Smoke consequences of new wildfire regimes driven by climate change

Final report to the Joint Fire Science Program
Project 12-S-01-2

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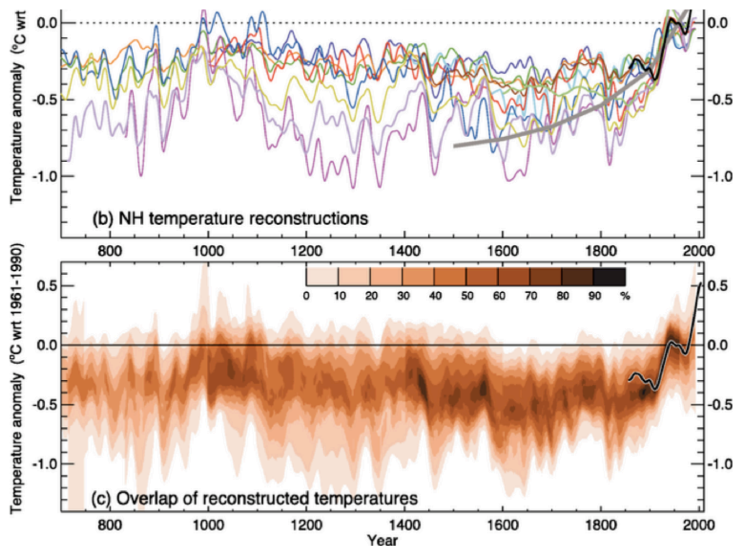

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Summary

Smoke from wildfires has adverse biological and social consequences, and various lines of evidence suggest that smoke concentrations in the future may be more intense, more frequent, more widespread, or all of the above. In this document, we review 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 present relevant details of each component of the system, offer suggestions for the elements of a modeling agenda, and give some general guidelines for making choices among potential components. We address a prospective audience of researchers who we expect to be fluent already in building some or many of these components, so our guidelines are not prescriptive nor do they 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.

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Introduction

Smoke from wildfires has adverse biological and social consequences. Smoke inhalation can be lethal, and sub-lethal concentrations have adverse effects on both short-term and long-term human health, particularly in sensitive populations, such as the very young, the very old, those with respiratory or heart problems, and the occupationally exposed, such as firefighters, who inhale smoke during highly aerobic physical activity (EPA -- http://www.epa.gov/airquality/particlepollution/). On December 14, 2012, the EPA revised the National Ambient Air Quality Standards (NAAQS) for the annual average concentration of fine particulate-matter (PM) from 15 $\mu g/m^3$ to 12 $\mu g/m^3$, based on a recent integrated science assessment (US EPA 2009) that pointed to the adverse health impacts of particulate black carbon (BC). The chemical speciation of PM emitted in wildfires may be as significant a factor in these health outcomes as its ambient concentrations. In a California wildfire study, Wegesser et al. (2009) showed that the alveolar macrophages have a different and inherently more toxic response to an equivalent concentration of both fine and coarse particulate matter (PM) emitted from wildfires than from other sources. Oxidative stress, leading to multiple and often severe health problems, occurs from the aromatic chemical compounds emitted in wildfires (Laks et al. 2008), or from inhalation of carbon-centered free radicals from reactive metals (Leonard et al. 2007).

Of primary concern for human health are smoke concentrations in local airsheds, but what is effectively local may cover many square kilometers (e.g., the Russian fires of July 2010) 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 downwind in sufficient concentrations to be the principal source of air pollution over large areas (Strada et al. 2012). Particulate matter under 2.5 μm in aerodynamic diameter ($PM_{2.5}$) is especially toxic because it can penetrate deeply into lung tissue, and can have lasting effects from a single exposure (Dockery et al. 1993, Pope et al. 2002). Furthermore, highly toxic dioxins and furans are an oft-neglected product of biomass combustion (Gullett et al. 2008).

In the days and weeks following wildfire ignitions, smoke may be transported hundreds of kilometers downwind, exacerbating regional haze, especially in National Parks and wilderness areas that have been designated as “Class I” areas because of their pristine air quality. Across the

American West, for example, days with the worst air quality in these protected areas (http://vista.cira.colostate.edu/improve/) are nearly always associated with wildfires upwind, particularly in the West and Southeast (US EPA 1999 -- Figure 1).

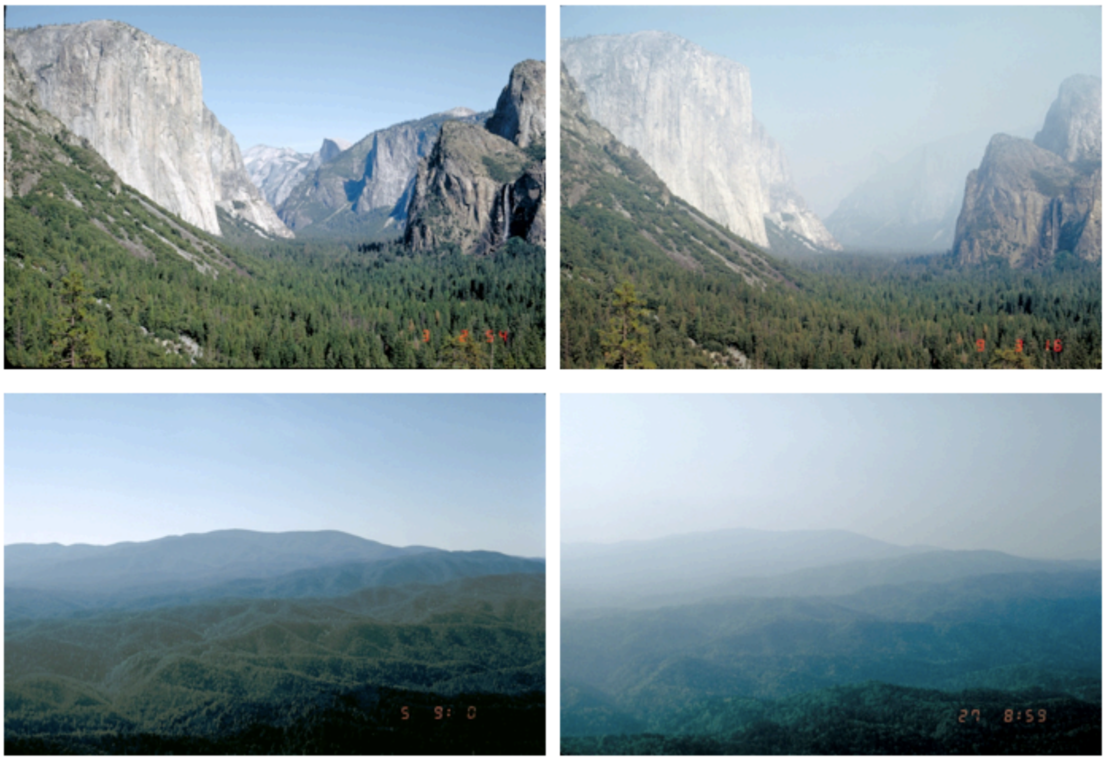

Figure 1. Examples, from IMPROVE website, of pristine (or nearly so) vs. degraded air quality in National Parks, reflecting haze from wildland fire, other pollutants, or both. Upper panels: Yosemite National Park. Lower panels: Great Smoky Mountains National Park. Photos courtesy of IMPROVE (http://vista.cira.colostate.edu/improve/).

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 annual area burned will increase through the coming decades, dramatically in some regions (McKenzie et al. 2004, Flannigan et al. 2009 and references therein, Littell et al. 2010, Pechony and Shindell 2010, Liu et al. 2012). In some ecosystems, fire severity may also increase, but 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), both directly (e.g., droughts, heat waves) and indirectly (fires) driven by a warming climate.

The straightforward view of warming climate affecting fire regimes, which in turn affect 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 acknowledged that this linear view hides much complexity in the form of interactions, feedbacks, and spatial variability. For example, Littell et al. (2009) found that the simple paradigm “hotter and drier = more fire” was appropriate for most of the northwestern U.S., where fuels are always present and fuel moisture is the principal limiting factor (Figure 2). In contrast, fuel availability is often limiting in the arid Southwest and much of the Great Basin, such 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. Krawchuk and Moritz (2011) reinforced and generalized such contrasts in an overview of global fire regimes, and these authors (2011) and McKenzie and Littell (2011, 2013) theorize 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 non-linear response reflects the significant interactions of both climate and fire with vegetation, which can be as strong a driver of fire regimes as climate itself (Higuera et al. 2009).

Further 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, potentially affecting the short-term variability of climate, such as convective precipitation (Bollasina et al. 2011, Jiang et al. 2012), which affects fire weather. Emission of greenhouse gases (GHGs), principally CO_2, is clearly a positive feedback to area burned and smoke via its associated climate 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 chemical composition and thus its 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. A similar uncertainty 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, Hayes et al. 2012, Huntzinger et al. 2012, King et al. 2012, Raymond and McKenzie 2012).

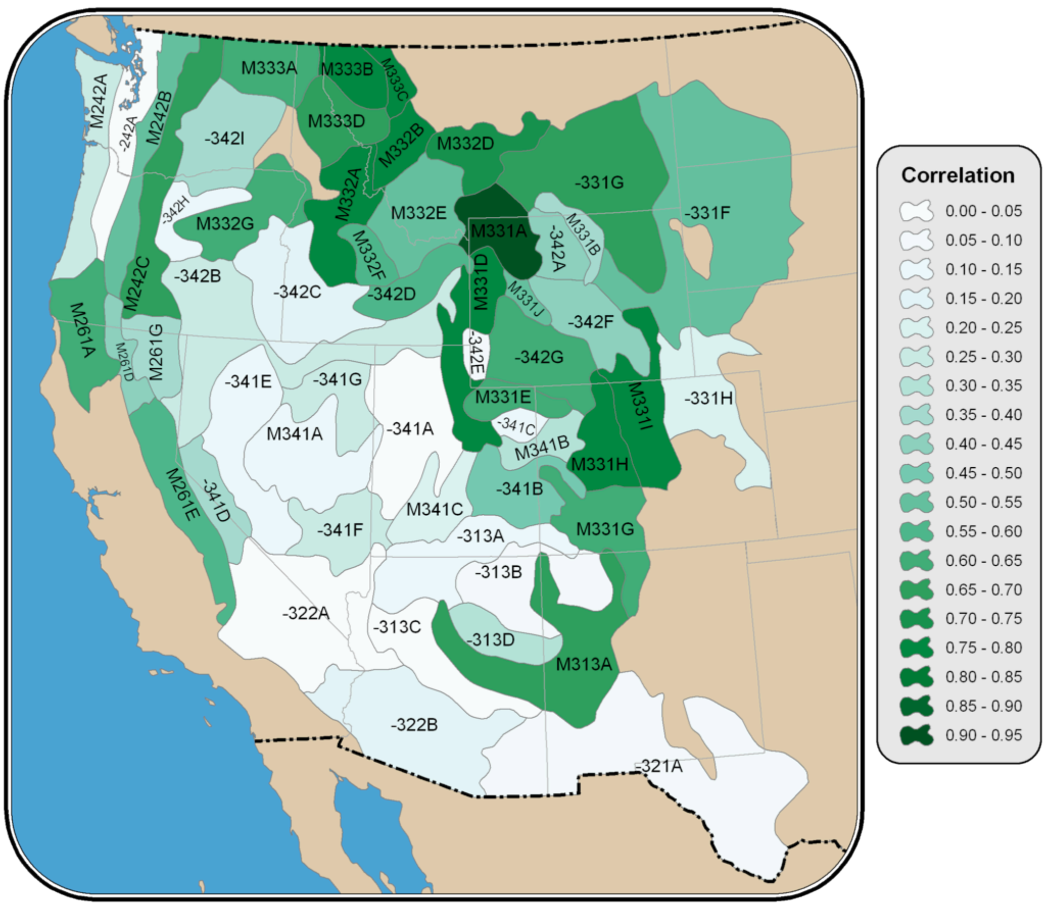

Figure 2. Correlations between annual area burned (1977-2006) and summer water-balance deficit (DEF = PET-AET: Potential - Actual EvapoTranspiration) in Bailey's ecosections across the western United States. Work extended from Littell et al. (2009) by McKenzie and Littell (2013). Darker colors suggest "hotter and drier = more fire" applies, because the correlation with DEF is stronger. ET was calculated by the Penman-Monteith method within the VIC hydrological model (Wigmosta et al. 1994).

A systems approach is needed to evaluate the relative importance of forcings, interactions, and feedbacks among climate, wildfire, vegetation (fuels), and air quality (in general), or pollutants emitted in smoke plumes (in particular) (Stavros et al. 2013). The knowledge base for this evaluation draws on research at widely different spatial and temporal scales. For example, 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 that affects prescribed burning, mechanical fuel treatments, and controlled and uncontrolled wildfires, compromising efforts to create more resilient landscapes in the future (Millar et al. 2007, Joyce et al. 2009, Peterson et al. 2011, Sommers et al. 2011). Of particular concern, if wildfires increase in size and frequency (Running 2006), are the ecological and economic tradeoffs between wildfire suppression and fuel treatments to reduce potential wildfire intensity and severity (Hurteau et al. 2008, 2011; Galik and Jackson 2009). Many fire-regime characteristics, such as fire intensity, severity, and size, are used to evaluate these tradeoffs, but perhaps the most important to society is how much smoke will be released during a fire (Bowman and Johnston 2005). 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.

Projections are needed to inform the global-change research community, 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, the global uncertainties associated with each, and the sources of error propagation within models and in the linking of models. We then offer guidelines for constructing and using the elements of a system to maximize both its physical, chemical, and biological reality and its robustness 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 choose component models, 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.

The geographic scope of this paper is the conterminous USA (CONUS), in that we focus on methods that can be applied over a generally recognized modeling domain (Figure 3, Mearns et al. 2012). 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 and air-quality models (i.e., the entire CONUS domain). A goal of this review and the research that it will inform is to be particularly relevant for application across the CONUS, but also to inform questions at finer (urban and exurban) or coarser (hemispheric or global) scales.

The modeling system

Figure 4 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 as conceptualized here, there are no independent drivers. In the sections that follow 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.

Figure 3. The NARCCAP (see text, p. 14) modeling domain (Mearns et al. 2012), typical of that used in regional climate modeling. The regional climate models in NARCCAP are dynamically downscaled over this domain from a group of global climate models at ~ 50 km horizontal resolution.

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 (Diffenbaugh and Ashfaq 2010, Coumou and Rahmstorf 2012, Hansen et al. 2012). For future projections, key inputs to *global climate models* (GCMs)[1] are the components of *radiative forcing*, the amount by which the Earth's total energy budget is out of equilibrium (Hansen et al. 2011). The principal forcings are greenhouse gases (GHGs), including CO_2, methane (CH_4) and O_3 among others, and aerosols (Forster et al. 2007).

The sign of GHG forcings (positive) is well established, although the variability around mean estimates is still substantial (note though that even 99% confidence intervals exclude zero). For example, *climate sensitivity*, by consensus definition the equilibrium response of Earth's annual temperature to a doubling of atmospheric CO_2, has been the subject of dozens of papers, theoretical or statistical (Aldrin et al. 2012 and references therein), using paleoclimatic

[1] 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, referring to some form of general circulation model (e.g., coupled atmosphere-ocean GCMs, or AOGCMs).

reconstructions (Hansen and Sato 2012), or output from global climate models (Forest et al. 2006). A good review is at http://www.realclimate.org/index.php/archives/2011/11/ice-age-constraints-on-climate-sensitivity/.

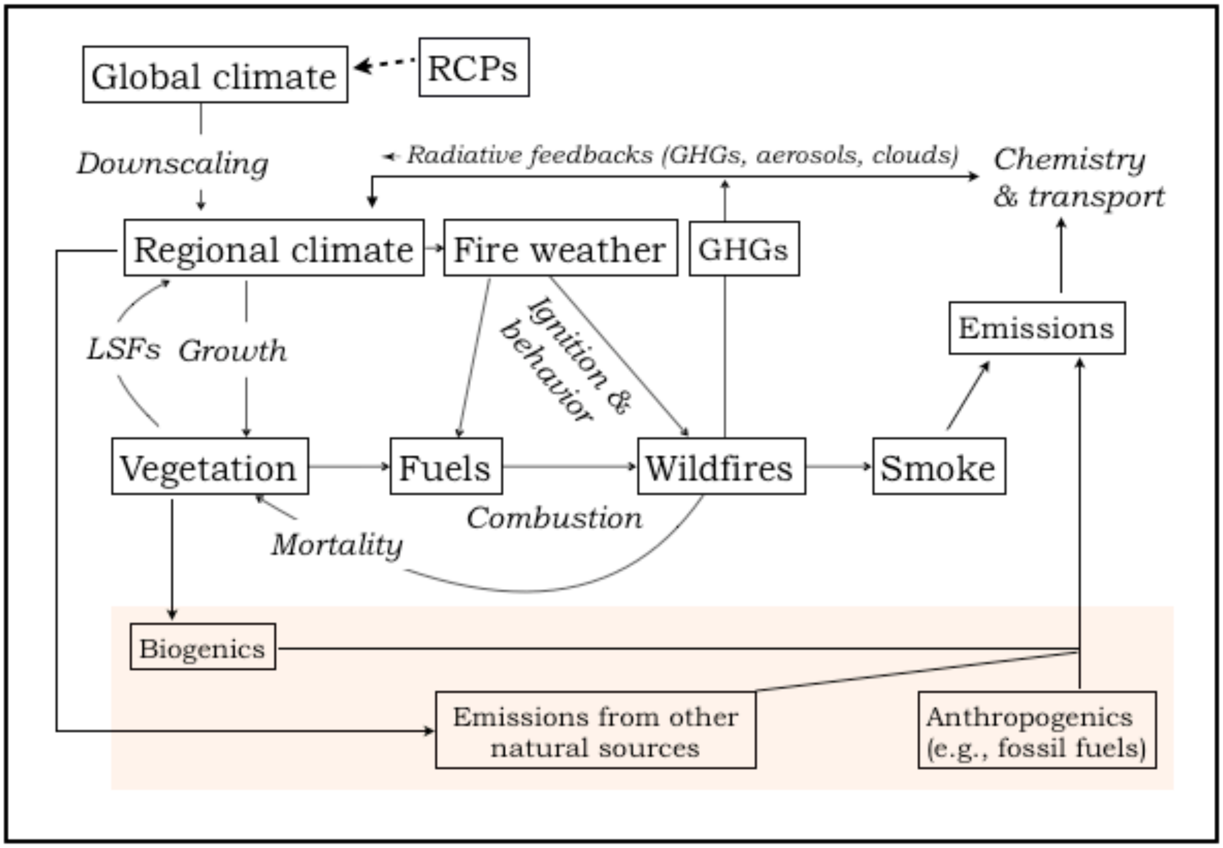

Figure 4. Master flowchart for a modeling system to predict smoke consequences of changing fire regimes in a warming climate. Items in boxes are the elements of the modeling system. Italicized terms are processes that should be represented explicitly by model(s). LSFs = land-surface feedbacks. GHGs = greenhouse gases. 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 (e.g., RCPs = representative concentration pathways), without modeling feedbacks to global climate, but radiative feedback from aerosols, clouds, and GHGs is dynamic at the scale of regional climate.

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 5 shows the relative contributions to the global forcing estimates from the major anthropogenic atmospheric constituents, along with the uncertainty in each (Forster et al. 2007). A key part of near-future research will be to estimate aerosol forcing better, because it contributes to Earth's energy balance significantly, and may also confound estimates of climate sensitivity (Hansen et al. 2011).

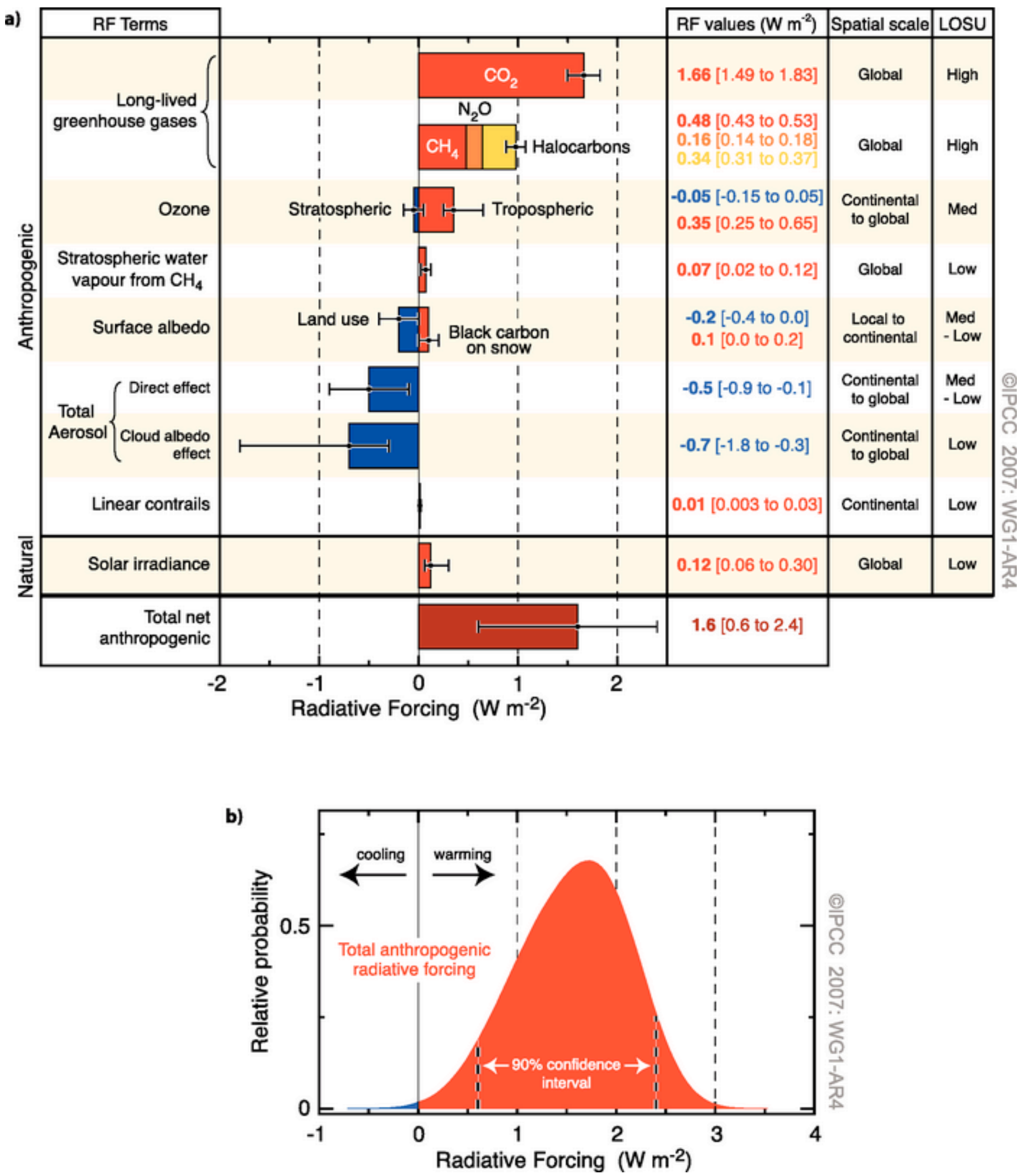

Figure 5. (a) Radiative forcing of the Earth's climate, from the IPCC 4th Assessment Report (AR4) (Forster et al. 2007). Error bars represent 90% confidence intervals. LOSU = level of scientific understanding. (b) Probabilistic representation of the total net anthropogenic forcing in (a). See Bond et al. (2013), however, for possible modification to the aerosol component.

Recognizing the importance of this variability in radiative forcing, the IPCC has, over the years, built and refined *socio-economic scenarios* (SRES -- Nakicénovic and Swart 2000), to supply bottom-up estimates of radiative forcing to global climate models. 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. Indeed, in ecosystem simulation experiments in which both multiple global climate models and multiple SRES scenarios are used, outcomes can be sensitive to both choices. For example, Hawkins and Sutton (2009) discuss the relative importance of uncertainty in projections of climate change for time horizons of 30 to 40 years, the timeline of concern for studying climate-related changes in fire regimes, and show that at these timescales the emissions-scenario uncertainty is nearly as large as that of the global climate model.

In its Fifth Assessment Report (AR5), whose working-group reports will be completed 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 Concentration Pathways* (RCPs) essentially retrofit socio-economic 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 CMIP5 (5th Climate Model Intercomparison Project -- Taylor et al. 2012), will implement factorial designs using ensembles of global climate models and RCPs. Given this new currency for future projections, those who use the output of global climate models will need to consider tradeoffs 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.

To project smoke consequences of climate change across the CONUS, we require climate inputs at resolutions fine enough to capture, at least crudely, the spatial variability of both climate and landforms. Global climate models typically run at horizontal resolutions of > 100 km^2, with many being much coarser than that, although modeled spatial resolution has increased steadily since the first IPCC reports in the 1990s. Resolutions of 4-36 km^2 provide order-of-magnitude gains in capturing spatial variability, although local phenomena important for fire are not resolved even at these scales. *Regional climate models* (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 the CONUS domain (e.g., Figure 3) when run at 36 km^2, and detailed regional modeling when run at resolutions down to 4 km^2 (Salathé et al. 2008).

RCM domains are not closed systems (with respect to atmospheric, oceanic, and land-surface processes and interactions), as is the Earth as a whole. RCMs therefore must be "forced" at the boundaries of their domains by output from a global climate model. These *boundary conditions* both initialize and update RCM simulations 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* (van Storch et al. 2000), 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. 2012a,b; 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).

Spatial variability within global climate models is of course still important, and substantial departures from future global means are likely in regional-scale changes. There is also considerable within-region uncertainty in different realizations of global models. For example, Deser et al. (2012a, 2012b) found that internal variability among runs of just one global model (CCM3) under just one SRES scenario (A1B) produced non-zero probabilities of opposite changes in seasonal temperature and precipitation, enough, for example, to force opposite projections of wildfire area burned predicted by current models.

An alternative to RCM simulations for some meteorological applications is *statistical downscaling* (Wilby and Wigley 1997, Salathé 2005), in which sub-regional 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). Statistical downscaling can "learn" from the temporal properties of global climate models, by incorporating non-stationarity in output time series to refine what is otherwise a temporally static product (Abatzoglou and Brown 2012). It can also correct for biases known to be associated with particular global climate models, but future projections still assume stationarity of the empirical relationships that drive the downscaling. For our purposes, a particularly significant drawback is that statistically downscaled fields do not capture mesoscale circulations dynamically, and those are critical for modeling smoke transport and its effects on air quality.

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. Ensembles of global models can also incorporate the different RCPs (Taylor et al. 2012), as they have previously incorporated different SRES scenarios. With the computational burdens of global climate models, 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 lack of agreement on what even is a good metric for evaluation (Knutti et al. 2010).

The question of which RCMs to link to which global climate models may be as important as the choice of a "best" model in either category. For example, Pierce et al. (2009) argue that for providing boundary conditions for an RCM, multi-model ensembles at the global scale are better than single runs or replicates of one model, because the ensembles tend to correct rather than amplify biases. This "cancellation of offsetting errors" (Pierce et al. 2009) is convenient, when demonstrated by comparing model output to observations, but does not in itself ensure that the correction is not coincidental and may disappear in future projections. Nevertheless, the complexity of current models likely precludes the more robust analysis of simultaneous outputs and model structures that is possible for ecosystem models (Kennedy and Ford 2011).

A continental- and regional-scale assessment particularly germane to predicting vegetation, fire, and smoke in the CONUS is the North American Regional Climate Change Assessment Program (NARCCAP -- Mearns et al. 2009, 2012). Figure 3 shows the domain of this effort, which applied reanalysis-based boundary conditions to drive six RCMs, across North America and for four smaller domains, followed by future projections using four coupled atmosphere-ocean general circulation models (AOGCMs). NARCCAP focused on the uncertainties associated with dynamic downscaling, complementing global-scale efforts to distinguish natural variability in the climate system from the effects of anthropogenic radiative forcing. NARCCAP represents state-of-the-art regional outputs except that (1) it is tied to the now retired SRES scenarios; specifically they used only A2, in order to achieve adequate replication in global and regional model ensembles, and (2) most of the downscaling did not include spectral nudging.

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 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" but also incorporate the major disturbances associated with the domain in question. For the CONUS, this means wildfire.

Climate-smart vegetation models come in two flavors: empirical models (involving *inverse modeling* or "inversions" in modeler jargon) that fit predictor variables (climate) to response (vegetation) via statistical estimation or machine-learning algorithms, and process-based simulations (involving *forward modeling*) that 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 enumerated in many ways. For two overviews of the comparison see Cushman et al. (2007) and Littell et al. (2011). A clear advantage of the process-based approach is that it is dynamic and connects more easily to other dynamic models (e.g., RCMs). We therefore focus on process-based models in what follows, 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 global climate models). *Dynamic global vegetation models* (DGVMs) simulate vegetation response to climate, and can be adapted across a continuum of scales (resolutions) more easily than the climate models themselves, which are more constrained to intrinsic scales of atmospheric processes, although the range of scales they simulate is broader than that of DGVMs. 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. 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 even RCMs. Topography and land-water variations also contribute to small-scale atmospheric boundary-layer processes (e.g. land-sea breezes, drainage flows, local precipitation) that affect vegetation. Even with the higher resolutions of RCMs, many of these small-scale atmospheric processes that impact vegetation are not captured. Conversely, it is difficult to upscale effects of vegetation processes, such as evapotranspiration, radiative shading, and wind modification, cogently to produce radiation budgets suitable for 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*. Typically these number 5-12 (Quillet et al. 2010), although some, e.g., MC1 (Bachelet et al. 2001, 2003), use as many as 24. Individual species distributions overlap (e.g., sometimes two species overlap over a majority of both of their ranges) and are spatially discontiguous at multiple scales, and so resolving vegetation to individual species at a global scale constitutes false precision. Within regions of the CONUS, however, species are known to establish and survive in response to abiotic (e.g., soils) and biotic (e.g., competition for light and nutrients) factors besides climate (Iverson et al. 2008, Franklin 2010). The fire ecology of plants also differs greatly among species within life forms (Wright and Bailey 1982, Agee 1993, Bond and van Wilgen 1996); 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.

An additional problem with vegetation that is not resolved to species is that 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 and Brown 1997, Prichard et al. 2007). Typically loadings of these fuels cannot be inferred from live vegetation (Keane et al. 2012b) (this problem is magnified when species are not known, as in DGVMs); attempts to establish predictive relationships have largely failed (Brown and Bevins 1986, Raymond et al. 2006, Keane et al. 2012a). 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. 2012b). 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).

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 drivers' operating over a range of spatial and temporal scales (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. 2012). 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. Both the U.S. and Canada have developed fire-danger prediction systems that incorporate variables related to fire weather; in the U.S. the National Fire Danger Rating System (NFDRS -- Cohen and Deeming 1985), and in Canada the Canadian Forest Fire Danger Rating System (CFFDRS -- http://cwfis.cfs.nrcan.gc.ca/en_CA/background/summary/fwi). Composite indices calculated therein are deterministic products of the data streams from weather and climate models, and are fundamentally easier to predict confidently than actual fires (see examples in Flannigan et al. 2009). There is a strong tradition of this in operational fire forecasting (Lawson and Armitage 2008, Liu et al. 2012, NWCG 2012), but it is also relevant to predicting responses to climate change. For example, Chen et al. (2009) used NFDRS indices to simulate future fires at a daily time step across the CONUS. We emphasize that fire weather is a useful concept that is broader than the specific weather variables used by the fire danger rating systems. There are other fire-weather variables derived from climate models that could potentially be used as indicators of future atmospheric conditions conducive to large or erratic fires; for example, the Haines Index (Winkler et al. 2007), the Haines index coupled with a measure of turbulent kinetic energy (Heilman and Bian 2010, 2012), and the FWI (composite) from the CFFDRS.

Given the limitations associated with projecting empirical fire predictions into the future, 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 and increase the number of replicates. Modules also vary in the degree to which fire-regime properties are *emergent* (McKenzie and Kennedy 2011), i.e., they arise directly from drivers (e.g., climate, fuels) simulated within the DGVM, or prescribed, e.g., 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 may still require careful parameter choices, even if fire is predominantly emergent, but avoids 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. A further consideration, rarely considered in landscape fire models, is the "meteorology" generated by the fire and its interactions with the atmosphere in spreading fire and transporting smoke away from the fire. Estimates of variation in fire severity, in particular, at the "landscape" scale 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, some further specification of 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 smoke delivery and dispersal, and dictating trajectories of successional development that will govern future smoke production. There is a computational cost, however, such that they are intractable for regional-scale modeling, and even if this limit were overcome, the cost, in person-hours and dollars, of assembling the required spatially explicit databases to run LFSMs across the CONUS 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) used LFSMs to evaluate potential 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. LFSMs can also nudge and calibrate DGVMs, and perhaps eventually can be used to scale down DGVMs. See "Research needs" (below).

Other disturbances interact with each other and with fire to produce novel landscape behaviors that ultimately influence combustion and smoke dynamics (Bigler et al. 2005, Allen 2007). For example, tree mortality from the mountain pine beetle across much of the inland Northwest 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.

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}–$10m^2$), fire spread and intensity are conditioned by properties of fuel (mass, availability, spatial arrangement, and moisture), ignition (type, intensity, frequency, and spatial distribution), and ambient weather (air temperature, wind speed, atmospheric turbulence, and humidity) and its interactions with the fire-induced meteorology. Smoke characteristics therefore depend on both environmental conditions and fuels, which determine total emissions, and the type of combustion (flaming, 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 proportionately more CO and particulate matter (PM). Other emitted organic gases transform in the atmosphere (secondary organic aerosols -- SOAs), which add to PM to increase the atmospheric aerosol loading (Hennigan et al. 2011, Bond et al. 2013).

Smoke emissions from a wildfire needed for modeling inputs depend on area burned, biomass consumed (what proportion of available fuels actually burns), 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. 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. These proportions are codified as *emission factors* (Andreae and Merlet 2001).

The long history of on-the-ground management of fire and smoke in the U.S. has produced a wealth of models, estimators, and conceptual frameworks. The Smoke Emissions Model Intercomparison Project (SEMIP -- Larkin et al. 2012), an analogue of the CMIPs and funded by the Joint Fire Science Program, compared the performance and sensitivity of many of the available models. An exhaustive enumeration of the models is beyond our scope here; instead, we provide some examples of products germane to projections of smoke across the CONUS. Larkin et al. (2012) provide much more detail.

Fuels are spatially heterogeneous at multiple scales; these scales differ among fuel types such as canopy fuels vs. dead wood (Keane et al. 2012a,b), but all are much finer than the spatial scales associated with RCMs or with smoke dispersion models that provide the back end of our proposed modeling system (Figure 4). Consequently, an aggregated spatial data layer, 1-km resolution or coarser, is needed. There are three CONUS-wide 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. (2013) provide a detailed analysis. All share an overarching limitation, however, in that as coarse-scale data layers they cannot be expected to replicate fuels exactly, either their amount or configuration, for particular points on a landscape, because of the scaling issue noted above (Keane et al. 2012a,b). For example, the FTGs, even though scaled up to 250-m resolution from FIA (Forest Inventory and Analysis -- http://www.fia.fs.fed.us/) field data, are poorly correlated with FIA validation plots that were used to build them (Keane et al. 2013). This scale mismatch needs to be acknowledged in coarse-scale future projections of smoke.

A further concern for fuels is that there is 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. For the FCCS and FTG, this is relatively straightforward in theory, because classes are directly linked to vegetation types *a priori*, but can be difficult to apply because of the weak empirical relationships between vegetation classes and fuel characteristics (Shankar 2006, Ran et al. 2007, Zhang et al. 2010, Keane et al. 2012a). The FLMs may be more problematic because they are identified by an iterative process that includes a fire-effects model (Lutes et al. 2009), but very possibly no more difficult to implement in the end.

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., BURNUP -- Albini and Reinhardt 1997) use physics-based heat-transfer equations to calculate combustion and then apply emissions factors to estimate smoke production. Emiprical models (e.g., CONSUME -- Prichard et al. 2007) fit regressions to field-based estimates of consumption and use fitted values from these with the same emissions factors. French et al. (2011) compared estimates from six models of carbon emissions from wildfires in North America, and the aforementioned SEMIP project (Larkin et al. 2012) compared five models for consumption and emission factors. Details are in those publications, and there was substantial variability among models for different fuel types under different conditions, but the spatial scaling issues associated with fuel characterization (above) do not obtain, so overall uncertainty associated with consumption and emissions calculations is less problematic.

The consequences of smoke are felt in local airsheds and downwind. 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. 2012) track gases and particulates, from local to regional and continental scales, carried by modeled meteorology. What follows draws on Goodrick et al. (2012), who provide much more detail on the state of the art in smoke-transport modeling *per se*.

Eulerian (grid-based) models focus on observing the passage of *parcels* (jargon for whatever is being tracked, e.g., 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 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.

Although they are increasing in sophistication, *puff dispersion* models (Langrangian models that follow puffs) are typically not designed to represent atmospheric chemistry, but rather to provide a fast screening tool, often used in regulatory air-quality assessments to characterize the atmospheric dispersion of plumes and estimate their maximum impacts at receptor locations. Thus they typically lack the detailed process representations (e.g., cloud dynamics and chemistry) to consider the atmospheric chemical transformations and interactions of plumes from various emission sources and source sectors that are needed to simulate the atmospheric composition over large regions. Their typical usage is in performing near-source impact estimates, often using worst-case assumptions on emission rates to assess the incremental impacts of individual sources such as power plants and industrial stacks on areas within a certain impact radius of the source. For example, the CALPUFF modeling system (Scire et al., 2000) is used in the development of EPA's Federal implementation Plans to quantify the incremental impacts of point and area emission sources and assess the visibility benefits of control technologies at national parks within a 300-km radius of each source. In these bounding estimates, in addition to holding the emissions from the source at the highest value over the period of interest, numerous simplifying assumptions are made on atmospheric composition. For example, species such as NH_3 that are not being evaluated for control measures may be set to constant background values throughout the study period, or use monthly or longer-term average values, 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 in that sense better able to track individual pollutant species, often $PM_{2.5}$ (e.g., Scire et al. 2000). On the other hand, state-of-science grid-based models are structured more efficiently to invoke submodels of relevant atmospheric chemistry and physics that evolve pollutant-species composition and secondary aerosol formation. The Community Multiscale Air Quality (CMAQ -- http://www.cmaq-model.org/) model (Byun and Schere, 2006) is a grid-based model with a long record of usage (Appel et al. 2012), and is the product of an open-source development project sponsored by the EPA since 1993 (the so-called "Models-3"). CMAQ not only tracks the primary emissions 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) at as fine a time scale as computational resources will allow. The finest spatial resolution of the model used to date (specifically in urban-scale assessments) is 1 km. WRF-CHEM (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 global climate model).

Chemistry transport models (CTMs) such as CMAQ and the Comprehensive Air Quality Model with extensions (CAMx; Environ 2011 and references therein), used to study urban-to-regional scale fire impacts on air quality, represent the spatial heterogeneity and temporal variability of primary and precursor species: elemental carbon, particulate organic matter, SOAs, CO, NOx and VOCs. These models are used with prescribed meteorology to simulate the long-range transport, vertical mixing, entrainment, mixing, and chemical processing in clouds; wet and dry removal; and the detailed gas-phase, aqueous, and particulate chemical transformations of pollutants over a few days to several months. Process algorithms for the evolution of reactive plumes, and treatment of the oxidation pathways and phase partitioning of secondary organic aerosol, simulate plume dynamics and chemistry following the onset of a fire event (Carlton et al. 2008, Karamchandani et al. 2012). CMAQ and CAMx have a long history of continuous refinement, review, and usage, and have been evaluated against observations around the globe, showing reliability in their predictions of criteria pollutants (Hanna et al. 2005, Itahashi et al. 2012, Rao et al. 2012). Tools such as the Decoupled Direct Method (Dunker et al. 2002, Cohan et al. 2006), developed specifically to quantify the model sensitivities, enable a process-level understanding of emission uncertainties and their sources, and are coming into greater usage for this purpose (Napelenok et al. 2006). The meteorological simulation data used to drive these models are generated *a priori* without dynamic coupling to atmospheric chemical processes, however, so these models do not model the effects of the feedbacks of aerosols on the radiation budget (see *Feedbacks*, below).

The spatial resolution of smoke-transport models is typically ≥ 4 km^2, too coarse to resolve the dynamics of key physical processes involved in smoke transport, especially initially (i.e., plume rise). *Full-physics* models (*sensu* Goodrick et al. 2012) invoke computational fluid dynamics (CFD) to model processes involved in plume development explicitly. As with full-physics fire-behavior models (Linn et al. 2002, Mell et al. 2007, Finney et al. 2012), and analogous to explicit cloud microphysics in RCMs, CFD-based models are currently impractical for simulations over the domains we are considering here (regional or CONUS-wide), and have yet to incorporate chemistry, although they show promise for some local applications (Valente et al. 2007).

With the multiple components of the proposed modeling system, 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 non-linear computations and re-scaling of data. Here we describe briefly two modeling frameworks and one such processor (of the latter type) that are currently available and widely used, while recognizing that there are many other examples.

The BlueSky smoke modeling framework (Larkin et al. 2009 -- http://www.blueskyframework.org/) simulates smoke emissions and dispersion from both real-time fire observations and simulated fires. Users have choices among spatial data layers for fuels, consumption and emissions models, plume-rise algorithms (i.e., how smoke is lofted into the atmosphere), and dispersion models. BlueSky has both operational and research (development) versions, with the former having undergone extensive testing and sensitivity analysis on its individual components (Larkin et al. 2012, Raffuse et al. 2012).

The Wildland Fire Emissions Information System (WFEIS; http://wfeis.mtri.org/) is a publicly available Web-based tool for computing emissions from wildland fires anywhere in the continental United States or Alaska (McKenzie et al. 2012). A principal use of WFEIS outputs is spatially explicit estimates, at regional scales, of the effects of fire on the carbon cycle (French et al. 2011), but in the process it calculates smoke emissions with Consume (http://www.fs.fed.us/pnw/fera/products/consume.html), one of the fuel-consumption modules in BlueSky that is widely used by fire managers. Like BlueSky, WFEIS has a development version and will be enhanced to incorporate simulated fires (e.g., future fires) and update spatial fuels data.

The Sparse Matrix Operator Kernel Emissions (SMOKE) processor (http://www.smoke-model.org/index.cfm) uses numerically efficient sparse-matrix operations to process large volumes of emissions data by emissions sector, including smoke emissions from wild and prescribed fires, for use with air-quality models. SMOKE achieves efficiency in throughput by separating the steps of chemical speciation, temporal allocation, and spatial disaggregation and gridding of inventoried sectoral emissions into sequential matrix multiplications. Air-quality models are coarsely gridded spatially in comparison to the areal extents of fires, partly for computational reasons but also because they are limited by the underlying spatial resolution of the meteorology. They use short model time steps (10-15 minutes) and aggregation time steps (hourly), however, compared to the reporting period of regional emissions inventories, typically annual for most emission sectors, including fires. Emissions data come in many forms, but there are usually scale mismatches with the air-quality models in space, time, or both. SMOKE developers have provided guidelines for creating “SMOKE-ready” data, such that it is now feasible, for example, to automate partially the integration of simulated fire emissions with models like CMAQ. Plume rise for point-source wildfires is calculated online in CMAQ, as for other point sources, e.g., from power plants.

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. In this section we focus on the atmospheric compositional changes due to smoke emissions, and their (mostly) positive feedbacks to radiative forcing. Bond et al. (2013) estimated this forcing to be the most important after GHG forcing, with black carbon and other short-lived climate forcers contributing up to 75% of the total aerosol forcing, even when integrated over 100 years after emission.

Feedback of aerosols from wildfires contributes to the surface energy budget, with consequences for planetary boundary layer height (PBLH) and photolysis rates. In a modeling study of the August 2007 wildfires in the Western U.S., Jiang et al. (2012) found that the direct aerosol feedback to the radiation budget reduced photolysis rates for NO_2 by up to 75%, thereby decreasing ozone. Further reductions in ozone occurred due to a decrease in surface solar heating that reduced the surface temperature by 2 deg. K, and due to associated changes in tropospheric chemistry. These reductions counteracted the increases in ozone mixing ratios that come from two sources: lowering of PBLH from the aerosol direct radiative feedback, and large NO_x and VOC emission fluxes from the wildfires. Inclusion of the aerosol direct radiative feedback in simulations corrects the overestimates typically seen of ozone in the vicinity of fire plumes if this feedback is ignored.

Cloud-aerosol interactions give rise to significant aerosol radiative feedbacks, which constitute the greatest uncertainty in radiative-forcing estimates (Forster et al. 2007). The aerosol (indirect) radiative feedback has at least two forms: (1) enhancement of cloud reflectance (albedo) due to an increase in the number of 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, due to the suppression of drizzle as a result of the decrease in cloud droplet diameter, and the longer time taken for cloud droplets to grow into rain drops through collision and coalescence (Albrecht 1989). This latter feedback 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 is estimated to be as large in magnitude but opposite in sign as the radiative forcing estimate for greenhouse gases (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.

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. Fasullo and Trenberth (2012) found that seasonal variability in relative humidity (RH) correlates well with cloud cover, and that in the Northern Hemisphere the summertime average RH over the subtropical oceans from 1989-1999 is well correlated with the equilibrium climate sensitivity of climate models. This provides a possible observational constraint on the models, although several other factors that may or may not correlate with the subtropical RH variability also 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 semi-direct effect of absorbing aerosols on clouds. A modeling study by Hansen et al. (1997) on low clouds showed a warming of the cloud base due to an increase in static stability from the scattering of radiation by aerosols below the cloud. Ackerman et al. (2000) found similar results in Large Eddy Simulations, where a black-carbon layer heated the lower troposphere, evaporating the cumulus clouds due to reduced convection in the boundary layer and lower relative humidity. 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. The semi-direct effect is defined differently in different studies, however, some of which include the longwave radiation response to changes in land surface and tropospheric temperature. This had led some authors (Penner and Zhang 2003) to conclude that biomass combustion aerosol may not produce a climate warming, but recently Bond et al. (2013) showed that the direct radiative forcing of black carbon is approximately +0.71 W m^{-2}. If correct, this is a huge radiative impact, with significant contributions from biomass burning to the total.

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 both negative (in tropical forests) and positive (in boreal forests) feedbacks to climate warming (Bonan 2008, Swann et al. 2010). 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 global climate models 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).

All of these feedbacks are also important for regulatory concerns. Wildfires increase tropospheric ozone production due to the large amounts of NOx and VOC emitted in 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 35ºN in the eastern and mid-western U.S. (Wotawa and Trainer

2000). A concern raised by these increases from the perspective of air-quality management is that urban ozone mixing ratios, especially in NO_x-limited areas, would be more sensitive than rural areas due to the *in situ* oxidation of CO transported into the airshed in wildfires by local NOx emissions (McKeen et al. 2002). Areas marginally in attainment of the NAAQS for 8-hour ozone could become non-compliant during fire events.

Further scaling issues

We have alluded earlier to the challenge to comprehensive simulation models for climate, fire, and air quality presented by the disparate scales, both temporal and spatial, at which the processes of relevance for these interactions occur. We introduced scaling problems associated with vegetation, fuels, and fire; here we provide examples of scale disparities associated mainly with the atmospheric domain.

Regional assessments of wildfire impacts on the ecosystem under a changing climate require reliable predictions of of meteorological variables, not only over time periods and spatial extents of large enough magnitudes to represent changes in synoptic circulations, but also at a sufficiently fine spatial resolution to characterize regional or even finer-scale variability in fuel loads and fire weather. As these vary across differing scales in different parts of the country (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 and their potential health impacts. For example, Kreidenweis et al. (2001) used observed concentrations in Big Bend National Park during May 1998 wildfires in Mexico to improve information on aerosol physical and chemical properties, and found significant differences in the aerosol composition in these plumes from those found in Africa and South America. They also demonstrated the role of aerosol aging along the plume transport path in determining the final composition observed at the receptor location, showing that procsses must be captured at multiple scales of space and time to characterize regional-scale spatial variation properly.

A cost-effective way to address some of these scale disparities is through downscaled modeling at urban to regional scales, using RCMs forced by the synoptic circulations projected by a global climate model. 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. 2012a,b). Analysis nudging tends to suppress the variability at wavelengths resolved by the RCM, however, which may limit the usefulness of this method (Rockel et al. 2008, Bowden et al. 2012a). Despite this issue, Otte et al. (2012) showed that within the Weather Research and Forecasting (WRF -- Skamarock et al. 2008) model, the extremes are predicted better when applying either form of nudging than with no interior grid nudging. Many RCM simulations use spectral nudging because it focuses on nudging only to wavelengths that can be resolved by the input data.

It is important in these downscaled studies to understand the limitations of using 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 sub-grid scale when the model resolution is coarse, e.g., ~ 100-300 km in the case of climate models. Provision must be made in multiscale studies to switch from implicit to explicit representations, for example, of cloud physical and chemical processes and precipitation when the grid resolution is refined. Similar considerations apply to the use of reactive plume models to simulate fire-plume dynamics and dispersion of pollutants into the ambient air. Models currently in use (e.g., CMAQ and CAMx) automate this switching, or can be configured at run time to compile and build the appropriate process sub-model when running multiple nested simulations. A modular modeling structure is very useful in this regard, and also provides a platform in which algorithms can be easily replaced when improved process formulations become available, or when alternative algorithms need evaluation against existing ones.

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 techniques in the RCMs need to be tested 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.

Building models

We are proposing a modeling system whose conception, construction, and use require expertise in multiple disciplines and diverse technical skills. Process formulations in climatology, meteorology (including cloud and radiation interactions), atmospheric chemistry, vegetation and landscape ecology, fuel and combustion science, and reconciliation of their differing spatial and temporal scales inform the model content; numerical methods, large-database management, and software architecture inform its implementation. Consequently, we expect that collaborative efforts will be the norm, with each individual PI 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. Not all modeling-system constructions will follow the same path. In what follows we provide a modeling agenda advocating the most detailed representations of all processes (see Table 1, pp. 62-65), then a set of general criteria for evaluating modeling systems, and then four example modeling pathways that exemplify the variety of plausible choices one might make for specific applications.

Figure 6 gives four example pathways to building an integrated system, based on the "master" flowchart in Figure 4. These combinations are by no means exhaustive, but they present variations on a theme for meeting the following four criteria that we believe are essential for moving the science and software forward to understand 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). For example, RCMs that are well validated with respect to meteorological outputs

can have very different outcomes when used for air-quality assessment (Hogrefe et al. 2004, Leung and Gustafson 2005, Gustafson and Leung 2007, Menut et al. 2012).

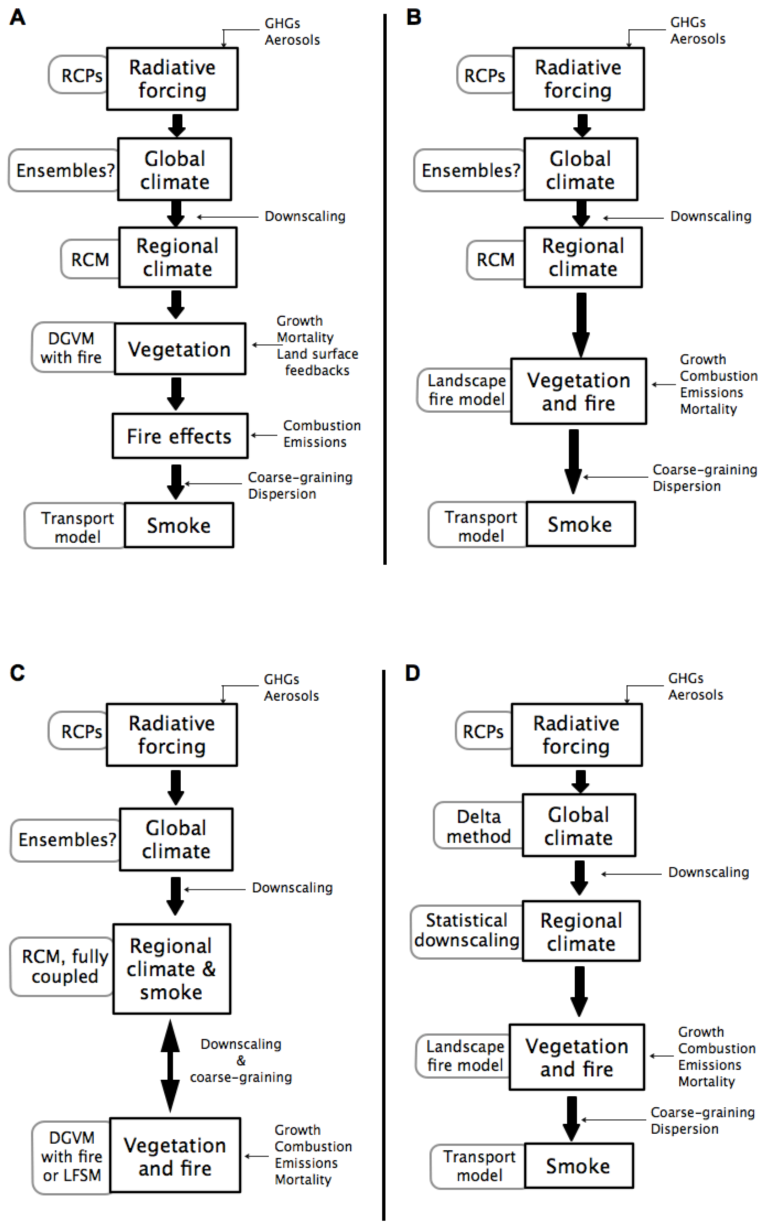

Figure 6. Example pathways for realizing models abstracted by the flowchart in Figure 4. Criteria for choices include 1) minimizing cumulative error, 2) algorithmic and computational feasibility, 3) transparency of outcomes, 4) robustness to future projections. GHG = greenhouse gases. RCPs = representative 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.

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 resolution cannot be run across the CONUS (Keane et al. 2002). More challenging is optimizing the tradeoff between model rigor and complexity and sufficient replication to capture a distribution of outcomes. This replication may be parsed further into ensemble modeling at some stage (probably regional climate modeling) vs. replication of one model (Pierce et al. 2009, Knutti et al. 2010).
3. Transparency of outcomes. This is analogous to the "black box" issue, but focuses on understanding why 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, and is globally recommended in modeling, though not always implemented. Just as important, however, is semantic or logical transparency. Can you explain, in words or perhaps symbols, why your model produced a certain outcome? For example, an outcome may be counter-intuitive, and be the one stochastic realization that produced an outlier to expectations (Deser et al. 2012b). Transparency could mean the difference between (a) discarding a good theory or casting out the outlier(s) or (b) refining or extending the range of inference.
4. Robustness to future projections. There is the classic problem of *pattern matching* (also sometimes called "wiggle matching") (Cushman et al. 2007), seen as over-fitting[2] in empirical models and over-calibration in simulation models. Whether adding explanatory variables, or tuning parameters, or both, there can be tradeoffs between matching observations and maintaining flexibility to operate in a changing domain. For example, McKenzie et al. (2004) fit linear regressions of log (area burned) to temperature and summer precipitation for 11 western states, then projected models onto future climates from two global climate models. The cooler and wetter climate model realization produced unrealistically high burned-area projections for most states (although these are often cited); the more extreme climate model projected physically impossible values for annual area burned, and was not reported. More

[2] von Neumann is reported (Silver 2012) to have said "With four parameters I can fit an elephant, and with five I can make him wiggle his trunk."

subtly, Mote and Salathé (2010), in projecting future climate for the Pacific Northwest, used weighted means of output from 20 climate models, with the weights being a function of the accuracy of the models in matching observations within the region. Intuitively, this is an improvement on unweighted ensembles, which have their own issues (Knutti et al. 2010), but makes the assumption of stationarity in the observation-model crosswalk.

Pathway A in Figure 6 is perhaps the simplest in that scaling issues (see above) are restricted to the initial downscaling of global climate output to an RCM. The DGVM includes fire algorithms, including fire-effects calculations, at its native scale (*sensu* Arora and Boer 2005, Lenihan et al. 2008). Information flows mostly in one direction; no coupling (see above) is used except for static land-surface feedbacks to the RCM. Key sources of error are mismatches between the native scales of vegetation processes and fire effects, and the feedbacks between them, and omission errors (of key spatial processes driving fire and fuels [Keane et al. 2012b]). Algorithmic and computational feasibility is likely moderate-to-good. Transparency depends on the individual components and their history with the modelers. Robustness to future projections is likely compromised because without coupling, model states will "wander" into plausible but vanilla futures that do not reflect feedbacks.

Pathway B replaces the DGVM with an LFSM such as FireBGCv2 (Keane et al. 2011), which combines mechanistic algorithms from DGVMs with spatial processes and disturbances at multiple fine scales (compared to DGVMs). Once again information flows in one direction, even more so than in "A" because LFSMs as currently implemented do not feed back to RCMs. Scaling error of one type (mismatch of process and scale) will be reduced, although there will still be cross-scale error propagation (McKenzie et al. 1996). Algorithmic and computational feasibility is possible only if detailed processes are restricted to representative sample landscapes and extrapolated across the rest of the domain (CONUS). Transparency once again depends on the individual components, but is likely inversely related to the complexity of the LFSM (Keane et al. 2004). Robustness to future projections of fire and smoke may be higher, at least at fine scales, than for systems using DGVMs, for one because *landscape memory* (Peterson 2002, McKenzie et al. 2011), in its simplest form the legacy of past disturbances, i.e. fires, is meaningful only at the finer scales at which LFSMs operate.

Pathway C involves fully coupled modeling of all regional processes. WRF-CHEM (Grell et al. 2011) and WRF-CMAQ (http://www.epa.gov/amad/Research/Air/twoway.html) are examples of ongoing efforts in that direction, which is an objective of numerous modeling groups (Grell and Baklanov 2011). Currently, we know of no fully coupled implementation of all the model components. As with Pathway A, a key part of error propagation will be associated with downscaling and coarse-graining. Algorithmic and computational feasibility will surely be a limiting factor, leading to fewer replicates than with systems whose models run more independently. Transparency may be questionable, but will be improved by specifying interim outputs judiciously, so as to avoid an end product that was produced in too many stages to comprehend. Logical transparency may indeed be greater, however, than for uncoupled models with their associated "loose threads". Robustness to future projections should ideally be high, under the assumption that capturing dynamic processes is important, and that feedbacks really matter.

Pathway D is the opposite of Pathway C, in that the simplest methods are proposed for each step except the fire modeling *per se*. Both global and regional climate are statistically downscaled, leaving the computational space mostly open for an LFSM, which could be replicated enough times to ensure coverage of the range space of all the landscape processes simulated mechanistically (Loehman and Keane 2012). Errors will come from the absence of dynamic interactions, to the degree that this Pathway would probably be difficult to move past peer review. Computations will be feasible, and transparency fairly high. Robustness for the future might be acceptable for average predictions, but capture variance poorly, and extremes probably not at all (NOTE: the latter is a problem for all models).

It is easy to say, and not particularly helpful, that no one system will produce the best answers for every question regarding smoke consequences, and that choices of models and linkages should depend on the specific question at hand. Conversely, it would be misleading to be too prescriptive, given the uncertainties at each step in the process, and the variety of objectives within the overarching goal of future projections. Consequently we present some guidelines that could serve as a checklist for aspiring modelers of future fire and smoke.

1. Coupled is better than disconnected (dynamic is better than static)

We have described some of the many feedbacks in the Earth system. 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 (see #5 below). 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 assumptions about which system changes can be discounted (effects of circulation on atmospheric chemistry in the former, climate-vegetation-fire interactions in the latter). We believe that these assumptions are largely untenable.

2. Distributions are better than points (but don't 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. For example, frequency distributions of fire sizes appear to follow power laws in some regions (Moritz et al. 2011), while deviating from them in others (Reed and McKelvey 2002). Multiple realizations of a simulated fire regime could be compared to these predictions, which of course are unlikely to be stationary themselves in a changing climate.

One must, of course, control the number of combinations needed to generate distributions. Models that are completely deterministic, such as the fire-effects modules Consume (Prichard et al. 2007) and the First-Order Fire Effects Model (Reinhardt and Brown

1997), may have only one replicate each when used in ensembles (Larkin et al. 2012). Conversely, stochastic distributions of fuels at the regional scales associated with modeling might be more realistic (Keane 2012).

A final concern is where to use means from ensembles, and at what level in the modeling, as opposed to preserving the variability within them for use at the next stage. For example, air-quality models such as CMAQ 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 CMAQ outputs can be afforded and still project future variability with some confidence? What level of decadal sampling is required in the input synoptic circulations for the driving RCM, and what is the minimum number of air-quality simulation years to capture intra-annual (seasonal), interannual, and inter-decadal variability? 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.

3. Watch out for scale mismatches

Some scale mismatches are intrinsic to the modeling system we are proposing (Figure 4). Perhaps the largest is between fire-behavior and fire-effects algorithms and the models that drive them (RCMs and DGVMs), and 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). We have suggested above that 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 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), albeit with some success due to careful evaluation and calibration by the modelers. 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.

4. 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 feedbacks are positive or negative? Will simplification or omission of interactions and feedbacks produce robust projections? What about phenomenological or stochastic representation of fire at broad spatial scales? This may be better than risking the error propagation across scales associated with using mechanistic algorithms (McKenzie et al. 1996), but basic elements of fire science, such as arrangement, abundance, and condition (moisture) of fuels and the effects of wind and slope, should not be ignored.

Two further considerations affect the optimal threshold of simplicity: (1) tradeoffs 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, especially for low-severity fire (but see Swetnam et al. 2011). 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).

5. Give yourself a chance to be wrong (also give yourself a chance to be right)

This one applies particularly to model developers, and is related to the problems of over-fitting and over-calibration, and to the robustness of future projections. Observations, and verification or "validation", are important for simulation modeling, but bringing them in too soon and adjusting will be counter-productive, because it may camouflage basic errors in model content (Ford 2000). Being "wildly wrong" at some stage may be the most informative thing that can happen.

Different models confront these issues in different ways. For example, RCMs solve equations for conservation of mass and energy, based on a clear understanding of the physics. Approximations, or adjustments, occur for physics that are too complex to resolve at the scale of the models. Informed choices of parameters based on first principles are weighed against matching outcomes to observations such as instrumental climate records. 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, i.e., for the future (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 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. A similar, though less obvious, omission is the outcome of using statistical downscaling to represent regional climate. Although this may be more efficient for some meteorological applications, it precludes the explicit simulation of mesoscale circulations that are necessary for transport models. A third potential pitfall is that global climate models and RCMs use land-cover data that may very well deviate from the real future state, which calls into question the driving meteorology for coupled models. This issue can take subtler forms; for example, 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, Kennedy and McKenzie 2012).

6. Decide which uncertainties you can live with

This is partly about avoiding "show-stoppers", such as in #5 above, but also about the issue of resolving trade-offs. For example, 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 CONUS-wide modeling one might eschew a finer-scale landscape fire model, out of concern 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. Alternatively, one could invent a way to scale up LFSMs to DGVMs (McKenzie et al. 1996).

Some choices and tradeoffs may not be purely scientific, but relate to available data and resources and wider socio-political 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). Similarly, more historical observations and model outcomes are associated with the NARCCAP projections than if making a fresh start with RCMs and the AR5 global model output, but with the former approach one risks having an anachronistic product.

Research needs

An integrated Earth-science model of the one we envision will of course 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 that we believe address important needs for the modeling system as a whole: two 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.

Trade-offs: uncertainty, feasibility, and optimizing ensembles and coupled models

We alluded earlier to the unanswered questions about ensembles of global climate models (see Knutti et al. 2010). The evaluation of ensembles of chemistry-transport models, coupled and decoupled from RCMs, is at an even earlier stage, but the uncertainties associated with single realizations are analogous to those of global climate models.

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. Such evaluation usually invokes a Bayesian framework. For example, inverse modeling with Bayesian hierarchical methods provides a nuanced approach to 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) used Bayesian model averaging in a 200-member ensemble of CMAQ simulations to interpret the comparisons of model results with observations of 8-hr ozone concentrations. Such techniques can be used to diagnose structural errors in ensemble members, and to understand the effectiveness of control strategies probabilistically.

A next step in the use of these well established probabilistic methods would be to extend ensembles to the coupled modeling that we have proposed, while specifically varying levels of complexity, for example in the specification of fires via the choice of DGVM. In other words, a rigorous probabilistic comparison would supersede a qualitative evaluation of alternatives such as those in Figure 6. The computational burden of generating the requisite multi-year 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; for example, in an international initiative to evaluate process representations in air-quality models in different airsheds (Rao et al. 2012). Such an effort would inform the question of how much complexity is needed to provide useful projections of smoke consequences.

Scaling, landscape complexity, and model evaluation

What are the biases, errors, and scaling factors associated with representing fire regimes and smoke production at coarse enough spatial scales for CONUS-wide modeling to be feasible, with respect to both computational limits and data availability? 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, such as the mountains of both the West and East, there is much within-(DGVM)cell heterogeneity in the fine-scale controls on fire, topography, and fuels.

In those cases, LFSMs might provide a surrogate for the ground-based observations that are unavailable for future projections. Of course no model is error-free, but then neither is a raster-based data layer extrapolated directly from observations (Keane et al. 2013). LFSMs run over select "validation" domains could effect a cross-scale sensitivity analysis of a DGVM, holding global settings (RCP, global climate model, downscaling method, etc.) constant. What landscape process matters most among those that are missing at the scale of DGVMs? 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 accounting for 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 CMIP5, NARCCAP, or SEMIP. "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.

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 term. Abrupt climate changes are documented for the Holocene and before, and are an evolving concern for scientists and policy-makers world-wide (CCSP 2008). Extreme climate events in recent years are linked statistically to ongoing 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 (Cunningham and Reeder 2009), their extent and homogeneity of severity (e.g., recent New Mexico fires, C.D. Allen, *pers. comm*.), or their smoke consequences (the Russian fires of July 2010 and the 2012 fires in the American West).

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). On landscapes of the West, 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 and references therein). 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. 2009, 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 Johnson 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 non-linearities or strong positive feedbacks will change with no warning. Given the inherent non-linearity 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. Following the second part of our guideline #3 (above), 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, following our guideline #6, 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).

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. Realizing this (something the authors came to early on though not immediately), 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. 2013), 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 July 4, 2050 than it was on July 4, 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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Table 1. Agenda for a modeling system, classified by system component, spatial and temporal scale of operation, and specific problem(s) addressed. "Scale" is represented by practical (perhaps only quasi-practical) ranges. The disparity in scales is clear and is a problem in itself (see text) (GCM – general circulation model; RCM - regional climate model, DGVM - dynamic global vegetation model, LSFM - landscape fire succession model, CTM - chemistry transport model, BC - black carbon, VOC - volatile organic carbon).

Component	Spatial and temporal Scale	Problem addressed	Solution
Regional climate	4-36 km^2 Hourly to daily	Meso- and finer-scale processes need representation at those scales. Spatial processes (e.g., mesoscale circulations) needed for smoke transport.	Downscaled climate using suitable boundary conditions (would need implicit schemes except at resolvable scales for some processes, e.g., sub-grid modeling of clouds). Nudging approaches capture region-specific synoptic circulations consistent with the driving GCM. Dynamic downscaling (from GCM) suitable for linkage to atmospheric CTMs, nested down to spatial resolutions of interest.
Vegetation	<1-36 km^2 Monthly to decadal	Dynamically changing vegetation in response to climate, disturbance, and biotic interactions. Scaling	Species differences in vegetation represented; fuel components simulated independently; succession included in live biomass predictions; mixed species and multiple strata simulated explicitly. Temporal scale of inputs to the model may need aggregation from the RCM time scale to one-month intervals.

Component	Spatial and temporal Scale	Problem addressed	Solution
Fire	30 m^2 -1km^2 Daily to annual	Fire is stochastic Fire is contagious Scaling	Fire regimes are an emergent outcome of fire weather, ignitions, and fuels. Fire-regime properties (frequency, severity, extent) are not pre-specified. Fire is represented as a spatial process, at least implicitly. A coarse-scale surrogates for fire ignition, spread and termination; fuel characterization suitable for fire simulation
Smoke emissions	30 m^2 - 1 km^2 Daily to annual	Emissions are specific to fuel type and combustion phase. Fuels vary at fine spatial scales. Different pollution species interact differently with atmosphere. Other emissions (e.g., biogenic) interact with smoke constituents in atmosphere. Scaling	A translation of plant biomass and necromass to fuel loads, partitioned into live and dead (woody) fuels, then to size classes, and fuel type. Explicit accounting for fuel variation across space. 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. Speciated emissions of major anthropogenic and natural emission source sectors other than wildfires. Spatial allocation and temporal disaggregation of emissions for use in CTMs.

Component	Spatial and temporal Scale	Problem addressed	Solution
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 multi-scale 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^2 - ~30 km^2	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 multi-phase multi-pollutant 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.

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 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, shift in species) are explicitly modeled.
		Scaling	Minimize errors in feedbacks between components modeled at different scales; reliable sub-grid schemes, switching to explicit representations at the appropriate scales (e.g., clouds).

Table A1. Acronyms used more than once in the text or figure captions.

Acronym	**Meaning**
AET	Actual evapotranspiration
AOGCM	(coupled) atmospheric-ocean general circulation model
BC	black carbon
CAMx	Comprehensive Air Quality Model with Extensions
CCN	cloud condensation nuclei
CFD	computational fluid dynamics
CFFDRS	Canadian Forest Fire Danger Rating System
CLM	Community Land Model
CMAQ	Community Multiscale Air Quality (model)
CMIP	Climate Model Intercomparison Project
CONUS	conterminous United States
DEF	water-balance deficit
DGVM	dynamic global vegetation model
FCCS	Fuel Characteristic Classification System
FIA	Forest Inventory and Analysis
FLM	Fuel Loading Model
FTG	Forest Type Group
FWI	Fire Weather Index
GCM	global climate model OR general circulation model
GHGs	greenhouse gases
IMPROVE	Interagency Monitoring of Protected Visual Environments
IPCC	Intergovernmental Panel on Climate Change
LFSM	landscape fire succession model
LSFs	land-surface feedbacks
NAAQS	National Ambient Air Quality Standards
NARCCAP	North American Regional Climate Change Assessment Program
NFDRS	National Fire Danger Rating System
NOx	oxides of nitrogen
PBLH	planetary boundary layer height
PET	Potential evapotranspiration
PM	particulate matter
RCM	regional climate model
RCPs	Representative Concentration Pathways
RH	relative humidity
SEMIP	Smoke Emissions Model Intercomparison Project
SMOKE	Sparse Matrix Operator Kernel Emissions
SOA	secondary organic aerosol
SRES	Special Report on Emissions Scenarios
VOC	volatile organic compound
WFEIS	Wildland Fire Emissions Information System
WRF-CHEM	Weather Research and Forecasting (model) with Chemistry

Table A2. This is a sampling of models, frameworks, and projects useful for coupling climate, vegetation, wildfire, and air quality in North America. This list is not exhaustive. Models given more than cursory treatment in the text are noted. RCM - regional climate model. DGM - dynamic global vegetation model. LFSM - landscape fire succession model. FCS - fuel classification system. FE - fire effects. FB - fire behavior. FD - fire danger. SE - smoke emissions. ST - smoke transport.

Type	Model	URL or citation	Description
Climate			
RCM	Fifth Generation NCAR/ Pennsylvania State Mesoscale Model (MM5)	Grell et al. 1994, Gustafson and Leung 2007	MM5 is a non-hydrostatic, mesoscale atmospheric model that simulates the hydro-climate dominated by orographic effects and cold-season processes. Note that MM5 is no longer actively supported as an operational model by NCAR, having been superseded by WRF.
RCM	Canadian RCM (CRCM)	Caya and Laprise 1999, Plummer et al. 2006	CRCM is a mesoscale non-hydrostatic community model that uses an efficient semi-implicit, semi-lagrangian numerical scheme, which allows for relatively fine spatial (45km) and temporal resolution (15 minutes). The regional model nests a high-resolution limited-area model with a coarser-resolution global driving model.
RCM	Weather Research and Forecasting (WRF)	Skamarock et al. 2008	WRF is a mesoscale weather-forecasting model for research and operational purposes that operates at a broad range of spatial scales (meters to thousands of kilometers). The modeling framework is designed to be flexible and efficient at incorporating physics into a dynamic solver.

Type	Model	URL or citation	Description
RCM	Regional Spectral Model (RSM)	Juang and Kanamitsu 1994, Han and Roads 2004	RSM is a hydrostatic spectral model that uses primitive equations in two nested components: (1) high-resolution regional spectral models (different by region), and (2) a low-resolution global spectral model. Spectral models have been shown to produce better forecasts than grid-point models especially at large scales or near the surface and are computationally efficient.
Vegetation (Quillet et al. (2010) has a more exhaustive review)			
DGVM	MC1	Bachelet 2001, Bachelet et al. 2003	MC1 represents the effects of climate on ecosystem structure and function for a wide range of spatial scales from landscape to global. MC1 links three modules that simulate biogeography, biogeochemistry and fire disturbance. The fire component, MC-FIRE, is a complex process-based module that simulates the occurrence, behavior, and effects of severe fires that then feeds back into the model to represent carbon and nutrient pools as well as vegetation structure.
DGVM	Canadian Terrestrial Ecosystem model (CTEM)	Arora and Boer 2005	Coupled with the Canadian Land Surface Scheme (CLASS), CTEM is a mechanistic model that simulates three live vegetation pools and two dead carbon pools to produce estimates of water, energy and CO2 flux at the land-atmosphere boundary. CTEM includes a process-based fire component (FIRE) that incorporates fuel availability, flammability and ignition source into area burned estimates based on fire spread and fire duration.
DGVM	Community Land Model Vertion 4 (CLM4)	Oleson et al. 2010, Kluzek 2012	CLM4 is a coupled dynamic vegetation model with a carbon and nitrogen component (CN). CN includes a fully prognostic treatment of the terrestrial carbon and nitrogen cycles as mediated by biological mechanisms of plants and soil dynamics. Fire is included in this component as a modified LPJ-Glob-FIRM that translates the original annual time step to the sub-daily time step of CLM.

Type	Model	URL or citation	Description
DGVM	Lund-Potsdam-Jena (LPJ-DGVM)	Thonicke et al. 2001, Sitch et al. 2003, Thonicke et al. 2010, Prentice et al. 2011	LPJ-DGVM is a process-based model representing large-scale terrestrial vegetation dynamics and land-atmosphere carbon and water exchanges. There are three commonly used fire modules: Global FIRe Model (Glob-FIRM), SPread and InTensity of FIRE (SPITFIRE), and Land surface Process and eXchanges (LPX). Glob-FIRM links statistical relationships based on the historical record for fire season length with process-based algorithms for estimating fuel conditions on moisture to determine area burned and fire effects such as fire spread. It does not account for human-altered fire regimes. SPITFIRE is processed based and simulates fire occurrence (distinguishing between human and naturally ignited fires), spread, and the amount of fuel consumed with intermediate complexity to represent the consequences for mortality and regeneration of plant functional types. LPX is very similar to SPITFIRE except that it only accounts for: lightning ignited fire regimes, geographic patterns of seasonality with only one parameter, variability of drying in different components of the fuel, and decomposition of litter, which improves seasonal fire timing.
Landscape Fire Succession (Keane et al. (2004) has a more exhaustive review)			
LFSM	FireBGCv2	Keane et al. 2011	FireBGCv2 is a complex, mechanistic, individual-tree, spatially explicit, gap model that operates across and within spatial and temporal scales. The model incorporates empirically derived deterministic functions that represent well understood ecological processes, such as autotrophic respiration, and stochastic functions for highly variable, less studied, and difficult to quantify processes, such as fire ignition, tree mortality, and snag fall. FireBGCv2 simulates fire behavior, fuel consumption, smoke, and carbon and nitrogen pools across the landscape.
LFSM	EMBYR	Gardner et al. 1996, Hargrove et al. 2000	EMBYR is an event-driven, grid-based model that uses probabilities to simulate wildfires and landscape pattern stochastically in heterogeneous areas. It simulates fire ignition, spread, and a qualitative index for fire severity calculated as a linear function of fuel type, fuel moisture, wind speed, and spread rate for a given cell.

Type	Model	URL or citation	Description
LFSM	LANDscape SUccession Model (LANDSUM)	Keane et al. 2002	LANDSUM is a spatially explicit, rather simple, vegetation dynamics model that simulates succession as a deterministic process and disturbance, like fire, as a stochastic process. This model assumes that all successional pathways will eventually converge to a stable or climax plant community (i.e. potential vegetation type). Fire is represented by three phases in the model: initiation, spread and effects, all of which are stochastically simulated.
LFSM	LANDIS	Mladenoff and He 1999, Mladenoff 2004	LANDIS is a spatially explicit model for studying species-level forest succession with changes in large (hundreds to thousands of hectares), heterogeneous forest landscape pattern from windthrow, fire, and management such as harvesting. It is designed to operate stochastically at a range of spatial resolutions over an extended period of time.
LFSM	LandClim	Schumacher et al. 2006	LandClim is a model modified from LANDIS as a landscape-level model that simulates climate-fire-vegetation dynamics. Modifications include quantitative descriptions of forest structure, explicit incorporation of competition, climatic, and edaphic influences on population dynamics, and inclusion of fire regime as an emergent ecosystem property based on climate and fuel load. LandClim simulates vegetational succession cell-by-cell, while representing fire, windthrow, harvesting, and dispersal in a landscape model.
LFSM	LANDSIM	Roberts and Betz 1999	LANDSIM uses autecological characteristics of specific species to predict species' behavior under recurrent disturbance, like fire, by aggregating spatially explicit sites, each representing unique locations on the landscape. LANDSIM distinguishes between physical indicators (e.g. disturbance intensity and severity) and biological indicators (e.g. survival), both of which are used in concurrence with the species-assigned fire tolerance to determine species recovery after disturbance. LANDSIM has been applied at a variety of scales from stand to landscape.

Type	Model	URL or citation	Description
Fuels			
FCS	Fuel Loading Models (FLM)	Lutes et al. 2009	FLM is a fuel classification of fuel loadings (e.g. duff, litter, fine woody debris, and logs) that produce significantly different emissions and maximum fuel surface temperature. FLM used classification tree analysis to estimate critical fuel loadings associated with ten different fire-effects groups, defined by classifying soil temperature and emissions from the First Order Fire Effects Model (FOFEM). (SEE TEXT)
FCS	Landscape Fire and Resource Management Planning Tools Prototype Project (LANDFIRE)	Rollins 2009	LANDFIRE provides consistent and comprehensive geospatial maps of vegetation, wildland fuel, fire regimes and ecological departure from historical conditions. LANDFIRE was developed for landscape-level fire management operations. It incorporates a variety of geospatial technologies including biophysical gradient analysis, remote sensing, vegetation modeling, ecological simulation, and landscape disturbance and successional modeling (using LANDSUM).
FCS	Fuel Characteristic Classification System (FCCS)	Ottmar et al. 2007	FCCS catalogues fuelbeds and classifies them based on their capacity to support fire and consume fuels at a variety of spatial scales for each existing fuelbed stratum including canopy, shrubs, non-woody, woody, litter-lichen-moss, and duff. The system then classifies each fuel bed based on fire potentials, which provides and index for the capacity of the fuelbed to support fire behavior. (SEE TEXT)
Fire Effects, fire behavior, fire danger			
FE	First-order Fire Effects Model (FOFEM)	Reinhardt et al. 1997	FOFEM is a national model for first-order fire effects that concern the direct and immediate consequences (e.g. tree mortality, fuel consumption, mineral soil exposure, and smoke) of fire. The model is broken into four regional models that are further divided into forest cover types.

Type	Model	URL or citation	Description
FD	National Fire Danger Rating System (NFDRS)	Cohen and Deeming 1985	NFDRS provides empirically derived indices for measuring wildland fire potential using local weather and fuel classifications as defined by fuel models within the system.
FD	Canadian Forest Fire Danger Rating System (CFFDRS)	Stocks et al. 1989, Lawson and Armitage 2008	CFFDRS, an empirically developed fire danger classification system, has two major components: (1) Fire Weather Index (FWI), which provides numerical indices of relative fire potential based solely on weather observations, and (2) Fire Behavior Prediction (FBP), which accounts for variability in fire behavior among fuel types.
FB	FIRETEC	Linn 1997, Linn et al. 2002	FIRETEC is a physics-based wildfire model that uses a transport approach to represent average behavior of gases and fuels in regions with nonhomogeneous vegetation and terrain. The model is divided into parts that account for microscopic details with macroscopic resolution of fire behavior by simulating an evolving set of coupled physical processes.
FB	BehavePlus	Andrews 1986, Andrews 2009	BehavePlus, an extension of the BEHAVE fire behavior prediction model, has as primary outputs surface fire spread and intensity, safety zone size, point source of fire, fire containment, spotting distance, crown scorch height, tree mortality, and probability of ignition. BehavePlus incorporates fire modeling from the original BEHAVE but also includes new fire models.
FB	FARSITE fire area simulator	Finney 1998 -- www.fire.org	FARSITE uses many of the same fire models as BEHAVE, but it is more designed to model fire growth across variable fuel and terrain under changing weather, i.e. when more detailed spatial and temporal information is required for a simulated fire.
FE	CONSUME	Prichard et al. 2007	CONSUME predicts the amount of fuel consumption, emissions, and heat release from burning based on weather data, the amount of fuel, and fuel moisture. The model is useful for determining when and where to prescribe a burn or plan for a wildland fire. Consume can be used for most forests, shrub lands, and grasslands in North America.

Type	Model	URL or citation	Description
FB	Wildland urban interface Fire Dynamics Simulator (WFDS)	Mell et al. 2007	WFDS is a physics-based, two- or three-dimensional model with separate but coupled models for thermal degradation of soil and gas-phase combustion. It operates best over hundreds of meters because of the heavy computational resources required. The model simulates fire spread through trees (crown fuels) and shrubs (surface or crown fuels, depending on the height of the shrub) using computational fluid dynamics.
Smoke			
SE	Sparse Matrix Operator Kernel Emissions (SMOKE)	http:www.smoke-model.org/index.cfm	SMOKE is an emissions processing system that creates gridded and speciated, hourly emissions for input into air quality models using a sparse matrix approach, which allows rapid and flexible processing of inventoried sectoral emissions. SMOKE can process emissions from area, biogenic, mobile, and point sources, using global, regional and local inventories. It has been linked to the BlueSky smoke emissions model, to process wildfire emissions inputs to the CMAQ model (see below).
ST	Comprehensive Air quality Model with eXtensions (CAMx)	ENVIRON 2011	CAMx is a photochemical dispersion model that simulates the emission, dispersion, chemical reaction, and deposition of particulate air pollution in the troposphere over a range of scales from sub-urban to continental on a system of nested, three-dimensional grids. A major benefit of CAMx is that it can be configured to match the horizontal and vertical grid structures of any meteorological model used to provide input.
ST	VSMOKE	Lavdas 1996	VSMOKE is a Gaussian-plume smoke-dispersion model that estimates smoke impacts from prescribed burning (but can also be applied to agricultural fires or wildfires) on air quality and visibility. VSMOKE is designed for use by atmospheric dispersion modeling specialists.

Type	Model	URL or citation	Description
ST	Simple Approach Smoke Estimation Model (SASEM)	Riebau et al. 1988	SASEM is a Gaussian-plume smoke-dispersion model that has minimal data and computational requirements and is easily applied by fire-management field personnel. The model estimates plume rise, emissions concentration, and a distance range of violated air-quality standards using fireline intensity, wind speed, atmospheric stability, average fuel loading, and fuel type.
ST	CALPUFF	Scire et al. 2000	CALPUFF is a general non-steady state, air-quality modeling system with three main components to (a) simulate meteorology within a user-defined modeling domain (CALMET), (b) calculate pollutant concentrations due to puffs of emissions dispersed from user-defined emission sources and chemically transformed during transport to user-specified receptor sites within the domain (CALPUFF), and (c) post-process the results into visibility impairment estimates at those sites (CALPOST).
ST	HYbrid Single Particle Lagrangian Integrated Trajectory (HYSPLIT)	http://ready.arl.noaa.gov/HYSPLIT.php	HYSPLIT is a simple air parcel trajectory model (i.e. it computes the trajectory of a single pollutant particle) used to simulate complex dispersion and deposition of air pollutants. HYSPLIT assumes either puff or particle dispersion on a three-dimensional grid.
ST	FLEXPART	Stohl et al. 1998	FLEXPART is a Lagrangian particle dispersion model that simulates long-range transport, diffusion, deposition, gravitational settling, and radioactive decay of tracers from point, line, area or volume sources. The model performs best under undisturbed meteorology (i.e. in the absence of fronts).
ST	DaySmoke	Liu et al. 2010	DaySmoke is a particle dispersion model that consists of four sub-models that simulate: (1) plume rise, (2) particle trajectory, (3) large eddy parameterization, and (4) hourly emissions estimates.

Type	Model	URL or citation	Description
ST	Community Multi-scale Air Quality (CMAQ)	Foley et al. 2009, Wong et al. 2012 -- http://www.cmaq-model.org/	CMAQ is a multi-scale model that simulates various chemical and physical processes important for determining the concentration, composition, transformations and distribution of gas- and particulate-phase pollutants and their precursors in the atmosphere. CMAQ can be run with meteorological inputs generated offline, or in online mode as WRF-CMAQ through a two-way coupling to the mesoscale meteorological fields of the WRF model. This coupled system captures radiative feedbacks of aerosols and clouds to the radiation budget and photolysis rates. (SEE TEXT)
RCM/ ST	WRF/Chem	Grell et al. 2005, Grell et al. 2011	WRF/Chem is a coupled meteorology--chemistry model. WRF/Chem couples physical and chemical processes (e.g. transport, deposition, emission, chemical transformation, aerosol interactions and their feedbacks to photolysis and the radiation budget) to simulate dynamically the chemical evolution of atmospheric trace gases and particulate matter and their interactions with meteorological fields.
RCM/ ST	MM5/Chem	Grell et al. 2000	Similar to WRF/Chem (above), MM5/Chem couples physical and chemical processes to simulate aerosol interactions with atmospheric dynamics simulated by MM5. Both WRF/Chem and MM5/Chem use the same mechanisms to simulate gas-phase and particulate chemistry and microphysics.
Physics plume model	Active Tracer High-Resolution Atmospheric (ATHAM)	Herzog et al. 1998, Oberhuber et al. 1998, Trentmann et al. 2002	ATHAM is a non-hydrostatic, full-physics, three-dimensional, plume model originally designed for volcanic emissions, but has since be adapted and used for wildfire emission estimates for turbulence, transport, cloud microphysics, gas scavenging, and radiation. ATHAM uses the Cartesian grid with an implicit time-stepping scheme.

Type	Model	URL or citation	Description
Modeling Frameworks			
	Bluesky	Larkin et al. 2009 -- http://www.blueskyframework.org/	Bluesky is a smoke emissions modeling framework that links together state-of-the-art models of meteorology, fuels, consumption, emissions, and air quality. Because the framework offers multiple choices of model in each modeling step, it allows for direct comparison between similar components. (SEE TEXT)
	Wildland Fire Emissions Information System (WFEIS)	McKenzie et al. 2012 -- http://wfeis.mtri.org/	WFEIS is a publicly available tool for estimating wildland fire emissions. WFEIS overlays recent and past fire perimeters on FCCS fuel maps at one-kilometer spatial resolution to calculate fuel consumption and daily emissions using CONSUME. (SEE TEXT)
Model Comparisons			
	Coupled Model Inter-comparison Project Phase 5 (CMIP5)	Taylor et al. 2012 -- http://cmip-pcmdi.llnl.gov/cmip5/	CMIP5 is a coordinated climate model experiment designed to highlight major gaps in understanding of past and future climate changes by providing a multi-model comparison that assesses the mechanisms responsible for model differences, examining climate predictability, and understanding why similarly forced models produce a range of responses. (SEE TEXT)
	Smoke and Emissions Model Inter-comparison Project (SEMIP)	http://www.airfire.org/projects/semip/	SEMIP is a project to compare modeling approaches from fire activity through emissions and dispersion. Several models and datasets are available for each modeling step: fire information, fuel loading, total consumption, and time-profiles of consumption, emissions, plume rise, and dispersion. (SEE TEXT)

Type	Model	URL or citation	Description
	Air Quality Model Evaluation International Initiative (AQMEII)	Rao et al. 2010	AQMEII is a permanent forum that constantly monitors the advancement of regional-scale air quality models and model evaluation strategies in North America and the European Union. The primary goals are to exchange expert knowledge, identify knowledge gaps, evaluate uncertainties, initiate coordinated research projects, and develop a common strategy for model development, evaluation, and research priorities.
	NARCCAP	Mearns et al. 2012	NARCCAP is a systematic examination of separate and combined uncertainties in future climate projections of RCMs across the North American continent using different atmosphere-ocean general circulation models to provide boundary conditions. (SEE TEXT)

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