Biotic Multipliers of Climate Change

Phoebe L. Zarnetske *et al.*

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switching speeds of 500 ps were reached for the smallest cells. They used computer simulations to help identify a structural origin to this speed increase, which they believe is induced through thermal prestructuring (see the figure, panel A). As measured during this electronic priming, a resistance dip suggests some permanent preswitching structural modification.

The effects of priming the human brain can be imaged by monitoring the brain's frontal region activity using an electroencephalogram (*5*). In an analogous fashion, Nam *et al*. extend our understanding of the phase-change mechanism by using in situ transmission electron microscopy (TEM) to watch switching directly. By using single-crystal GST nanowires, which provide an open geometry, they viewed the material during the actual switching process (see the figure, panel B). Their direct observation of amorphization in a crystalline phase-change material revealed astonishing insight into the phase-change mechanism. When a voltage was applied across the nanowire, the TEM imaging showed visible contrast changes associated with the now characteristic resistance dip. With a continuously increasing current, defects became mobile and began to propagate along the direction of hole-carrier motion.

At the point of lowest resistance, the movement jammed and a tangled region of highly accumulated dislocations formed, which was followed by switching into an amorphous state. This glassy state appeared as a clear bright line and was confirmed as amorphous by electron diffraction measurements. Nam *et al*. make the analogy of traffic on a highway, in which a simple analytical model predicts a sharp catastrophic jamming transition when the vehicle density exceeds a certain fraction of the maximum packing density (*6*). In an inspired next step, they created a notch in their nanowire, akin to closing a lane on a busy highway. Defects piled up and an amorphous band appeared at the restriction (see the figure, panel C).

Recently, it has been argued that PCM materials do not change from glass to crystal by melting to a liquid and resolidifying, but rather transform via an all solid-state process. Nam *et al*. may have provided visual evidence of this hypothesis. As Kolobov *et al*. (*7*) explained, "distortions in the crystalline phase may trigger a collapse of long-range order, generating the amorphous phase without going through the liquid state, upsetting yet another commonly held belief that attributes the change in properties to the loss of long-range order."

Unlike human brains, today's computers deal with processing and memory separately. Data are constantly moved around, resulting in a speed and power "bottleneck." Kuzum *et al*. (*8*) describe brain-inspired computing and identified phase-change materials as ideal for the implementation of synaptic plasticity. Unlike binary memory applications, they used the continuous transition between resistance levels of phase-change states in an analog manner to emulate biological synapses. Wright *et al*. demonstrated that phase-change materials can both store and process information simultaneously (*9*) and could be used to make artificial neurons and synapses. Another major hurdle is power consumption; supercomputers consume substantially more energy than the human brain while "thinking" (*10*). These studies, along with recent new PCM designs by Xiong *et al*. (*11*), show that there is promise for power reductions through the use of PCM technology.

The studies by Loke *et al*. and Nam *et al*., along with related work in other labs, should not only pave the way for phase-change memories with ultrafast switching speeds, low-energy consumption, and reduced memory cell sizes, but also lead to a better understanding of the mechanisms responsible for the phase-change phenomena that could further improve switching speeds. The potential to emulate the human nervous system is gaining increasing attention, as these combined works provide further evidence that phase-change materials could be used to make artificial neurons and synapses.

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ECOLOGY

Biotic Multipliers of Climate Change

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A focus on species interactions may improve predictions of the effects of climate change on ecosystems.

Many species face uncertain fates under climate change. Some will persist by shifting their range or adapting to local conditions, whereas others will be lost to extinction. Efforts to lessen the impacts of climate change on biodiversity depend on accurate forecasts. Most studies aiming to identify likely winners and losers consider species one at a time with a "climate envelope" approach that correlates species' occurrences with climatic and environmental variables. Using this method, researchers have predicted that by 2050, 15 to 37% of species will be faced with extinction (*1*). But which species are most likely to be under threat? And how will their loss affect the broader ecological community?

The climate envelope approach ignores a core truth of ecology: Species interact with each other in ways that deeply affect their viability. Certain species impart particularly strong effects on others. Consequently, climate change impacts on these species could initiate cascading effects on other species. In effect, these species act as biotic multipliers of climate change. The inherent complexity of species interaction networks has discouraged their consideration in predictions. Emerging research illustrates that trophic interactors are especially strong candidates for biotic multipliers of climatic change. Focusing on these species and their interactions is one path through the complexity.

Recent findings highlight the importance of undisturbed vertical interactions involv-

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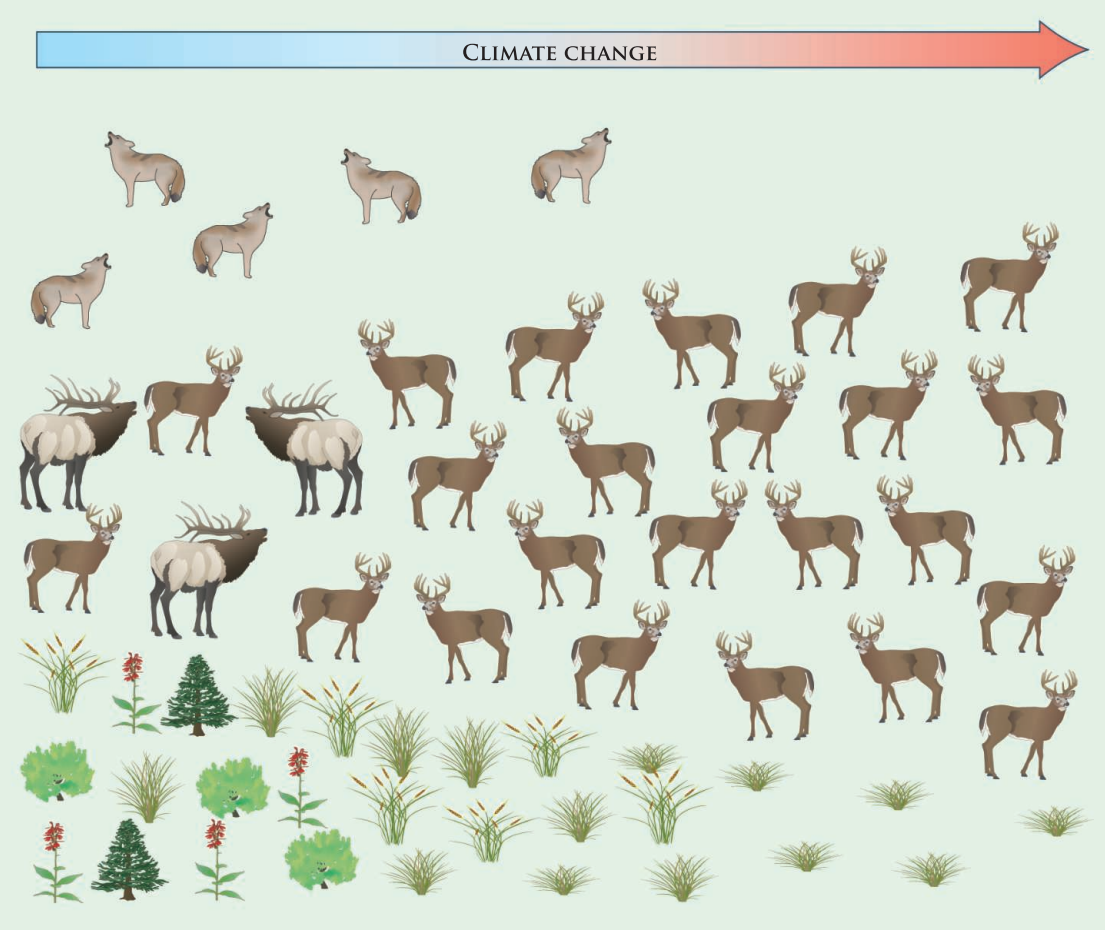

Climate change and species interactions. Recent findings suggest that climate change should affect top consumers more strongly, disrupting vertical interactions and thereby affecting many species across trophic levels. In this general example, climate change reduces top predators, leading to an increase in herbivores, and a decrease in plants. As a result, the community experiences an overall decrease in both species diversity and stability.

ing top consumers as climate changes (*2*). Vertical interactions include those between consumers and their resources (e.g., predator-prey), as opposed to lateral interactions between species in the same trophic level (i.e., interspecific competition).

Why top consumers? Adding or removing top consumers leads to disproportionate changes in community composition across trophic levels (*3*, *4*). Moreover, species in higher trophic positions are more sensitive to changing temperatures (*5*). Therefore, climate change may have especially strong effects on top-consumer extinctions and range shifts. In turn, these effects can ripple through an entire food web, multiplying extinction risks along the way.

These ideas are supported by insights from recent artificial warming and top herbivore exclusion experiments in Arctic Greenland. The coincident warming of tundra vegetation and removal of caribou and muskoxen herbivores decreased plant species diversity and lowered community stability (*2*). In contrast, undisturbed vertical interactions between herbivores and plants promoted community stability by mediating the outcomes of lateral competitive interactions among tundra plants (*2*). A similar outcome occurred in the paleontological record, where extinctions of large herbivores altered vegetation communities and fire regimes (*6*).

These destabilizing outcomes are also seen in studies of top predators. On Isle Royale (an island in Lake Superior, USA), rising winter temperatures combined with canine parvovirus produced a trophic cascade: Declining wolf populations caused moose populations to surge and balsam fir to decline (*7*). In the rocky intertidal of the North American Pacific Coast, higher temperatures led to range contractions in mussel species, exacerbating keystone predation by seastars, which resulted in the decline and local extinction of certain mussel species (*8*).

These findings contribute to an emerging idea that when climate change disrupts vertical interactions through an increase or decrease in top consumers, we can expect to see a multiplier effect on many species across trophic levels (see the figure). In the examples cataloged thus far, communities generally become less stable and less diverse. In addition, climate change is expected to compound the risk for top consumers that are already threatened by additional anthropogenic stressors (*9*).

Although the importance of vertical interactions is well-founded, much remains to be learned. Climate can affect interaction strength and direction in multiple ways (*10*, *11*), including strengthening competitive effects (*12*) that influence multiple species (*13*). However, climatic disruption of lateral interactions could affect fewer species than the disruption of vertical interactions because of functional redundancies within trophic levels. Variation in climate might also ameliorate effects by superior competitors and thus promote stability of the overall community (*2*).

Though recent models emphasize the need to consider multiple interacting species (*14*), models should also assess under which conditions vertical versus lateral interactions are important and which local interactions are most likely to scale up to alter regional and global species distribution patterns. Frameworks exist to accommodate different types of species interactions and varying sensitivities to environmental change in a local food web (*15*). One approach is to vary the relative climatic sensitivity of vertical versus lateral interactions in food web models and examine the consequences for extinctions within local communities. Across broader spatial scales, species interactions can be incorporated into multispecies distribution models via interaction matrices (*16*), and the biotic multiplier effect can be tracked by following how changes in the abundances of target species (such as top consumers) alter community composition in space and time.

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Above all, identifying biotic multipliers will depend on high-resolution biodiversity data to parameterize models and test predictions. With rare exceptions, such community-level data do not currently exist at the temporal and spatial scales necessary to understand climate change impacts. The investments in collecting this needed information would be substantial, but the benefits include forecasting and thus avoiding major losses of species and the services they provide.

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ATMOSPHERIC SCIENCE

Carbon from Tropical Deforestation

Estimates of carbon emissions from tropical deforestation differ widely.

Daniel J. Zarin

How much carbon is emitted from tropical deforestation? Attempts to answer this question have generally relied on data from national inventories. More recently, sufficient satellite data have become available to provide independent estimates. On page 1573 of this issue, Harris *et al*. (*1*) report a global estimate of tropical deforestation emissions derived entirely from satellite data. For the period from 2000 to 2005, those emissions are much lower than previously reported.

In 2007, the Intergovernmental Panel on Climate Change (IPCC) concluded that the "best estimate" of net carbon emissions from tropical land use change in the 1990s was 1.6 ± 0.6 petagrams of carbon per year (Pg C year^{-1}), equivalent to ~20% of greenhouse gas emissions from human activities during that decade (*2*). That and most other estimates have relied to varying degrees on national self-reporting to the Global Forest Resources Assessment of the United Nations Food and Agricultural Organization (FAO) (*3*). However, the quality of those data are uneven (*4*), the reported extent of forest cover and deforestation differs from that found in satellite surveys (*5*), and the forest carbon estimates are based on a broad set of assumptions (*3*). Satellite-based analyses of forest cover have since improved estimates of the extent of deforestation across the tropics (*6*, *7*), but satellite data that are sufficient for the task of estimating forest biomass, and hence carbon stock (~50% of biomass), have only recently become available.

Gross deforestation emissions. Harris *et al*. provide an independent benchmark for national gross deforestation emissions for 2000 to 2005 [see table S2 in (*1*)], shown here for the top five emitting countries (peat emissions not included). The 90% prediction interval around those emission estimates is substantial. To reduce that uncertainty, the authors suggest using higher-resolution satellite data to estimate forest cover loss at the country level. DRC, Democratic Republic of Congo.

In the past year, two groups have independently published maps of tropical forest carbon stocks based on multisensor satellite data calibrated with ground measurements. Saatchi *et al*. (*8*) estimated those stocks at 247 Pg C. Using a different methodology, Baccini *et al*. reported a remarkably similar estimate of 228.7 Pg C (*9*). They also used their map, spatial information on the location of deforestation (*6*), and the FAO data (*2*) to generate an estimate of net carbon emissions from tropical deforestation of 1.0 Pg C year^{-1} for the period from 2000 to 2010.

Harris *et al*. now assess gross carbon emissions from tropical deforestation—as opposed to net emissions, which include forest regrowth—without resorting to the FAO data. (Gross carbon emissions from deforestation are defined as the area of gross forest loss multiplied by the carbon stock of the forest before clearing.) The authors use satellite-based analyses of the geographic distribution of tropical forest carbon stocks (*8*) and of both the location and quantity of tropical deforestation (*6*, *7*). The study overcomes a mismatch in the spatial scales of the carbon stock and deforestation maps through a repeated, randomized statistical sampling

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