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Key Points:

- Smoke from future wildfires will be an increasing hazard and feedback to climate
- Integrated models are needed to predict future smoke
- Models must incorporate complex feedbacks across scales while being tractable

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Smoke consequences of new wildfire regimes driven by climate change

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Abstract Smoke from wildfires has adverse biological and social consequences, and various lines of evidence suggest that smoke from wildfires in the future may be more intense and widespread, demanding that methods be developed to address its effects on people, ecosystems, and the atmosphere. In this paper, we present the essential ingredients of a modeling system for projecting smoke consequences in a rapidly warming climate that is expected to change wildfire regimes significantly. We describe each component of the system, offer suggestions for the elements of a modeling agenda, and provide some general guidelines for making choices among potential components. We address a prospective audience of researchers whom we expect to be fluent already in building some or many of these components, so we neither prescribe nor advocate particular models or software. Instead, our intent is to highlight fruitful ways of thinking about the task as a whole and its components, while providing substantial, if not exhaustive, documentation from the primary literature as reference. This paper provides a guide to the complexities of smoke modeling under climate change, and a research agenda for developing a modeling system that is equal to the task while being feasible with current resources.

1. Introduction

Smoke from wildfires has adverse biological and social consequences. Smoke inhalation can be lethal, and sublethal concentrations have adverse effects on both short-term and long-term human health, particularly in sensitive populations, or the occupationally exposed, such as firefighters, who inhale smoke during highly aerobic physical activity. On 14 December 2012, the Environmental Protection Agency (EPA) revised the National Ambient Air Quality Standards (NAAQS) for the annual average concentration of fine particulate matter (PM) from 15 to 12 $\mu g/m^3$, based on a recent integrated science assessment [*U.S. EPA*, 2009] that pointed to the adverse health impacts of particulate black carbon (BC). The chemical speciation of PM emitted by wildfires may be as significant a factor in these health outcomes as its ambient concentrations [*Wegesser et al*., 2009].

Of primary concern for human health are smoke concentrations in local airsheds, but what is effectively local may cover many square kilometers in the case of large fires ("megafires") or clusters of fires fanned by extreme fire weather. Prevailing winds or convective winds generated by fires themselves transport smoke in sufficient concentrations to make it the principal source of air pollution over large areas [*Strada et al*., 2012]. PM under 2.5 μm in aerodynamic diameter ($PM_{2.5}$) is especially toxic because it can penetrate deeply into lung tissue, with lasting effects from a single exposure [*Dockery et al*., 1993; *Pope et al*., 2002]. Smoke may be transported hundreds of kilometers downwind, exacerbating regional haze, especially in national parks and wilderness areas that have been designated federally as "Class I" areas because of their pristine air quality. Across the American West, for example, days with the worst visibility in these protected areas are nearly always associated with wildfires upwind (Figure 1) [*U.S. EPA*, 1999].

Climate change will exacerbate air-quality problems if projections of future fire regimes in a warming world are even reasonably accurate. Historical and contemporary studies of fire climatology suggest that

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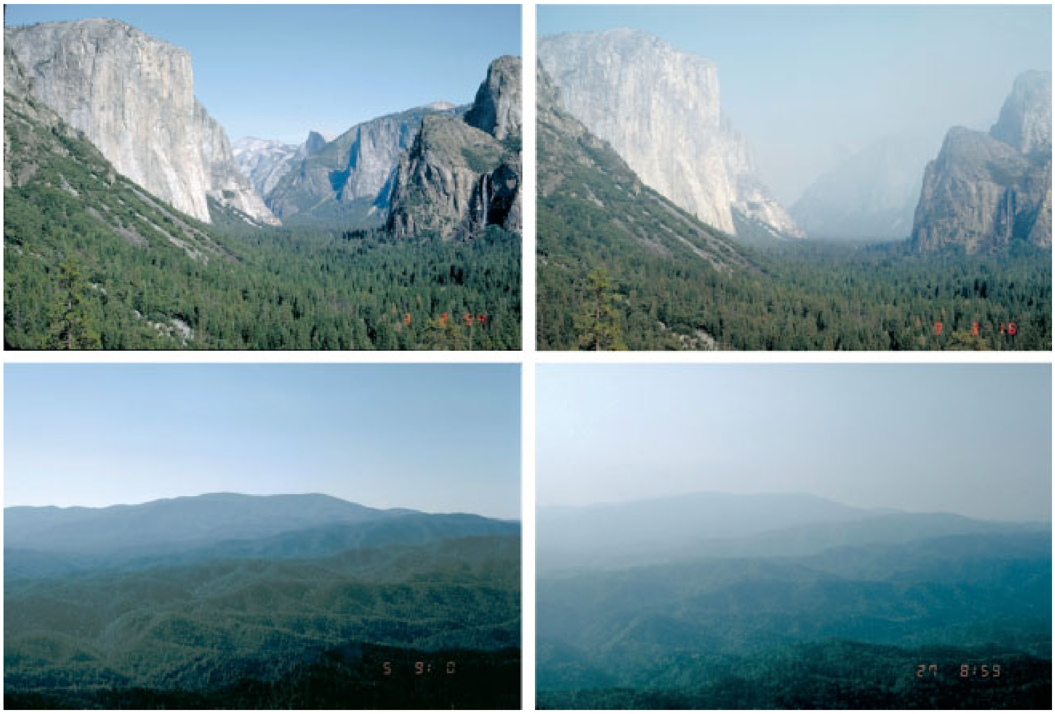

Figure 1. Examples, from IMPROVE (Interagency Monitoring of Protected Visual Environments) website, of pristine (or nearly so) vs. degraded air quality in National Parks, reflecting haze from wildland fire, other pollutants, or both. Upper panels: Yosemite National Park. Lower panels: Great Smoky Mountains National Park. Photos courtesy of IMPROVE (http://vista.cira.colostate.edu/improve/).

annual area burned will increase through the coming decades, dramatically in some regions [*McKenzie et al*., 2004; *Flannigan et al*., 2009; *Littell et al*., 2010; *Liu et al*., 2013]. In some ecosystems, *fire severity*, the aggregate effect of fire on ecosystem structure and function, may also increase, especially in ecosystems with fuel accumulations from fire exclusion. Even if it does not, burned-area increases alone would add to the cumulative effects of smoke from wildfires. More extreme events are also expected [*Diffenbaugh and Ashfaq*, 2010; *Coumou and Rahmstorf*, 2012; *Hansen et al*., 2012; *Reichstein et al*., 2013; *Stavros*, 2013], both directly (e.g., droughts and heat waves) and indirectly (fires) driven by a warming climate.

The straightforward view of warming climate increasing the area burned by fire, which in turn affects air quality, is compelling and is supported by both empirical evidence and process-based models. *Flannigan et al*. [2009] reviewed the climate-fire literature and found wide agreement on increased area burned in a warmer climate, but there are two reasons why increases cannot continue indefinitely. First, simply, fires will eventually run out of real estate. Second, even when statistics are robust or process-based algorithms are fully "mechanistic," most projections assume stationarity of fire-climate dynamics. This stationarity ignores negative feedbacks from changes in vegetation and changing lag effects of previous years' climate. For example, *Littell et al*. [2009] found that the simple paradigm "hotter and drier = more fire" was appropriate for most of the northwestern USA, where fuels are always present and fuel moisture is the principal limiting factor. In contrast, fuel availability is often limiting in the arid Southwest and much of the Great Basin, so that abundant precipitation in the previous year "sets up" current-year fire seasons. *Holz et al*. [2012] found similar contrasts, forced by oceanic teleconnections, along a latitudinal gradient in Chile, as did *Pausas and Paula* [2012], at finer scales, in Mediterranean ecosystems of the Iberian Peninsula. In an overview of global fire regimes, *Krawchuk and Moritz* [2011] theorized that the fire-climate coupling shows a unimodal response along a wet-dry gradient of fire-season weather, such that a warming climate will produce both positive and negative feedbacks in fire climatology. This nonlinear response reflects the significant interactions of both climate and fire with vegetation, which can be as strong a driver of fire regimes as the climate itself [*Higuera et al*., 2009].

Fire feedbacks to climate include (1) the direct effects of biomass burning on radiation budgets [*Randerson et al*., 2006; *Balshi et al*., 2009; *Amiro et al*., 2010], (2) albedo changes associated with disturbances and other vegetation dynamics [*Randerson et al*., 2006; *Lee et al*., 2011; *O'Halloran et al*., 2012; *Anderegg et al*., 2013], and (3) more subtle feedbacks of air-chemistry changes to atmospheric boundary-layer dynamics [*Bollasina et al*., 2011; *Jiang et al*., 2012]. The best understood feedback is emission of greenhouse gases (GHGs), principally CO_2, which exerts a positive radiative forcing [*Simmonds et al*., 2005; *Langmann et al*., 2009]. The effect of aerosols on the global radiation budget is less well understood and could be positive or negative depending on aerosol chemical composition and thus their optical properties (i.e., absorbing vs. scattering aerosol content) and the presence of clouds, so the sign of the feedback from this component of fire emissions is unclear. Uncertainties about the carbon cycle are also significant [*Bodman et al*., 2013]. For example, what is the potential for burned areas, particularly forests, to regenerate fast enough to continue to be a carbon sink [*Liu et al*., 2011; *Ghimire et al*., 2012; *King et al*., 2012; *Raymond and McKenzie*, 2012].

A systems approach, drawing on research at widely different spatial and temporal scales, is needed to evaluate the relative importance of forcings, interactions, and feedbacks among climate, wildfire, vegetation (fuels), and pollutants emitted in smoke plumes. Regional-scale climatology and synoptic and mesoscale weather are important for understanding fire-atmosphere interactions, but equally important are fine-scale couplings that determine fire intensity and plume dynamics [*Heilman and Bian*, 2010; *Potter*, 2012]. Similarly, fire-vegetation interactions can be modeled at regional scales, giving comprehensive spatial coverage [*Quillet et al*., 2010], but key landscape processes that influence the fuel dynamics that determine fire spread, and therefore fire sizes, can be captured only over smaller domains [*Keane et al*., 2004].

Fire managers will be faced with a changing climate and choices about balancing prescribed burning, mechanical fuel treatments, and controlled and uncontrolled wildfires to create more resilient landscapes in the future [*Millar et al*., 2007; *Peterson et al*., 2011; *Sommers et al*., 2011]. Of particular concern, if wildfires increase in size and frequency, are the ecological and economic trade-offs between wildfire suppression and fuel treatments to reduce potential wildfire intensity and severity [*Galik and Jackson*, 2009; *Hurteau et al*., 2011]. Many fire-regime characteristics, such as fire intensity, severity, and size, are used to evaluate these trade-offs. Perhaps, the most important to society is how much smoke will be released during a fire [*Bowman and Johnston*, 2005], because of its diverse consequences across multiple scales. For example, public health in local communities is affected by smoke from prescribed and wildland fires, as are regional vistas and global GHG concentrations. Future projections must therefore provide enough detail to be of use to local management of smoke, besides having the scope to inform larger-scale decisions and include global feedbacks to the atmosphere from fires.

Projections are needed to inform the global-change research community, and to support strategic planning for adaptation and mitigation at scales from local to national and tactical and operational decision making to deal with changing fire regimes and their smoke consequences in real time. In this paper, we identify the components of a modeling system to produce such projections, and review research to date on the feasibility of different approaches to developing system components, the global uncertainties associated with each, and the sources of error propagation within components and their linkage. We emphasize the complexities and feedbacks in smoke modeling under a nonstationary climate. We then offer guidelines for constructing and using the elements of a system to maximize both its robustness and its realism in representing physical, chemical, and biological processes and to minimize its potential biases. As with geographic route planning, when navigating a path of even modest complexity, no single set of directions is likely to be optimal for all the important criteria. We offer several perspectives on how to design components, identify weaknesses, and distinguish intrinsic limitations from those that can be overcome. Lastly, we present three major research challenges that we believe are particularly significant for advancing the science of modeling future smoke consequences, realizing that many other research needs associated with the modeling system as a whole, or with parts of it, could be enumerated.

We focus on methods that can be applied over a generally recognized modeling domain, such as the conterminous USA (Figure 2), but that can be generalized to other regions around the world. Within that domain, we consider a range of spatial scales from those associated with landscape fire and succession models [e.g., *Keane et al*., 2004] to those associated with regional climate models (RCMs) and air-quality models.

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2. The Modeling System

Figure 3 shows the essential elements of the modeling system we are proposing. Climate, weather, vegetation, fire, and smoke interact with each feeding back to the system at one or more points, such that there are no independent drivers as conceptualized here. In the following sections we outline the tasks that elements of the system should perform, with extensive reference to how these tasks have been addressed in the literature to date. Feedbacks among elements are important, as are scale mismatches and cross-scale interactions; these are addressed explicitly at the end of this section.

2.1. Downscaled Climate and Weather

Climate is, of course, the overarching driver of our system, given projections of continued warming and associated changes in variability and extremes [*Coumou and Rahmstorf*, 2012; *Hansen et al*., 2012]. For future projections, key inputs to global climate models (GCMs) [The abbreviation "GCM" is often seen for both "global climate model" and "general circulation model." We use the more general term "global climate model" throughout, except in tables, where we refer to some form of general circulation model (e.g., coupled atmosphere-ocean GCMs or AOGCMs).] are the components of radiative forcing, the amount by which the Earth's total radiation budget is out of equilibrium [*Hansen et al*., 2011]. The principal forcings are from GHGs, including CO_2, methane (CH_4), and O_3, among others, and aerosols [*Forster et al*., 2007].

Figure 2. The North American modeling domain from *Mearns et al*. [2012], typical of that used in regional climate modeling. The regional climate models in *Mearns et al*. [2012] are dynamically downscaled over this domain from a group of global climate models at ~50 km horizontal grid spacing.

The sign of GHG forcings (positive) is well established, although the variability around mean estimates is still substantial. For example, climate sensitivity, the equilibrium response of Earth's annual temperature to a doubling of atmospheric CO_2, has been the subject of many papers, both theoretical and statistical [*Aldrin et al*., 2012], using paleoclimatic reconstructions [*Hansen and Sato*, 2012] or output from GCMs [*Forest et al*., 2006].

The sign of aerosol forcings is generally assumed to be negative [*Forster et al*., 2007], i.e., cooling the Earth, although the numbers are less well constrained than those for GHGs, and are different for different aerosol species. Figure 4 shows the relative contributions to the global forcing estimates from the major anthropogenic atmospheric constituents, along with the uncertainty in each. A key part of near-future research will be to estimate the aerosol forcing better, because it contributes to Earth's energy balance significantly, and may also confound estimates of climate sensitivity [*Hansen et al*., 2011].

Recognizing the importance of this variability in radiative forcing, the Intergovernmental Panel on Climate Change (IPCC) has, over the years, built and refined socioeconomic emissions scenarios (SRES, Special Report on Emissions Scenarios) [*Nakicénović and Swart*, 2000] to supply bottom-up estimates of radiative forcing to GCMs. The names of commonly used scenarios, such as A1, A1B, A2, B1, and F1, are familiar not only to climate scientists but also to other modelers who project the effects of climate change on ecosystems into the future. In its Fifth Assessment Report (AR5), however, whose working-group reports are expected between September 2013 and October 2014, the IPCC has replaced the SRES approach with a top-down approach that specifies a set of radiative-forcing outcomes. These representative

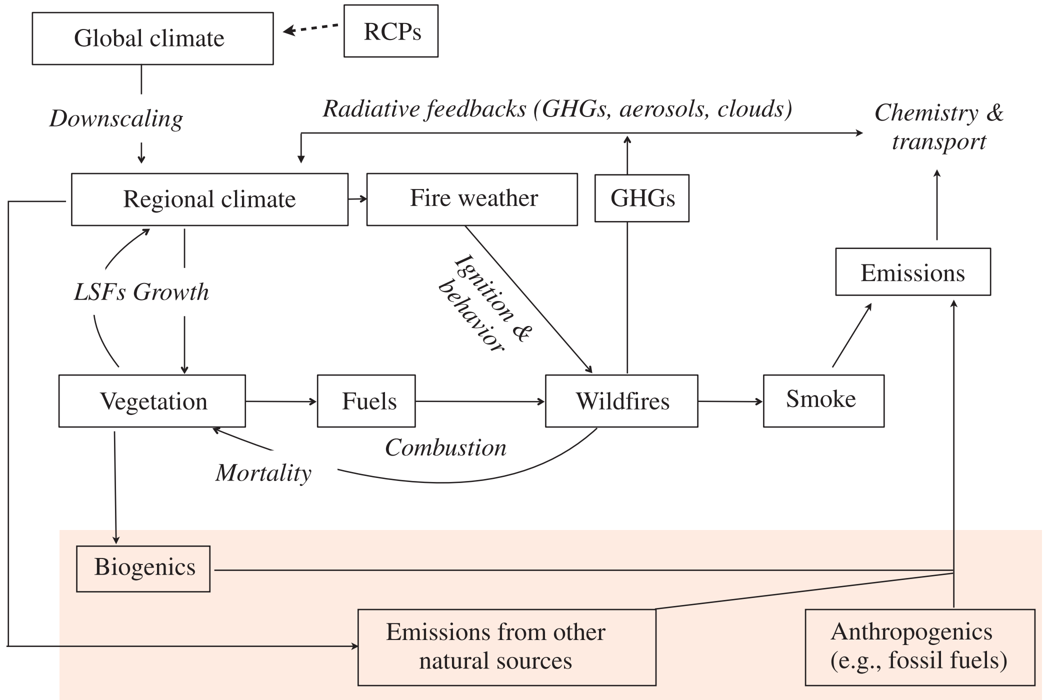

Figure 3. Master flowchart for a modeling system to predict smoke consequences of changing fire regimes in a warming climate. Items in boxes are the elements of the modeling system. Italicized terms are processes that should be represented explicitly by model(s). LSFs, land-surface feedbacks; GHGs, greenhouse gases; RCPs, representative concentration pathways. Note that explicit methodology for representing elements and processes is not specified. Some feedbacks associated with coupled modeling are not included (see text). Components inside the highlighted area need to be accounted for but are not modeled explicitly within the system. For our purposes, radiative forcing at the global scale is fixed, without modeling feedbacks to global climate, but radiative feedback from aerosols, clouds, and GHGs is dynamic at the scale of regional climate.

concentration pathways (RCPs) essentially retrofit socioeconomic patterns over time such as to specify four levels of net positive radiative forcing (2.6, 4.5, 6.0, and 8.5 W m^{-2}) in 2100 [*Moss et al*., 2010; *van Vuuren et al*., 2011]. Climate simulation experiments associated with the AR5, such as the Fifth Climate Model Intercomparison Project (CMIP5) [*Taylor et al*., 2012], will use ensembles of GCMs and RCPs. Given this new currency for future projections, those who use the output of GCMs will need to consider trade-offs between the applicability of the new (RCP) vs. the old (SRES) scenarios and the availability of data streams from the AR5 vs. those from previous assessments. An uncertainty of the RCPs for our purposes is that some elements of radiative forcing associated with smoke emissions are poorly constrained (see section 2.5), as are other forcings and feedbacks not associated with fire [*van Vuuren et al*., 2011].

To project smoke consequences of climate change at regional scales, we require climate inputs at resolutions fine enough to capture, at least crudely, the spatial variability of both climate and landforms. GCMs typically run at horizontal grid spacing of 100–300 km, with many being much coarser than that, although modeled spatial resolution has increased steadily since the first IPCC reports in the 1990s. Grid spacings of 4–36 km provide order-of-magnitude gains in capturing spatial variability, although local phenomena important for fire are not resolved even at these scales. RCMs, of which there are many, provide this increased horizontal resolution, though at computational costs significant enough to limit their domain size. RCMs provide blanket coverage of subcontinental domains (e.g., Figure 2) when run at 36 km, and detailed regional modeling when run at grid spacings down to 4 km [*Salathé et al*., 2008].

RCMs do not model closed systems (with respect to atmospheric, oceanic, and land-surface processes and interactions), in contrast to GCMs. They must therefore be "forced" at the boundaries of their domains by output from a GCM. These boundary conditions feed RCM simulations continuously such that ideally, RCM output downscales global climate without introducing biases (i.e., departures from global-model averages) within the regional domain. The effects of boundary conditions may be extended explicitly into the regional domain to limit such departures [*Rockel et al*., 2008]. Spectral nudging [*von Storch et al*., 2000],

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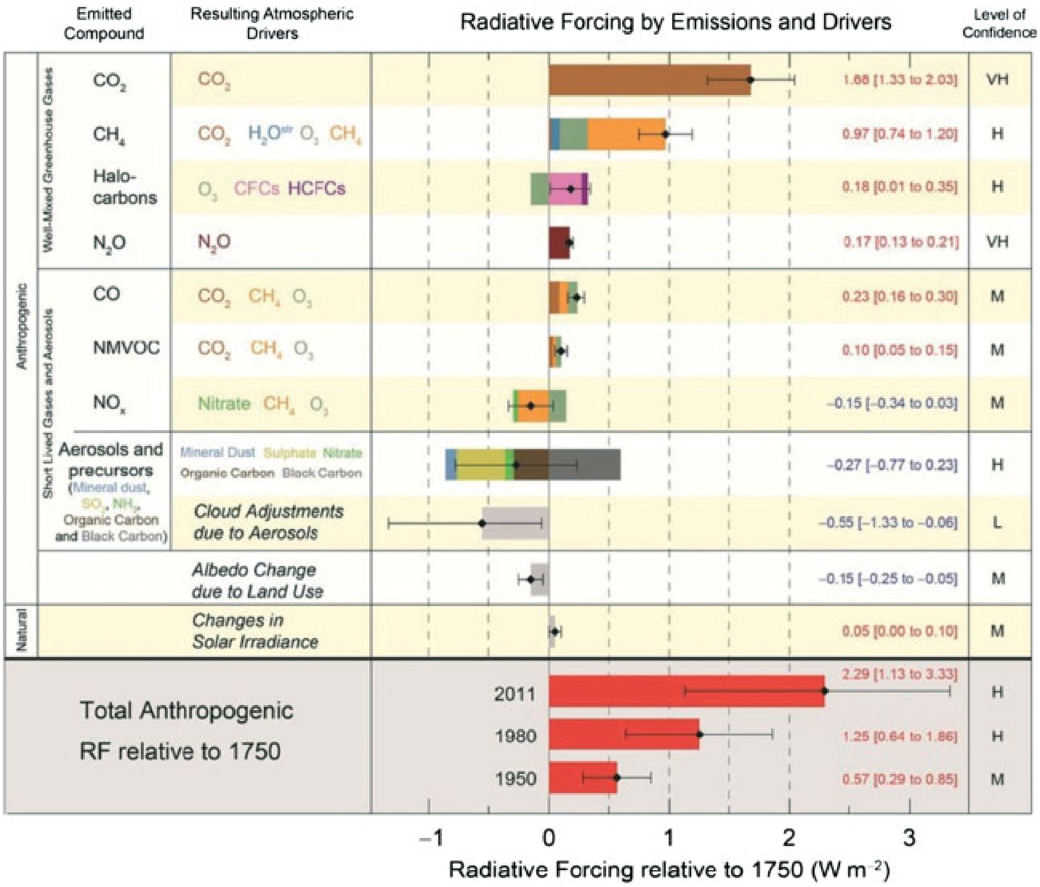

Figure 4. Radiative forcing of the Earth's climate, from the IPCC Fifth Assessment Report (AR5) [*Intergovernmental Panel on Climate Change (IPCC)*, 2013]. Error bars represent 90% confidence intervals. See *Bond et al*. [2013], however, for possible modification to the aerosol component.

which adjusts simulation trajectories some distance into the regional domain using high-frequency components of the global-model signal, has been shown to be an effective way to constrain the large-scale circulation to the driving global fields without limiting the development of the mesoscale atmospheric circulations predicted by the RCM. It also improves the mean and extreme statistics of near-surface meteorological fields, which drive air quality predictions [*Bowden et al*., 2013, 2012; *Otte et al*., 2012]. Even with such adjustments, however, RCMs can still propagate biases from global model outputs [*Plummer et al*., 2006; *Abatzoglou and Brown*, 2012].

An alternative to RCM simulations for some meteorological applications is statistical downscaling [*Wilby and Wigley*, 1997; *Salathé*, 2005], in which subregional heterogeneity across the domain (e.g., temperature gradients based on lapse rates or orographic influences on precipitation) is applied to the global-model outputs of interest. Such a procedure can be more time efficient than running an RCM, particularly for calculating variables of interest for fire weather [*Abatzoglou and Brown*, 2012]. For our purposes, however, there are two significant drawbacks: (1) statistically downscaled fields do not capture mesoscale circulations dynamically, and those are critical for modeling smoke transport and its effects on air quality, and (2) statistical downscaling focuses on surface weather, not the three-dimensional (3D) structures needed to model smoke transport. In both global and regional simulations, ensembles are a heuristic way of establishing ranges of variability and distributions of key outputs [*Tebaldi and Knutti*, 2007]. Ensembles can be parallel runs of different models, replicates of the same model (because there are stochastic elements of most models, outputs will vary), or both. They can also use different RCPs [*Taylor et al*., 2012], as they have previously used different SRESs. With the computational burdens of GCMs, combinatorial explosion is a real danger, so bounds must always be set on the number of combinations used. In general, quantitative evaluation of ensemble methods is still at an early stage, with limitations including the use of equal-weighted averages [but see *Mote and Salathé*, 2010], the necessarily small numbers of models used, the absence of extreme behavior emerging from averages, and the lack of agreement on what is a good metric for evaluation [*Knutti et al*., 2010].

2.2. Climate-Vegetation Models

At regional to continental scales, climate is the key driver of spatial patterns in vegetation, but responses may lag in ecosystems with long-lived species, even in a rapidly changing climate, because mature trees are often resilient to modest temperature changes. Severe disturbances change the dynamic, however, by killing mature trees and confronting seedlings, a more vulnerable life stage, with a new climate. Disturbances are therefore perhaps the principal driver of vegetation change, more than the direct effects of climate change, in many temperate and boreal ecosystems [*Littell et al*., 2010; *Barrett et al*., 2011]. Consequently, models that project future vegetation must not only be “climate-smart” and address CO_2 fertilization [*Keenan et al*., 2013] but also incorporate the major disturbances associated with the domain in question. For many ecosystems, this means wildfire.

Climate-smart vegetation models can be divided into two types: empirical models, involving inverse modeling, and process-based simulations, involving forward modeling. The former fit predictor variables (climate) to response (vegetation) via statistical estimation or machine-learning algorithms, whereas the latter simulate carbon dynamics and other element cycles informed by physiological models of photosynthesis, respiration, and decomposition. These two approaches have been compared exhaustively, and the strengths and weaknesses of both are enumerated in many ways [*Cushman et al*., 2007; *Morin and Thuiller*, 2009]. A clear advantage of the process-based approach is that it is dynamic and connects more easily to other dynamic models (e.g., RCMs). Therefore, we focus on process-based models in the following sections, while allowing that empirical models might also be coerced into a dynamic modeling system.

Process-based vegetation models predict plant responses to climate at many spatial scales [*Neilson et al*., 2005], from the individual stand to global (matching that of GCMs). Dynamic global vegetation models (DGVMs) simulate vegetation response to climate, and can be adapted across a continuum of spatial scales more easily than the climate models themselves, which are more constrained to the intrinsic scales of atmospheric processes. Recent DGVMs incorporate land-surface feedbacks to atmospheric processes, modifying, at a minimum, the radiation budgets of RCMs [*Krinner et al*., 2005; *Bonan*, 2008; *Quillet et al*., 2010; *Bonan et al*., 2011; *Li et al*., 2012]. This argues for coupled modeling of climate and vegetation for future projections, with its concomitant increase in complexity, rather than running climate models independently.

A significant challenge in climate-vegetation modeling is rectifying the scales of weather in a changed climate with the scales of vegetation dynamics relevant to smoke production (i.e., fuels). Smaller-scale phenomena associated with the atmospheric boundary layer, such as cold-air ponding, frost pockets, and atmospheric inversions, are important drivers of vegetation and difficult to extract from RCMs. Topography and land-water variations also contribute to small-scale atmospheric boundary-layer processes (e.g., land-sea breezes, drainage flows, and local precipitation) that affect vegetation. Even with the finer grid spacing of RCMs, many of these small-scale atmospheric processes that affect vegetation are not captured. Conversely, it is difficult to scale up the effects of vegetation processes, such as evapotranspiration, radiative shading, and wind modification, cogently to modify radiation budgets for capturing feedbacks to climate dynamics. The significance of these scaling issues for the vegetation dynamics per se has not, to our knowledge, been resolved in the literature.

A disadvantage of DGVMs, as opposed to empirical climate-vegetation models, is that they generally do not distinguish individual plant species, but rather resolve taxonomy only to life forms or plant functional types. Although resolving vegetation to individual species at a global scale is impractical, the growth, succession, and disturbance (fire) ecology of plants differs greatly among species within life forms [*Wright and Bailey*, 1982; *Agee*, 1993; *Bond and van Wilgen*, 1996], and fire-effects models in particular depend on parameters that are specific to plant species. Furthermore, species are the “currency” for many land managers charged with predicting and controlling smoke from wildfires. For all these reasons, crosswalks are needed between the functional types in DGVM output and the species central to fire-effects models.

Further assumptions and uncertainties come with deriving fuel composition and loadings from vegetation. Much of the fuel that contributes to smoke production comes from dead surface fuels, particularly duff and coarse wood, whose consumption mainly occurs in the smoldering phase [*Reinhardt et al*., 1997; *Prichard et al*., 2007]. Typically, loadings of these fuels cannot be inferred from live vegetation [*Keane et al*., 2012a]; attempts to establish predictive relationships have largely failed [*Brown and Bevins*, 1986; *Raymond et al*., 2006; *Keane et al*., 2012a], and this problem is magnified when species are not known, as in DGVMs. Moreover, different classes of dead fuel loadings are rarely correlated because each has unique decomposition and deposition rates, meaning that each class must be modeled, or derived heuristically, independently from the others [*Keane et al*., 2012a]. The compounding of uncertainties in this process further argues for modeling fine-scale interactions between fire and vegetation explicitly (see discussion of landscape fire models below).

2.3. Predicting Fire

Fire climatology and the triggers for individual wildfires are both well understood intuitively. Retrospective analyses of fires rarely miss the necessary and sufficient conditions, and fire seasons, in hindsight, are rarely surprising. Nevertheless, quantitative predictive models for fire are limited by scale mismatches between drivers and responses [*Littell et al*., 2009], and by the stochastic nature of fire, such that models that predict annual or seasonal area burned at fairly broad scales are the most successful [*Flannigan et al*., 2009, and references therein, *Liu et al*., 2013]. In general, estimating aggregate properties of fire regimes, such as annual area burned, is more tractable than predicting the timing, exact locations, or perimeters of individual fires [*Kennedy and McKenzie*, 2010].

A tractable subtask of fire prediction is generating metrics of fire weather. Composite indices can be calculated as deterministic products of the data streams from weather and climate models, and are fundamentally easier to predict confidently than are actual fires [*Flannigan et al*., 2009; *Abatzoglou and Kolden*, 2013]. There is a strong tradition of this in operational fire forecasting [*Lawson and Armitage*, 2008; *National Wildfire Coordinating Group*, 2012; *Liu et al*., 2013], but it is also relevant to predicting responses to climate change. For example, *Chen et al*. [2009] used fire-danger indices to simulate future fires at a daily time step across the continental USA (CONUS). Besides fire-danger indices, there are other fire-weather variables derived from climate models that can be used as indicators of future atmospheric conditions conducive to large or erratic fires; for example, the Haines Index [*Winkler et al*., 2007], or the Haines Index coupled with a measure of turbulent kinetic energy [*Heilman and Bian*, 2010, 2013].

A promising recent trend is the development of fire modules within DGVMs [*Arora and Boer*, 2005; *Lenihan et al*., 2008; *Kloster et al*., 2010; *Thornicke et al*., 2010; *Prentice et al*., 2011; *Li et al*., 2012]. With their relatively coarse time steps and spatial resolution, DGVM-based fire modules are compelled to do enough "averaging" to avoid the pitfalls of trying to pin down a stochastic process too precisely. Fire modules in DGVMs can be quite complex, even to the point of including fire-behavior and fire-spread algorithms, albeit at coarse scales [*Arora and Boer*, 2005; *Lenihan et al*., 2008; *Pfeiffer and Kaplan*, 2012], or constrained to intermediate complexity [*Li et al*., 2012] to facilitate efficiency. They also vary in the degree to which fire-regime properties are emergent [*McKenzie and Kennedy*, 2011], i.e., arising directly from drivers such as climate or fuels simulated within the DGVM, or prescribed, e.g., by specifying fire-return intervals or fire cycles a priori. The latter type draws on historical fire regimes dating back to the middle Holocene, providing an implicit calibration to centuries of fire-climate observations [*Marlon et al*., 2009, 2012; *Hessl*, 2011]. The former type eschews that calibration, thereby avoiding the no analog problem: projected climate, even in the near term (decades), is outside of the Holocene range [*Williams and Jackson*, 2007].

Fire is a contagious spatial process [*Peterson*, 2002; *McKenzie and Kennedy*, 2011] in that ensuing landscape patterns and associated fire effects (e.g., smoke generation and dispersion) are the product of interactions through space of fire-generated energy and flammable fuels. Spatial variability is thus a function of both variable landscape structure and these interactions. Fire-prone landscapes exhibit varying degrees of *landscape memory* [*Peterson*, 2002; *McKenzie et al*., 2011], e.g., the cumulative effects of previous burn boundaries influence future fires. Without an explicit mode of fire spread, these effects are difficult to capture [*Keane and Finney*, 2003].

Estimates of variation in fire severity, in particular, are critical both for quantifying the timing and amount of smoke produced by combustion of both surface and canopy fuels [*Keane et al*., 2012a, 2012b] and for estimating the fire-produced energy that lofts smoke into the atmosphere where it can be transported downwind. In forests in particular, species composition introduces further variability because tree-species' adaptations to fire vary widely [*Agee*, 1993]. Consequently, even though both empirical models and process-based DGVMs are reasonably successful in predicting area burned at broad scales, accounting for within-cell heterogeneity, both taxonomic (functional types to species) and spatial (variability in fuel type and amount), is desirable.

Landscape fire succession models (LFSMs)[*Keane and Finney*, 2003; *Keane et al*., 2004] provide this level of detail, creating complex patterns across the landscape that influence fire spread and smoke dispersion, and dictating trajectories of successional development that will govern future smoke production. The computational cost makes them intractable for regional-scale modeling, however, and even if this limitation were overcome, the cost, in person-hours and dollars, of assembling the required spatially explicit databases to run LFSMs at regional scales will probably always be prohibitive. LFSMs may, however, prove invaluable for identifying the weaknesses in DGVMs associated with their insufficient resolution for landscape processes that are critical for predicting smoke [*Keane et al*., 2011; *McKenzie et al*., 2011]. For example, *Cary et al*. [2006, 2009] and *Keane et al*. [2013a] used LFSMs to evaluate designs of coarse-scale vegetation models and found that it is critical that DGVMs include a simulation of burned area and vegetation development but need not incorporate fine-scale weather or topography interactions explicitly.

Other disturbances interact with each other and with fire to produce novel landscape behavior that influences combustion and smoke dynamics [*Bigler et al*., 2005; *Allen*, 2007]. For example, tree mortality from the mountain pine beetle across much of the northwestern USA is expected to increase with global warming [*Bentz et al*., 2010], and interacts in complex ways with fire [*Hicke et al*., 2012], introducing additional spatial and temporal heterogeneity in fire severity, with implications for smoke production. Grazing, logging, and pathogens also modify surface and canopy fuels. Implicit acknowledgment of these influences is warranted, as they may change unidirectionally or synergistically in a warming climate.

2.4. Predicting Smoke

Fire effects such as smoke production reflect the relative strengths of multiple drivers, interacting at variable scales of space and time [*McKenzie et al*., 2011]. At fine scales (10^{-1} – $10\ m^2$), fire spread and intensity are determined by properties of fuel (mass, availability, spatial arrangement, and moisture), ignition (type, intensity, frequency, and spatial distribution), and weather (air temperature, wind speed, atmospheric turbulence, and humidity) and its interactions with fire plumes. Smoke characteristics therefore depend on both environmental conditions and fuels, which determine total emissions, and the type of combustion (flaming or smoldering), which determines the chemical composition of smoke. Flaming combustion, associated with greater fire intensity, produces proportionally more CO_2 than smoldering, whose output has proportionally more CO and PM.

Smoke emissions from a wildfire depend on area burned, biomass consumed, biomass composition (fuel type and size), and the proportion of emissions in chemical species, typically but not restricted to CO_2, CO, methane (CH_4), volatile organic compounds (VOCs), and PM. Other emitted organic gases transform in the atmosphere to form secondary organic aerosols (SOAs), which increase the atmospheric aerosol loading and the radiative forcing [*Hennigan et al*., 2011; *Bond et al*., 2013]. The emission rate of PM with aerodynamic diameter smaller than 2.5 μm ($PM_{2.5}$) is calculated separately because PM is especially harmful to lung tissue in this size range. All these proportions are codified as emission factors [*Andreae and Merlet*, 2001].

Fuels are spatially heterogeneous at multiple scales; these scales differ among fuel types such as canopy fuels vs. dead wood [*Keane et al*., 2012a, 2012b], but all are much finer than the spatial scales associated with RCMs or with smoke-transport models. Consequently, an aggregated spatial data layer of fuels, 1 km resolution or coarser, is needed. For example, in the CONUS there are three classifications in current use: (1) fuel loading models (FLMs) [*Lutes et al*., 2009], with 27 distinct models, (2) fuel characteristic classification system (FCCS) [*McKenzie et al*., 2007], with 250 fuelbeds mapped across the CONUS and Alaska, and (3) forest type groups (FTGs) [*Ruefenacht et al*., 2008], with 141 initial vegetation types aggregated to 20. Each of these spatial layers has strengths and weaknesses [*Keane et al*., 2013b], but all share an overarching limitation, in that as coarse-scale data layers they cannot replicate fuels exactly for particular points on a landscape, because of the scaling issue noted earlier [*Keane et al*., 2012a, 2012b]. This scale mismatch needs to be acknowledged in future projections of smoke. A further concern for fuels is that there is currently nothing like a dynamic global fuel model. Future fuel loadings for fire modeling need to come from a dynamic crosswalk from vegetation types predicted by DGVMs or their analogues. Such crosswalks are difficult because of the weak empirical relationships between vegetation classes and fuel characteristics [*Shankar*, 2006; *Zhang et al*., 2010; *Keane et al*., 2012a].

First-order fire-effects models estimate consumption and emissions based on fuel loadings, fuel types, and fuel condition (chiefly moisture of live and dead fuels). There are two approaches in common use. Process-based models [e.g., *Albini and Reinhardt*, 1997] use heat-transfer equations to calculate combustion and then apply emission factors to estimate smoke production. Empirical models [e.g., *Prichard et al*., 2007] fit regressions to field-based estimates of consumption and use fitted values from these with the same emissions factors. There is substantial variability among models for different fuel types under different conditions [*French et al*., 2011; *Larkin et al*., 2012], but the overall uncertainty associated with consumption and emissions calculations is less problematic than for fuels per se [*Liu et al*., 2011].

Projections of smoke emissions need to quantify them at their source and track their concentrations and locations over time. Smoke-transport models [*Goodrick et al*., 2013] track gases and particulates, from local to regional and continental scales, carried by modeled meteorology. What follows draws on *Goodrick et al*. [2013], who provide much more detail on the state of the art in smoke-transport modeling.

Eulerian (grid-based) models focus on observing the passage of parcels (whatever is being tracked, e.g., air, trace gases, and PM) past points in a fixed grid representing 3D space (i.e., the atmosphere), whereas Lagrangian models follow the 3D trajectories of individual parcels through space and time. Lagrangian models follow either air parcels (puffs) or particles. The former represent volumes of air that carry a specific amount of some pollutant (e.g., $PM_{2.5}$), whereas the latter represent infinitesimal volumes, requiring more computation because there will be far more particles than puffs within a given volume.

Puff dispersion models (Lagrangian models that follow puffs) are typically not designed to represent atmospheric chemistry, but rather to provide a fast screening tool for air-quality assessments to characterize the transport of plumes and their impacts at receptor locations. Thus, they typically do not simulate cloud dynamics or the atmospheric chemical transformations and interactions of plumes from various emission sources that are needed to estimate atmospheric composition over large regions. Their typical usage is in performing near-source estimates, often using worst-case assumptions on emission rates to assess the incremental impacts of individual sources such as power plants and industrial stacks. For example, CALPUFF [*Scire et al*., 2000] is used in the U.S. EPA's Federal Implementation Plans to assess the visibility benefits of control technologies at U.S. national parks within a 300 km radius of each emission source. Numerous simplifying assumptions are made on atmospheric composition. For example, species such as NH_3 that are not being evaluated specifically may be set to constant background values or to monthly or longer-term averages, under the assumption that changes will not propagate into significant differences in regional haze.

In theory, Lagrangian models are more dynamic than grid-based (Eulerian) models, and hence better able to track individual pollutant species, often $PM_{2.5}$ [*Scire et al*., 2000]. On the other hand, grid-based models simulate actual atmospheric conditions with greater fidelity by invoking submodels of relevant atmospheric chemistry and physics that evolve pollutant-species composition and secondary aerosol formation from multiple emission sources. For example, the Community Multiscale Air Quality (CMAQ, http://www.cmaq-model.org/) model [*Byun and Schere*, 2006] not only tracks the primary emission products from fire, but like other *photochemical models*, it also simulates other significant atmospheric compositional changes from wildfires, such as changes in ozone and secondary PM concentrations [*Chen et al*., 2009]. WRF-Chem (Weather Research and Forecasting (model) with Chemistry) [*Grell et al*., 2011] is another variation on this theme, in that it couples atmospheric chemistry directly with meteorology from a *limited area model* (an RCM explicitly nested within a GCM).

Chemistry-transport models (CTMs) such as CMAQ and the Comprehensive Air Quality Model with Extensions (CAMx) [*Environ International*, 2011, and references therein] represent the spatial heterogeneity and temporal variability of primary and precursor species such as elemental and primary organic carbon, PM,

SO_2, CO, NO_x (oxides of nitrogen), and VOCs. Typically they run at grid spacing of 4–36 km. These models are used with prescribed meteorology to simulate the long-range transport, vertical mixing, entrainment, and chemical processing in clouds; wet and dry removal; and the detailed gas-phase, aqueous, and particulate chemical transformations of pollutants. Process algorithms simulate plume dynamics and chemistry relevant for modeling compositional changes following the onset of a fire event [*Carlton et al*., 2008; *Karamchandani*, 2012]. The meteorological simulation data used to drive these models are typically generated a priori without any coupling to atmospheric chemical processes, and so CTMs do not simulate the effects of aerosol feedbacks on the radiation budget (see section 2.5).

The spatial resolution of smoke-transport models is typically ≥4 km, too coarse to resolve the dynamics of key physical processes involved in smoke transport, especially initially (i.e., plume rise). *Full-physics* models [in the sense of *Goodrick et al*., 2013] invoke computational fluid dynamics (CFD) to model processes involved in plume development explicitly [*Linn et al*., 2002; *Mell et al*., 2007]. CFD-based models are currently impractical for simulations over the regional domains we are considering here, and have yet to incorporate chemistry, but they do show promise for some local applications [*Valente et al*., 2007].

With the multiple components of the proposed modeling system (Figure 3), establishing and maintaining model linkages can be a substantial task. Researchers are building integrated frameworks for smoke modeling and linkage modules that range from automated creation of comma-delimited output files to complex processors that involve both nonlinear computations and rescaling of data [*Larkin et al*., 2009; *McKenzie et al*., 2012].

2.5. Feedbacks

Changes in atmospheric composition and the land surface due to wildfires have feedbacks to the climate, which may exacerbate fire frequency and intensity in the future. Atmospheric compositional changes from wildfire emissions contribute to the positive radiative forcing due to CO_2, water vapor, and BC, whereas organic aerosol emitted from fires exerts a negative forcing. The short-lived forcing effects from BC-rich industrial-era emission sources have been recently estimated to be substantial (up to 75%) compared to the forcing effects of the longer-lived GHGs from the same sources, even when the forcing is integrated over 100 years [*Bond et al*., 2013].

Feedback of aerosols from wildfires contributes to the surface energy budget, with consequences for planetary boundary layer height (PBLH) and reducing photolysis rates for NO_2 by up to 75%, thereby decreasing ozone [*Jiang et al*., 2012]. These and other ozone reductions counteract the increases from two sources: lowering of PBLH from the aerosol direct radiative feedback, and large NO_x and VOC emission fluxes from wildfires. *Jiang et al*. [2012] found that including the direct radiative feedback of fire aerosols in models reduces the overestimation of ozone downwind in the absence of this feedback. The negative forcing from absorption of solar radiation can also influence atmospheric dynamics at fairly broad scales. For example, using a RCM, *Liu* [2005] found that reduced solar radiation weakened the North American trough in midlatitudes, reducing rainfall and acting as a positive feedback from wildfire to drought.

Cloud-aerosol interactions produce significant aerosol radiative feedbacks, which constitute the greatest source of uncertainty in radiative-forcing estimates [*Forster et al*., 2007]. The aerosol (indirect) radiative forcing has at least two forms: (1) enhancement of cloud reflectance (albedo) due to an increase in cloud condensation nuclei (CCN) activating on aerosols, thus reducing the cloud droplet diameter for a given cloud liquid water content [*Twomey*, 1974], and (2) longer cloud lifetime, from suppression of drizzle as a result of the decrease in cloud droplet diameter, and the longer time taken for cloud droplets to form rain drops [*Albrecht*, 1989]. This latter effect also increases cloud thickness [*Pincus and Baker*, 1994]. The increases in cloud albedo and cloud lifetime reduce the surface temperature by intercepting solar radiation, but warm the atmosphere by absorbing upwelling radiation from the surface. The magnitude of the albedo effect is difficult to quantify on the global scale, because cloud albedo varies in response to the highly variable nature of cloud types and liquid water path. The cloud lifetime effect is also difficult to quantify because of the high degree of natural variability in cloud cover and cloud liquid water content, and the uncertainties in measuring the collection efficiency of cloud droplets [*Haywood and Boucher*, 2000]. As a result, the global mean uncertainty in the aerosol indirect forcing may be as large as the radiative forcing from GHGs [*Forster et al*., 2007]. Because smoke from fires enhances the indirect forcing of aerosols through the addition of CCN, the uncertainty in future fire estimates magnifies the overall uncertainty associated with aerosols. The impacts of this interaction on precipitation are highly variable, and depend in part on the aerosol composition and the location of the aerosol layer relative to the cloud [*Rosenfeld et al*., 2008].

Uncertainty in the indirect radiative forcing estimate is further complicated by the weak correlation in models of climate change between the short-term and long-term feedbacks of clouds [*Dessler*, 2010]. As observational studies allow only a short-term evaluation of these models, establishing such a correlation is necessary to be able to extrapolate to the long-term behavior of climate. Seasonal variability in relative humidity may provide an observational constraint on the models [*Fasullo and Trenberth*, 2012], but other factors need to be considered, e.g., feedbacks from high-altitude clouds, snow and ice, and water vapor [*Dessler*, 2010].

Another feedback of significance for wildfire emissions is the semidirect effect of absorbing aerosols on clouds. The signs of the direct and indirect radiative forcing are negative, but the forcing from absorbing aerosols is positive, taking into account only the reduction in cloud cover [*Hansen et al*., 1997; *Ackerman et al*., 2000]. The semidirect effect is also defined differently in different studies, leading some authors [*Penner et al*., 2003] to conclude that biomass combustion aerosol may not produce a climate warming. *Bond et al*. [2013] pointed out, however, that there are uncertainties in estimating the semidirect forcing, including those in the location and extent of the aerosol layer above cloud. They also estimated that the direct radiative forcing from sources of BC to be approximately $+1.1\ \mathrm{W\,m^{-2}}$, and that the semidirect effect of BC has an average range of $-0.1 \pm 0.2\ \mathrm{W\,m^{-2}}$. If the former is correct, this is a huge radiative impact.

Vegetation and the land surface as a whole also produce important feedbacks to climate. Forests in particular affect radiation budgets, the hydrologic cycle, and atmospheric composition, providing negative (in tropical forests), positive (in boreal forests), and uncertain (temperate forests) feedbacks to climate warming [*Bonan*, 2008; *Swann et al*., 2010, 2012]. Vegetation affects the exchange of heat, moisture, momentum, and chemical fluxes between land surface and atmosphere, and is also a natural source of VOCs that are precursor species for ozone and aerosols. Vegetation feedbacks to the atmosphere are therefore a crucial component in modeling meteorology, climate, and smoke chemistry and transport. For example, the Community Land Model Version 4 (CLM4) couples dynamic vegetation with carbon and nitrogen dynamics from a terrestrial biogeochemistry model [*Thornton et al*., 2009; *Bonan et al*., 2011; *Lawrence et al*., 2011]. Land surface models such as included in CLM4 establish boundary conditions (from below) for the atmospheric-physics equations that are solved numerically in RCMs [*Bonan*, 2008], analogously, though at much finer scales, to boundary conditions (at the lateral boundaries and from above) provided by GCMs to RCMs. Because land-surface models are terrestrially rather than atmospherically based, their boundary conditions can be validated realistically with satellite observations [*Lawrence and Chase*, 2007].

Atmospheric and land-surface feedbacks are also important for regulatory concerns. Wildfires increase tropospheric ozone production due to the large amounts of NO_x and VOC emitted by fire plumes [*McKeen et al*., 2002]. Long-range transport of boreal fire plumes in Canada during June 1995 elevated CO levels as far south as 35°N in the eastern and mid-western USA [*Wotawa and Trainer*, 2000]. These increases affect urban ozone mixing ratios, especially in NO_x-limited areas, more than rural areas due to the in situ oxidation of CO transported into the airshed in wildfires by local NO_x emissions [*McKeen et al*., 2002]. Areas marginally in attainment of the NAAQS for 8 h ozone could become noncompliant during fire events.

2.6. Further Scaling Issues

We have alluded earlier to scaling problems associated with vegetation, fuels, and fire, but there are also scale disparities associated with the atmospheric domain. Reliable predictions of meteorological variables are needed not only over time periods and spatial extents large enough to represent changes in synoptic circulations, but also at a sufficiently fine spatial resolution to drive regional or even finer-scale variability in fuel loads and fire weather. As these vary across differing scales in different regions [*Keane et al*., 2012b], region-specific modeling of fuels, fire weather, and atmospheric chemistry and transport is needed to quantify future air-quality responses to wildfires. For example, aerosol composition of plumes is region-specific, as is aerosol aging along plume-transport paths and with different rates of dispersion [*Kreidenweis et al*., 2001].

A cost-effective way to address scale disparities in meteorological fields is through downscaled modeling with RCMs forced by the synoptic circulations from a GCM. Four-dimensional data assimilation [*Stauffer and Seaman*, 1990; *Stauffer et al*., 1991], including analysis grid-point nudging and spectral nudging, ensures consistency in the large-scale circulation between the input data and the RCM [*Bowden et al*., 2013, 2012] and avoids the damping of extreme values [*Otte et al*., 2012].

Downscaled modeling combines explicit models for some of the fine-scale processes, such as aerosol-cloud interactions, that typically occur at 1–10 km spatial extent, and the parameterized (implicit) treatment of these processes at the subgrid scale when the model grid spacing is coarse, e.g., ∼36 km in the case of RCMs. Provision must be made in multiscale studies to include the effects of subgrid processes such as cloud transport and chemistry, and precipitation, and switch from implicit to explicit representations when the grid resolution is refined. *Alapaty et al*. [2012] showed that convective parameterizations, often not included in climate modeling, have a significant impact on regional estimates of deep convection and precipitation and the indirect radiative forcing of aerosols. Similar considerations apply to reactive plume models that simulate fire-plume dynamics and dispersion of pollutants. Most importantly from a climate perspective, although subgrid convective cloud parameterizations are available in current RCMs, their radiative impacts are not included in most. *Alapaty et al*. [2012] showed the importance of including the radiative feedback of deep convective clouds for correcting the overprediction of precipitation in the Southeastern USA, and for improved prediction of radiative fluxes used in biogenic emissions estimates; this would also have implications for dynamic vegetation models.

Scale disparities can be starkly evident in coupled modeling, because cross-scale translations are needed that are both robust and efficient. One example is the treatment of the meteorological fields when using RCMs coupled to an atmospheric chemistry and transport model. Data assimilation is needed in the RCMs to ensure that the finer-scale feedback of atmospheric trace constituents to the meteorology is not suppressed while capturing the effects of the large-scale circulation.

3. Building Models

We are proposing a modeling system whose conception, construction, and use require expertise in multiple disciplines and diverse technical skills. Consequently, we expect that collaborative efforts will be the norm, with each individual participant or group bringing a set of tools to the effort. Logistical constraints will operate, in that not all combinations of system components will be possible for a particular collaborative effort. Nevertheless, we focus here on identifying the optimal combinations of model components, to maintain the most general perspective, and eschew consideration of the feasibility of specific combinations, which is the task of particular collaborations. We provide a modeling agenda advocating the most detailed representations of all processes (Table 1), a set of general criteria for evaluating modeling systems, and four example modeling pathways (Figure 5) that exemplify the variety of plausible choices one might make for specific applications. These pathways present variations on a theme for meeting the following four criteria that we believe are essential for projecting future smoke consequences of changing fire regimes.

1. *Minimizing cumulative effects of errors, uncertainties, and biases*: These all accumulate in translation across scales and across disciplines. For example, fire algorithms originally developed at fine spatial scales are applied at regional scales in DGVMs [*Arora and Boer*, 2005; *Lenihan et al*., 2008], and error propagation can be complex and nonlinear [*Rastetter et al*., 1992; *McKenzie et al*., 1996]. Alternatively, coupling models at the same scale but from different disciplines can lead to errors that are “idiomatic” (as in translating human languages).
2. *Algorithmic and computational feasibility*: Clearly whatever modeling system is being used must be able to run in a reasonable time. For example, even if there were sufficient input data, a landscape fire model at 30 m grid spacing cannot be run at continental scales [*Keane et al*., 2002]. More challenging is optimizing the trade-off between model rigor and complexity and sufficient replication to capture a distribution of outcomes.
3. *Transparency of outcomes*: Why do realizations of one model, or of different combinations of models, produce different results? Did you get the right answer for the wrong reasons [*Dennis et al*., 2010]? Sensitivity analysis leads to quantitative transparency, but just as important are semantic and logical

Table 1. Agenda for a Modeling System, Classified by System Component, Spatial and Temporal Scale of Operation, and Specific Problem(s) Addressed[a]

Component	Spatial and Temporal Scale	Problem Addressed	Solution
Regional climate	4–36 km hourly to daily	Mesoscale and finer-scale processes need representation at those scales	Downscaled climate using suitable boundary conditions (would need implicit schemes except at resolvable scales for some processes, e.g., subgrid modeling of clouds). Nudging approaches capture region-specific synoptic circulations consistent with the driving GCM
		Spatial processes (e.g., mesoscale circulations) needed for smoke transport	Dynamic downscaling (from GCM) suitable for linkage to atmospheric CTMs, nested down to spatial resolutions of interest
Vegetation	<1–36 km monthly to decadal	Dynamically changing vegetation in response to climate, disturbance, and biotic interactions	Species differences in vegetation represented; fuel components simulated independently; succession included in live biomass predictions; mixed species and multiple strata simulated explicitly
		Scaling	Temporal scale of inputs to the model may need aggregation from the RCM time scale to 1 month intervals
Fire	30 m–1 km daily to annual	Fire is stochastic	Fire regimes are an emergent outcome of fire weather, ignitions, and fuels. Fire-regime properties (frequency, severity, and extent) are not prespecified
		Fire is contagious	Fire is represented as a spatial process, at least implicitly
		Scaling	A coarse-scale surrogates for fire ignition, spread, and termination; fuel characterization suitable for fire simulation
Smoke emissions	30 m–1 km daily to annual	Emissions are specific to fuel type and combustion phase	A translation of plant biomass and necromass to fuel loads, partitioned into live and dead (woody) fuels, then to size classes, and fuel type
		Fuels vary at fine spatial scales	Explicit accounting for fuel variation across space
		Different pollution species interact differently with atmosphere	Speciation profiles for pollutants and their precursors emitted in smoke, consistent with chemical mechanisms for speciated PM, ozone, and toxics used in the air-quality model
		Other emissions (e.g., biogenic) interact with smoke constituents in atmosphere	Speciated emissions of major anthropogenic and natural emission source sectors other than wildfires
		Scaling	Spatial allocation and temporal disaggregation of emissions for use in CTMs
Smoke transport	0–1000s of km	Biomass combustion plumes are transported (and sensed by air quality monitors) 1000s of km from point of origin	Need a multiscale modeling approach for consistent science in representing processes from regional (continental and beyond) down to local scale. At least capture rise of the smoke plume vertically to calculate emissions in the vertical model layers, and dispersion into the atmosphere of the most important constituent emissions (BC, VOCs, NO_3, etc.) prior to atmospheric chemistry calculations
		Plumes themselves are emitted at ~10s of m in extent and dilute into ambient air	Plume-in-grid models that are coupled to the CTM capture details of plume dispersion and dilution into the ambient air over several hours; keep track of chemical budgets, mass conservation
Atmospheric chemistry	1 km–~30 km	Some chemical transformations occur in the smoke plume	Advanced plume treatment model tracks chemical transformation that occurs in reactive plumes as plume dilutes
		Volatile organic species emitted in smoke have a wide range of physical, chemical, and optical properties	Secondary organic aerosol models are increasingly more detailed in treatment of varying volatility of "families" of species
		Troposphere-stratosphere exchanges, especially affecting stratospheric ozone	Represent other emission sectors within a regional-to-urban scale chemistry transport model that includes a detailed chemical mechanism for multiphase multipollutant interactions, in addition to horizontal and vertical transport algorithms (dispersion)
		Interactions among smoke emissions and atmospheric constituents from other emission sources	Atmospheric CTMs that extend into the lower stratosphere to account for exchange; at least specify upper chemical boundary condition from output of a global CTM
		Scaling	Reconcile scales of transport and meteorology with scales of chemistry

Table 1. (continued)

Component	Spatial and Temporal Scale	Problem Addressed	Solution
Feedbacks	All relevant scales	Feedbacks of atmospheric constituents (CO_2, CH_4, O_3, water vapor, and aerosol species). Black and brown carbon vary in optical properties due to the mixing state	A radiative transfer model that treats wavelength-dependent scattering and absorption of solar radiation by gases and aerosols, and models the impacts on the radiation budget, and the resulting meteorological fields (two-way coupling of meteorology and chemistry). Detailed treatment of black carbon in internal and external mixtures and of optical properties of brown carbon species (organic carbon)
		Feedbacks of clouds to radiation budget, uncertain in the presence of black carbon	A cloud scheme appropriate to the scale of the atmospheric CTM, with radiative impacts of cloud droplets; represent size-dependent aerosol scavenging by clouds; ideally use a cloud microphysical model for droplet growth and activation to calculate radiative impacts
		Feedbacks of vegetation to the atmosphere	A land-surface and vegetation model with two-way coupling to the meteorology, capturing feedbacks of vegetation to the surface energy budgets, moisture fields, and convective motions in the boundary layer
		Fire feedbacks to vegetation (mortality and fuels)	DGVM that includes fire or LFSM, where fire effects (loss of biomass, change in fuel type, and shift in species) are explicitly modeled
		Scaling	Minimize errors in feedbacks between components modeled at different scales; reliable subgrid schemes, switching to explicit representations at the appropriate scales (e.g., clouds)

GCM, general circulation model; RCM, regional climate model; DGVM, dynamic global vegetation model; LFSM, landscape fire succession model; CTM, chemistry transport model; BC, black carbon; VOC, volatile organic carbon.
[a]"Scale" is represented by practical (perhaps only quasi-practical) ranges. The disparity in scales is clear and is a problem in itself (see text). This agenda can be considered to be a superset of realistic expectations for our proposed system.

transparency. Can you explain why your model produced a certain outcome? An outcome may be counterintuitive, and be the one stochastic realization that produced an outlier to expectations [*Deser et al*., 2012]. Transparency could mean the difference between (a) discarding a good theory or outlier(s) in its predictions or (b) refining or extending the range of inference.

4. *Robustness to future projections*: Whether adding explanatory variables, or tuning parameters, or both, there can be trade-offs between matching observations and maintaining flexibility to operate in a changing domain. When taken too far, the former leads to overfitting in empirical models and overcalibration in simulation models.

No one system will produce the best answers for every question regarding smoke consequences, and choices of models should depend partly on the specific question at hand. Consequently, we present some guidelines that could serve as a checklist for aspiring modelers of future fire and smoke.

Coupled is better than disconnected (dynamic is better than static): One complication of forward modeling is that not all influences or causes are unidirectional. We re-emphasize that feedbacks in the system are significant, whether the simple (conceptually) feedback of fire to vegetation structure or the complex interactions between land-surface processes, aerosols, and clouds that modify climate. Models that ignore feedbacks by not coupling key components will be structurally wrong from the start. Similarly, both states and rates change. Static fields (e.g., statistical downscaling) or assumptions of stationarity in processes (e.g., "hotter and drier = more fire") reflect largely untenable assumptions about which system changes can be discounted (effects of circulation on atmospheric chemistry in the former and climate-vegetation-fire interactions in the latter).

Distributions are better than points (but do not regress away extremes): Almost all measured (or simulated) outcomes in the Earth sciences have ranges of variation, even if the processes underlying them are deterministic. Models that produce a single outcome will be wrong [*Silver*, 2012] and fragile. Ensembles, whether one or more runs of a group of models, as in the CMIP5 [*Taylor et al*., 2012], or replicates of a single model that has stochastic elements, provide a plausible range of outcomes. With enough replication, a distribution of outcomes might be estimated, and compared to theoretical predictions.

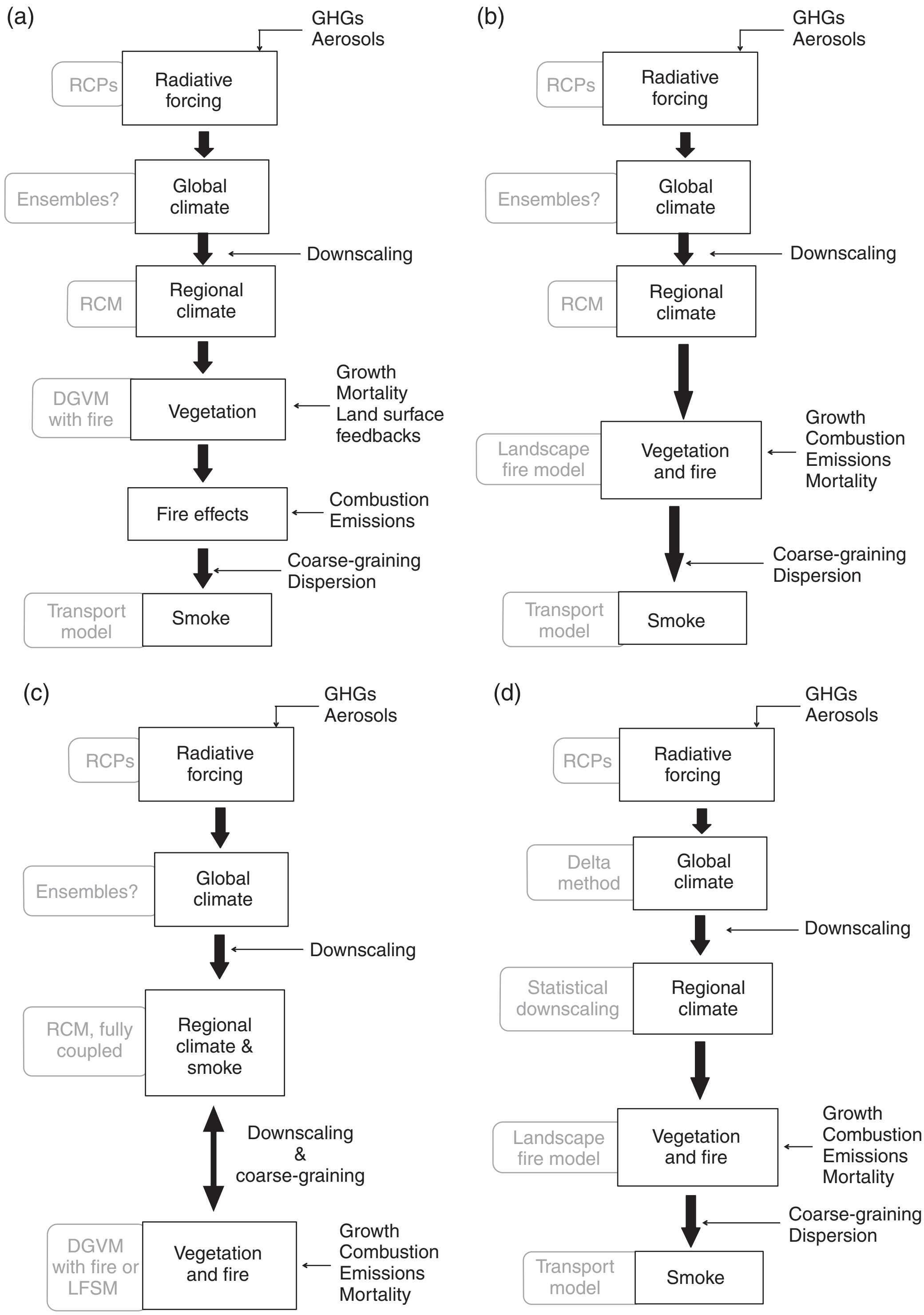

Figure 5. Example pathways for realizing models abstracted by the flowchart in Figure 3. Criteria for choices include (1) minimizing cumulative error, (2) algorithmic and computational feasibility, (3) transparency of outcomes, and (4) robustness to future projections. GHG, greenhouse gases; RCPs, representative concentration pathways; RCM, regional climate model; DGVM, dynamic global vegetation model; LFSM, landscape fire succession model. (a) Fire is incorporated in a DGVM and fire effects are computed at coarse scales. (b) Fire is modeled at a finer scale in a model that combines fire occurrence with fire effects. (c) Regional climate and air chemistry are coupled with fire occurrence external. (d) Global and regional climate are not dynamic, but represented statistically.

Another concern is where, and at what level in the modeling, to use means from ensembles as opposed to preserving the variability within them. For example, air-quality models are time-consuming to run, but simulated fires that provide their inputs are often generated stochastically [*McKenzie et al*., 2006]. How small a sample size of model outputs can be afforded and still project future variability with some confidence? To date, regional-scale air-quality models have not had wide usage in the ensemble sense, although ensemble methods have been established [*Lewellen et al*., 1985] and applied for some time in meteorological modeling.

Watch out for scale mismatches: Some scale mismatches are intrinsic to the modeling system we are proposing. Perhaps, the largest is between fire-behavior and fire-effects algorithms and the models that drive them (RCMs and DGVMs), and those that they inform (smoke-dispersion models). In particular, the spatial scales at which fuel abundance varies across a landscape may be the most obvious [*Keane et al*., 2012b]. Some error propagation is unavoidable, but a further concern is that in attempting to "scale up" fire occurrence and fire effects, algorithms are used, of necessity, outside their proper domain of application. For example, the classic point-based fire-behavior algorithm [*Rothermel*, 1972] built from laboratory experiments has been used in DGVMs to predict fire area and fire effects at regional scales and monthly time steps [*Lenihan et al*., 2008]. In contrast, *Arora and Boer* [2005] apply a heuristic representation of fire probability and fire spread. Their model solves one scaling problem by operating at a daily time step, but is opaque to validation with measurements, unlike a model that simulates processes at their native scales.

As simple as possible, but no simpler (Einstein): As all models are simplifications of reality, how much detail can be ignored or subsumed into thoughtful parameter choices? The classic case is understanding radiative forcing: one does not need coupled AOGCMs to conclude that there is an energy imbalance from the greenhouse effect. This is based on 100+ year-old science [*Arrhenius*, 1896]. But how much, where, how quickly, and which forcings are positive or negative? Will simplification or omission of interactions and feedbacks preclude robust projections?

Two further considerations affect the optimal threshold of simplicity: (1) trade-offs between model complexity and replication, which are generally inversely related, and (2) limits on information available for evaluating increased complexity. Concerning the latter, for example, our best measurements are for the contemporary period. For the historical period (roughly pre-1900), we have no fuels data, no fire-start dates, and usually only a rough idea of fire perimeters. Historical fire spread must be reconstructed indirectly, and with necessarily simpler models [*Kennedy and McKenzie*, 2010]. There are no measurements for the future, other than the range of possibilities starting at the present, which we can simulate, but many complexities therein, though manageable for the present for which we have observations, constitute false precision when applied to the future, especially for fire [*Kennedy and McKenzie*, 2012].

Give yourself a chance to be wrong (also give yourself a chance to be right): Observations, and verification or "validation," are important for simulation modeling, but bringing them in too soon and tuning the model to fit them will be counterproductive: it may camouflage basic errors in model content or not account for feedbacks that are present in observations [*Ford*, 2000]. Being "wildly wrong" at some stage may be the most informative thing that could happen.

Different models confront these issues in different ways. For example, RCMs and air-quality models solve equations for conservation of mass and energy, based on a clear understanding of the physics and chemistry. In contrast, vegetation and fire models usually involve empirical relationships and parameters that are fit statistically. Maximizing the explanatory power of a model by uncritically adding predictor variables and statistical interactions makes a model less robust to predictions outside its domain [*Cushman et al*., 2007].

On the other hand, it is possible to start out with faulty assumptions that ensure the inevitability, rather than the chance, of being wrong. For example, we encountered more than one paper attempting to project emissions into the middle of the 21st century that assumed that fuels would be the same (both abundance and spatial arrangement) as for the current period. Such a model is wrong from the start, and correspondence with the real future will be coincidental. Another potential pitfall is assuming that the natural fire regimes for particular vegetation types are stationary. Instead, modeled fire regimes should be emergent rather than prescribed [*Keane et al*., 2011; *McKenzie and Kennedy*, 2011].

Decide which uncertainties you can live with: Some models seem to "get right" certain regions, while having poorer skill more generally [*Mote and Salathé*, 2010]. If this is an RCM, one might sacrifice the global skill to have the best possible inputs for estimating smoke emissions at a finer scale of interest. Conversely, for regional modeling one might eschew a finer-scale landscape fire model, out of a need for efficiency or wall-to-wall coverage, and assume that there are no consistent biases associated with ignoring landscape features such as topography and spatial patterns of fuels.

Some choices and trade-offs may not be purely scientific, but relate to available data and resources and wider sociopolitical concerns. For example, the "tried-and-true" SRES pathways have seen much use not only in climate modeling but also for ecosystem models of many kinds [*Littell et al*., 2011]. In contrast, the RCPs are expected to be the paradigm for the future, but have a much shorter history, although experiments are now underway [*Taylor et al*., 2012].

4. Research Needs

An integrated Earth-science model of the scope we envision will out of necessity have components at various stages of development, with each being subject to improvement with ongoing and new research. Instead of trying to enumerate these possibilities, we focus on three areas that we believe address important needs for the modeling system as a whole: two that are mainly technical and the third of wider societal import. For each, we propose specific research objectives, while recognizing that many others would be possible and fruitful.

4.1. Optimizing Ensembles and Coupled Models

We alluded earlier to the unanswered questions about ensembles of GCMs [see *Knutti et al*., 2010]. The evaluation of ensembles of CTMs, coupled and decoupled from RCMs, is at an even earlier stage, but the uncertainties associated with single realizations are analogous to those of GCMs.

Dennis et al. [2010] reviewed the probabilistic evaluation of air-quality models, which involves Monte Carlo methods to quantify the uncertainties in model inputs and those associated with stochastic variation within ensembles. Inverse modeling with Bayesian hierarchical methods provides a nuanced approach for evaluating the agreement of models with observations [*Riccio et al*., 2006]. Bayesian model averaging is an ensemble technique that approximates an optimal classification (in our case weighted output from model realizations), or hypothesis, based on Bayes theorem [*Hoeting et al*., 1999; *Pinder et al*., 2009]. Such techniques can be used to diagnose structural errors in ensemble members, and to understand the effectiveness of emission control strategies probabilistically.

A next step would be to extend ensembles to the coupled modeling that we have proposed, while specifically varying levels of complexity, such as in the specification of fires via the choice of DGVM or in the level of feedbacks included in the system. A rigorous probabilistic comparison would supersede a qualitative evaluation of alternatives such as those in Figure 5. The computational burden of generating the requisite multiyear input data, for example, from RCM(s) of choice and from relevant emission inventories, could be prohibitive, but efforts to consolidate input data for a common basis of comparison are already underway in atmospheric CTMs [*Rao et al*., 2012]. Such an effort would inform the question of how much complexity is needed to provide useful projections of smoke consequences.

4.2. Scaling and Process Complexity

What are the biases, errors, and scaling factors associated with representing fire regimes and smoke production at coarse enough spatial scales for regional modeling? In some ecosystems whose spatial heterogeneity is minimal or varies at coarse scales (e.g., gentle or simple topography), fire and smoke modeling at the spatial scale of the typical DGVM may be adequate. In others, particularly in mountains, there is much within-(DGVM) cell heterogeneity in the fine-scale controls on fire, topography, and fuels.

In these latter cases, LFSMs might provide a surrogate for the ground-based observations that are unavailable for future projections. Of course no effect model is error-free, but then neither is a raster-based data layer extrapolated directly from observations [*Keane et al*., 2013b]. Running LFSMs over select "validation" domains could effect a cross-scale sensitivity analysis of a DGVM, holding global settings (RCP, GCM, downscaling method, etc.) constant. What landscape process matters most among those that are missing at the scale of DGVMs? Is it something as direct as fire spread controlled by topography and patchy fuels, or as complex as the effects of large high-severity patches on seed sources [*Turner et al*., 1999]? At a minimum, cross-scale comparisons could lead to specifying within-cell variation in a DGVM, but there also might be a potential for developing more quantitative scaling laws [*Falk et al*., 2007; *McKenzie and Kennedy*, 2011]. Such a project would be collaborative along the lines of the CMIP5. "Validation" sites, i.e., landscapes within the DGVM domain that would be simulated with the LFSM, could be selected along environmental gradients thought to be associated with the importance of fine-scale processes for informing broader-scale projections.

Similarly, there is much greater spatial heterogeneity and temporal variability in processes governing the emissions, secondary production (gas-, particulate and aqueous-phase chemistry), and transport (in clear air and in clouds) of aerosols from smoke than represented in the climate models used to provide inputs to models of vegetation, fuels, and fire activity. Cross-scale comparisons are thus very important for understanding the smoke impacts on air quality, and ultimately the radiation budget, which complete the cycle of modeling described here. Examining the effects of scale refinement on the atmospheric chemical budgets and their radiative impacts can, at a minimum, suggest the optimum grid spacing needed to provide a computationally feasible yet scientifically defensible and informative approach. As noted previously, such refinement may also necessitate inclusion of subgrid effects or explicit treatment of some processes. Similar considerations apply in determining the sampling frequency of climate model outputs to perform RCM simulations, and thus chemistry-transport modeling: what are the optimum RCM modeling frequency and time period over which the climate signal and its perturbations due to smoke emissions can be discerned?

4.3. Abrupt Changes and Extreme Events, Thresholds, and Tipping Points

The first two of these are closely related, as are the second two, and all are similar in that they can be costly in both the short and long terms. Abrupt climate changes are documented for the Holocene and before, and are an evolving concern for scientists and policy-makers worldwide [*Climate Change Science Program*, 2008]. Extreme climate events in recent years are linked statistically to climate change [*Coumou and Rahmstorf*, 2012; *Hansen et al*., 2012], which is considered abrupt in the context of paleoclimatology. Wildfires can be extreme in their peak intensity, their extent and homogeneity of severity, or their smoke consequences.

In our proposed modeling system, thresholds and tipping points are ecological boundaries that are crossed by some climatic or other environmental forcing, from which return may be impossible or unlikely, or at best hysteretic. For example, drought stress driven by increasing temperatures, and ensuing tree mortality, can have multiple adverse consequences for forests [*Anderegg et al*., 2013], including exceeding the evolutionary plasticity of many species [*Choat et al*., 2012]. Forests with mature trees that are relatively complacent to temperature increases, at least for the near future, could fail to regenerate after high-severity fires because seedlings will not survive in a new climate (i.e., warmer than the Little Ice Age climate in which their predecessors established) [*Littell et al*., 2010]. More subtly, but with significant human consequences, smoke pollution in local airsheds and background concentrations across broader areas could exceed tolerance thresholds, both regulatory and more basically physiological.

Some recent literature suggests that there are detectable quantitative indicators of upcoming abrupt changes, or "regime shifts" [*Biggs et al*., 2009; *Scheffer et al*., 2009, 2012; *Wang et al*., 2012], which with careful monitoring might be used to mitigate or even forestall or prevent change. Other work, both ecological [*Doak et al*., 2008; *Hastings and Wysham*, 2010] and more interdisciplinary [*Taleb*, 2007; *Casti*, 2012], suggests that extreme events and threshold crossings may, like earthquakes, be impossible to predict more precisely than specifying return times or probabilities for events of certain magnitudes [*Ditlevsen and Johnsen*, 2010; *Parmesan et al*., 2011; *Loehman and Keane*, 2012]. At best, the indicators may be present in only a subset of circumstances. For example, *Hastings and Wysham* [2010] show that properties proposed as indicators, such as changing variance [*Carpenter and Brock*, 2006] or skewness [*Guttal and Jayaprakash*, 2008], or slowing down of dynamics [*Chisholm and Filotas*, 2009], are present in only a small subset of dynamical systems approaching regime shifts. Systems with pervasive nonlinearities or strong positive feedbacks will change with no warning. Given the inherent nonlinearity and uncertainties in the climate system [*Rial et al*., 2004], looking for advance indicators of regime shifts in our climate-fire-smoke system may be a fool's errand.

A more tractable research goal, in a simulation framework such as we are proposing, is to leave the system dynamics "free" to follow unexpected extreme trajectories, albeit with low probability, so as to identify the broadest range possible of consequences. We need to ensure that we not "regress away extremes" when using ensembles and concentrating on mean responses. For example, a DGVM that uses static plant functional types, a fire module that specifies fire frequency or limits maximum fire extent or severity, or a combustion module that limits plume height restrict outcomes to the "known unknowns." It will be more illuminating for modelers to allow themselves to be wildly wrong (or extreme) to experience the (simulated) consequences. With this wider perspective, resilient strategies in response to regime shifts will be more transparent and more feasible [*Peterson et al*., 2011; *Taleb*, 2012].

5. Conclusions

The complex issues involving projections of wildfire and smoke consequences in a rapidly changing climate can be addressed best by modelers with diverse skills and resources. Acknowledging this, we have eschewed exact prescriptions or presenting any prototype systems. Rather than suggesting a "corporate" approach, something often favored by agencies and in many ways easier to track, we suggest that researchers take advantage of their own specific expertise, and that of their collaborators, even if it means different model structures and outcomes that are less easily compared with other projects. There is fruitful material for designing creative comparisons in the literature we cite [e.g., *French et al*., 2011; *Larkin et al*., 2012; *Taylor et al*., 2012; *Keane et al*., 2013b], and no lack of potential metrics and criteria (some better than others) for evaluation. A final caveat is that projections will be the outcome of many stochastic processes, of which "what actually happens," whether in the future or in historical observations, is just one realization. Expectations should be scaled accordingly. For example, we cannot answer whether haze in Glacier National Park will be worse on 4 July 2050 than it was on 4 July 2000, but we should have a reasonable idea whether it will be worse, on average, in midsummer of the 2040s than it was in midsummer of the 1990s. Projections will be most relevant when uncertainties, from both knowledge gaps and intrinsic stochastic variation, are understood and quantified.

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