Missing climate feedbacks in fire models: limitations and uncertainties in fuel loadings and the role of decomposition in fine fuel succession

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Key Points:

- Developing Earth system models for climate-fire interactions requires understanding and overcoming uncertainty in fuel succession processes.
- Models that simulate fuel succession differ in how they parameterize and represent fuel decomposition; key assumptions are often hard-coded.
- Sensitivity to parameter and model structure uncertainty increases with climate warming and decreases with increasing precipitation.

Abstract

In recent decades, climate change has lengthened wildfire seasons globally and doubled the annual area burned. Thus, capturing fire dynamics is critical for projecting Earth system processes in warmer, drier, more fire prone future. Recent advances in fire regime modeling have linked land surface and Earth system models with fire behavior models. Such models often rely on fine surface fuels to drive fire spread, and while many models can simulate processes that control how these fuels change through time (i.e., fine fuel succession), fuel loading estimates remain highly uncertain. Uncertainties are amplified in climate change forecasts when initial conditions and feedbacks are not well represented. The goal of this review is to highlight fine fuel succession as a key uncertainty in model systems. We review the current understanding of mechanisms controlling fine fuel succession (with an emphasis on decomposition), describe how these mechanisms are incorporated into models, and evaluate the strengths and uncertainties associated with different approaches. We also use three state-of-the-art fire regime models to demonstrate the sensitivity of decomposition projections to both parameter and model structure uncertainty and show that sensitivity increases dramatically under future climate warming. Given that many of the governing decomposition equations are hard-coded in models and often based on individual case studies, substantial uncertainties are currently ignored. To understand future climate-fuel-fire feedbacks, it is essential to be transparent about model choices and uncertainty. This is particularly critical as the domain of Earth system models is expanded to include evaluation of future wildfire regimes.

Plain Language Summary

Wildfire is a critical force regulating carbon retention globally. This is especially true in coniferous forests, which store more than one third of the earth's terrestrial carbon. Fine, dead materials on the forest floor (i.e., fine surface fuels) play a key role in driving fire spread. Thus, modeling the role of fire in Earth system processes requires reliable estimates of fine surface fuel loading and projections of how it will change over time (i.e., fine fuel succession). To accomplish this, we need models that can account for complex interactions among climate and vegetation—including the effects of temperature and precipitation on plant growth, mortality, litterfall, and litter decay—and that link these dynamics with projections of future wildfire. Although many models are designed to simulate these processes, fuel loading estimates remain highly uncertain. In this paper, we review the current understanding of mechanisms controlling fine fuel succession, describe how these mechanisms are represented in models, and evaluate the strengths and uncertainties associated with different approaches. We conclude with recommendations for future research needed to better model how climate change will influence fuels, wildfire, and carbon retention.

1 Introduction

Changes in climate, land management, and residential development are rapidly modifying global fire regimes (Bowman et al., 2017), and with them, the structure and function of ecosystems and watersheds (Schoennagel et al., 2017; Smith et al., 2014). These changes are particularly pronounced in the coniferous forests of western North America (Abatzoglou et al., 2017). Within forested fire regimes, fine surface fuel layers (including plant litter and fine woody fuels < 7.6 cm in diameter Table S1) propagate fire both horizontally and vertically from the forest floor into the canopy and are a key component of fire spread, hazard, and intensity (Rothermel, 1972; Thaxton & Platt, 2006). Accurately predicting fine surface fuel loading is crucial for forecasting future fire hazard and optimizing fuel management. This includes estimating the longevity of fuel treatments (Hood et al., 2020; Keane, 2008; Stephens et al., 2012; Tinkham et al., 2016; Vaillant et al., 2015), calculating treatment costs (Calkin & Gebert, 2006), and determining how they will affect future carbon (C) stocks (Campbell & Ager, 2013).

Fine surface fuel loading is a key driver of fire spread and behavior in models, particularly those based on Rothermel (1972), such as FARSITE, BEHAVE, and SPITFIRE (Andrews, 2007; Finney, 1998; Thonicke et al., 2010). However, in-situ fuel measurements can be time consuming and expensive. Synoptic remote sensing datasets are generally insufficient because surface layers are often obscured by overlying canopies (Mutlu et al., 2008; Seielstad & Queen, 2003). Apart from unmanned aerial vehicle or terrestrial lidar studies, datasets lack the precision needed to accurately represent fire-scale fuel characteristics that are needed for wildfire modeling (Loudermilk et al., 2009). As a result, fire risk and hazard assessment rely fuel characterizations that are typically derived from a generalized fuel scheme, such as the Scott and Burgan (2005) 40 stylized fuel models (Keane, 2013), the Australian Bushfire Fuel Classification (M. Cruz et al., 2018), and the Canadian Forest Fire Fire Behavior Prediction System (Forestry Canada, 1992). These classification systems are often designed to work with a particular fire behavior model such as Rothermel (1972) or Australian models that are designed for different fuel types and may or may not accept fuel loading as input (M. G. Cruz et al., 2015; Gould et al., 2008). Although fire behavior models are useful in operational fire management, fuel arrangement, loading, and physical and chemical properties remain highly uncertain at large scales (Benali et al., 2017; Keane, 2013; Prichard et al., 2019).

To address this uncertainty, process-based fire regime models have emerged for estimating how climate, fuels, and fire interact (e.g., LandClim; Gaillard et al., 2014, FireBGC; Keane et al., 2011, and RHESSys-WMFire; Kennedy et al., 2017). Many of these models include litter as a component of the fine surface fuel load and litter dynamics play an important role in fire activity. Fire regime models are not designed to predict the path of specific fires but are a powerful tool for simulating the interactions and feedbacks controlling fire regimes through time (Keane et al., 2004). Useful models must be able to resolve the mechanisms driving fine fuel succession—including plant growth, litterfall, mortality, and decomposition—over space and time (Fig. 1; Agee and Huff, 1987). Fine fuel succession results from the balance between accumulation (productivity then phenology/mortality) and loss (combustion and decomposition), both of which are affected by climate change (Fig. 2). However, existing models include various simplifications that may lead to large uncertainties in fire regime projections.

For process models to be reliable, they must be continually confronted with observations and empirical data, including data for parameterization, validation, evaluating uncertainty, and improving the way we represent various mechanisms. Empirical studies can help improve our representation of litter turnover but there are disconnects between our empirical understanding and ability to model processes over fire-relevant scales. These disconnects arise because empirical studies typically focus on individual scales and rarely account for feedbacks that occur across scales—such as the effects of climate change on the microbial processes regulating fine fuel decomposition, its subsequent effects on fire, and feedbacks to soil biogeochemical processes (Fig. 1). Understanding these complex climate-fuel-fire feedbacks is critical for earth systems models that forecast future fire regimes.

Although common wildfire behavior models only include fine wood in their calculations (e.g., Rothermel, 1972), most of our theoretical understanding of decomposition has focused on litter and soil organic matter (SOM) layers, with woody fuel decomposition either represented as a constant scalar (e.g., Keane, 2008; Rebain et al., 2009) or derived from theories and models developed for litter and SOM (Keane et al., 2011; C. L. Tague & Band, 2004). Understanding uncertainty in models of woody fuel dynamics therefore requires understanding current theories of litter decomposition.

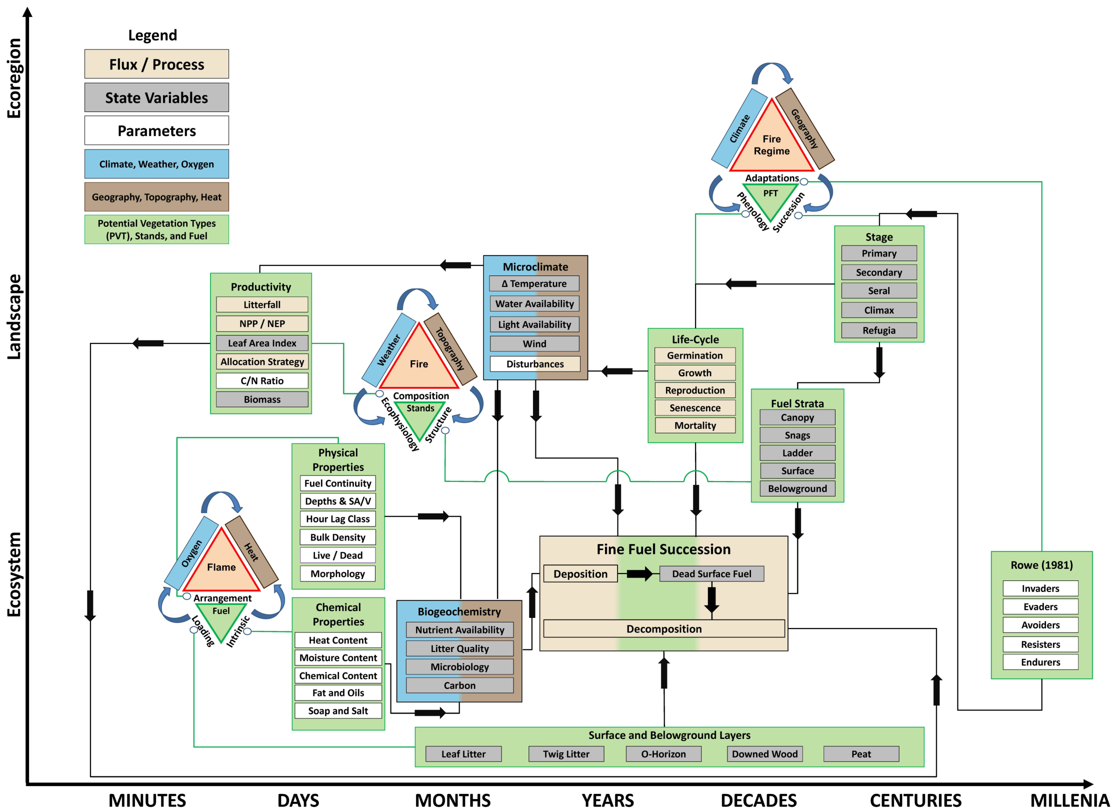

Figure 1: *The parameters, processes, and state variables driving fire across spatial and temporal scales. This is an adaptation and extension of the conceptual figure developed by Moritz et al. (2005), which expanded the fire triangle concept to incorporate the feedbacks among fire drivers and processes at multiple scales, ranging from flames to fire regimes. Dominant drivers at each scale are identified along the sides of each triangle. Here we illustrate the processes and feedbacks that are directly relevant to fine fuel succession, which controls fuel dynamics represented by the small green triangles at each scale. We use the term O-horizon to refer to litter (Oi horizon) and duff (Oe and Oa horizons).*

In this paper, we: (1) review the current understanding of mechanisms controlling both litter and fine woody fuel succession (with respect to fuel inputs and decomposition) and the fundamental equations used to represent these mechanisms, (2) describe how these mechanisms are incorporated into modeling systems that are used to investigate interactions among climate change, forest management, and future wildfire, and (3) evaluate the strengths and uncertainties associated with different approaches. We conclude with recommendations for future modeling and empirical research needed to improve forecasts of future fuel loadings, wildfire, and carbon retention.

Capturing fuel and fire dynamics is critical for projecting land surface and Earth system processes in warmer, drier, more fireprone future. The goal of this review is to highlight fuel succession as a key uncertainty in current models. While the importance of fuel and vegetation succession and limitations to characterizing them in models has been acknowledged in the U.S., Australia, Mexico, and China (Fry et al., 2018a; Huang et al., 2021; Matthews et al., 2012; Zazali et al., 2020), here we use a subset of North American models to illustrate critical uncertainties that exist across the fire regime modeling domain.

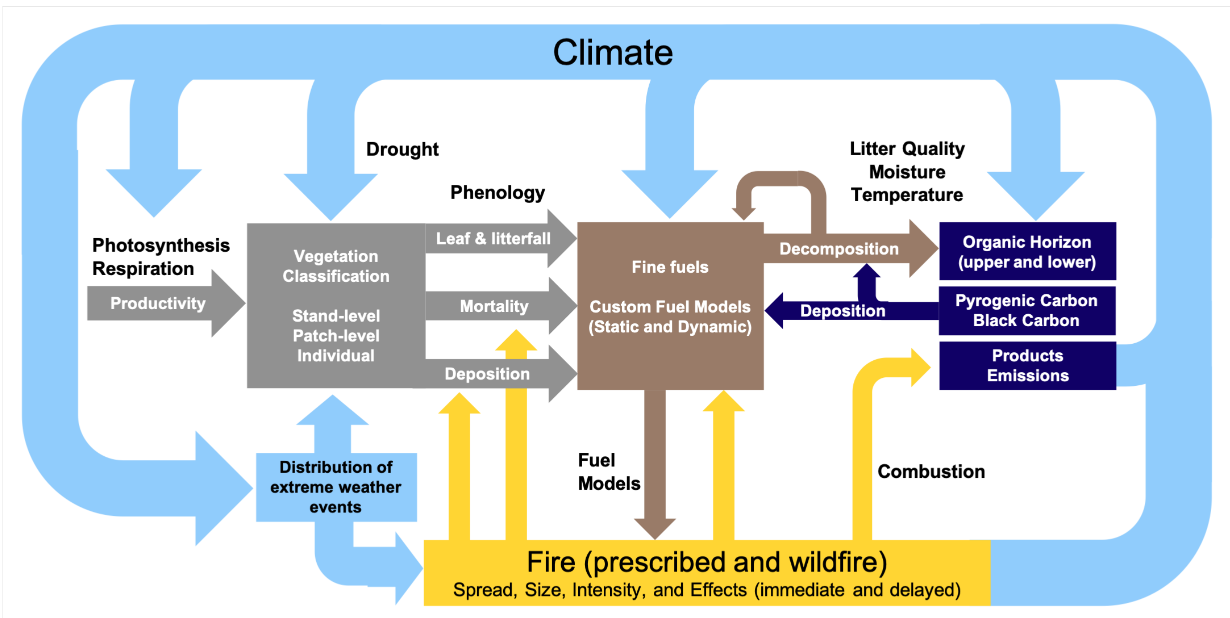

Figure 2: *Bidirectional climate-fuel-fire feedbacks that occur across spatial and temporal scales.*

2 Mechanisms controlling fine fuel succession

Here we define fine surface fuels broadly to include fine fuels (comprising plant litter and small twigs) and fine woody fuels (comprising woody fuels < 7.6 cm in diameter; Supplementary Table S1). Although most fire behavior models only include woody fuels in their calculations (Sullivan, 2007, 2009a,b), some fire regime models also include the entire fine fuel matrix (e.g., Kennedy et al., 2017). We define fine fuel succession as the balance between the input and removal of fuels (Fig. 2; Supplemental table S1). Fuel inputs are a function of vegetation productivity, turnover, and mortality, including background mortality and pulses of mortality due to disturbances. The classic Olson (1963) fuel accumulation model assumes that fuel succession is a function of the balance between the rate of fuel deposition and the rate at which it decays and represents this as a simple curve of fuel density over time. However, fuel loss can occur through multiple processes including decomposition, combustion, erosion, and herbivory. In addition, wildfire can alter both accumulation and losses at multiple spatial and temporal scales and climate change may modify both processes of fuel accumulation (through vegetation productivity and mortality) and decomposition.

While a great deal of progress has been made understanding and modeling the biophysical mechanisms controlling these processes, many uncertainties remain, and few studies have characterized how these uncertainties propagate into estimates of fine surface fuel loading, subsequent fire spread, and long-term carbon dynamics. Below we summarize our current understanding of the mechanisms controlling fine fuel succession. Harris et al. (2016) reviewed many of the vegetation processes controlling fuel loading and its effects on fire regimes. Here, we briefly describe some of these processes, and then focus particular attention on the role of fine fuel decomposition and the fundamental equations used to represent it. Most of these equations developed from studies of litter decomposition rather than in the context of fine surface fuels and fire. Decomposition is expected to accelerate under future warming (Hopkins et al., 2012), but its response to increasing temperature and drought remains highly uncertain.

2.1. Dead fuel accumulation

Vegetation type and climate regulate net primary productivity (NPP), litterfall, and mortality, which are the key processes driving fine surface fuel accumulation. Climate warming can increase NPP by increasing rates of photosynthesis (Y. Luo, 2007), lengthening the growing season (Sherry et al., 2007; Westerling et al., 2006), and increasing rates of nitrogen mineralization (Melillo et al., 1982; Xu & Yuan, 2017). However, temperature controls over NPP are also mediated through belowground resource availability, particularly water (Chapin et al., 2011). Thus, in arid and semiarid locations, rising temperatures can increase soil evaporation, aridity, and water limitation, thereby reducing NPP (Zhao et al., 2019). Temperature and moisture can also influence NPP indirectly through their effects on decomposition rates and nutrient supply.

As vegetation grows, it loses foliage to the ground as litter. Branches and twigs are shed to contribute to fine and coarse woody fuels. Disturbances such as drought, insect outbreaks, windthrow, and fire can also contribute to mortality and litterfall. Dead vegetation eventually falls to the ground (e.g., snagfall; Everett et al., 1999) to form litter and fine and coarse woody debris (Johnson et al., 2020; Peterson et al., 2015; Stenzel et al., 2019). Ultimately, through conservation of mass, fuel accumulation is less than or equal to NPP.

While modelers have made a great deal of progress in characterizing the mechanisms controlling photosynthesis and NPP, and how they are constrained by temperature, moisture, and nutrient availability (Farquhar & Von Caemmerer, 1982), some uncertainties remain. For example, it is not clear how NPP will respond to increasing atmospheric carbon dioxide (CO_2) concentrations. Growth chamber experiments have shown photosynthesis can increase with increasing CO_2 (Drake et al., 1997), yet CO_2 fertilization has had mixed effects among plant functional types in more natural, large-scale free-air CO_2 enrichment experiments (FACE; Ainsworth and Long, 2005). At large scales, and at sites with complex species assemblages, interactions between CO_2 fertilization and warming remain uncertain (Way et al., 2015). Because model projections of future fire regimes are highly sensitive to CO_2 fertilization and its effects on NPP and fuel loading (Ren et al. unpublished), modeling future fire requires improving our understanding of how atmospheric CO_2 concentrations will affect NPP and fine surface fuel succession.

2.2. Decomposition

The balance between NPP and decomposition plays a key role in both fire behavior and C cycling over multiple spatial and temporal scales. Because even small changes in this balance can substantially alter atmospheric CO_2 concentrations and global climate change, many studies have focused on how decomposition rates influence the net exchange of C between ecosystems and the atmosphere (net ecosystem exchange; NEE; e.g., Melillo et al., 1982; Schlesinger and Andrews, 2000; Kramer et al., 2017), or on how decomposition influences nutrient cycling and NPP (Lal, 2004). However, decomposition rates also play a key role in fine surface fuel loading, fire spread, and associated feedbacks with greenhouse gas fluxes. Thus, in addition to understanding the dynamics of old soil C stores and biogeochemical cycling, it is also crucial to understand how decomposition controls the residence time of fine surface fuels. Decomposition is controlled by three overarching factors: (1) environmental conditions, particularly temperature and moisture, (2) the amount and quality of substrate available for decomposers, and (3) microbial community structure and function (Melillo et al., 1982; Chapin et al., 2011).

2.2.1. Temperature and moisture

Physical environmental conditions in an ecosystem or landscape influence decomposition in large part through their effects on temperature and moisture. Therefore, wildfire modeling requires predicting future temperature and moisture regimes, not only for their direct effect on wildfire behavior and spread, but also how they will interact to drive fine fuel succession (Fig. 1). These variables respond to both top-down climate drivers and bottom-up environmental drivers—such as topography, soil properties, and vegetation cover—and they influence decomposition both directly and indirectly.

Temperature regulates decomposition directly through its effects on soil microbial activity and indirectly through its effects on litter and soil moisture. Increasing temperature increases microbial respiration rates exponentially across biomes. For example, in warm tropical forests, litter pools are small despite high rates of net primary productivity (NPP), whereas in temperate coniferous forests litter pools can be large even though NPP is much slower (Lieth, 1975; Chapin et al., 2011). Because temperature affects NPP and decomposition at different rates (Kirschbaum, 1995), it is crucial to understand mechanistic relationships between warming and litter decay to accurately predict fine fuel succession.

Traditionally, carbon cycling models have used empirically fitted temperature sensitivity functions (i.e., Q10) to describe how decomposition rates increase with warming (e.g., Luo et al., 2001; Reichstein et al., 2003; Davidson et al., 2006). Q10 is a measure of the extent to which 10°C rise in temperature increases the rate of a chemical reaction. However, fitting Q10 functions to soil respiration data has yielded highly variable temperature sensitivities (Davidson et al., 2006). For example, Q10 can vary with season (Janssens & Pilegaard, 2003), soil organic matter content and quality (Reichstein et al., 2005), soil moisture (Meyer et al., 2018), land cover (Yuste et al., 2004), elevation (Wang et al., 2013), and latitude (Zhou et al., 2009). Modeling the effects of temperature on decomposition is extremely difficult, because these environmental constraints can obscure the intrinsic temperature sensitivities of various substrates, and these constraints may themselves be sensitive to climate (Davidson & Janssens, 2006).

One of the biggest constraints on decomposition is moisture availability. Similar to plants, decomposers are most productive in warm moist environments where they are neither oxygen nor diffusion-limited. However, soil microbes are less sensitive than plants are to drought (Austin, 2002; Hanan et al., 2017; Jackson et al., 1988; Parker & Schimel, 2011), and therefore, in some locations, warming and drying may decrease NPP and fine surface fuel inputs while increasing decomposition, thereby reducing fuel loadings and fire hazard. Furthermore, drying-rewetting cycles may become more frequent with climate change and can stimulate decomposition of labile substrates while slowing rates for recalcitrant ones (Haynes, 1986).

While there is a clear need to account for temperature and moisture variability into C cycling models, there are several uncertainties that still must be resolved for future projections to be reliable. For example, the extent of future drought remains highly uncertain (Cook et al., 2020). While it is clear that temperatures and evapotranspiration (ET) will continue to increase, future precipitation is less predictable and thus for ecosystems that exist near the threshold of flammability to fuel-limitation, improved projections of future aridity will be extremely valuable for predicting fire hazard (Hanan et al., 2021).

Another limitation to modeling the effects of future aridity on decomposition comes from uncertainty in model structure. Models that represent moisture controls on decomposition tend to focus more on soil moisture than litter moisture. For example, in RHESSys-WMFire and FATES-SPITFIRE, the moisture controls influencing fine fuel decomposition are based on soil water content and soil matric potential, respectively (Andren & Paustian, 1987; C. L. Tague & Band, 2004), and the moisture controls influencing decomposition in LANDCLIM are a function of evapotranspiration (ET; Gaillard et al., 2014). However, these variables do not always operate on the same timescales as fine fuel moisture (Hatton et al., 1988). Although limited studies have assessed the mechanisms driving the adsorption of water by plant litter, Talhelm and Smith (2018) observed relationships between water adsorption and the structure and chemistry of leaf litter. Notably, it was shown that litter with high concentrations of heat content and lignin exhibited lower water adsorption (Talhelm & Smith, 2018).

Finally, temperature and moisture can interact in complex ways, and these interactions may not be multiplicative, which can lead to possible equifinality when attempting to estimate their individual contributions through lab experiments (Tang & Riley, 2020). This is evident when comparing historical and future projections for different C cycling models. In many cases, C cycling models can have convergent projections over the historical period and highly divergent projections in the future (Z. Luo et al., 2015). We know this is problematic for slow cycling soil C stores, but it has not been tested extensively for litter/fine surface fuels.

2.2.2. Litter quality

At a given temperature and moisture regime, decomposition rates can vary by several orders of magnitude due to differences in litter quality (Silver & Miya, 2001). Litter quality refers to the relative proportions of labile metabolic compounds in litter stores, such as sugars, amino acids, moderately labile compounds such as cellulose and hemicellulose, and recalcitrant compounds such as lignin (Chapin et al., 2011). Two common indices for litter quality are its C:N ratio and its lignin:N ratio (Taylor, 1989). Litter with relatively high N tends to be composed of more labile C compounds and less structural material, and will therefore decompose more quickly (Hobbie, 2000; Melillo et al., 1982). Litter quality also decreases rapidly with age because labile materials decompose quickly. Belowground resource availability is a key factor influencing litter quality—vegetation in high resource sites produces litter that decomposes quickly because the physiological traits that lead to high NPP, such as high surface to volume ratio and low C:N, also tend to favor rapid decomposition.

C cycling models represent decomposition as either (1) exponential decay, with a rate constant (k) that is fit empirically and associated with litter quality, or (2) as multiple sequential pools, that are increasingly recalcitrant. These approaches represent decomposition using first order kinetics (e.g., Running and Coughlan, 1988; Parton et al., 1998; Tague and Band, 2004; Nemani et al., 2005). A possible issue with both approaches is that they do not explicitly account for the role of microbes (Schimel, 2001). In other words, microbial decomposition processes are modeled using a single, first order equation that is controlled by the size of each C pool (e.g., Parton et al., 1987):

(1) $\frac{dC}{dt} = k * r_m * r_T * C$

In this equation, C is the size of a C pool, k is a first-order rate constant that is influenced by litter quality, and r_m and r_t are temperature and moisture scalars. In a multi-pool, first order model, each process has a single K value and a single set of temperature and moisture reducing functions.

2.2.3. Microbial community

In most biogeochemical models, decomposition is directly proportional to the size of the soil and litter C pools and includes rate coefficients that account for the effects of temperature, soil moisture, and litter quality (Georgiou et al., 2017). An implicit assumption in these first-order models is that the response functions do not change with the composition or size of the microbial community (Schimel, 2001). Research over recent decades, however, has shown that these assumptions can be problematic, particularly for slow cycling soil C pools, which can experience accelerated decomposition when inoculated with heterotrophic microbes (Z. Luo et al., 2015). First-order models are also potentially inadequate for representing processes such as priming, where the decomposition of soil organic C can be enhanced through plant root exudates or elevated CO_2 concentrations that stimulate the heterotrophic microbial community (Hungate et al., 1997).

More recently, models have attempted to capture the role of soil microbes in mediating decomposition and/or organic matter stabilization (e.g. Wieder et al., 2013; Kaiser et al., 2014; Hararuk et al., 2015) by explicitly representing enzymatic degradation of soil and litter C (i.e., through Michaelis Menten kinetics; Michaelis and Menton, 1913). In these models, decomposition rates depend on the sizes of both C and microbial pools. While such models may be needed to simulate decomposition of recalcitrant soil organic matter pools, they have not been tested in the context of fine surface fuels and wildfire. Furthermore, wildfire can dramatically reduce microbial biomass (e.g., Knicker, 2007; Hanan et al., 2016b, 2016a), and alter microbial function and enzyme activity over decadal timescales (Pellegrini et al., 2020). These feedbacks are also poorly represented in biogeochemical models.

3 Fuels and wildfire dynamics in land surface models

In this paper, we are concerned with how the fundamental mechanisms outlined in the previous section are incorporated into modeling systems that are used in forest management and planning as well as investigating how climate change will alter future wildfire regimes. Fire models range in their complexity from simple empirical models that can be used to classify large scale fire regimes (e.g., Littell et al., 2018) to fully physical models that have the potential to predict individual wildfires with precision (e.g., Mell et al., 2007a). Our ability to understand how climate change will affect future fire regimes is one of the most pressing questions in forest and vegetation management, yet many of the existing models at all scales inadequately represent the full system of feedbacks and abiotic and biotic dynamics (Fig. 1). Models that do consider climate-fuel-fire feedbacks may not be adequately evaluated for their performance with respect to fine fuel succession and how it influences wildfire spread, behavior, and effects.

3.1. Example models that do not incorporate climate-fuel feedbacks

Empirical, retrospective studies have provided valuable insight into climate-wildfire relationships at regional scales (e.g., Guyette et al., 2012; Abatzoglou and Williams, 2016; McKenzie and Littell, 2017; Littell et al., 2018), but these models do not explicitly represent fuel dynamics. Therefore, projecting these relationships into the future implicitly assume that vegetation and fuels will be stationary. Because empirical models rely on pattern-matching and do not account for climate-fuel feedbacks, they have limited utility in projecting future wildfire under novel climate and fuel bed conditions (McKenzie & Perera, 2015).

More complex models that rely on classical fire spread and behavior algorithms such as Rothermel (1972) typically classify the fuel bed into a stylized fuel model based on vegetation cover (e.g., Scott and Burgan, 2005). Stylized fuel models are not meant to precisely quantify fuels at a specific time or place, but instead provide exemplar fuel conditions for a given vegetation type. These fuel models provide the inputs needed for fire behavior models, which then predict fire behavior for a given fuel type. While it is possible for these classifications to be dynamic (e.g., depending on predicted stand conditions as in FFE-FVS; Rebain et al., 2009), stylized fuel models do not represent novel fuel beds that may arise from plant functional type conversions, climate change-driven changes in decomposition, or fuel treatments (Johnson et al., 2011; Kennedy et al., 2021; Varner & Keyes, 2009), and they coarsen the known variability in fuel loading and structure (Prichard et al., 2019). In models that use stylized fuel layers, predicted fire behavior is relatively insensitive to changes in fuel loading that would result from dynamic changes in the fuel bed (Sandberg et al., 2007), including those that arise from uncertainty in decomposition rates (Kennedy et al., 2021) and their relationship with climate.

3.2. Example models that do not incorporate fuel-fire feedbacks

Various regional or landscape-scale process models have been used to simulate carbon exchange between the atmosphere and terrestrial ecosystems, and many of these models also include algorithms for prescribing fire effects (e.g., CENTURY/DAYCENT; Parton, 1996; Parton et al., 1998, BIOME-BGC; Nemani et al., 2005, and RHESSys; Tague and Band, 2004). However, in these model systems, fire may be parameterized as an exogenous driver and is not represented as an emergent property of the fuel landscape. Although these model systems provide a powerful framework for mechanistically simulating climate-vegetation feedbacks following fire, they do not include fuel-fire feedbacks that are needed to simulate decadal-scale fire regimes.

For example, DAYCENT has been used to simulate how parameterized wildfires alter landscape biogeochemical processes (e.g., Gathany and Burke, 2012; Hudiburg et al., 2017). In these studies, the fire sub-model is parameterized to reduce C and N stores by a fraction that depends on a user-prescribed fire severity. Similarly, early implementation of wildfire in RHESSys involved simulating fires at fixed intervals and reducing C and N stores based on published estimates from empirical studies (e.g., Tague et al., 2009). In such applications, from the wildfire standpoint, fuels and climate are considered static even when vegetation and climate are dynamic. Other approaches involve initializing a watershed according to its fire history (Hanan et al., 2018) and/or prescribing a single wildfire at a set timepoint (e.g., Hanan et al., 2017). While these approaches are valuable for examining climate-vegetation feedbacks following fire, they would not be suitable for projecting future fire regimes because fire activity would not respond to changes in fuel loading associated with climate change or fuel self-limitation that results from increasing fire frequency (e.g., Hurteau et al., 2019).

There are many models that do incorporate bidirectional couplings to represent climate-fuel-fire relationships, many of which are reviewed and classified by Keane et al. (2004). In these models, climate, vegetation, and dynamic fuels inform wildfire spread, behavior, and effects using varying degrees of abstraction for the system of feedbacks represented in Fig 1. Rather than giving an exhaustive review of these models, we will next focus on three models that have been used in fire regime projections (i.e. LandClim, FireBGCv2, and RHESSys-WMFire) and are representative of the types of models in use. We focus on how these models simulate fine fuel succession with particular emphasis on their representation of decomposition.

3.2. Models that represent climate-fuel-wildfire feedbacks

LandClim, FireBGCv2, and RHESSys-WMFire simulate how interacting ecosystem processes pertaining to climate, vegetation, soils, hydrology, and disturbance influence C fluxes (Gaillard et al., 2014; Keane et al., 2011; Kennedy et al., 2017). However, they differ in the set of processes they emphasize, and in the scales that they represent. LandClim is a spatially explicit, stochastic landscape model that developed from LANDIS to incorporate large-scale disturbances such as fire and feedbacks with climate change (Gaillard et al., 2014; He et al., 1999). LandClim represents stand scale (i.e., 25-m) vegetation as the number and biomass of trees in cohorts. Processes such as growth and mortality are simulated at an annual time step, and landscape-scale processes, such as fire, wind, and seed dispersal are simulated at a decadal time step (Gaillard et al., 2014).

FireBGCv2 is adapted from BIOME-BGC to represent individual-tree-based succession and wildfire (Keane et al., 2011). FireBGCv2 operates at five distinct spatial scales, ranging from individual trees to entire landscapes and operates on a daily time-step. Physiological processes such as photosynthesis, respiration, and decomposition are calculated at the finest scales, whereas fire is implemented stochastically at a landscape scale.

RHESSys-WMFire is unique in that it fully couples the biogeochemical model with a hydrologic model to simulate processes such as streamflow, evapotranspiration, NPP, respiration, mineralization, nitrification, and C and N export to streams (C. L. Tague & Band, 2004). Most processes are modeled at a patch scale, which typically varies between 30-m and 270-m resolution. Subsurface and surface water are routed laterally between patches within sub-basins to produce streamflow. The largest spatial unit is the basin, which aggregates sub-basins and is a closed drainage area encompassing a single stream network. Like, FireBGCv2, RHESSys-WMFire also operates at a daily timestep.

These models also differ in the degree of complexity they use to represent fire. Both FireBGCv2 and LandClim simulate ignition and spread based on moisture, wind, and topography, given fuel presence. FireBGCv2 scales the probability of spread by a user-specified fire return interval, which is a surrogate for fuel accumulation that does not respond to changing climate and vegetation conditions. Fire behavior in FireBGCv2 is based on either Rothermel (1972) or Albini (1976) equations, which depend on intrinsic fuel properties and on fuel loading of different size classes. Fire effects are calculated using the FOFEM model (Reinhardt et al., 2001). LandClim calculates fire intensity as function of fuel load and moisture (Schumacher et al., 2006). Fire size in both LandClim and FireBGCv2 is limited by a user-specified maximum. In such representations, the effects of fine fuel succession on wildfire area burned and feedbacks with wildfire activity would not be emergent from model projections. To demonstrate the potential for fire self-limitation on future area burned, Hurteau et al. (2019) used the Dynamic Fire Extension of LANDIS-II, which modifies the fire size distribution using climate and fire-related changes in biomass. They found that when accounting for fire self-limitation, projections of future area burned in the Sierra Nevada were moderated by 14.3 percent.

RHESSys-WMFire produces fire spread maps over randomized ignitions and stochastic spread, providing probability distributions of fire activity over time. In addition to topography, wind, and climate (as in LandClim and FireBGCv.2), fire spread and effects also respond to dynamic changes in fuel loading (Bart et al., 2020; Kennedy et al., 2017), RHESSys-WMFire is therefore robust to climate non-stationarity and the positive and negative feedbacks that influence fuel dynamics fire regimes over time (Hanan et al., 2021).

The models described above, and other common models such as FFE-FVS (Rebain et al., 2009) and FATES-SPITFIRE (Thonicke et al., 2010), are adaptations of existing models that were not originally developed to simulate wildfire regimes. There has not been detailed assessment or validation of their prediction of surface dead biomass, which can play an important role in projected wildfire activity. For example, Kennedy et al. (2021) found that predicted fuel succession in FFE-FVS is particularly sensitive to uncertainty in the underlying decomposition rate.

Next, we compare the decomposition routines of LandClim, FireBGCv2, and RHESSys-WMFire and explore the sensitivity of these routines to simple changes in governing equations. We chose three models as examples of current state-of-the-art fire regime models, not to imply that these models are particularly problematic in this regard, but rather to illustrate potential uncertainties that occur in all models. We recognize that the results we present apply to many similar models of this type. Methods for the sensitivity analysis are detailed in Supplementary Text (Section S1).

4 Potential uncertainties in fine fuel loading due to climate-decomposition relationships

As described above, decomposition depends on temperature, moisture, litter quality, and microbial communities in complex ways that may not be simply additive or multiplicative (Tang & Riley, 2020). In the process models outlined in the previous section, decomposition is calculated separately for litter and for fine and coarse woody fuels, although the routines for woody fuels may be adapted from the litter equations.

Generally, the mathematical representation of changes to biomass decomposition is in the form of exponential decay with some exponential decomposition rate parameter (Equation 1). The models described above divide this into multiple conceptual pools, based on substrate quality, with varying linear decomposition rates (W. J. Parton et al., 1988). These models are updated on a discrete time step (e.g., daily or annually), rather than the continuous time model in Equation 1. The general form for a given pool would then be:

(2) $C_j(t+1) = C_j(t) - C_j(t)r_j$

C_j is the loading of fuel of a particular size class or pool, t is the time step (e.g., daily, annually) and r_j is the decomposition rate for that fuel pool ($k * r_m * r_T$ in Equation 1, for example). We will consider two sources of model uncertainty in this representation: parameter estimation uncertainty and model structure uncertainty.

4.1 Woody fuel decomposition rate parameter uncertainty

We use the LandClim equation for fine woody fuel decomposition to explore potential uncertainty in predicted decomposition rates due to uncertainty in parameter (coefficient) estimates. LandClim estimates the relationship between annual temperature and the annual rate of coarse wood decomposition (i.e., downed wood > 7.6 cm) based on Mackensen et al. (2003). In this study, the authors fit a curve to decomposition rates obtained across multiple studies in different locations:

(3) $r_w = 0.0166e^{0.093T_a}$

In this equation r_w is the rate of coarse wood decomposition and T_a is air temperature. To simulate fine wood (< 7.6 cm diameter) decomposition rates (r_{fw}), LandClim assumes that fine wood decomposes at 5 times the rate of coarse wood (Schumacher et al., 2006).

Each of the coefficients in the above expression are empirical (regression) estimates based on studies synthesizing multiple data sets, therefore each coefficient has an associated standard error and measures of unexplained variability. For example, the curve estimated in equation 3 explained 34% of the variability in decomposition rate, and there was noticeable increasing variability in decomposition rate as temperature increased (Mackensen et al., 2003), which might be of particular concern in climate scenarios with increasing temperature. At the maximum temperature of 25 degrees C, observed decomposition rates for coarse wood varied from ~0 to ~0.6. Given the fine wood multiplier of 5 in LandClim, this would propagate to decomposition rates of around 0 to 3.0. To explore the consequences of uncertainty in coefficient estimates on decomposition rates and fuel loadings, we conducted a simple sensitivity analysis (SA) by systematically varying coefficient values in the underlying equations, decoupled from other model processes. Unfortunately, standard errors were not given in the source material, making it difficult to determine plausible bounds of uncertainty. We evaluated ranges of coefficients +/- 33% of the empirical estimates and recorded both decomposition rate (Fig. 3) and percent of initial fuel loading remaining assuming no fuel inputs (Fig. 4).

Given that the relationship between temperature and fine woody fuel decomposition rate is exponential, the sensitivity of that relationship to the exponent must also be non-linear (Fig. 3; Supplementary Text; S1), as is the effect on future woody fuel loading (Fig. 4). The sensitivity of decomposition rate to model coefficients increases with increasing temperature, with the widest uncertainty bounds at the highest temperature. Note also that there is no moisture effect on decomposition rate in these calculations, although the source material showed a clear peak in decomposition at middle values of precipitation (Mackensen et al., 2003).

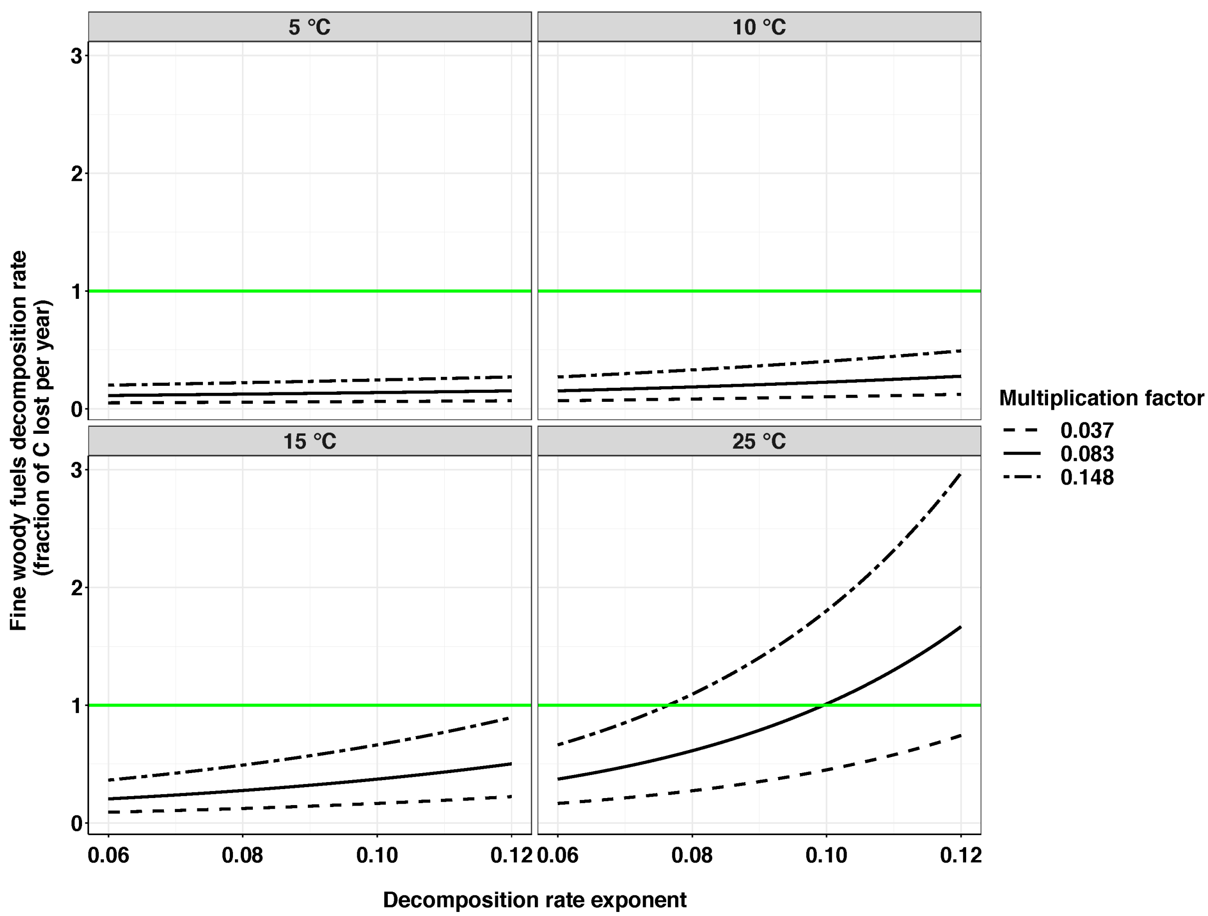

Figure 3: *Sensitivity of LandClim annual fine woody fuel decomposition rates to the parameter values in equation (3). The middle line is the hard-coded value in the model. The upper and lower lines illustrate how projected decomposition rates might vary if the components of the multiplication coefficient each increased or decreased by 33%. Model sensitivity to parameter uncertainty increases with increasing temperature.*

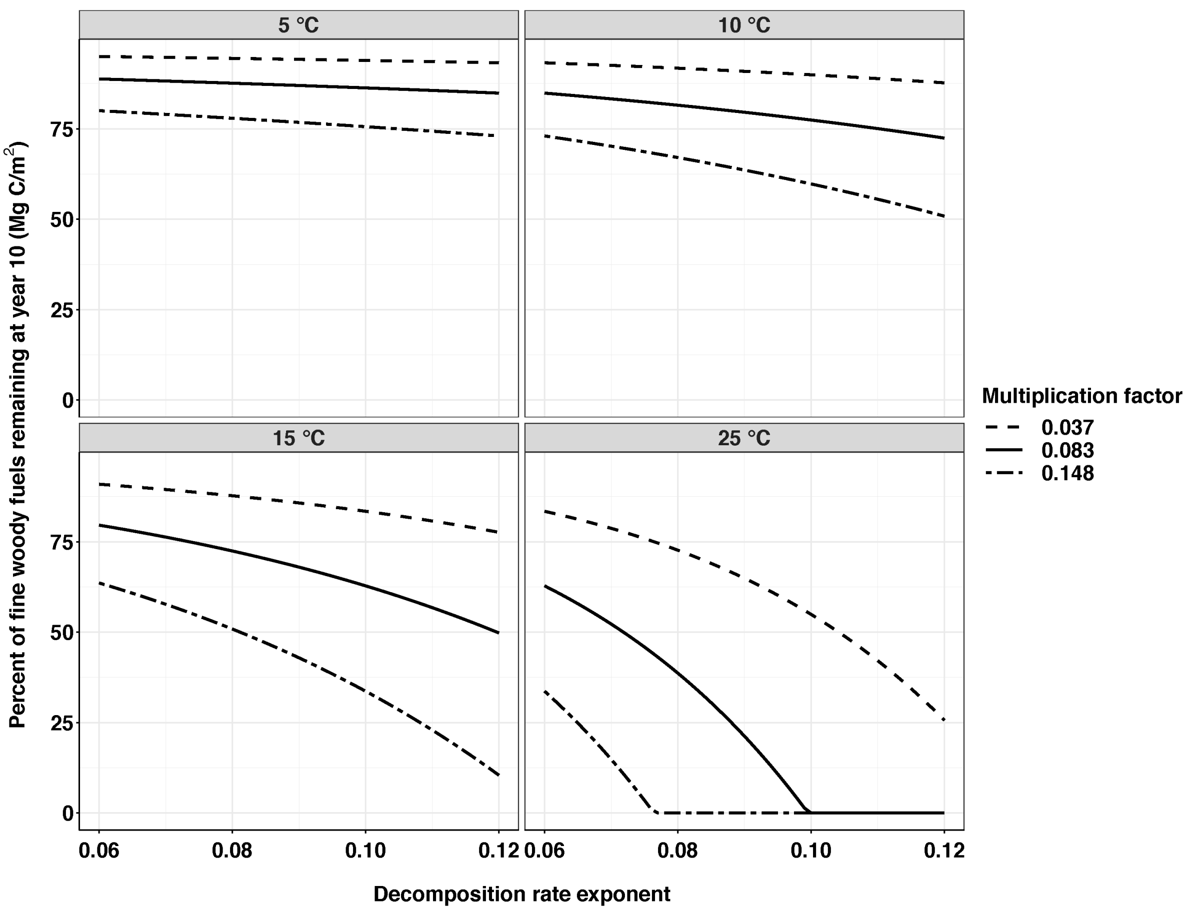

Figure 4: *Sensitivity of LandClim percent of fine woody fuel remaining at year 10 to the coefficient values in equation (2). The middle line is the hard-coded value in the model. The upper and lower lines illustrate how projected decomposition rates might vary if the components of the multiplication coefficient each increased or decreased by 33%. Model sensitivity to parameter uncertainty increases with increasing temperature.*

4.2 Sensitivity of decomposition rate to model structure

Next, we consider how models of litter decomposition are sensitive to model structure uncertainty. For models such as FireBGCv2 and RHESSys-WMFire, woody fuel loss is calculated based on the same underlying model structure as litter decomposition (Keane et al., 2011; C. L. Tague & Band, 2004), therefore any uncertainty in litter decomposition would propagate to uncertainty in woody fuel loss.

In this analysis, we consider decomposition parameter values to be fixed and compare the calculated litter decomposition rates among three model structures for a given stand moisture and temperature condition. We used RHESSys-WMFire to simulate a single patch the Trail Creek watershed in middle Rockies (Hanan et al., 2021) over the years 1980-2018 and output the characteristics necessary to calculate litter decomposition rates for three different model structures: LandClim (using actual evapotranspiration), FireBGCv2 (using soil temperature and soil water potential), RHESSys-WMFire (using soil temperature and soil water content; see Appendix S1 for details). We then calculated litter loss as a function of the decomposition rates for the three models, investigated how sensitive modeled decomposition rates are to changes in precipitation and mean soil temperature, and compared decomposition rates between models with changes in temperature and precipitation (Supplementary Text; S1). We also investigated how these comparisons changed when we increased average daily temperature by degrees C uniformly over the simulation period.

Calculation of litter decomposition rate in LandClim is achieved using an empirical regression equation estimated by Meentemeyer (1978) using data from multiple sources to estimate general relationships between foliage litter decomposition rate (r_l), annual actual evapotranspiration (AET), and percent lignin. The best fit synthesis model for foliage litter decomposition rate explained 70% of the variability and included AET as a main effect and an interaction between AET and lignin (represented by the ratio AET/lignin):

(4) $r_l = \frac{-1.31369+0.05350*AET+0.18472*\frac{AET}{lignin}}{100}$

FireBGCv2 (Keane et al., 2011) merges Biome-BGC (Running & Coughlan, 1988) biogeochemical processes with the FIRESUM (Keane et al., 1989) gap model. Litter decomposition rate is calculated as in Biome-BGC (Thornton, 1998), using a moisture and a temperature scalar. The moisture scalar ($r_{m.soilP}$) depends on the soil water potential (ψ) relative to the range of possible soil water potentials (min, max):

(5) $r_{M.soilP} = \frac{ln\left(\frac{\psi_{min}}{\psi}\right)}{ln\left(\frac{\psi_{min}}{\psi_{max}}\right)}$

The temperature scalar (r_T) depends non-linearly on the soil temperature (T_{soil}):

(6) $r_T = e^{308.56*\left(\frac{1}{71.02}-\frac{1}{T_{soil}+273.15-227.13}\right)}$

These multipliers are combined into a moisture * temperature decomposition rate scalar:

(7) $r_{scalar} = r_{M.soilP} * r_T$

For litter, this rate scalar is modified by litter pool according to additional scalars for the labile (kl_1), cellulose (kl_2), or lignin (kl_4) pools (k in equation 1). The final decomposition rate for each litter pool is then:

(8) $r_{li} = kl_i * r_{scalar}$

RHESSys-WMFire litter decomposition is similar to that for FIREBGC. RHESSys-WMFire uses the same temperature multiplier as above (equation 5), but instead the moisture scalar ($r_{m.soilW}$) has been modified to follow the NGAS model (W. J. Parton et al., 1996).

(9) $r_{m.soilW} = \sqrt{\left(\frac{\theta-b}{a-b}\right)^{d\left(\frac{b-a}{a-c}\right)}\left(\frac{\theta-c}{a-c}\right)^{d}}$

Where θ is soil water content. RHESSys-WMFire also includes a third scalar to represent nitrogen limitation by calculating the fraction of potential nitrogen mobilization (*f*; Tague and Band, 2004), so that the final decomposition scalar is:

(10) $r_{scalarR} = r_{m.soilW} r_T f$

The final decomposition rate is then calculated as above in equation 8 using the same kl scalars for each pool.

Litter decomposition in FireBGCv2 and RHESSys-WMFire is calculated on a daily timestep, whereas in LandClim it is calculated on an annual time step, resulting in a scale mismatch when comparing decomposition rates. To compare model structures on the same scale, we converted annual to daily decomposition rate using a mass balance approach (Supplementary Text; S1).

We found large differences in decomposition rates and litter losses among the three model structures, indicating substantial uncertainty in predicting litter loading (Fig. 5). RHESSys-WMFire decomposition rate is less sensitive to water limitation than the other two models (Fig. 6), as indicated by its flat relationship with precipitation (Fig. 7). While its water scalar increases with precipitation, that relationship is flat relative to the relationship between precipitation and the FireBGCv2 water scalar (slopes of 0.03 and 0.08, respectively).

The RHESSys decomposition rate is more sensitive to temperature, whereas the FireBGCv2 decomposition rate is more sensitive to precipitation (Fig. 7). Although both models have the same temperature scalar (equation 6), it is clear that the FireBGCv2 moisture scalar (equation 5) results in a stronger moisture limitation than the RHESSys moisture scalar (equation 7; Fig. 8). At low moisture availability, the decomposition rate for RHESSys-WMFire is much higher than that for FireBGCv2, but that gap narrows within increasing precipitation (Fig. 7). The stronger moisture limitation in FireBGCv2 seems to mask any additional temperature limitation relative to that exhibited by RHESSys.

The RHESSys-WMFire water scalar is less sensitive to precipitation than the water scaler in FireBGCv2. In RHESSys-WMFire the daily water scaler varies between approximately 0.4 and 1 and increases with annual precipitation. In FireBGCv2, the daily water scalar varies between 0 and 1 and increases with annual precipitation. Neither water scalar is influenced by temperature. Given these differences, at low moisture availability, the decomposition rate for RHESSys-WMFire is much higher than that for FireBGCv2, but that gap narrows within increasing precipitation (Fig. 7).

For both RHESSys-WMFire and FireBGCv2, the difference in decomposition rate with LandClim increases as temperature increases (Fig. 7). The difference decreases slightly with precipitation. Comparisons between RHESSys-WMFire and LandClim and FireBGCv2 and LandClim reflect the lack of direct temperature effects on litter decomposition in LandClim. Because LandClim only includes AET and lignin as controls on decomposition, temperature effects on decomposition only occur indirectly through their effects on decomposition.

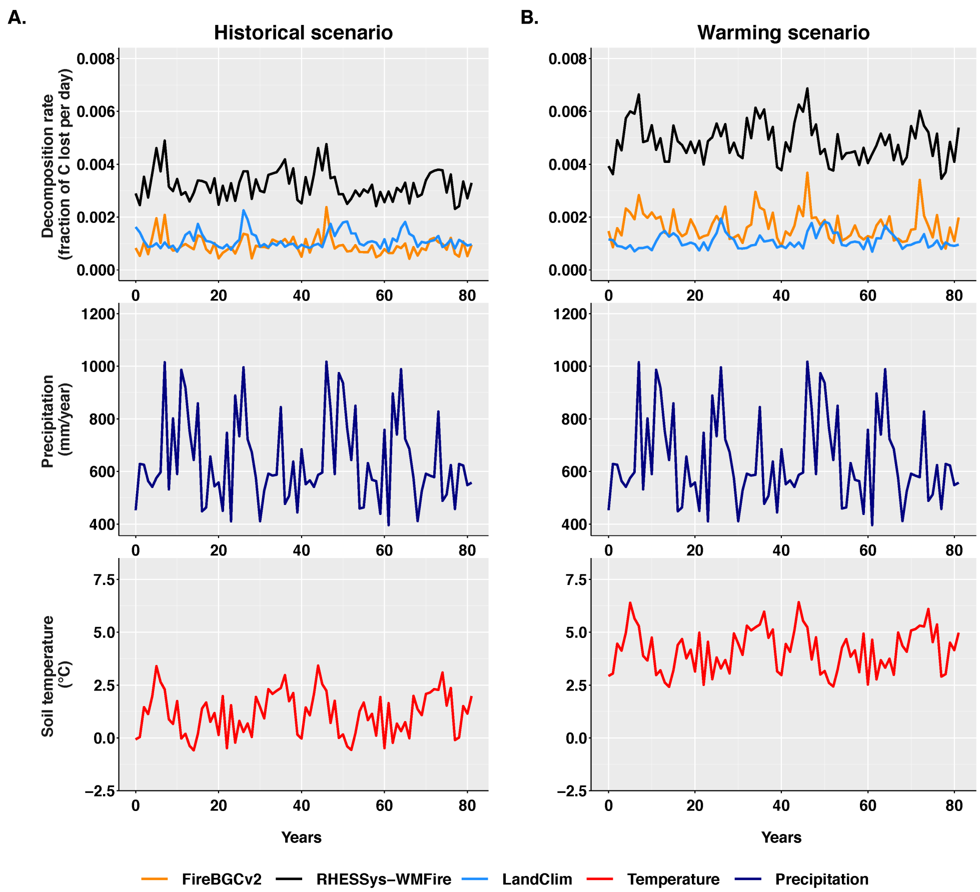

Figure 5: *Daily decomposition rate among the three model structures: LandClim, FireBGCv2, and RHESSys-WMFire (top panels) under historical (left) and +3 degrees warming scenarios (right). Precipitation and temperature inputs used to drive the sensitivity analyses are shown in the middle and bottom panels, respectively.*

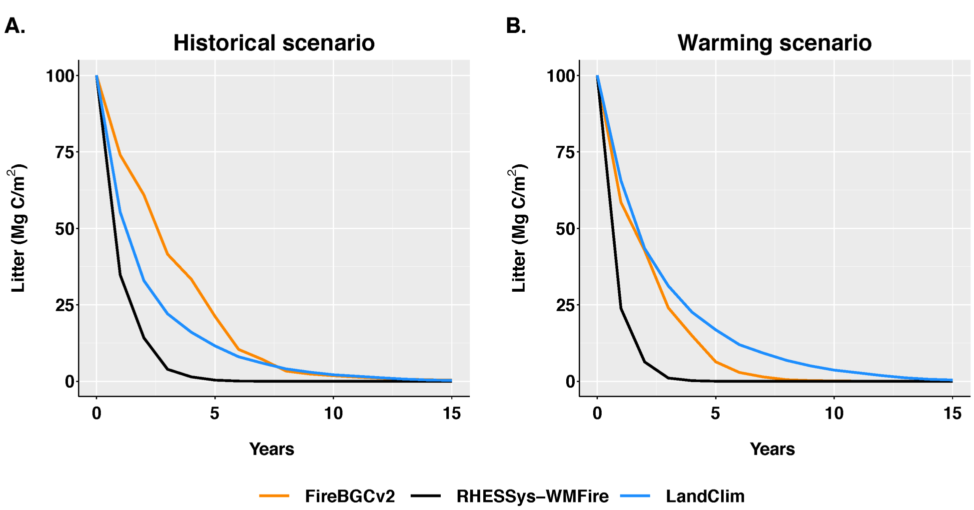

Figure 6: *Litter mass loss among the three model structures: LandClim, FireBGCv2, and RHESSys-WMFire (top panels) under historical (left) and +3 degrees warming scenarios (right).*

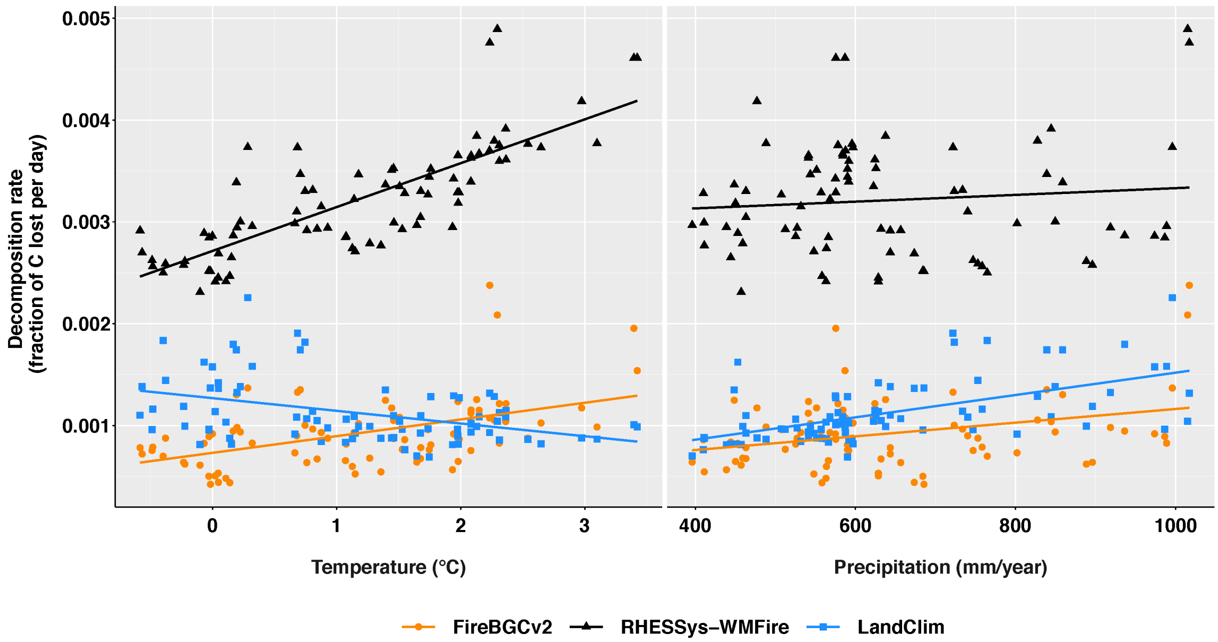

Figure 7: *Comparisons between model decomposition rates in response to temperature (left) and precipitation (right), with least squares regression lines shown for each model. The decomposition rate is calculated over an 81-year simulation and each dot represents 1 simulation year.*

5 Discussion

As Earth's climate continues to change, we need insights from both experiments and models to understand how fine surface fuel loading and its properties will vary over space and time, and how they will affect fire behavior and fire regimes. There are a vast number of fire models in existence, including empirical, mechanistic, stochastic, and various combinations of the three (Reinhardt et al., 2001; Sullivan, 2007, 2009a,b). These models are designed to target different spatial and temporal scales of fire forecasting, ranging from the physics of individual flames to fire regimes (Fig. 1; Keane et al., 2004; Harris et al., 2016).

Fire regime models use detail that matches land surface and/or Earth system models and therefore represent average conditions rather than individual fire behavior (McKenzie & Perera, 2015). Such models include mechanistic representations of fuel moisture and fuel loading, which support applications under climate change scenarios. However, there are large uncertainties in how these models represent fine fuel succession.

Here we examined two types model of uncertainty (parameter, and model structure) in three state-of-the-art fire regime models (LandClim, FireBGCv2, and RHESSys). We found that the sensitivity of projected decomposition to both types of uncertainty increases with climate warming and decreases with increasing precipitation (Figs. 3, 4, 8). These two drivers can also interact to influence both parameter and model structural uncertainty. The sensitivity of decomposition to model structure is highest at high temperature and low precipitation (i.e., under climate change scenarios; Fig. 7). In FireBGCv2 and RHESSys-WMFire sensitivity relating to temperature and precipitation can also interact. In LandClim, on the other hand, temperature is not included as a direct driver of decomposition, and therefore differences in decomposition projections between LandClim and other models also increase with warming.

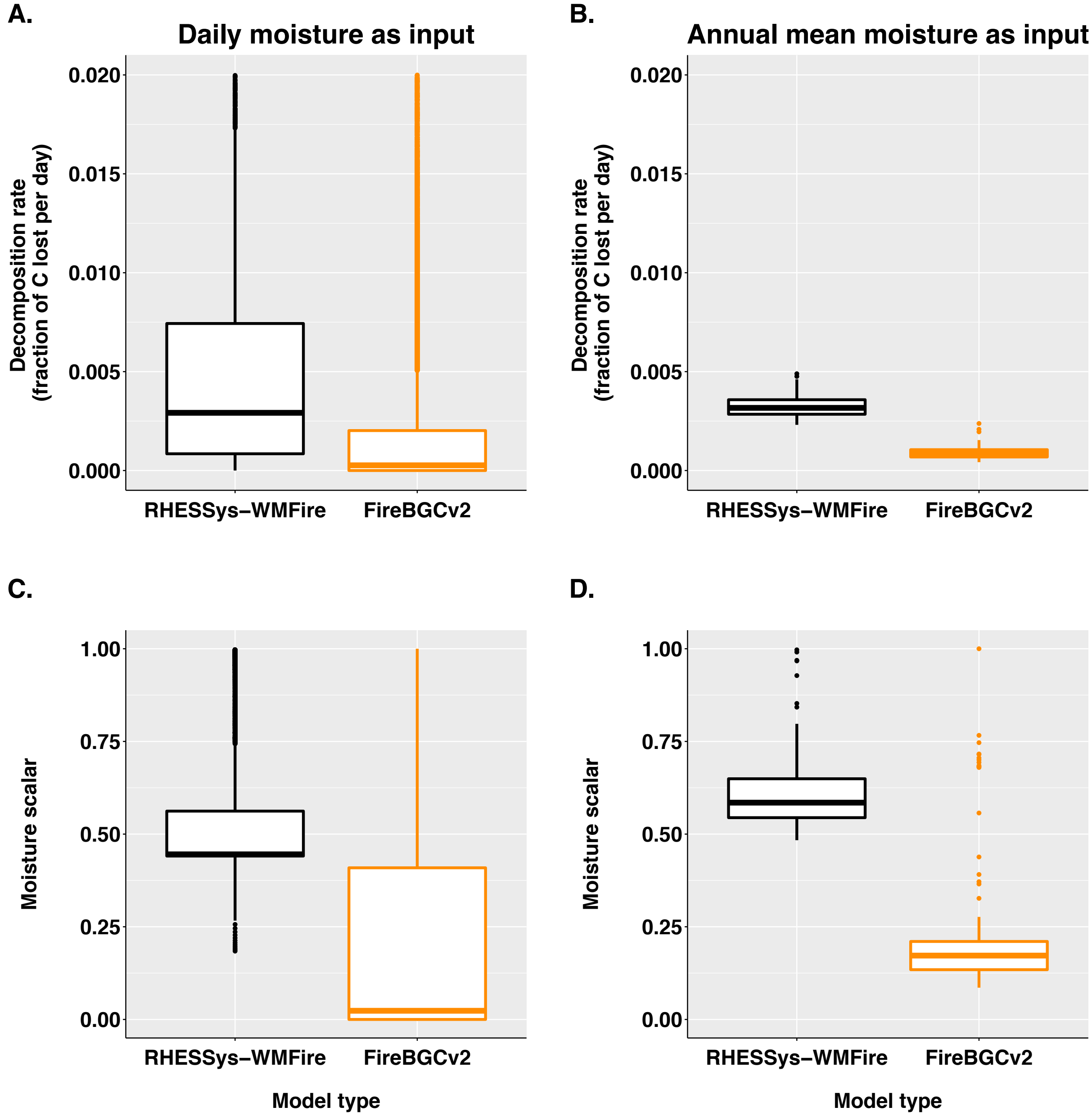

Figure 8: *Comparison of the distribution of daily (left) and annual (right) decomposition rate (top) and moisture scalar (bottom) values (rm.soilP, rm.soilW) between RHESSys-WMFire and FireBGCv2. FireBGCv2 tends to have much lower values for the moisture scalar with more variability, indicating greater sensitivity to moisture limitation than in RHESSys.*

Previous studies focused on SOM pools have found that the temperature and moisture sensitivities of decomposition can vary over space and time, interact in complex ways, and these interactions may not be multiplicative (Dijkstra et al., 2011; Steinweg et al., 2008). This can lead to possible equifinality (i.e., that a given end state can be reached by multiple paths) when developing model structure and parameterizations from lab experiments (Tang and Riley 2020), which is problematic when projecting future fire regimes under novel climates. As biogeochemical models are expanded to include evaluation of both wildfire regimes and wildfire effects on landscape processes, then assessment of the prediction of fine surface fuel loading and how dynamic fuel properties are represented in wildfire simulation becomes essential.

Another source of uncertainty comes from the representation of fuels themselves. For example, fire models that managers use for forest planning (e.g., Rothermel, 1972) only include the woody fuels. A prevailing challenge is that woody fuel decomposition and the interactions with fire are not well studied (J. C. Hyde et al., 2011; J. D. Hyde et al., 2012), in part because measuring mass loss of coarse woody fuels can be challenging (Fry et al., 2018b). When woody fuel decomposition is incorporated in models, it is often based on a constant value (e.g., FFE-FVS; Rebain et al., 2009), or a value adapted from litter models (e.g., FireBGCv2; Keane et al., 2011). Thus, in many models, uncertainty in decomposition rate propagates to uncertainty in the more "management-relevant" fuel layers.

Other challenges that arise with modeling climate-fuel-fire feedbacks include the incorporation of processes such as snag-fall decomposition (Stenzel et al., 2019) and delayed litterfall from scorched trees that otherwise survive fires (Espinosa et al., 2018; Keane, 2008). Therefore, to improve fire management in the future, we need to not only improve our models of litter decomposition, we also must develop better theories and models for the controls on fine woody decomposition.

5.2. Recommendations for future empirical and modeling research

Process-based fire regime models provide an opportunity to account for feedbacks among climate, fuels, and wildfire (Fig. 1), which enables us to evaluate how fire regimes and fire effects will be transformed in response to climate change and management actions. However, to appropriately account for such feedbacks we need to evaluate and improve our understanding of the fundamental processes and parameters we use to simulate fine fuel succession. We described several uncertainties in model structure and parameters used to represent decomposition, which may lead to large uncertainties in projecting future fire under climate change. To refine our modeling approaches, future research should (1) implement long term monitoring studies of fine fuel succession and compare model predictions to observed, (2) quantify and understand fuel succession-related parameter and model structural uncertainty, and (3) consider fuel dynamics and feedbacks when assessing climate-wildfire relationships.

Even though decomposition is a key component of landscape, regional and global C budgets, litter decomposition in land surface and Earth system models has not been thoroughly evaluated and most studies have focused on soil organic C stores rather than fine surface fuels (i.e., litter). To address this, Bonan et al. (2013) developed the long-term intersite decomposition experiment (LIDET; Bonan et al., 2013), which provided a 10-year study of litter decomposition at multiple locations across North and Central America. They used data collected at these sites to constrain temperature and moisture effects on decomposition in the community land model version 4 (CLM4; Lawrence et al., 2012), and found that simulated carbon loss was more rapid than the observations across all sites. The large discrepancies between the laboratory microcosm studies used to parameterize the CLM4 litter decomposition and the LIDET field study likely resulted from poorly constrained temperature, moisture, and nitrogen controls (Bonan et al., 2013).

While this long-term study provides valuable in-situ benchmarks for improving our process representation in models, it does not necessarily account for feedbacks between fire and fuel decomposition dynamics. Penman and York (2010) used a 22-year dataset to examine the relative influence of climate and fire history on rates of litterfall, decomposition, and fuel loading, in a coastal Eucalypt forest in south-eastern Australia and found that litterfall and decomposition were both influenced by temperature, recent rainfall, and fire history. However, such feedbacks are not currently well-understood or represented in models. While these studies are extremely valuable for evaluating and improving models, they are relatively rare—we need many more long-term decomposition studies across climates and fire regimes to better evaluate and improve our mechanistic representation of fine fuel succession in biogeochemical models—this must include studies of both litter and fine woody fuel decomposition.

In many respects, these long-term decomposition studies could follow the ‘body farm’ design (Bass et al., 2004), where examples of woody debris and litter from different species commonly found in a given fire regime are tracked over the long-term with associated factors such as fire intensity, microclimate variabilities, aspect, etc. (e.g., Cornelissen et al., 2017; Trettin et al., 2021). Ideally, these sites should be adjacent to sites where long-term data relevant to fires and ecosystems are also being collected, such as National Ecological Observatory Network, Critical Zone Observatory, Long Term Ecological Research Network, or the Smithsonian Forest Global Earth Observatory (ForestGEO) locations.

In addition, future research should consider fuel dynamics and feedbacks when assessing climate-wildfire relationships. Decomposition and fire have typically been studied separately, even though they can strongly interact (Cornelissen et al., 2017; J. C. Hyde et al., 2011). For example, repeated, low-intensity fires can reduce microbial CO_2 respiration rates and extracellular enzyme activity in coniferous forests, which may promote mineral soil C storage (Pellegrini et al., 2021). Additionally, decomposition is highly sensitive to nutrient availability and prescribed burning can deplete N and P litter stoichiometry, further slowing litter decay (Butler et al., 2019). However, such feedbacks are not well-represented in land surface models, which may cause us to overestimate decomposition in areas that experience increasing fire frequency or severity.

Results from these recent studies suggest that uncertainties associated with existing model structure and parameters must be thoroughly documented. Given that many of the governing decomposition equations are hard-coded in models and often based on individual case studies from a single location, a great deal of model structural uncertainty is currently ignored and difficult to characterize. To understand future climate-fuel-fire feedbacks, it is essential to be transparent about what model choices are being made, the reasons for those choices, and the associated uncertainty. This is particularly critical as the domain of biogeochemical models is expanded to include evaluation of future wildfire regimes, wildfire effects, and how we can mitigate the effects of climate change on wildfire through management.

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Conflict of Interest

The authors declare no commercial, financial relationships, or other conflicts of interest.

Data Availability

The datasets used to run the sensitivity analyses for this study can be found in the Open Science Forum: https://osf.io/zjsbv/?view_only=a348cf16e8f94957a575d43fb6c7032b

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