Machine Learning–based Observation-constrained Projections Reveal Elevated Global Socioeconomic Risks from Wildfire

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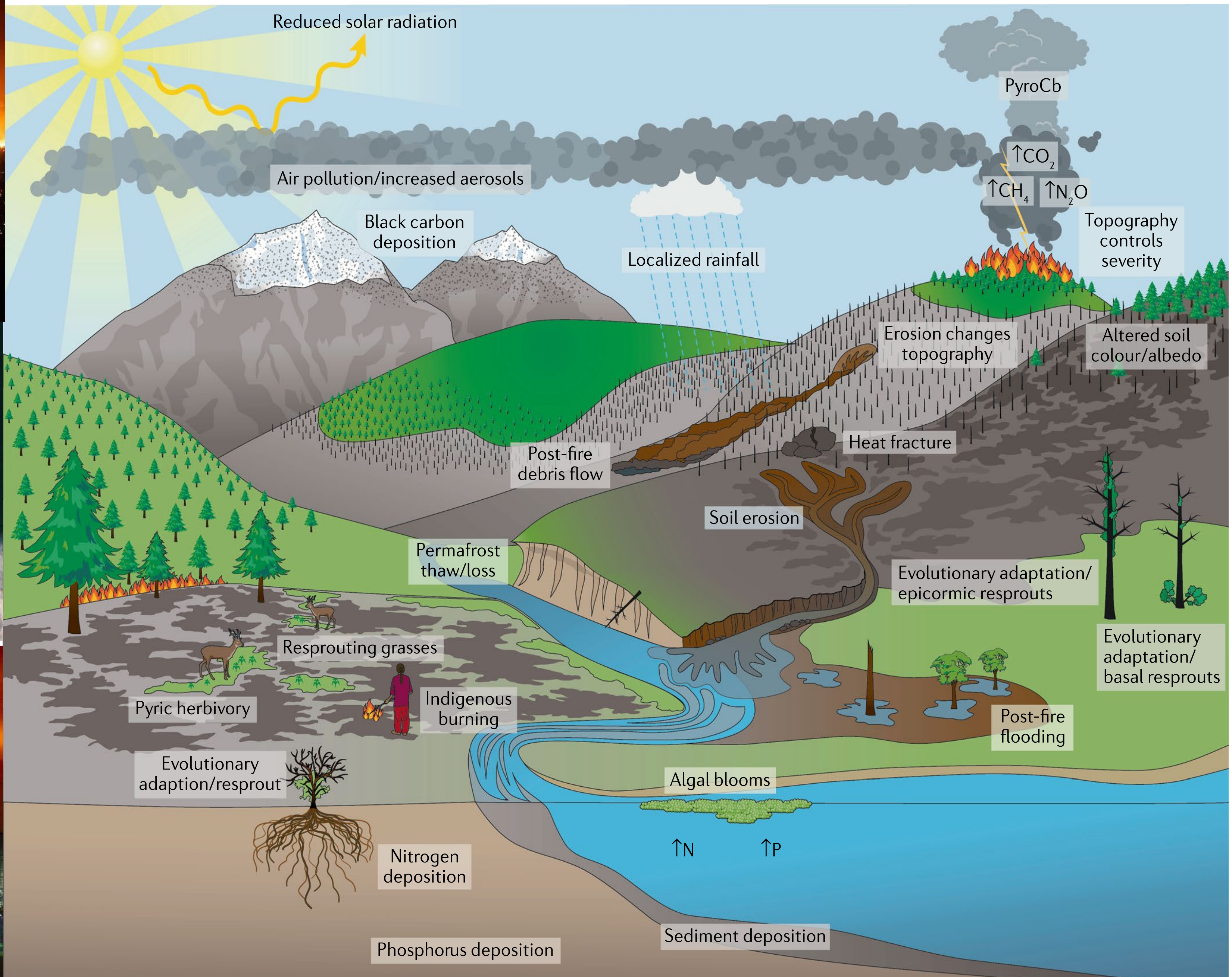
Fire in the Earth System

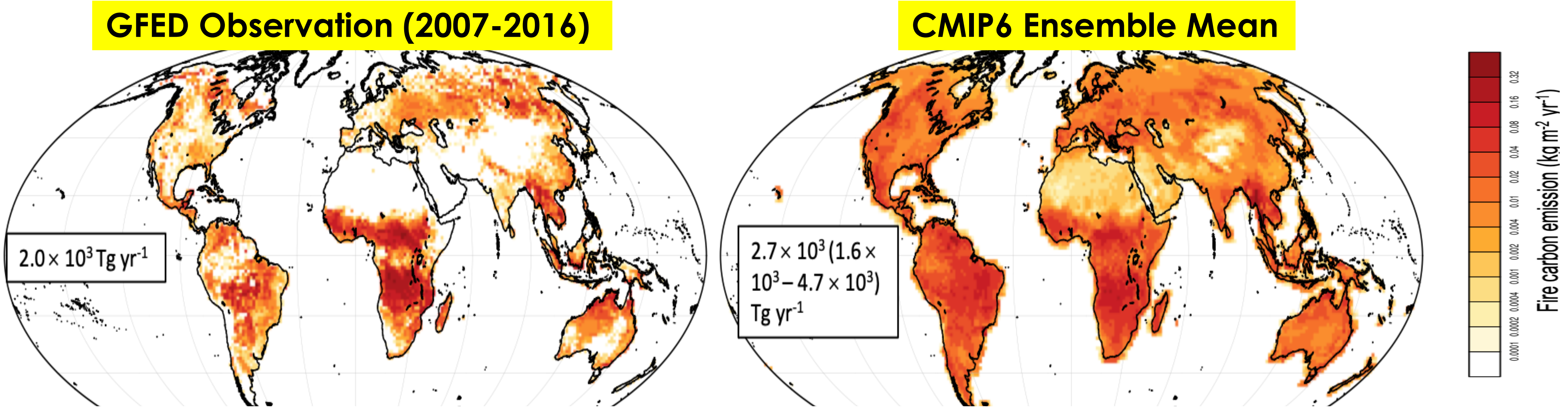

California, USA (Aug., 2020)

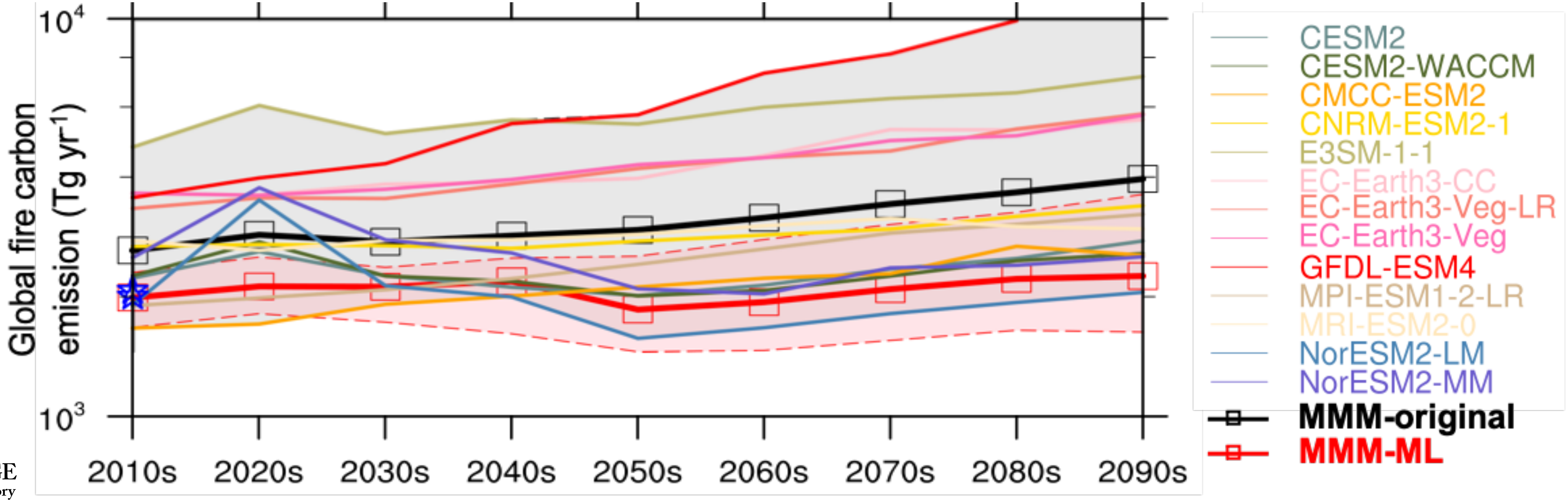

New South Wales, Australia (Dec., 2019)


Great Smoky Mountains, USA (Nov., 2016; Apr., 2022)



Historical and Projected Wildfire Activities in CMIP6 ESMs





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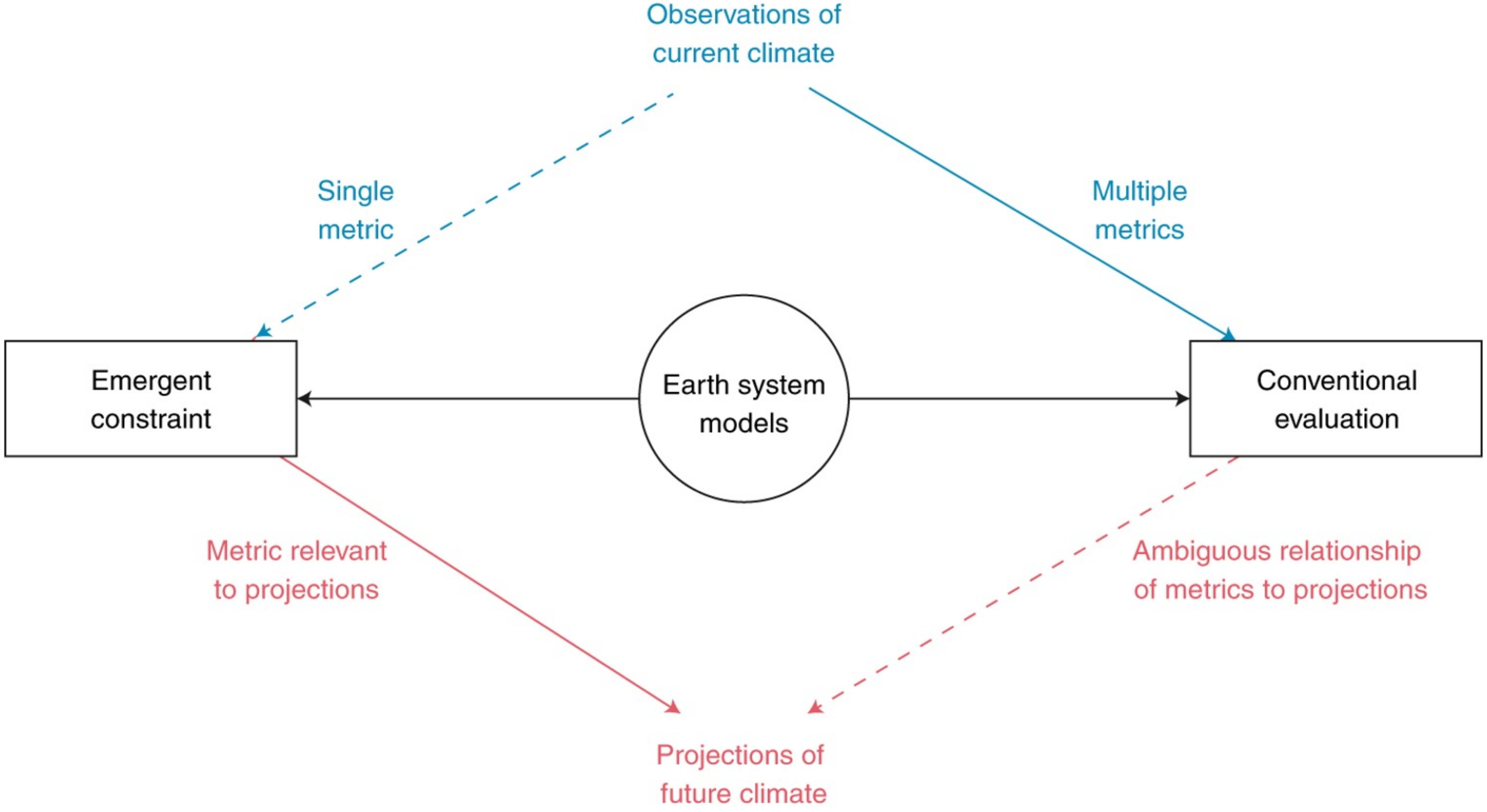
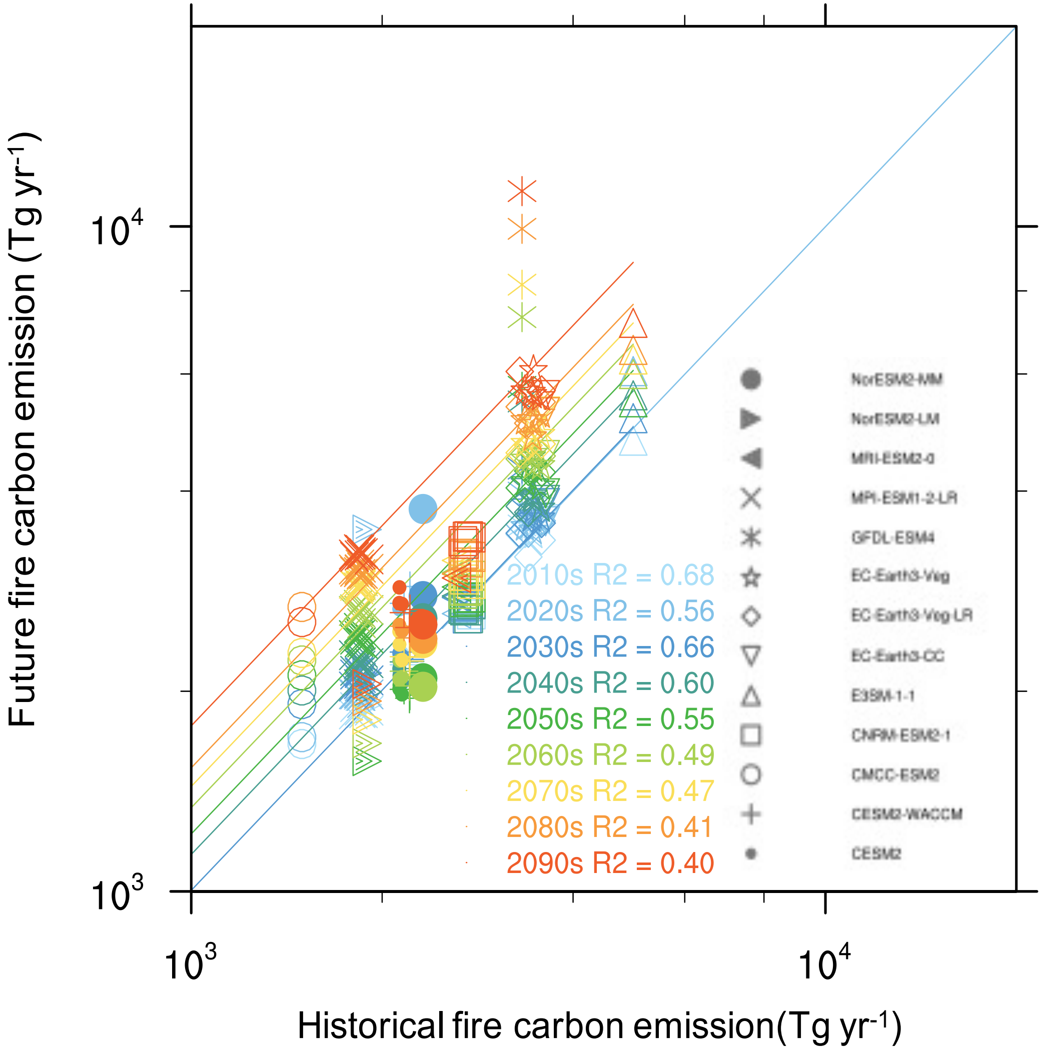
Ways to Reduce ESM Projection Biases

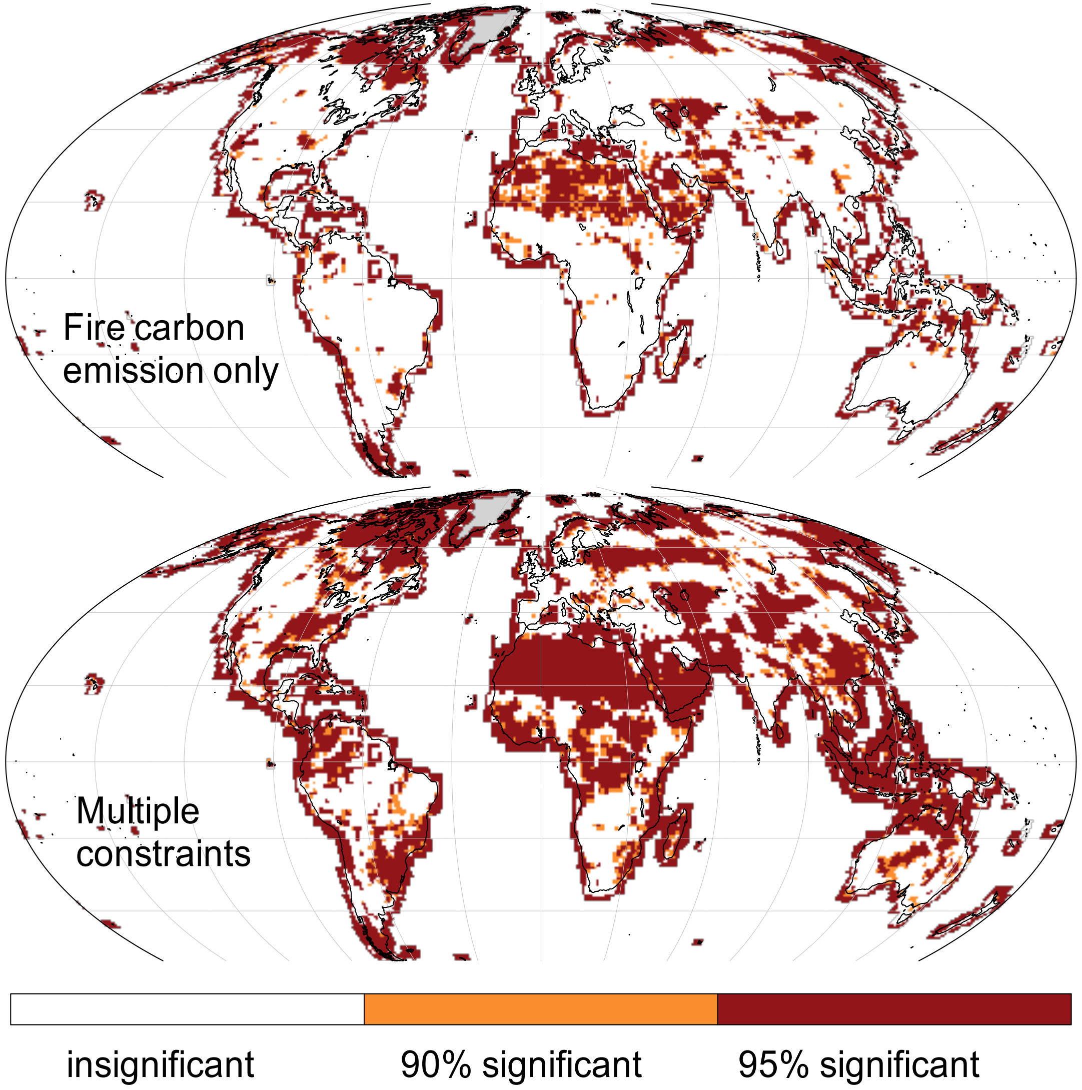


*Core concept of **Emergent constraint**: despite major differences across ESMs, relationships between elements of **current climate (X)** and **future climate** (**Y**) are implicit **within ESM** solutions of the partial differential equations governing physical and biogeochemical systems, i.e., **Y = f(X) + ε, where f is identified from a suite of ESMs.***

Hall et al. (2019)

Limited Applicability of Traditional Emergent Constraint





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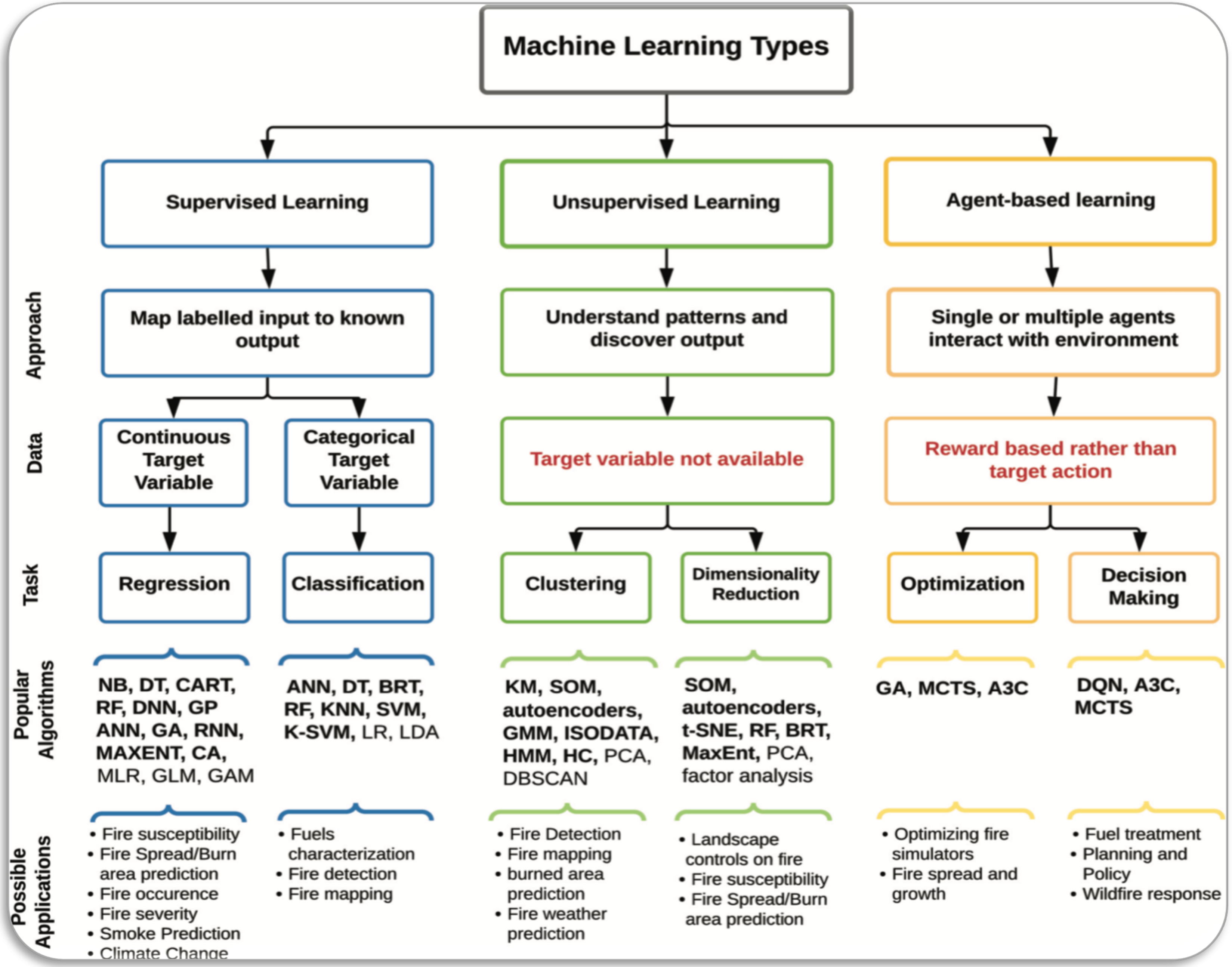
Wildfire Machine Learnings



Jain et al. (2020)

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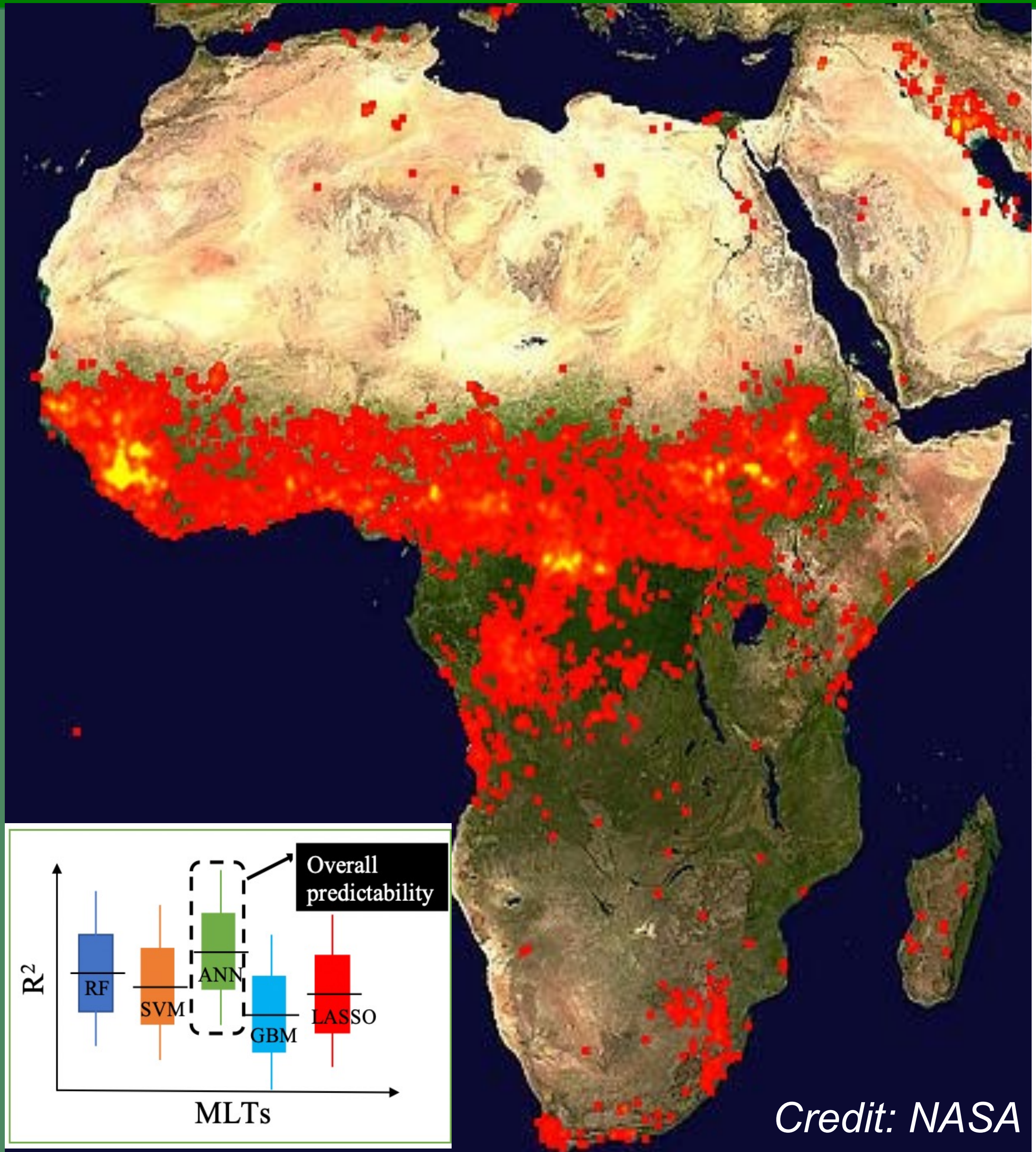
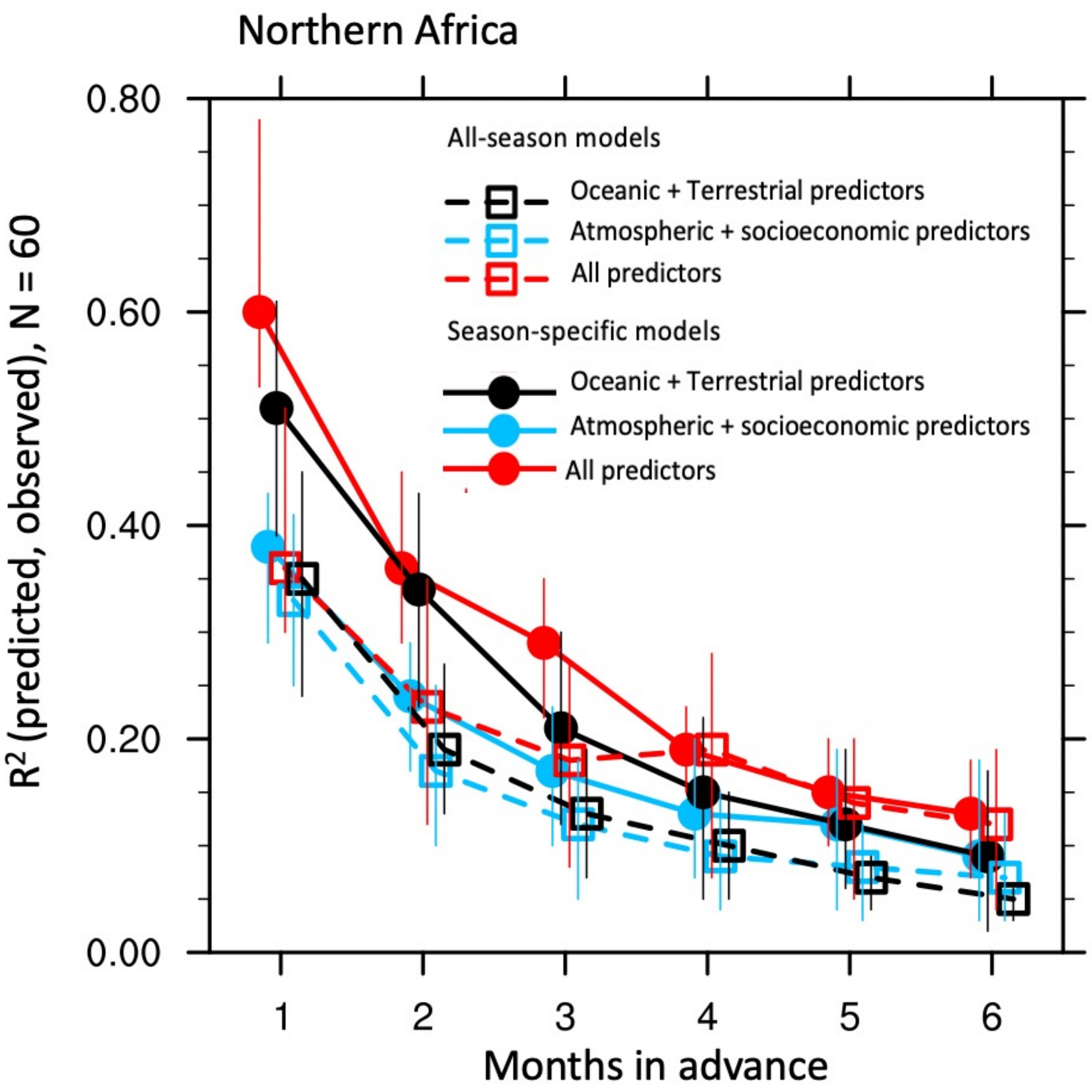
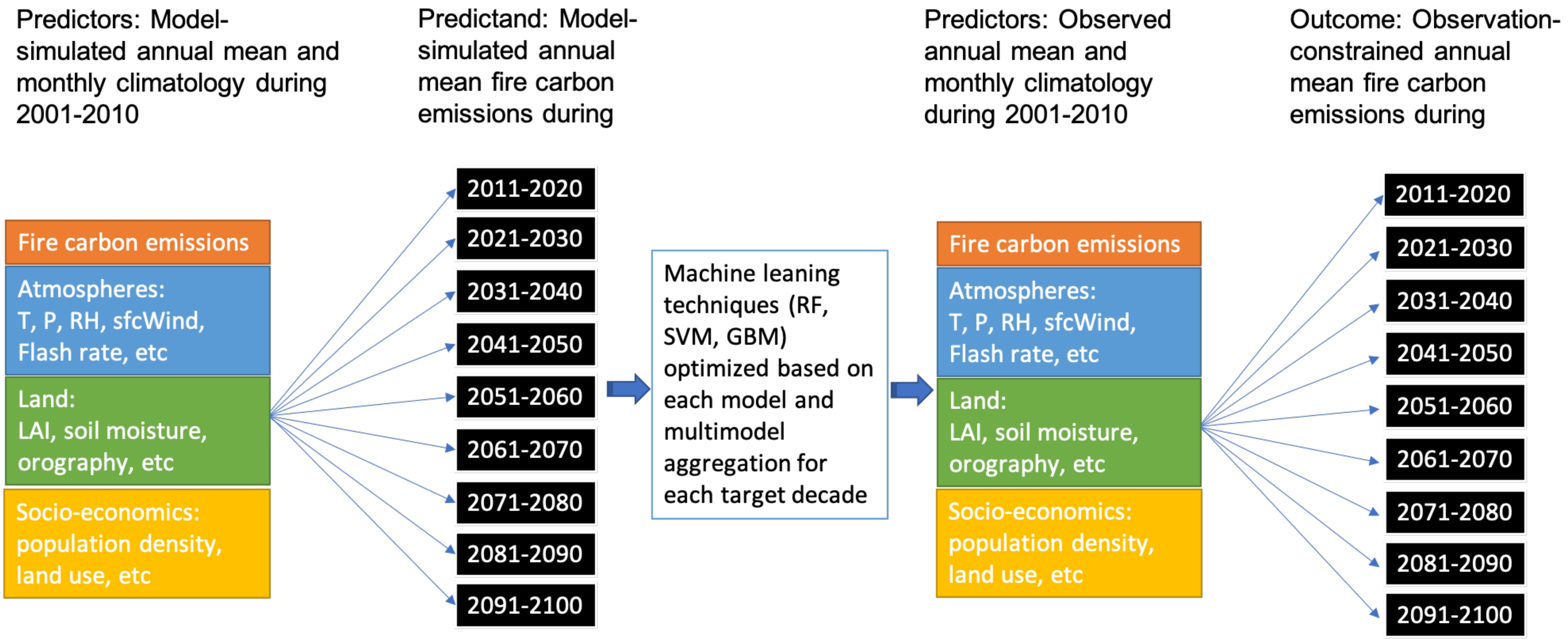
Predictability of African Fire Carbon Emission





Yu and Mao et al. (2020)

Schematic of the ML-EC Framework



Training dataset: the spatial sample (at 0.25˚ lat/lon) of decadal mean predictors and target variable (N = 11,325 for each ESM).

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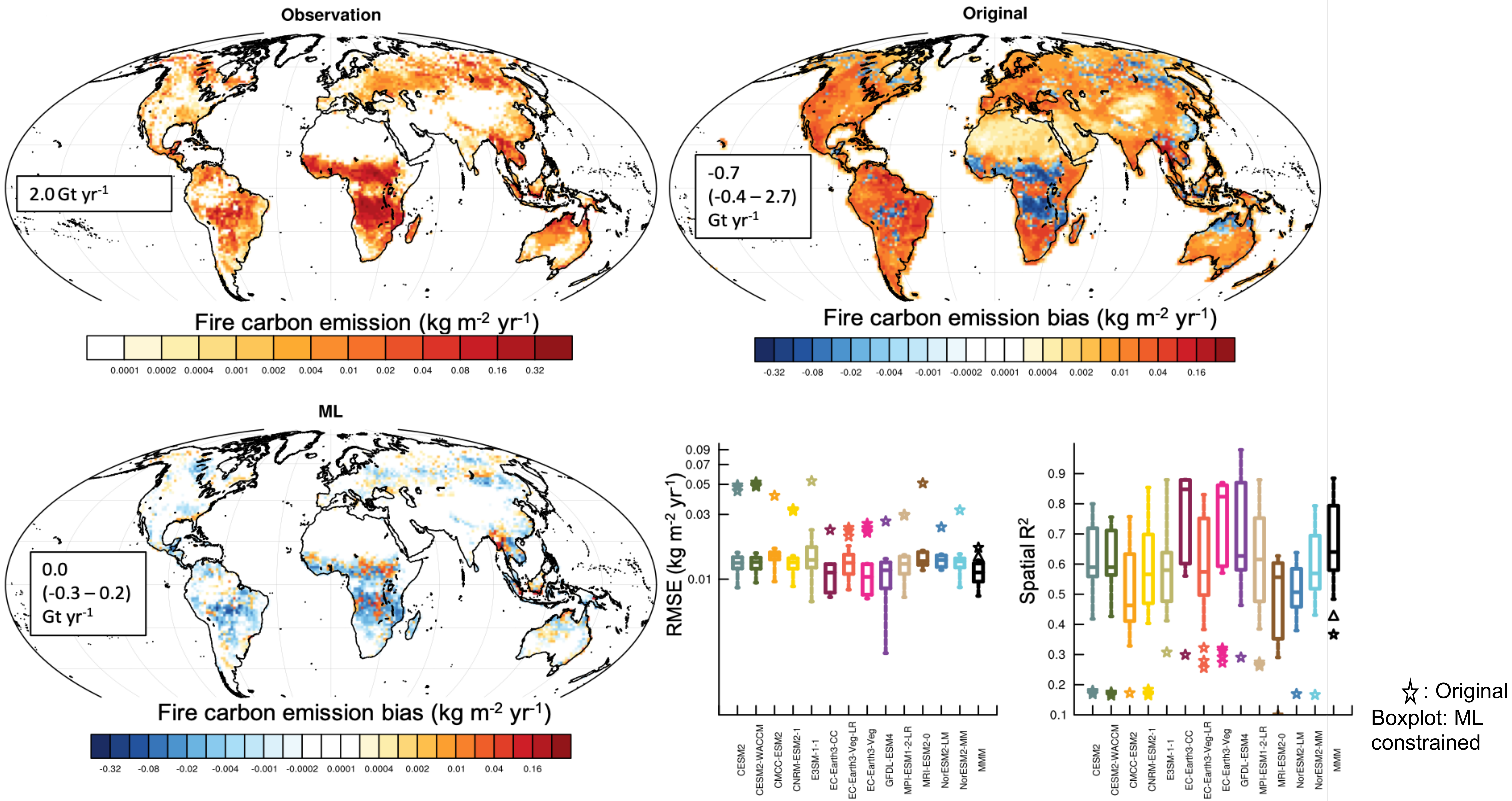
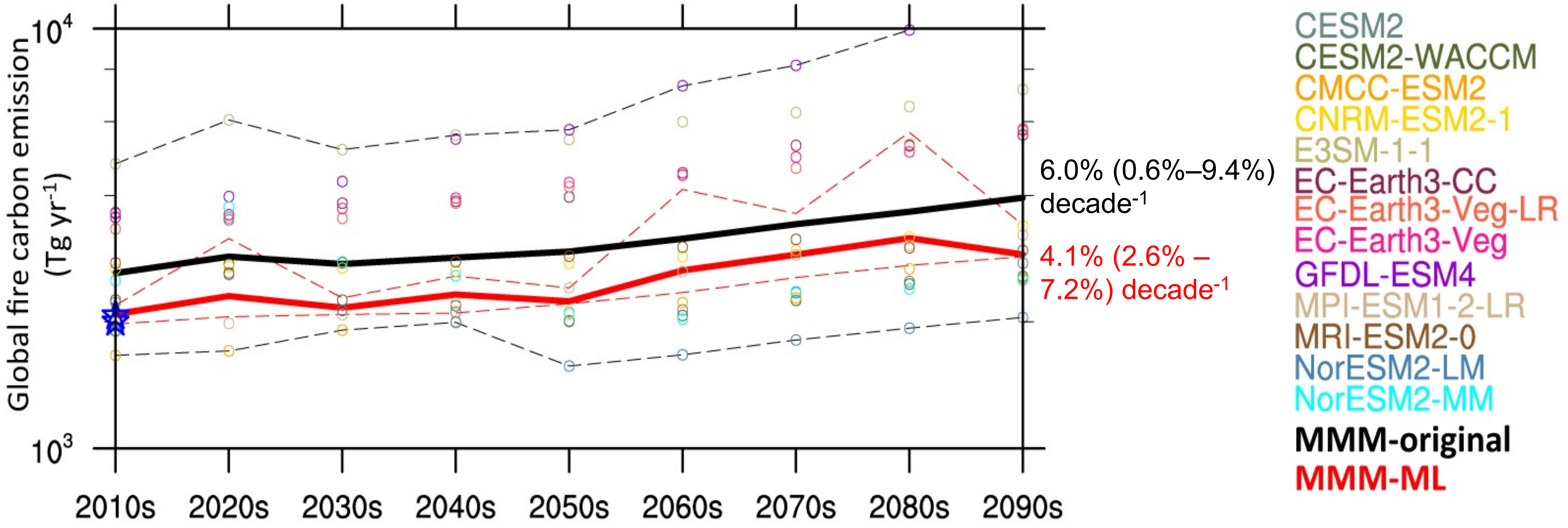
Validation of the Analytical Framework

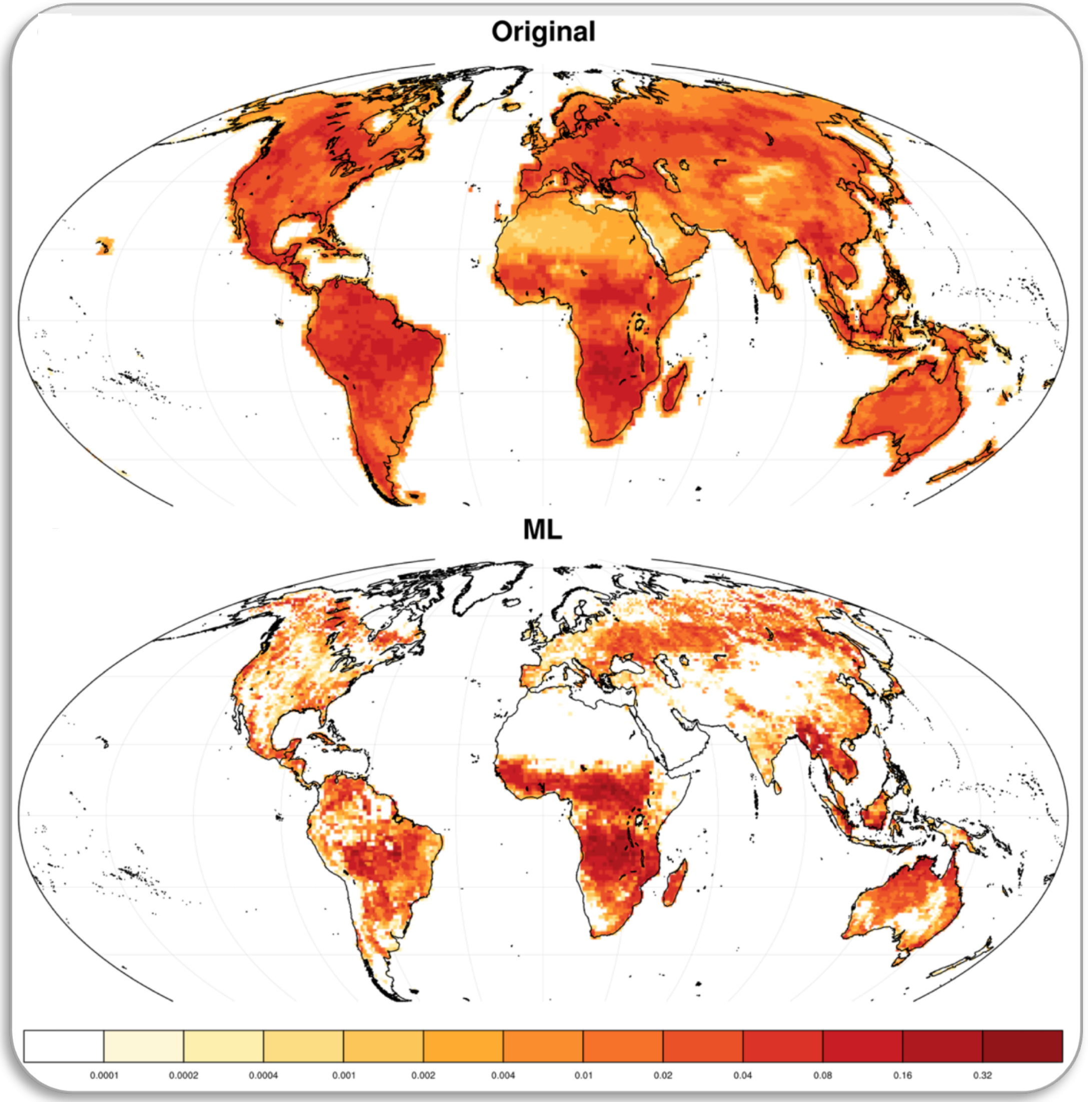


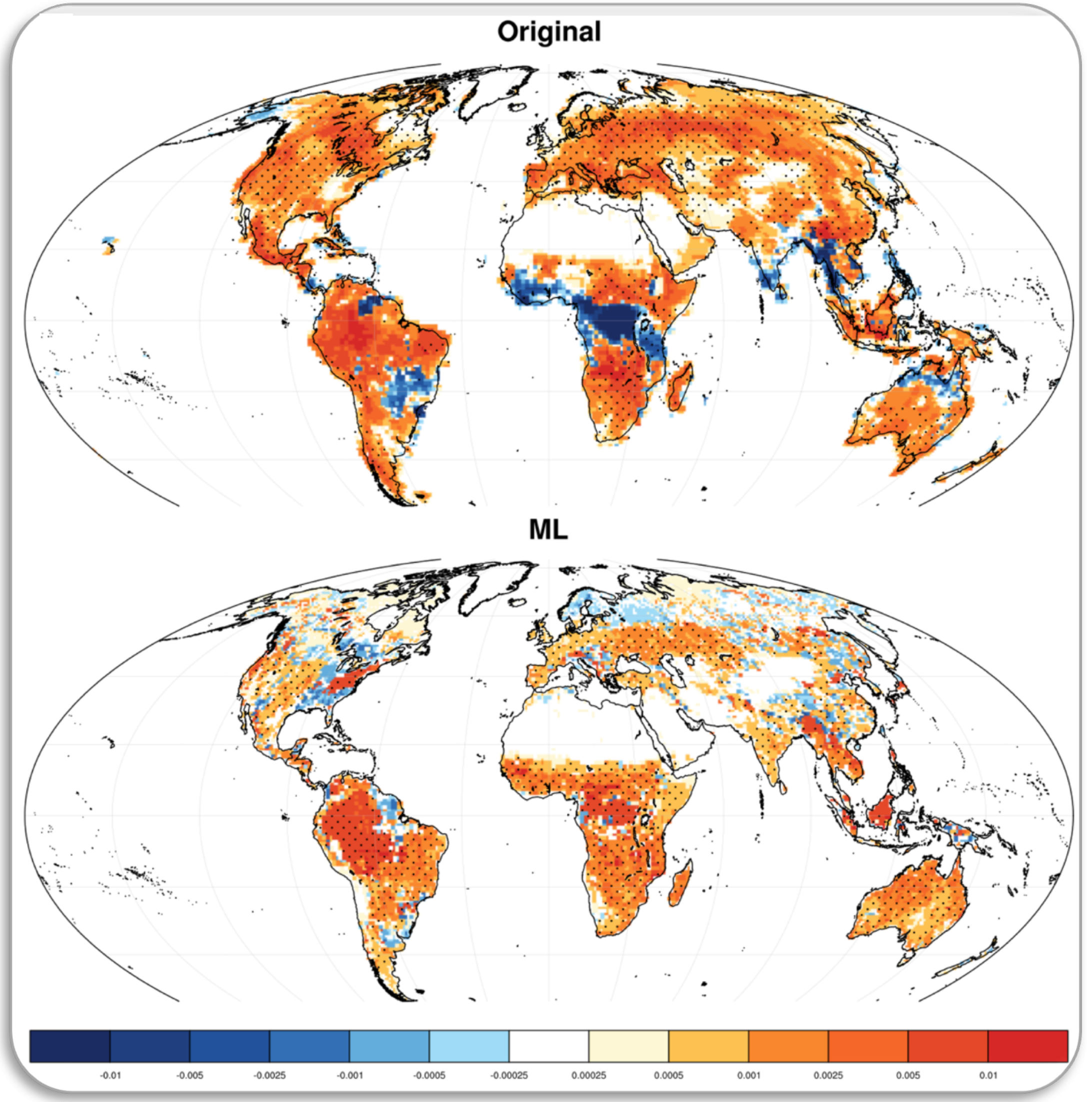
Use fire-relevant variables during 1997-2006 to predict fire carbon emissions during 2007-2016.

Fire Carbon Emissions Based on SSP5-85



Fire Carbon Emissions Based on SSP5-85

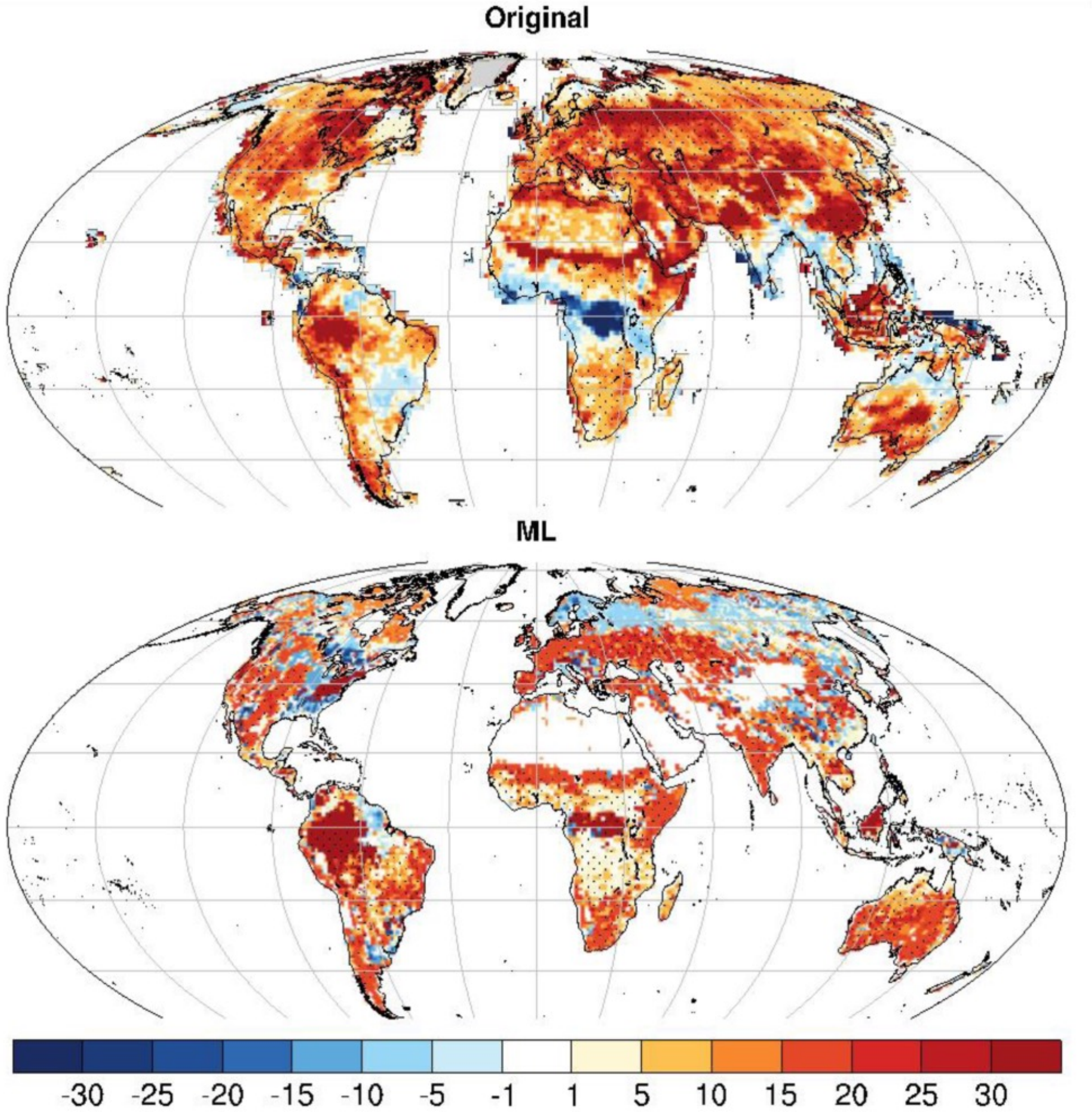




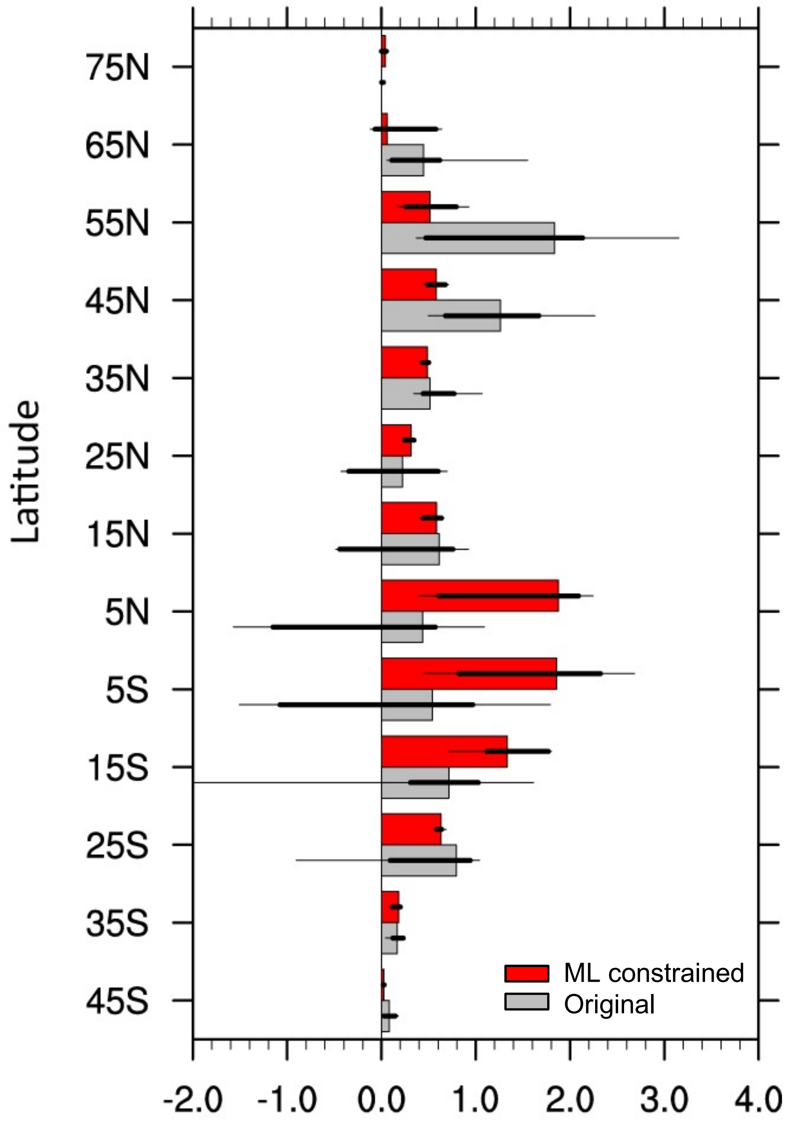
Fire carbon emission during 2090s ($kg\ m^{-2}\ yr^{-1}$)

Trend in fire carbon emission ($kg\ m^{-2}\ yr^{-1}\ dec^{-1}$)

Fire Carbon Emissions Based on SSP5-85



Trend in fire carbon emission (%dec⁻¹)



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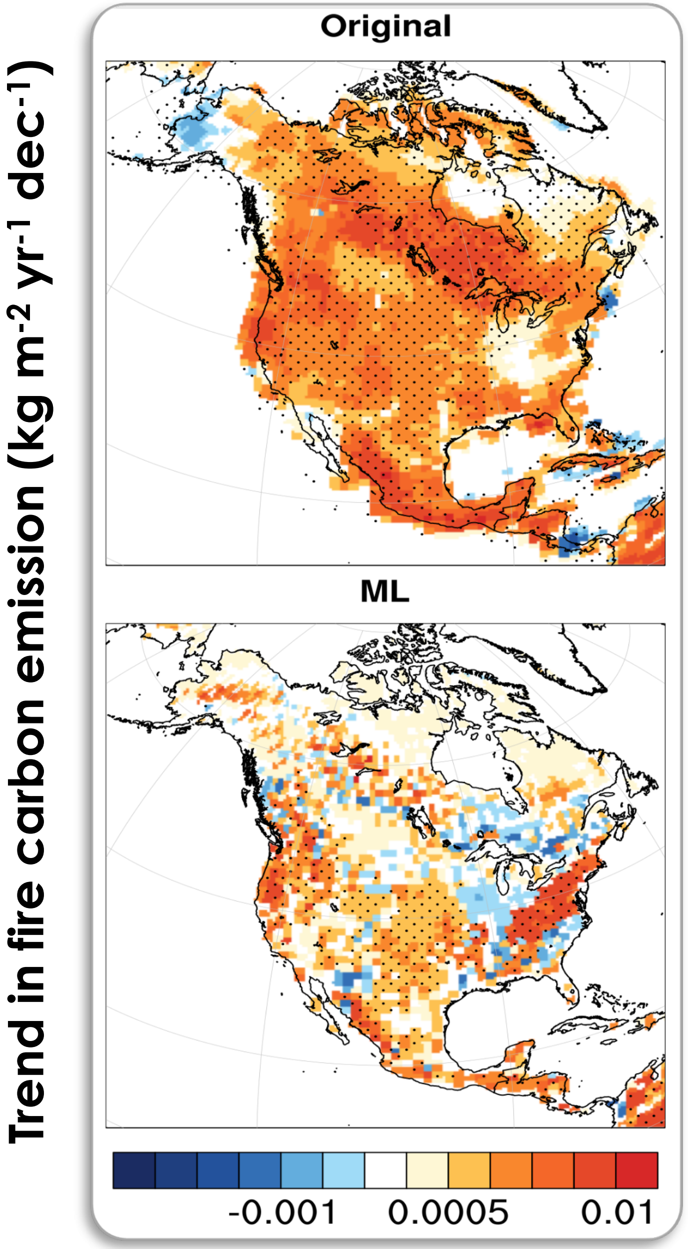
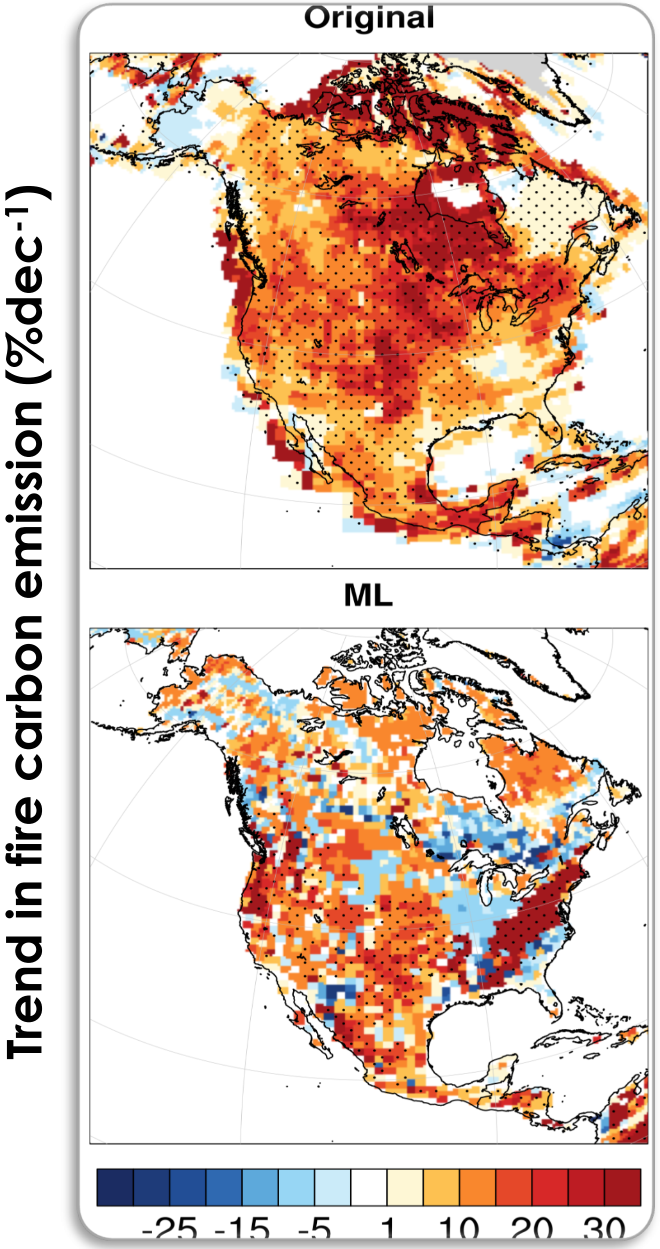
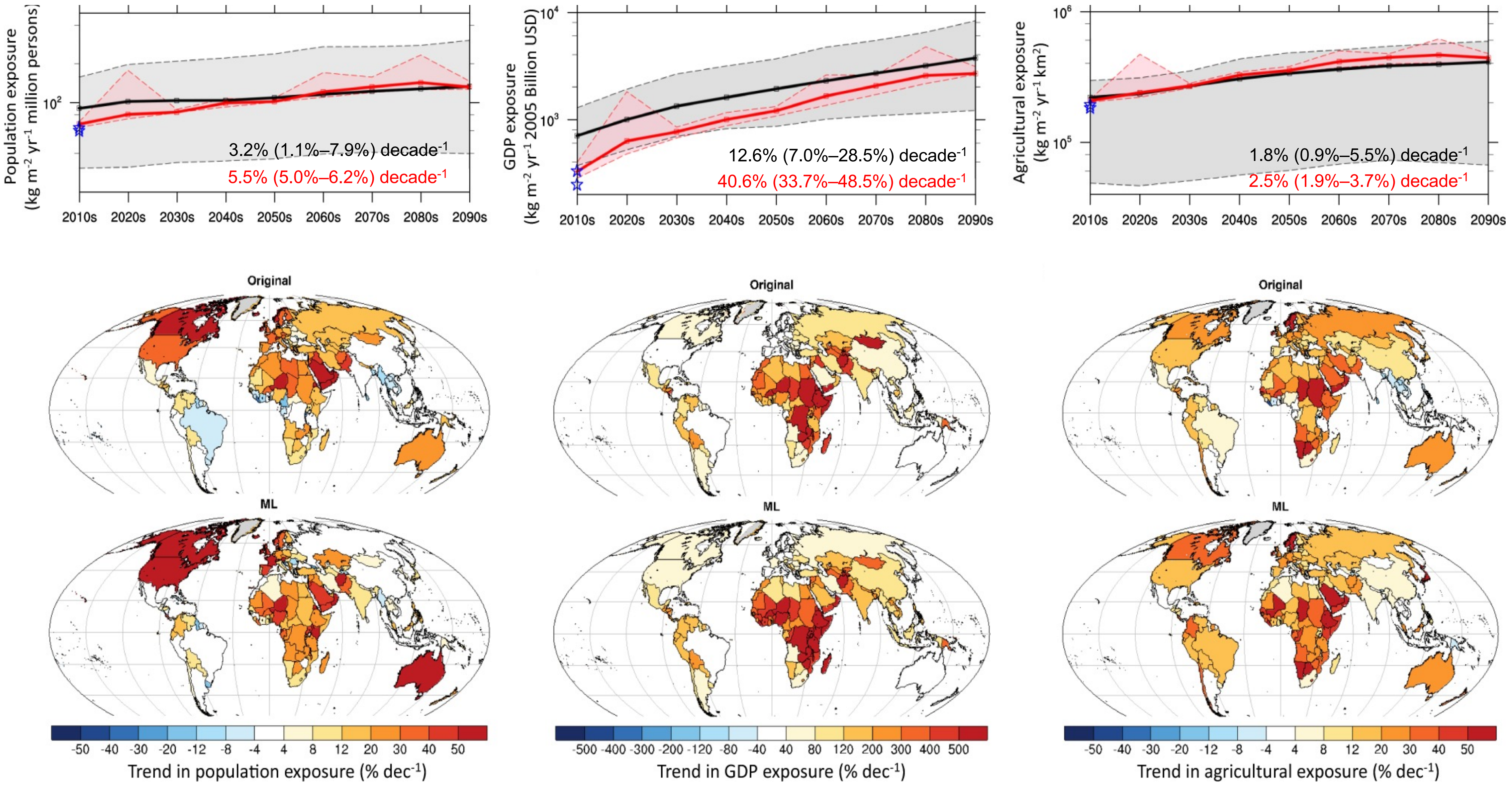
Fire Carbon Emissions Based on SSP5-85





Socioeconomical Exposure to Wildfire Changes



Decadal mean population (GDP, agricultural area) exposure = population (GDP, agricultural area) x fire carbon emission. Sum over all pixels in a country and then calculate trend.

Most Vulnerable Countries to Future Wildfire Changes

#	Population risk (10^3 kg m^{-2} y^{-1} person)			Gross domestic product risk (kg m^{-2} y^{-1} billion USD)			Agricultural risk (kg m^{-2} y^{-1} km^2)		
	Country	Trend (dec^{-1})	Rel. trend (% dec^{-1})	Country	Trend (dec^{-1})	Rel. trend (% dec^{-1})	Country	Trend (dec^{-1})	Rel. trend (% dec^{-1})
Original ensemble									
1	Bahrain	1.0	260	Djibouti	0.265	3,932	Yemen	18.3	97
2	Djibouti	4.8	200	Niger	0.781	2,111	Namibia	313.6	75
3	Yemen	34.3	110	Qatar	0.293	2,102	Norway	24.2	71
4	United Arab Emirates	11.9	90	Eritrea	0.270	1,644	Botswana	489.3	70
5	Niger	35.6	85	Somalia	0.156	1,629	Chad	529.9	67
6	Kuwait	2.2	70	Yemen	0.630	1,029	Sweden	210.4	59
7	Eritrea	20.1	70	Sudan	1.678	755	Sudan	1,753.9	57
8	Oman	3.9	60	Malawi	2.142	641	Switzerland	12.8	55
9	Luxemburg	3.4	66	Zambia	8.058	637	Eritrea	33.2	51
10	Ireland	5.3	60	Tajikistan	0.831	597	Oman	1.2	51
Observation-constrained ensemble									
1	Niger	58.7	141	Niger	0.778	2,102	Liberia	180.5	192
2	Uganda	402.1	108	Sierra Leone	1.065	2,070	Sierra Leone	284.6	171
3	Ireland	7.1	84	Uganda	5.695	2,009	Ireland	11.6	95
4	Nigeria	1,410.5	78	Malawi	4.173	1,249	Guinea	718.1	81
5	Yemen	22.0	72	Benin	2.391	1,233	Senegal	246.9	76
6	Sierra Leone	78.1	66	Democratic Republic of the Congo	13.028	1,227	Chad	586.8	74
7	Pakistan	348.0	56	Nigeria	36.966	1,112	Congo	110.8	74
8	Malawi	236.5	52	Yemen	0.641	1,046	Yemen	13.7	73
9	Benin	99.2	53	Guinea	2.504	991	Sudan	1,953.3	63
10	Democratic Republic of Congo	1,326.9	46	Burundi	0.487	789	The Gambia	21.4	58

African
Asian
European

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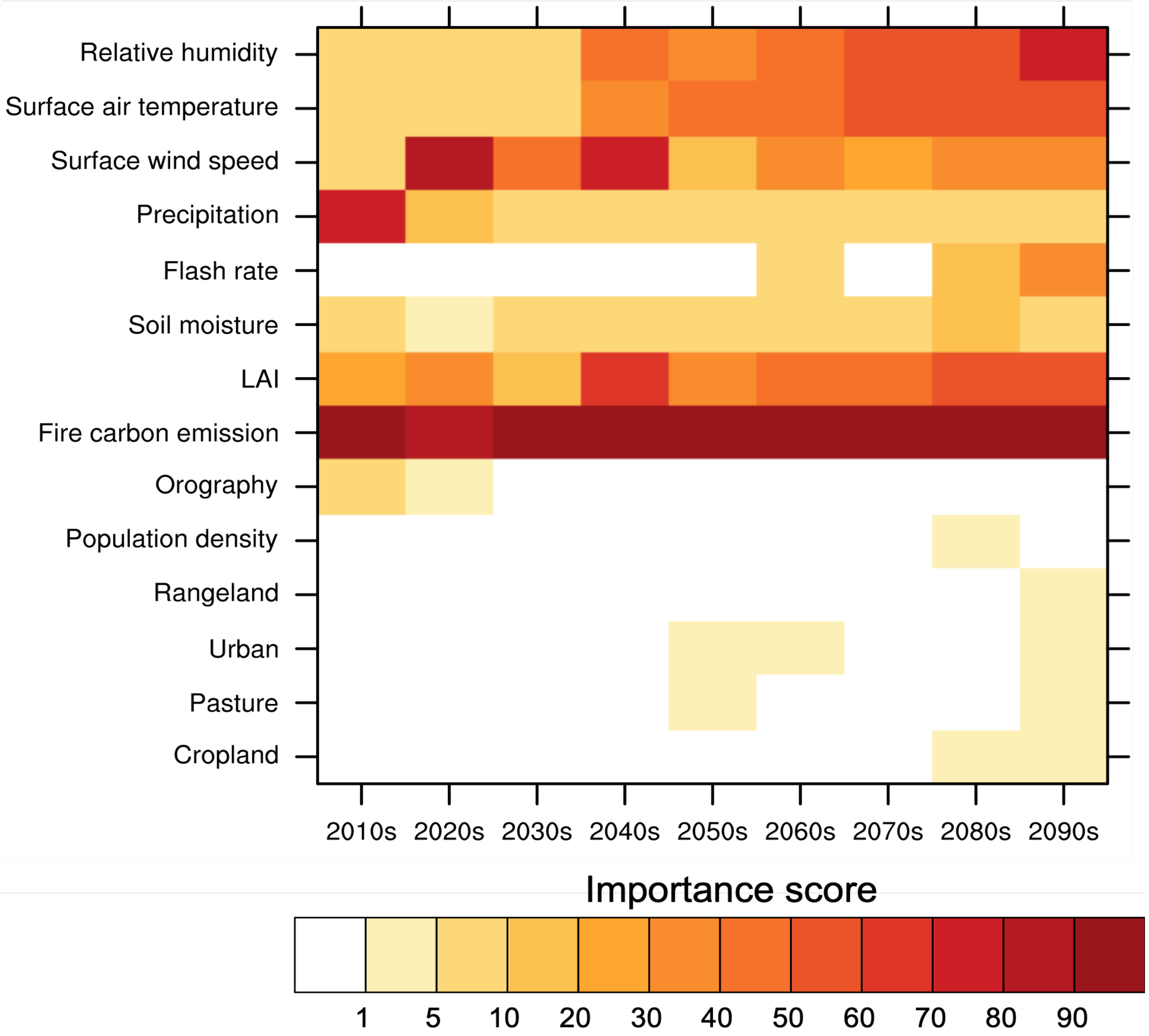
Importance of Historical Predictors for Future Fire



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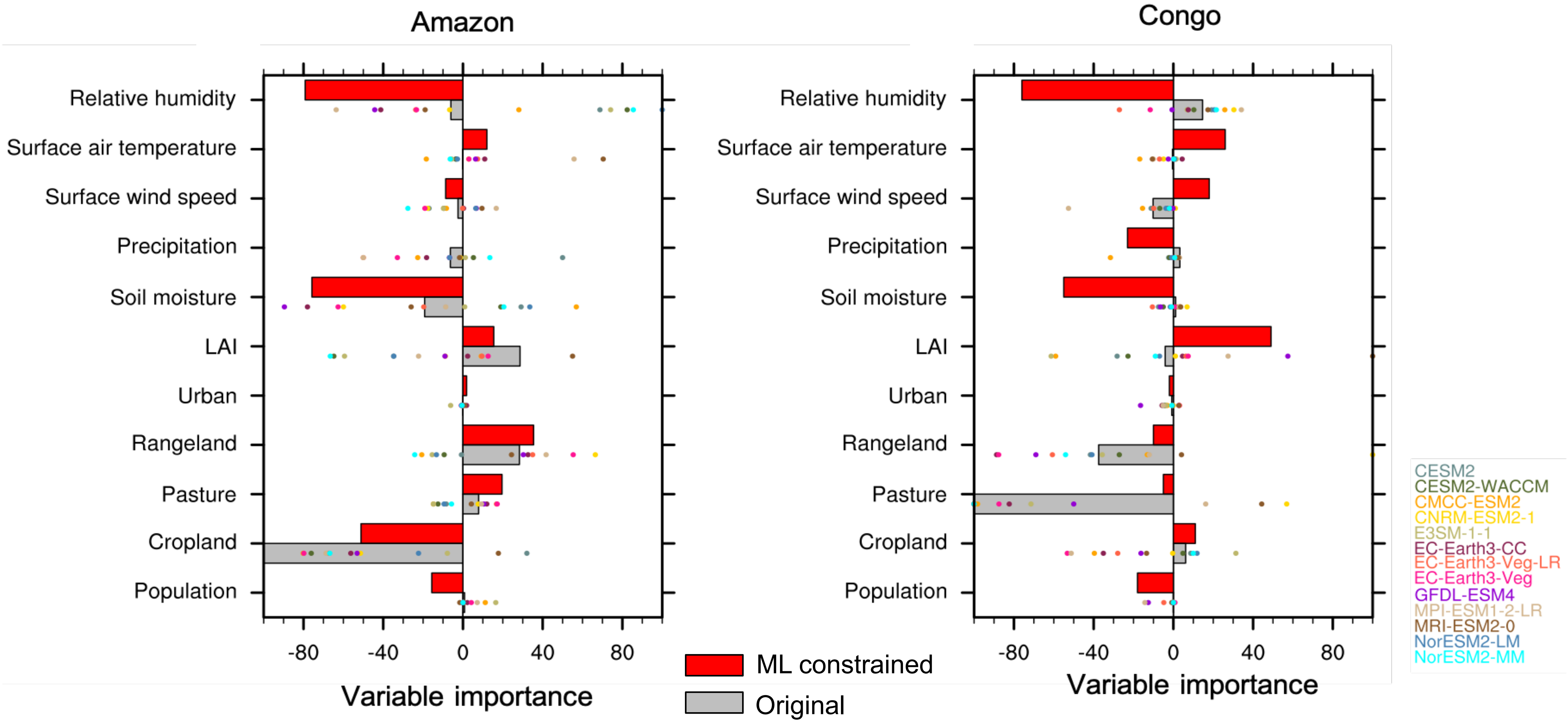
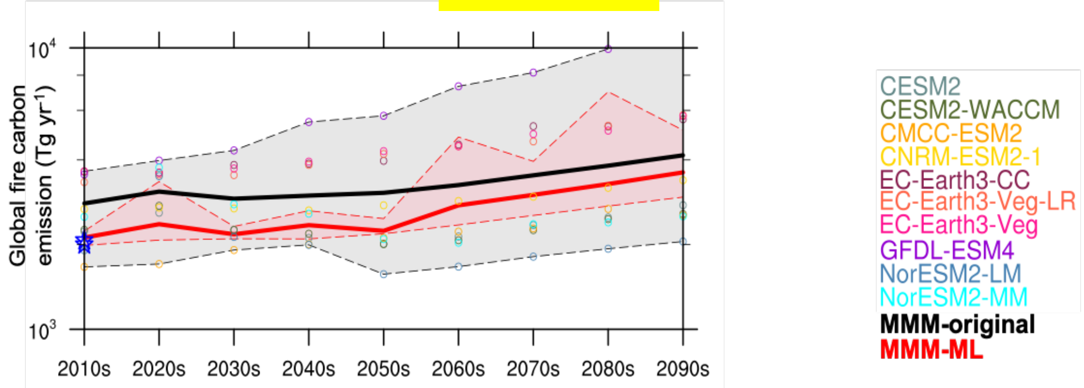
Importance of Factors' Trend to Future Fire

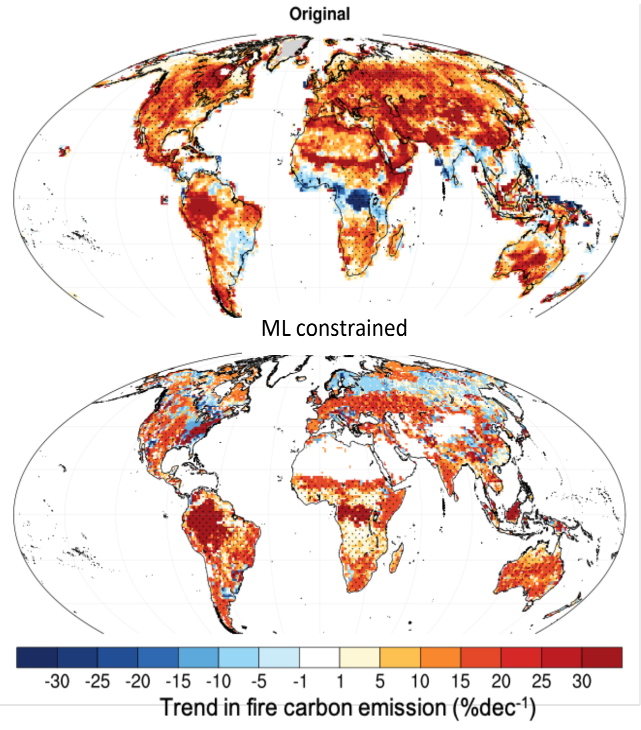


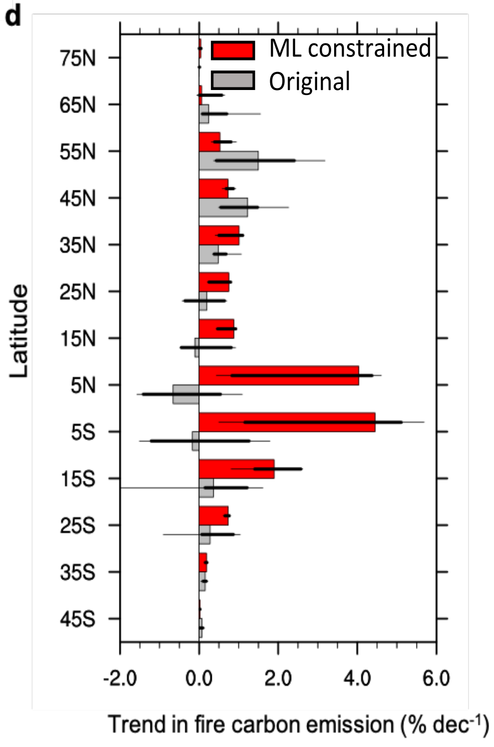
- In ML constrained, apply the current observational constraining framework to all fire-relevant variables;
- Obtain trends in all these fire-relevant variables;
- Assess the relative importance of these variables in regulating the spatial distribution of future fire carbon emissions for different regions;

Scenario-dependent Projections

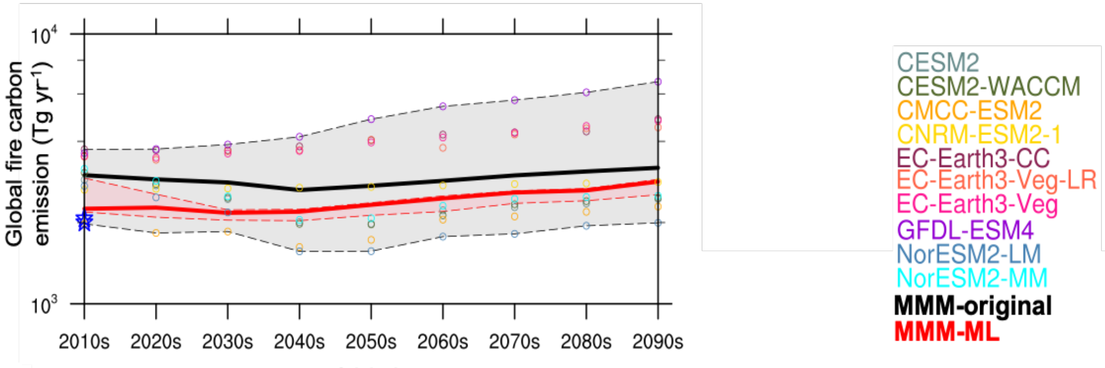
SSP5-85

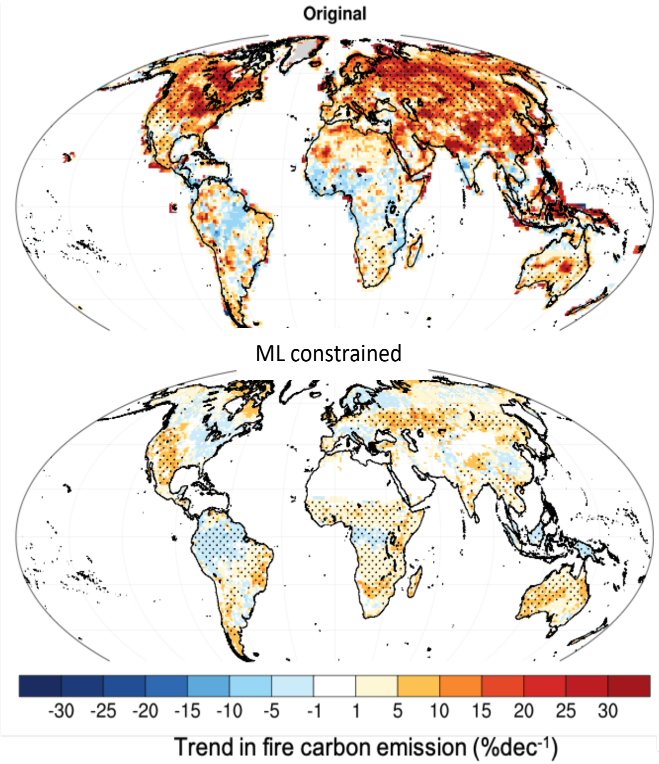


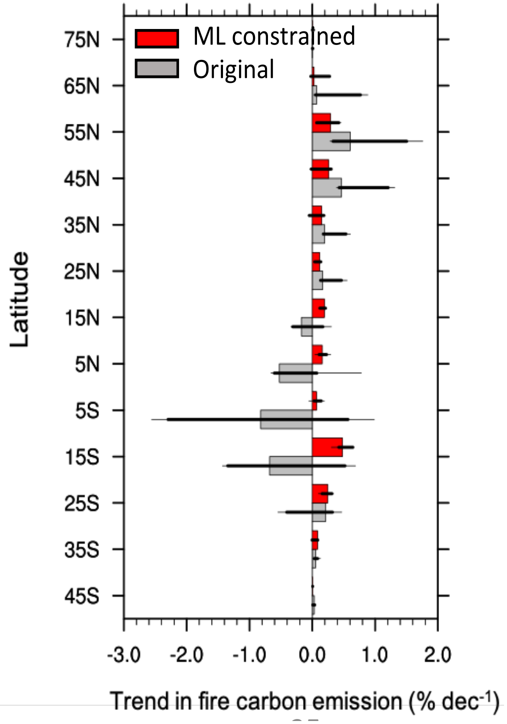




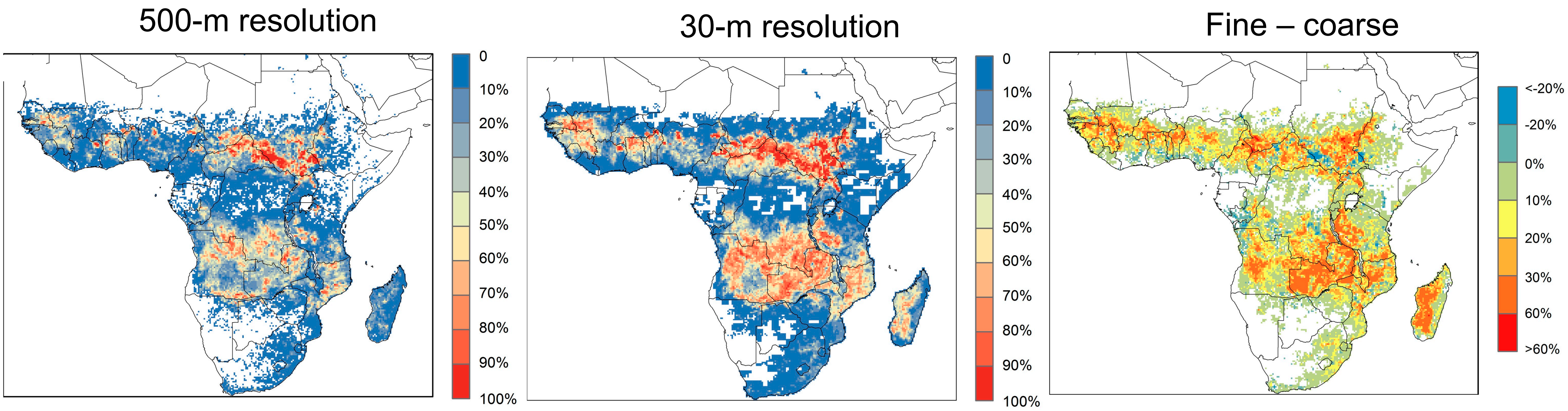
SSP2-45







Historical Observations



Burned area fraction in 2016 from satellite products with different spatial resolution (Ramo et al., 2021).

Models and Feedbacks

CMIP6 Model	Resolution (km)	Ensemble members	Land model	Fire model description
CESM2	100	3	CLM5	Natural and anthropogenic ignition sources and suppression of agricultural, deforestation, and peat fires[2,3]
CESM2-WACCM	100	5		
CMCC-ESM2	100	1	CLM4.5	
CNRM-ESM2.1	250	5	SURFEXv8.0 (ISBA)	Interactive natural fires[5]
E3SM-1.1	100	1	ELM v1.1	Same as CLM5
EC-Earth3-CC	100	1	LPJ-GUESS v4	Interactive natural fires[7]
EC-Earth3-Veg-LR	250	3		
EC-Earth3-Veg	100	5		
GFDL-ESM4	100	1	LM4.1	Distinct parameterizations for natural and agricultural wildfires, especially representing multiday and crown wildfires[9]
MPI-ESM1-2-LR	250	10	JSBACH3.20	Natural fires ignited by human activity and lightning, with up to 12-hour duration[10]
MRI-ESM2	100	1	HAL 1.0	N/A
NorESM2-LM	250	1	CLM5	Same as CLM5
NorESM2-MM	100	1		

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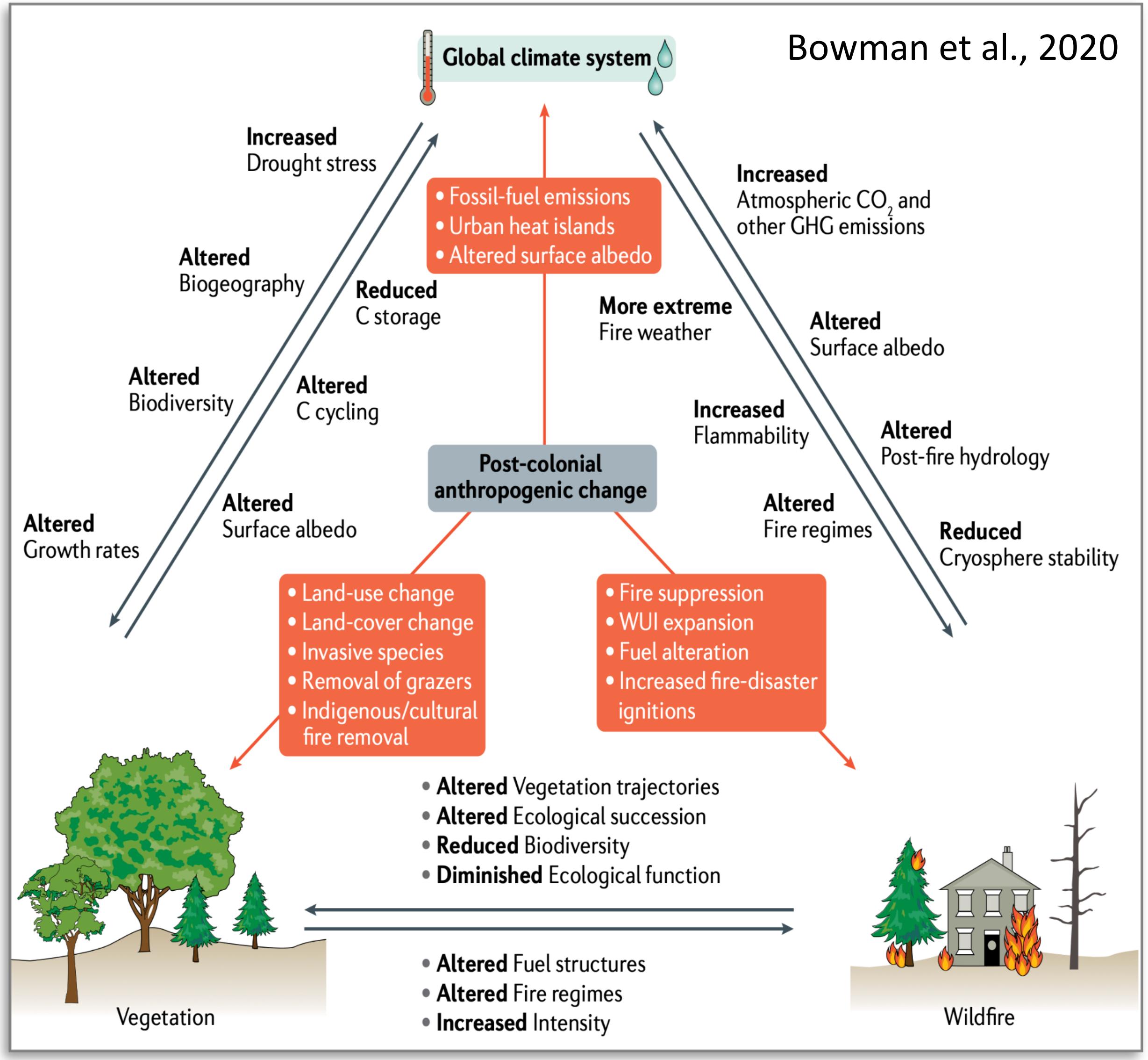
ESMs Analyzed in This Research



- Insufficient representation of these processes in ESMs
- Offline projection in current ML constraining framework

Take-home Messages

- 🔥 Credibility of future wildfire simulations by latest ESMs remains low because of modeling uncertainties and insufficient application of observational constraints for ESMs;
- 🔥 New ML-based EC framework is particularly useful for prediction and projection of variables with complex driving factors, such as wildfire regimes and extreme climates;
- 🔥 Constrained results showed further enhancement of wildfire activities in the historically fire-prone regions;
- 🔥 Concurrently enhanced wildfire activity and socioeconomic development call for mitigation and/or adaptation strategies to minimize potential socioeconomic loss caused by wildfires;

Thanks for Your Attention!
Questions and Comments?

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