication. Sources of uncertainty, their potential impacts on forecast information, and the identification of overriding controls that change slowly must be considered when deciding where efforts can be of most value. Two broad classes of recommendations address these goals. First is a definition of forecasting priorities through dialogue involving scientists, managers, and policy-makers. Priorities are based on potential benefits balanced against costs of business as usual. They should meet user needs and be scientifically feasible.

The second recommendation involves definition of a science agenda that includes (i) identifying data and research needs and (ii) setting priorities for estimation, propagation, and communication of uncertainty. Focus should be on the problems for which forecasts are now possible and those that are not presently forecastable but could become forecastable within a decade.

References and Notes

1. Supplemental text is available at *Science* Online at www.sciencemag.org/cgi/content/full/293/5530/657/DC1.
2. Adapted from the notion of (generalized) Fisher Information (as opposed to the Information Theory definition as the log-likelihood ratio).
3. M. MacCracken, www.esig.ucar.edu/socasp/zine/26/guest.html.
4. R. Lande, *Am. Nat.* **130**, 624 (1997).
5. S. W. Pacala *et al.*, *Ecol. Monogr.* **66**, 1 (1996).
6. B. W. Brook *et al.*, *Nature* **404**, 385 (2000).
7. D. Ludwig, *Ecology* **80**, 298 (1999).
8. J. S. Clark, M. Lewis, L. Horvath, *Am. Nat.* **157**, 537 (2001).
9. National Research Council, *Making Climate Forecasts Matter* (National Academy Press, Washington, DC, 1999).
10. S. R. Carpenter, M. G. Turner, *Ecosystems* **3**, 495 (2000).
11. H. H. Shugart, *A Theory of Forest Dynamics: The Ecological Implications of Forest Succession Models* (Springer-Verlag, New York, 1984).
12. D. N. Wear, P. Bolstad, *Ecosystems* **1**, 575 (1998).
13. D. Tilman *et al.*, *Science* **292**, 281 (2001).
14. G. P. Robertson, E. A. Paul, R. R. Harwood, *Science* **289**, 1922 (2000).
15. D. Wedin, D. Tilman, *Science* **274**, 1720 (1996).
16. W. H. Schlesinger, *Science* **284**, 2095 (1999).
17. C. S. Kolar, D. M. Lodge, *Trends Ecol. Evol.* **16**, 199 (2001).
18. G. G. Judge, W. E. Griffiths, R. C. Hill, W. E. Lutkepolh, T. C. Lee, *The Theory and Practice of Econometrics* (Wiley and Sons, New York, 1982).
19. S. P. Harrison, A. Stahl, D. Doak, *Conserv. Biol.* **7**, 950 (1993).
20. B. P. Carlin, T. A. Louis. *Bayes and Empirical Bayes Methods for Data Analysis* (Chapman & Hall, Boca Raton, FL, 2000).

21. Hierarchical modeling allows for simplification of models that have multiple sources of stochasticity by factoring to produce a set of conditional distributions. For instance, in population dynamics, the *n* members of a population can together define an (intractable) *n* dimensional distribution of demographic rates. A hierarchical structure renders the problem analyzable by factoring it into *n* conditional distributions that submit to Markov Chain Monte Carlo integration (*19*). J. S. Clark, in preparation.
22. Hierarchical models developed to estimate the many parameters needed for climate modeling can be adapted for estimation of invasion speed [C. Wikle, R. F. Milliff, D. Nychka, L. M. Berliner, *J. Am. Stat. Assoc.* **96**, 382 (2001)].
23. S. R. Carpenter, *Ecology* **77**, 677 (1996).
24. J. S. Clark *et al.*, *Am. J. Bot.* **86**, 1 (1999).
25. P. B. Reich *et al.*, *Nature* **410**, 809 (2001).
26. D. S. Ellsworth, *Tree Physiol.* **20**, 435 (2000).
27. E. Stokstad, *Science* **285**, 1199 (1999).
28. T. Brabets, *Evaluation of the Streamflow-Gaging Network of Alaska in Providing Regional Streamflow Information*, U.S. Geological Survey, Water Resources Investigations Report 96-4001 (1996).
29. N. Ferguson, K. Donelly, R. M. Anderson, *Science* **292**, 1155 (2001).
30. J. D. Earn, P. Rohani, B. M. Bolker, B. T. Grenfell, *Science* **287**, 667 (2000).
31. M. Pascual, X. Rodo, S. P. Ellner, R. Colwell, M. J. Bouma, *Science* **289**, 1766 (2000).
32. *Grand Challenges in Environmental Sciences: Special Report of the National Academy of Sciences* (National Academy of Sciences, Washington, DC, 2000). Available at: www.nap.edu/openbook/0309072549/html.
33. J. F. Richards, in *The Earth as Transformed by Human Action,* B. L. Turner *et al.*, Eds. (Cambridge Univ. Press, New York, 1990), pp. 163–178.
34. N. Ramankutty, J. Foley, *Global Biogeochem. Cycles* **13**, 997 (1999).
35. *Under the Weather: Climate, Ecosystems, and Infectious Disease* (National Academy of Sciences, Washington, DC, 2001).
36. G. E. Glass *et al.*, *Emerging Infect. Dis.* **6**, 238 (2000).
37. C. Dye, P. Reiter, *Science* **289**, 1697 (2000).
38. D. J. Rogers, S. E. Randolph, *Science* **289**, 1763 (2000).
39. Bio-Environmental Services, *The Presence and Implication of Foreign Organisms in Ship Ballast Waters Discharged into the Great Lakes*, vols. 1 and 2, prepared for the Water Pollution Control Directorate, Environmental Protection Service (Environment Canada, Ottawa, Ontario, 1981).
40. D. L. Strayer, *J. North Am. Benthölog. Soc.* **18**, 74 (1999).
41. T. F. Nalepa, G. L. Fahnenstiel, *J. Great Lakes Res.* **21**, 411 (1995).
42. D. Sarewitz, R. A. Pielke Jr., R. Byerly Jr., *Prediction in Science and Policy* (Island Press, Washington, DC, 2000).
43. D. Pimentel, L. Lach, R. Zuniga, D. Morrison. *BioScience* **50**, 53 (2000).
44. D. Sarewitz, R. A. Pielke Jr., in (*42*) pp. 11–22.
45. J. P. Benstead, J. G. March, C. M. Pringle, F. N. Scatena, *Ecol. Appl.* **9**, 656 (1999).
46. S. R. Carpenter, D. Ludwig, W. A. Brock, *Ecol. Appl.* **9**, 751 (1999).
47. P. Raskin, G. Gallopin, P. Gutman, A. Hammond, R. Swart, *Bending the Curve: Toward Global Sustainability*, Pole Star Report no. 8 (Stockholm Environment Institute, Stockholm, 2000).
48. N. Nakicenovic, *Emissions Scenarios* (Cambridge Univ. Press, Cambridge, 2000).
49. Supported by the Ecological Society of America, the Aldo Leopold Leadership Program, the National Science Foundation, the National Center for Ecological Analysis and Synthesis, and the Center for Global Change at Duke University.

Mind the gap.

NEW! *Science* Online's Content Alert Service

With *Science*'s Content Alert Service, European subscribers *(and those around the world)* can eliminate the information gap between when *Science* publishes and when it arrives in the post. This free enhancement to your *Science* Online subscription delivers e-mail summaries of the latest news and research articles published each Friday in *Science* – ***instantly***. To sign up for the Content Alert service, go to *Science* Online and eliminate the gap.

Science
www.sciencemag.org

For more information about Content Alerts go to www.sciencemag.org.
Click on the Subscription button, then click on the Content Alert button.