Wildfire prediction and modeling in global vegetation models (and Earth system)

Sam Rabin (NSF NCAR CGD)

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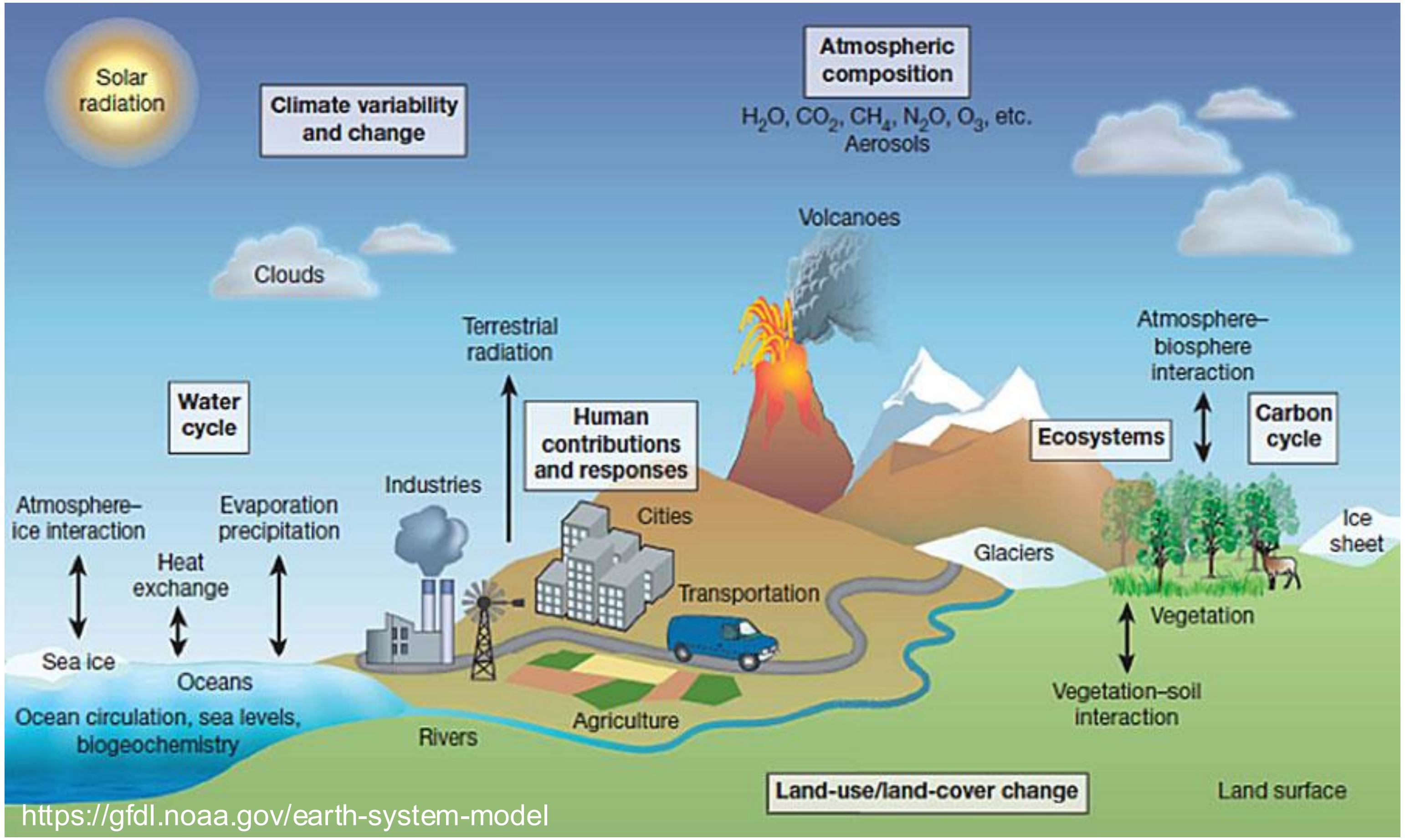
Outline

1. What are global vegetation models and what are they useful for?
2. How does fire work in GVMs?
3. How much should we trust GVM fire models?
4. What developments would help address prediction-related questions?

Earth system modeling enables the exploration of mechanisms behind large-scale questions.



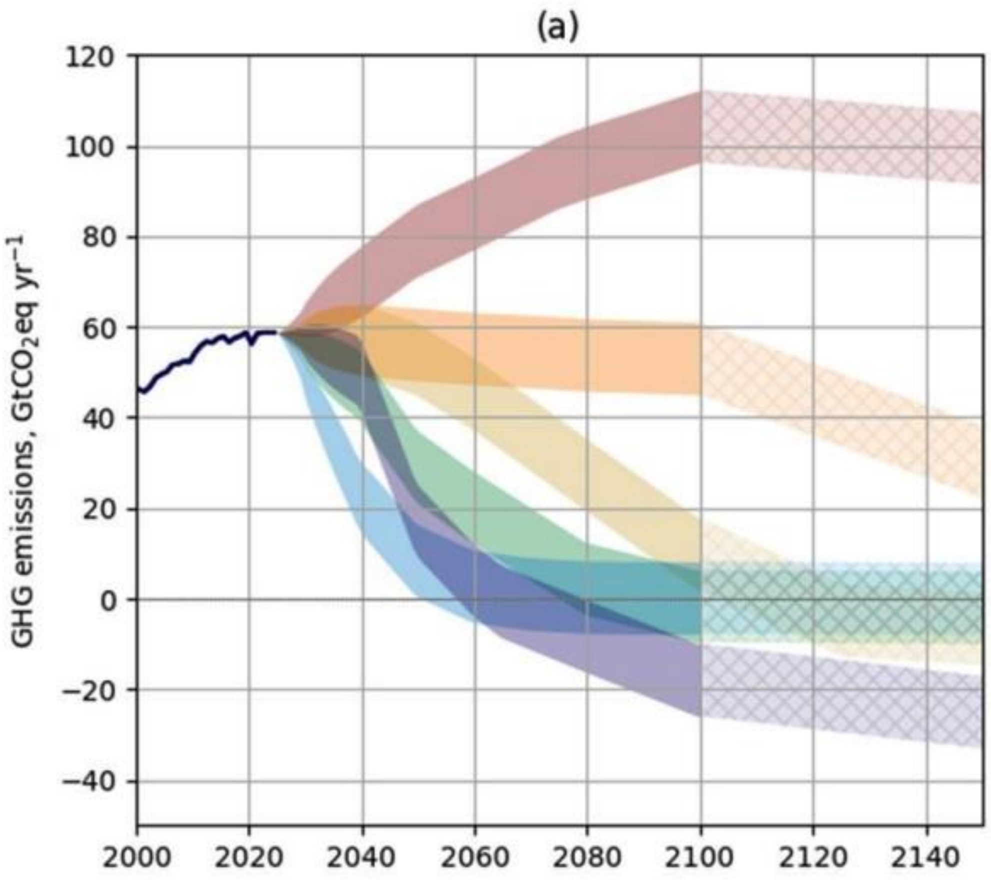
How do the land, atmosphere, ocean, etc. interact?

How would different long-term anthropogenic gas emissions affect climate and the rest of the Earth system?

How effective might different mitigation, management, and adaptation strategies be?

We tend to think in terms of **projections**, not predictions.

Projection (scenario) thinking



Greenhouse gas emissions in CMIP7 scenarios [(van Vuuren et al., in review, *EGUsphere*)]

Long time horizons: Decades to centuries.

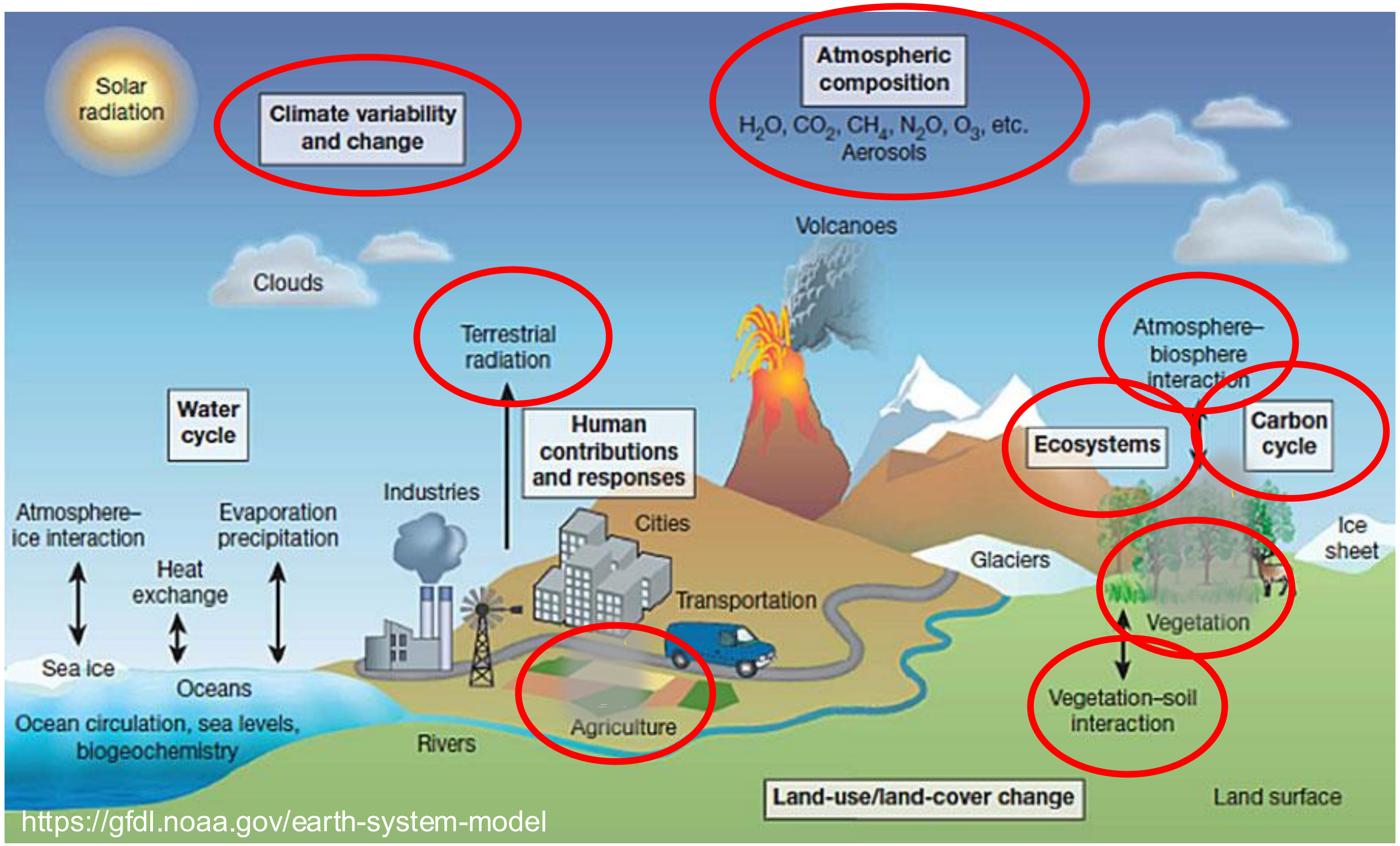
Human decision-making greatly affects outcomes but can't be "predicted."

Time-averaged analyses: We don't expect any one year to be "correct" due to sensitivity to initial conditions. We *do* hope to get trends, means, variability, etc. right.

These are especially important to keep in mind for parts of the Earth system that **humans directly interact with** and tend to **change slowly over time**.

E.g., vegetation.

Global vegetation models (alone or in ESMs): Applications to fire "prediction"



(Fire icons and red outlines mine)

How much fire and smoke will there be in the future?

How do fire and vegetation (and climate) feed back onto one another?

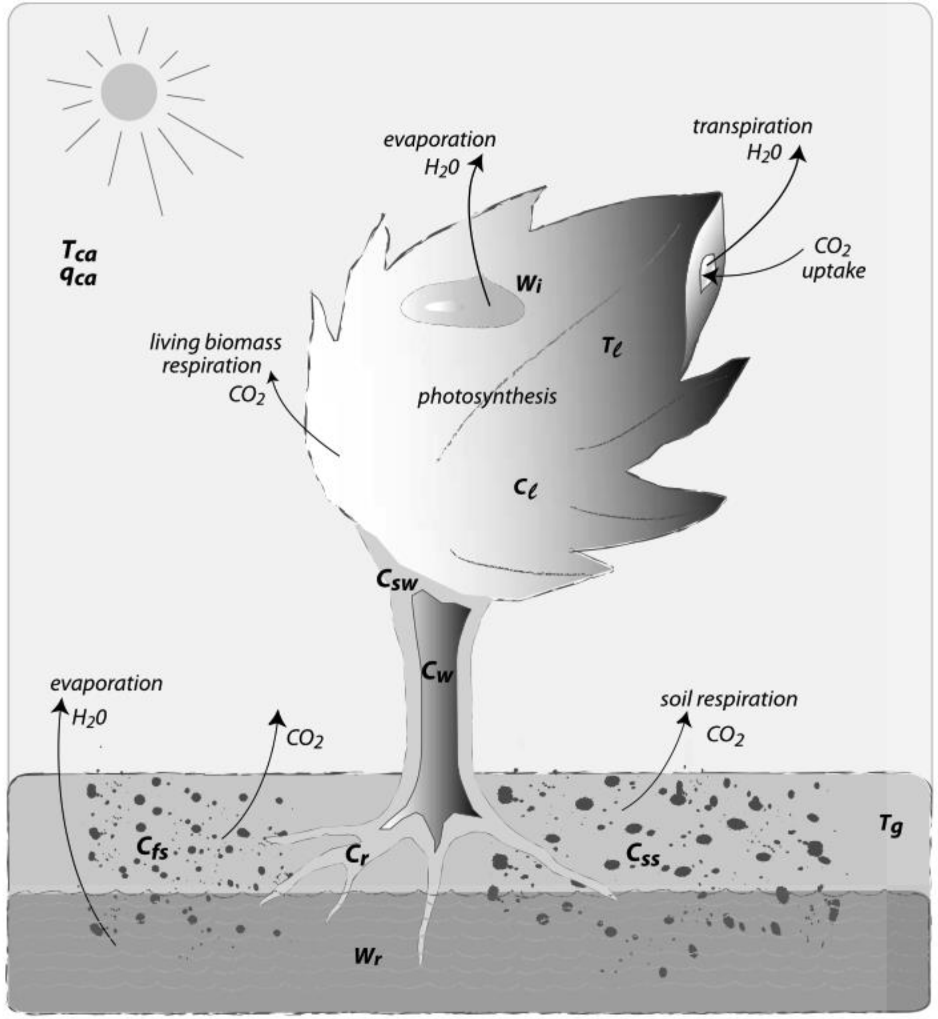
How can mitigation and adaptation be used to reduce long-term risk from wildfires?

How will changing fire regimes affect carbon conservation projects and political goals?

How do these models work?

(Dynamic) global vegetation models ([D]GVMs)

Plant physiology



[Shevliakova et al. (2009, Glob. Biogeochem. Cycles)]

(Dynamic) global vegetation models ([D]GVMs)

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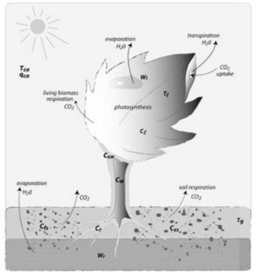
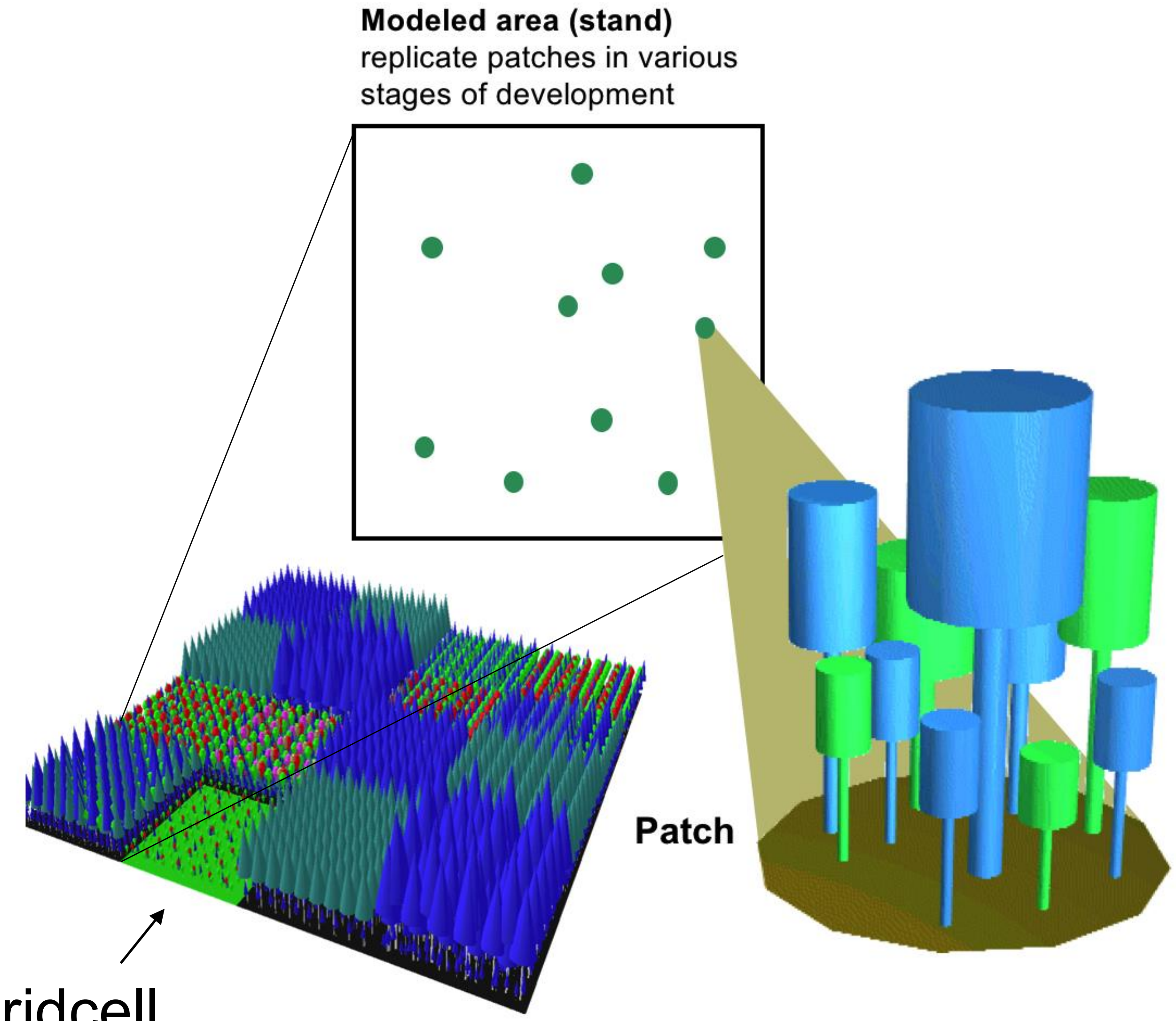


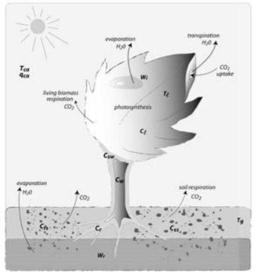
Competition & succession



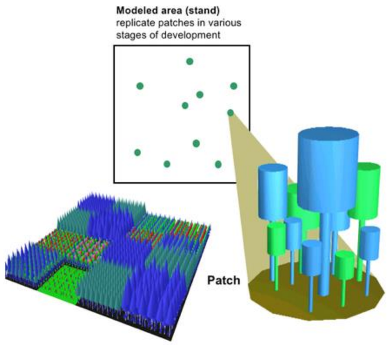
A gridcell

(Dynamic) global vegetation models ([D]GVMs)

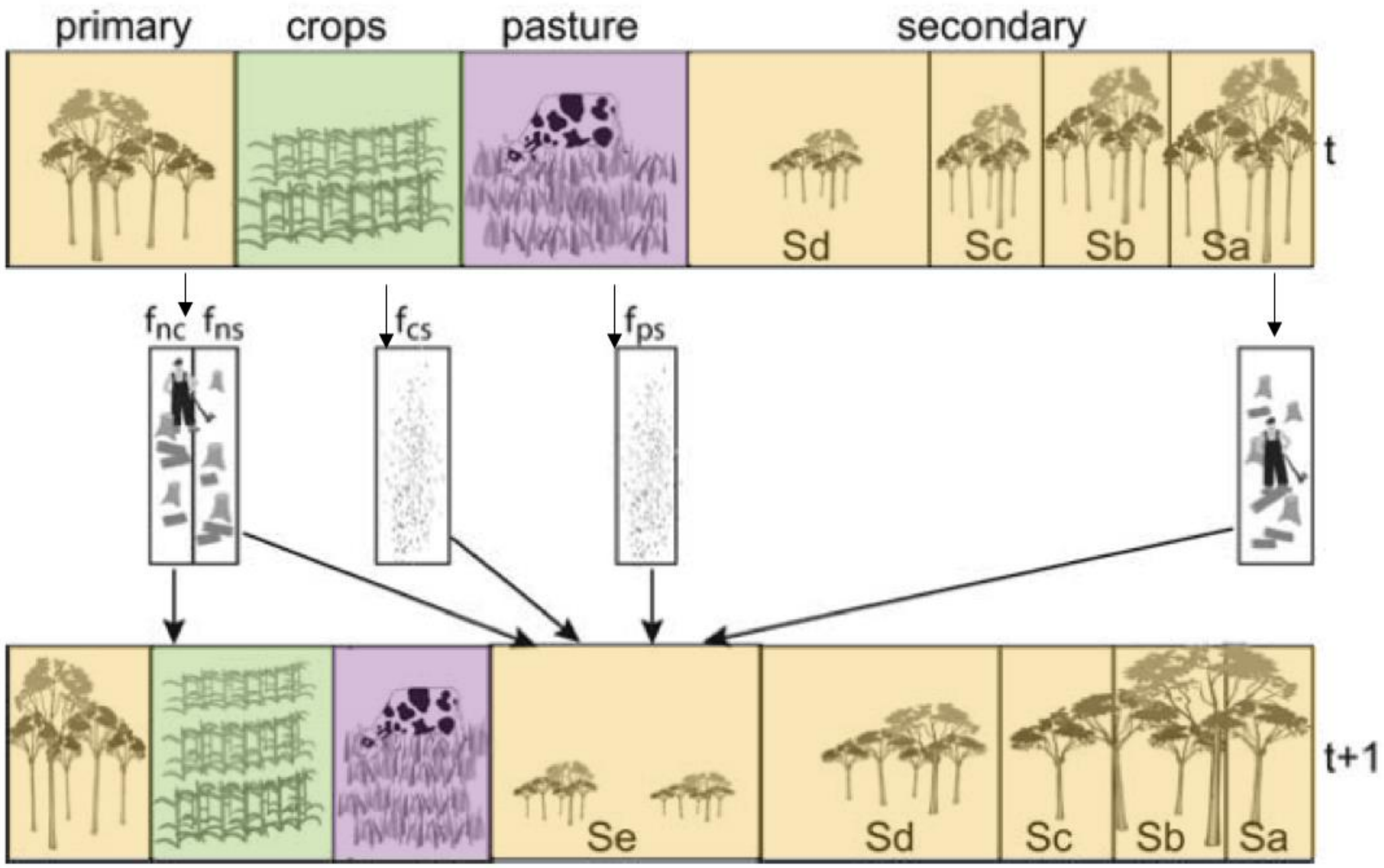
Plant physiology



Competition & succession



Land use & land-cover change



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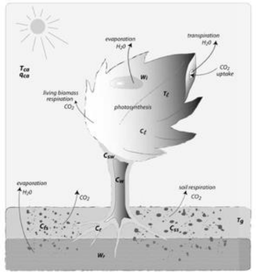
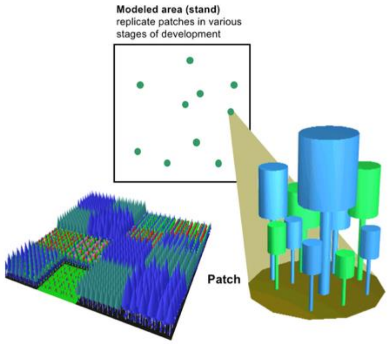


Competition &
succession



Land use &
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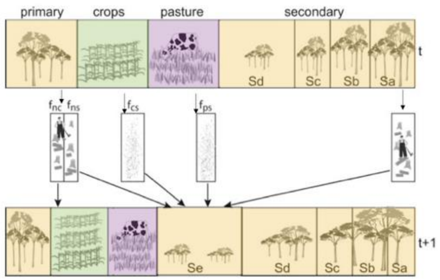
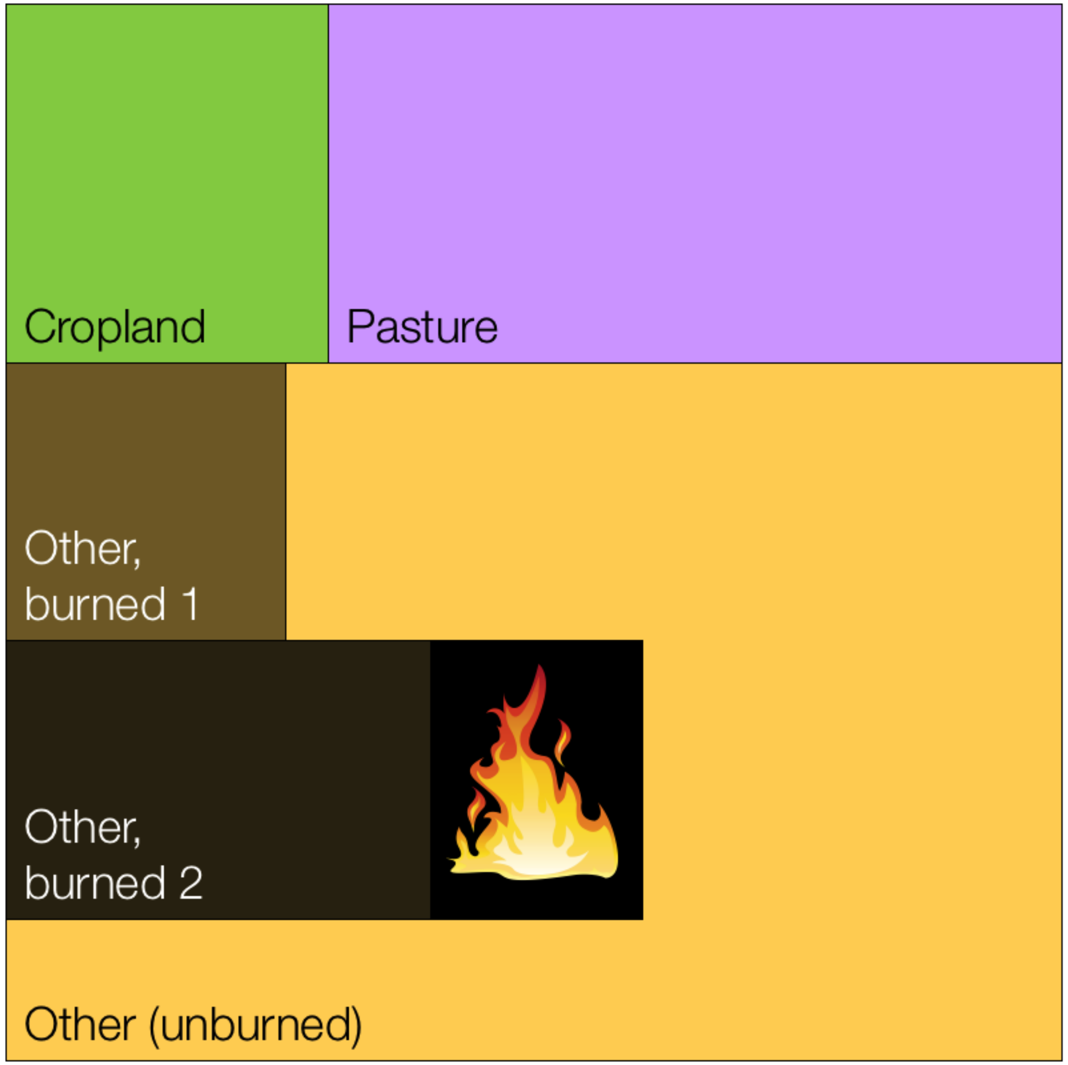
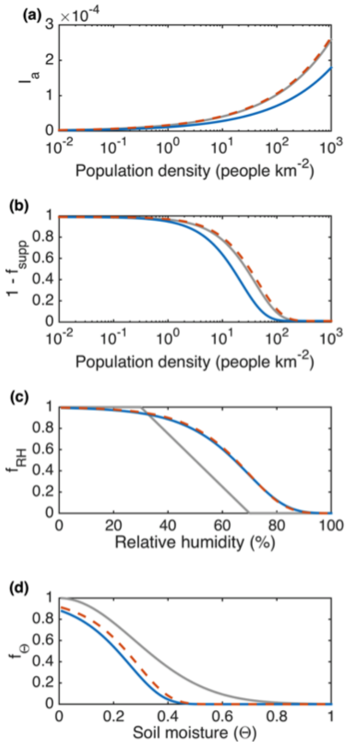


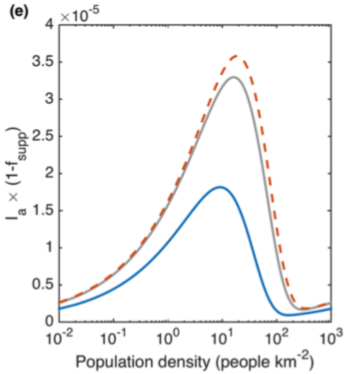
Disturbance

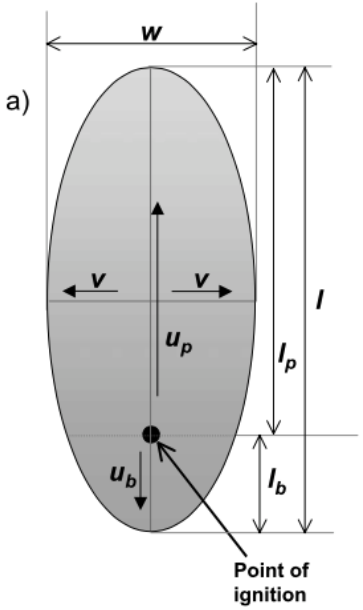


Need to simplify complex processes

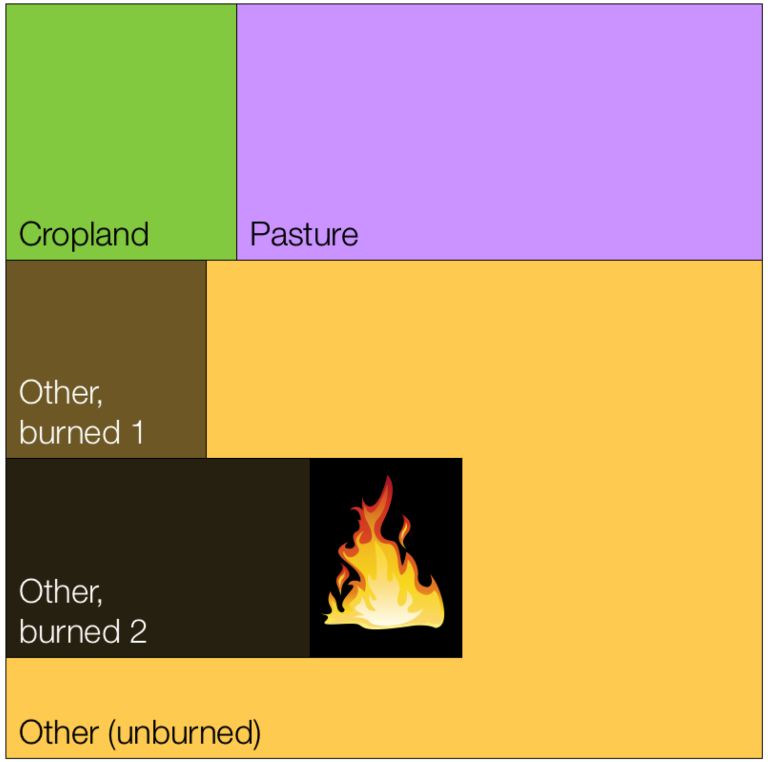
Need to simplify complex processes







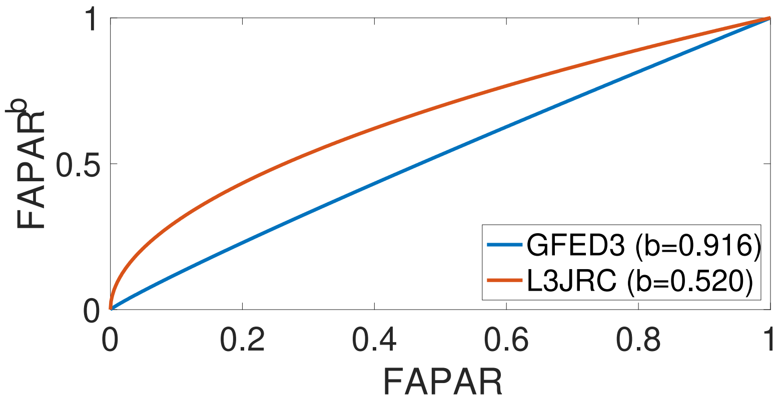
Model	Ellipse shape	ROS (m s^{-1})			
CLM-Li*	$LB = 1 + 10 \times (1 - exp[-0.06 \times W])$ $HB = \frac{LB+\sqrt{LB^2-1}}{LB-\sqrt{LB^2-1}}$	$ROS_f = \widehat{ROS}_{max} \times g_W \times \sqrt{S_\theta \times S_{RH} \times S_T}$, where $g_W = 0.05 \times \frac{2 \times LB}{1 + HB^{-1}}$.			10^{-6}
CTEM	See CLM-Li*	$ROS_f = \widehat{ROS}_{max} \times g_W \times g_\theta$, with g_W formulated the same as in CLM-Li*, $g_\theta = (1 - min[1, \frac{\theta_{root}}{0.3}])^2 \times \left(1 - \frac{L_{duff}}{L}\right) + (1 - min[1, \frac{\theta_1}{0.5}])^2 \times \frac{L_{duff}}{L}$, $L = L_{l,leaf} + L_{l,stem} + L_{d,litter}$, and $L_{duff} = L_{b,g} + L_{d,litter}$.			
JULES-INFERNO	n/a	n/a			
JSBACH-SPITFIRE	$LB = \begin{cases} 1.0 + 8.729 \times (1 - exp[-1.8W])^{2.155} & \text{Trees} \\ 1.1 \times (60W)^{0.464} & \text{Grasses} \end{cases}$	$ROS_f = \frac{I_R \times \xi \times (1 + \Phi_w)}{\widehat{\rho_b} \times \epsilon \times Q_{ig} \times 60}$ $ROS_b = ROS_f \times exp(-0.012 \times W \times 60)$			
LM3-FINAL*	See CLM-Li*	With g_W as CLM-Li*, Ground fires: $ROS_f = \widehat{ROS}_{max} \times g_W \times S_\theta \times S_{RH}$, Crown fires: $ROS_f = \widehat{ROS}_{max} \times g_W \times S_\theta \times S_{RH} \times 3.34$,			$^{-1})]^2 \times$
LPJ-GUESS-SIMFIRE-BLAZE	n/a	$3.3333 \times 10^{-5} \times FDI_{McA} \times (L_{d,litter} + L_{l,g})$ (only used for fireline intensity calculation)			
LPJ-GUESS-SPITFIRE	As JSBACH-SPITFIRE, with $LB = 1$ when wind speed $W < 1$.	See JSBACH-SPITFIRE			
LPJ-LMfire	See JSBACH-SPITFIRE	$ROS_f = \frac{ROS_{f,tree} \times H_w + ROS_{f,grass} \times H_h}{H_w + H_h}$, where $ROS_{f,tree} = \frac{I_R \times \xi \times (1 + \Phi_w)}{\widehat{\rho_b} \times \epsilon \times Q_{ig} \times 60} \times WF$, $ROS_{f,grass} = (0.165 + 0.534 \times W) \times exp(10.8 \times \omega_{x/*}) \times g_s$, wind factor $WF = min(2, 1 + exp[2 \times W - 20])$, and $g_s = -0.0848 \times min(\rho_{b,lg}, 12) + 1.0848$. ROS_b as JSBACH-SPITFIRE.	with $\geq$ 60% herbaceous cover, 3 mm otherwise.	etated land that is not crop-land.	$SF)$, slope factor $SF = \begin{cases} 1 & s < 1.7 \\ \left(\frac{5}{9}\pi \times s - 2\right)^{-1} & s \geq 1.7 \end{cases}$.
MC-Fire	n/a	$\frac{I_{R,R} \times \xi \times (1 + \Phi_w + \Phi_s)}{htsink}$, where $htsink$ (kJ m^{-3}) $= 37.2589 \times$ $\rho_b \times \left(\frac{L_d}{L} \sum_i \left[\frac{L_i}{L_d} \times exp\left(-\frac{1.38}{\sigma_i}\right) \times (250 + 1116\omega_i)\right] + \frac{L_l}{L} \sum_j \left[\frac{L_j}{L_l} \times exp\left(-\frac{1.38}{\widehat{\sigma_j}}\right) \times (250 + 1116\omega_j)\right]\right)$, i (dead fuel classes) $\in$ {1h, 10h, 100h} ($L_d = \sum_i L_i$), j (live fuel classes) $\in$ {herb, wood} ($L_l = \sum_j L_j$), $\sigma_{d,1h} = \widehat{\sigma_{d,1h}}$, $\sigma_{d,10h} = 1.09$, $\sigma_{d,100h} = 0.3$, and $\sigma_{d,1000h} = 0.08$.	n/a	n/a	$\frac{A_g \times (TSF + 1)}{\widehat{FRI}_{max} - dscalar \times \left(\widehat{FRI}_{max} - \widehat{FRI}_{min}\right)}$, where $dscalar = \begin{cases} \frac{BUI - \widehat{BUI}_*}{\widehat{BUI}_*} & \frac{L_{l,g}+L_{d,g}}{L_{l,g}+L_{d,g}+L_{d,1h}+L_{d,10h}} < 0.7 \\ \frac{FFMC - \widehat{FFMC}_*}{\widehat{FFMC}_*} & \frac{L_{l,g}+L_{d,g}}{L_{l,g}+L_{d,g}+L_{d,1h}+L_{d,10h}} \geq 0.7 \end{cases}$
ORCHIDEE-SPITFIRE	$LB = \begin{cases} 1.0 + 8.729 \times (1 - exp[-0.108W])^{2.155} & \text{Trees} \\ 1.1 \times (3.6W)^{0.464} & \text{Grasses} \end{cases}$	See JSBACH-SPITFIRE	See LPJ-GUESS-SPITFIRE	n/a	See JSBACH-SPITFIRE

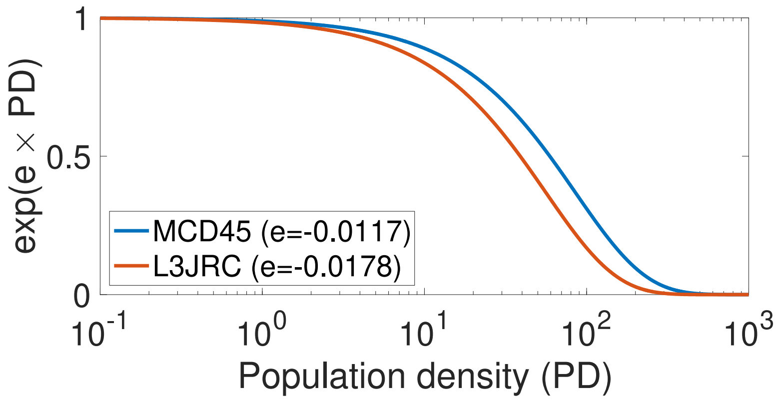


Empirical fire models ("top-down")

Advantages
- Simple, transparent
- Fast
- Easily parameterized

Disadvantages
- Underlying relationships could change in future





SIMFIRE (Knorr et al., 2016, *Biogeosci.*)

Fractional burned area per year (fire frequency) is computed as:

$$A(y) = a(B) F^b N_{\max}(y)^c \exp(-ep) \quad (1)$$

where y is the fire year[14], B is the biome type (based on vegetation type and height), F is the interannual average of annual maximum of monthly FAPAR (fraction of absorbed photosynthetically active radiation, a measure of vegetation continuity and leaf area), $N_{\max}$ is the annual maximum Nesterov index, and p is the population density (people km^{-2}). b, c and e are global parameters, and $a(B)$ denotes one parameter a for each of eight biome types. The particular form of equation (1) and the parameter values $a(B), b, c$ and e are taken from SIMFIRE optimized against global GFED3 burned area[36] for the complete range of population densities[14] (Supplementary Table 2). Annual fire frequency is redistributed to monthly values using the mean 2001–2010 GFED3 annual cycle of burned area within a varying

Process-based fire models (“bottom-up”)

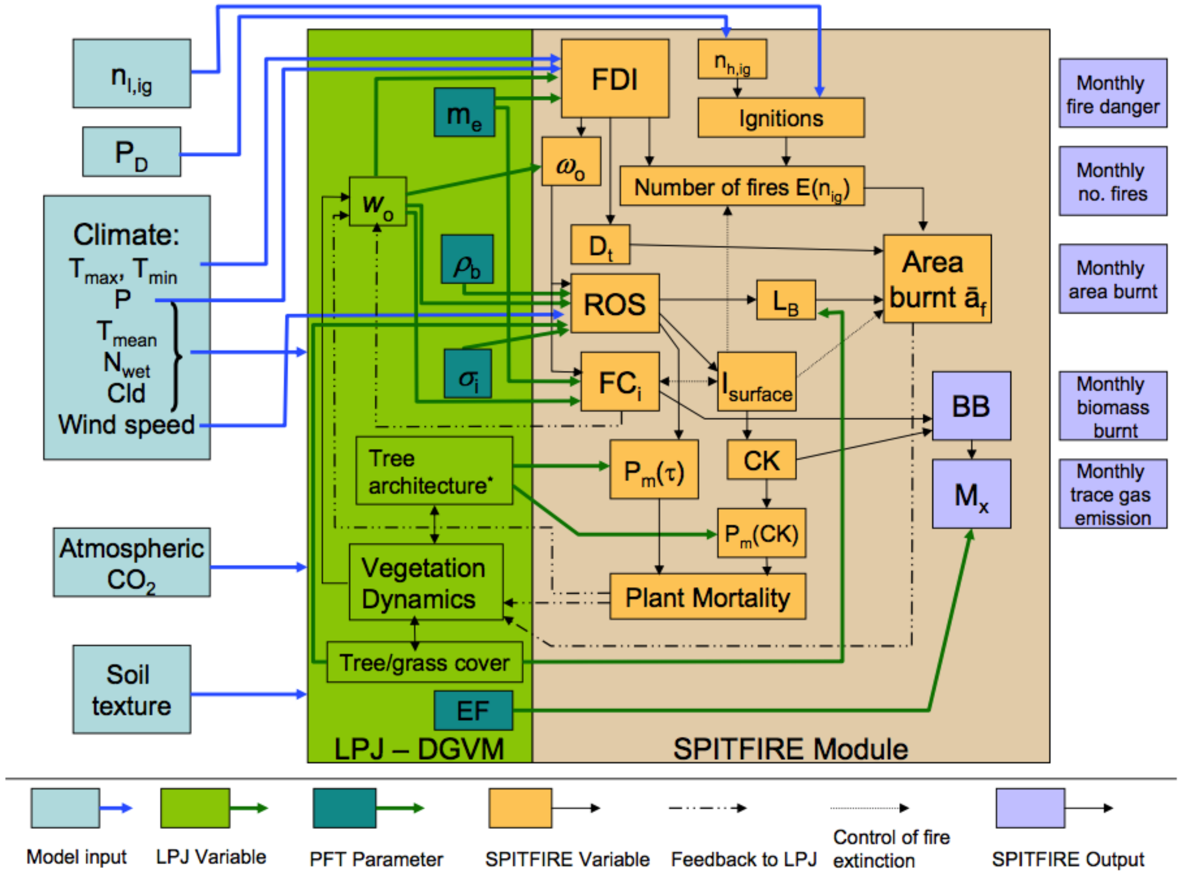
Advantages
- Capture mechanisms behind fire occurrence

Disadvantages
- Lots of moving parts
- Hard to understand
- Hard to parameterize
- End up using empirical functions anyway

and fire duration (CFFBG, 1992). The estimated fire duration (min) depends on the fire danger index:

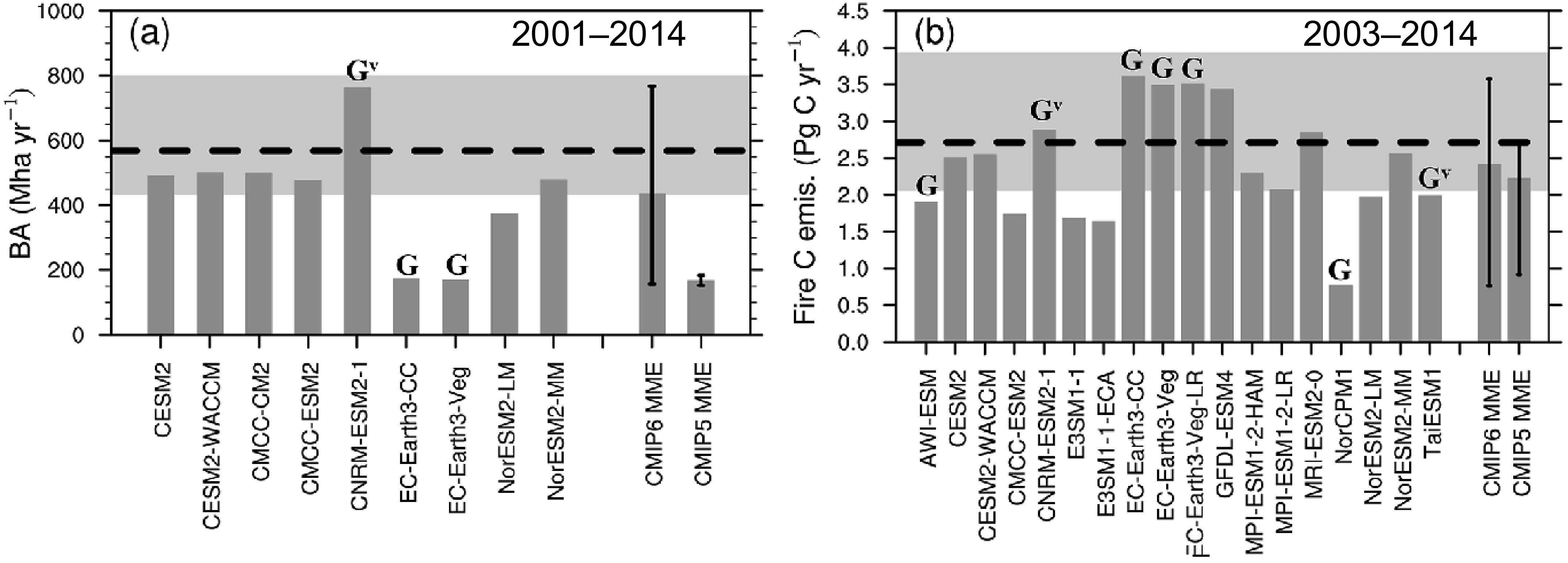
$$t_{\mathrm{fire}} = \frac{241}{1 + 240 \cdot e^{-11.06 \cdot FDI}}. \quad (14)$$

SPITFIRE (Thonicke et al., 2010, *Biogeosci.*)



Global fire model performance

Li et al. (2024, *GMD*) compared ESM burned area hindcasts from CMIP6 with observations:



CMIP6 models are generally on the low end of observed burned area.

Same for fire carbon emissions.

Global fire model performance

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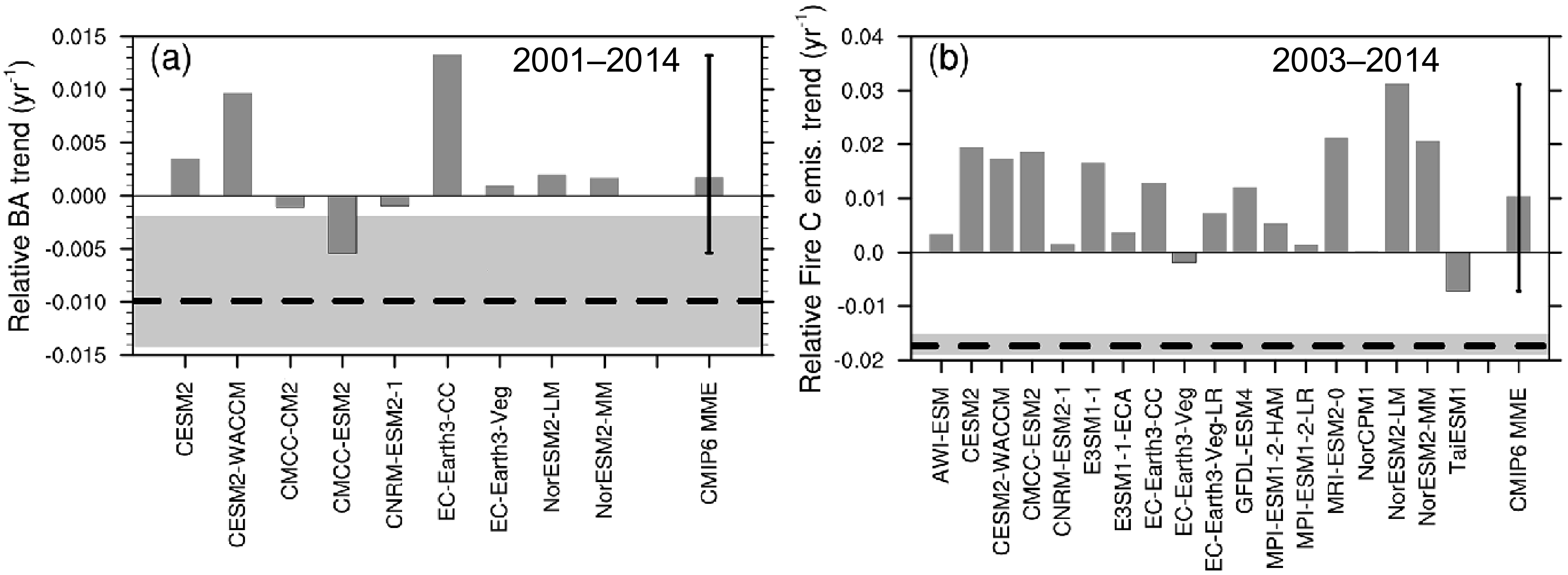
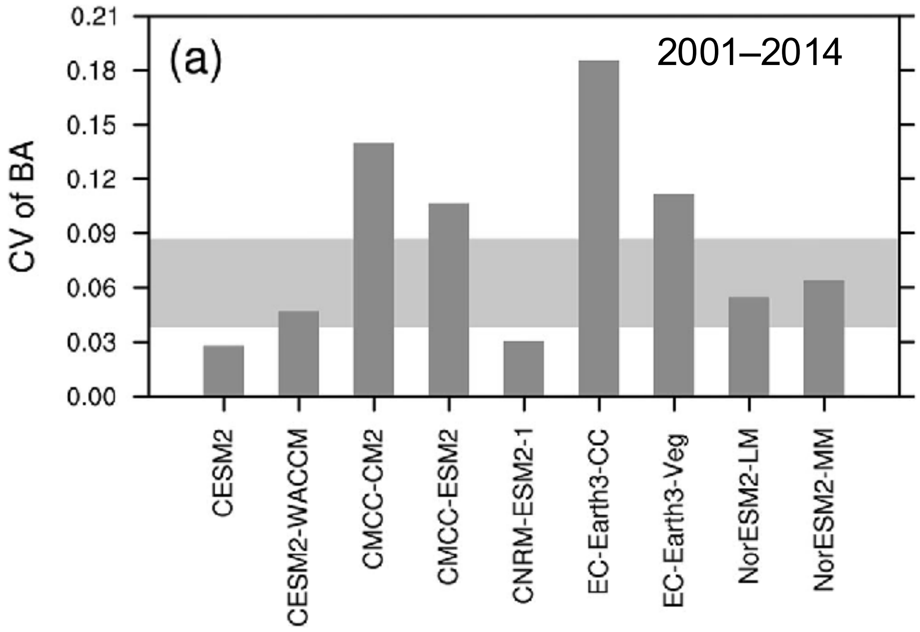


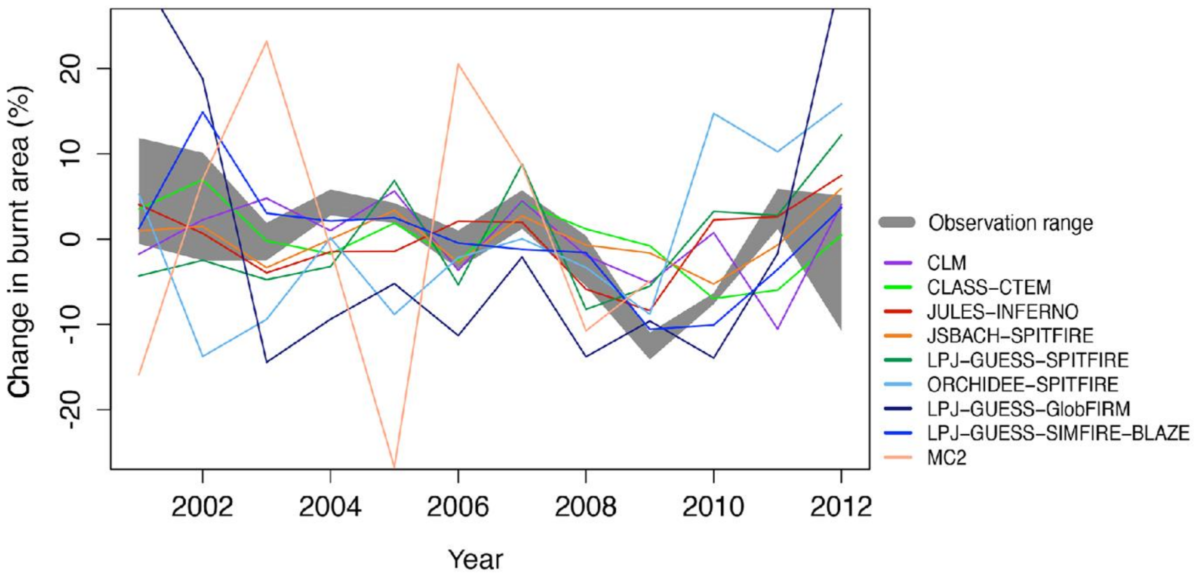
CMIP6 models *don’t* capture global trends.

Global fire model performance

[Li et al. (2024, *GMD*)](#) compared ESM burned area hindcasts from CMIP6 with observations:



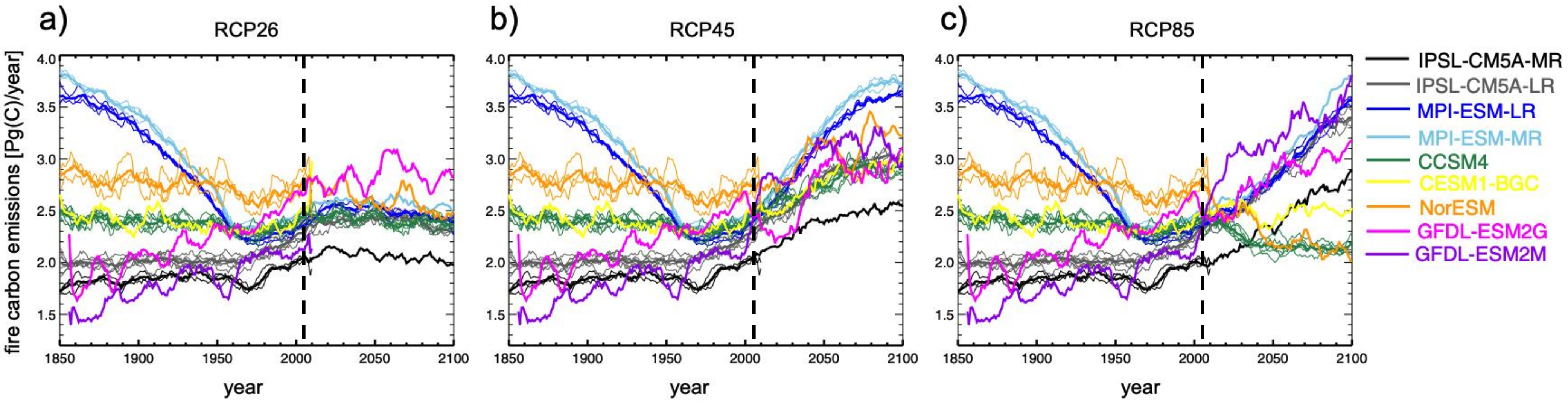
[Hantson et al. (2020, *GMD*)](#) did the same with non-ESM models using historical climate forcings:



Recent models *don't* really get interannual variability right.

Global fire model <u>projections</u>

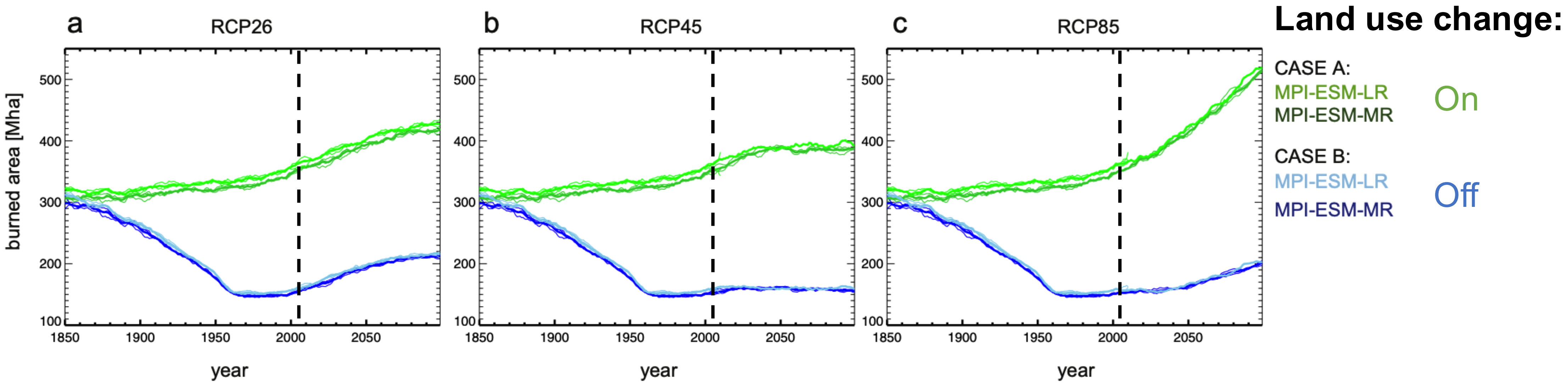
Kloster et al. (2017, *Glob. & Planetary Chg.*) compared
ESM burned area projections from CMIP**5**:



Older models disagree on future trends,
especially in scenarios of higher warming.

Global fire model projections

Kloster et al. (2017, *Glob. & Planetary Chg.*) compared ESM burned area projections from CMIP**5**:



Land use really matters (especially if you don't allow pasture fire!)

Andela et al. (2017, *Science*) Hantson et al. (2020, *GMD*) Jones et al. (2022, *Rev. Geophys.*) Li et al. (2024, *GMD*)

Factors driving GVM fire performance

- Models that get vegetation (fuels) right—especially seasonality and variability—tend to do better.
- Process-based fire models tend to do better than old empirical fire models.
- Simulating human fire use helps improve fire seasonality.
- Correctly accounting for direct and indirect land use effects on fire is important for capturing long-term trends.
- Population density effects vary widely among models and make a big impact on results.

Andela et al. (2017, *Science*) Hantson et al. (2020, *GMD*) Jones et al. (2022, *Rev. Geophys.*) Li et al. (2024, *GMD*)

Future directions

- Anthropogenic effects (intentional use, accidental ignitions, passive and active suppression)—regional parameterizations?
- Topographical effects
- Multi-day fire
- Forest die-offs (pests/disease, storms)
- Sub-gridcell, high-frequency changes in wind (gusts)
- Lightning in ESMs

Challenges: Computational cost; gridcells typically large

Machine learning: parameterize, choose between, or even augment process-based models

Thank you!

Email: samrabin@ucar.edu