EARTH & ENVIRONMENTAL SCIENCES

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Uncertainty reduction of earth system land models simulations with machine learning and causal network

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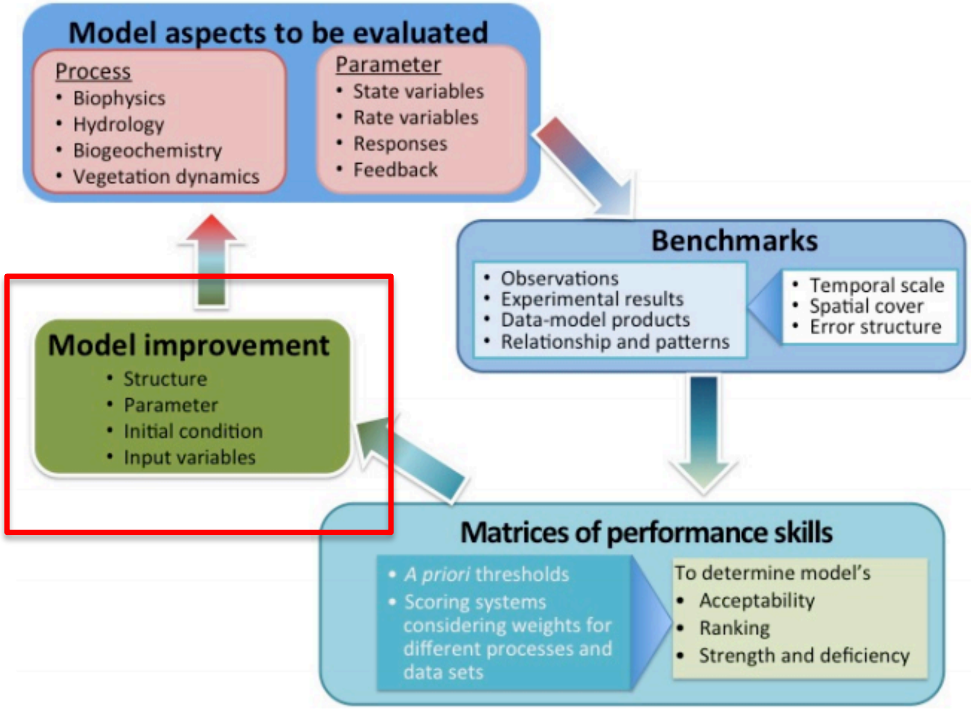


Luo et al., 2012

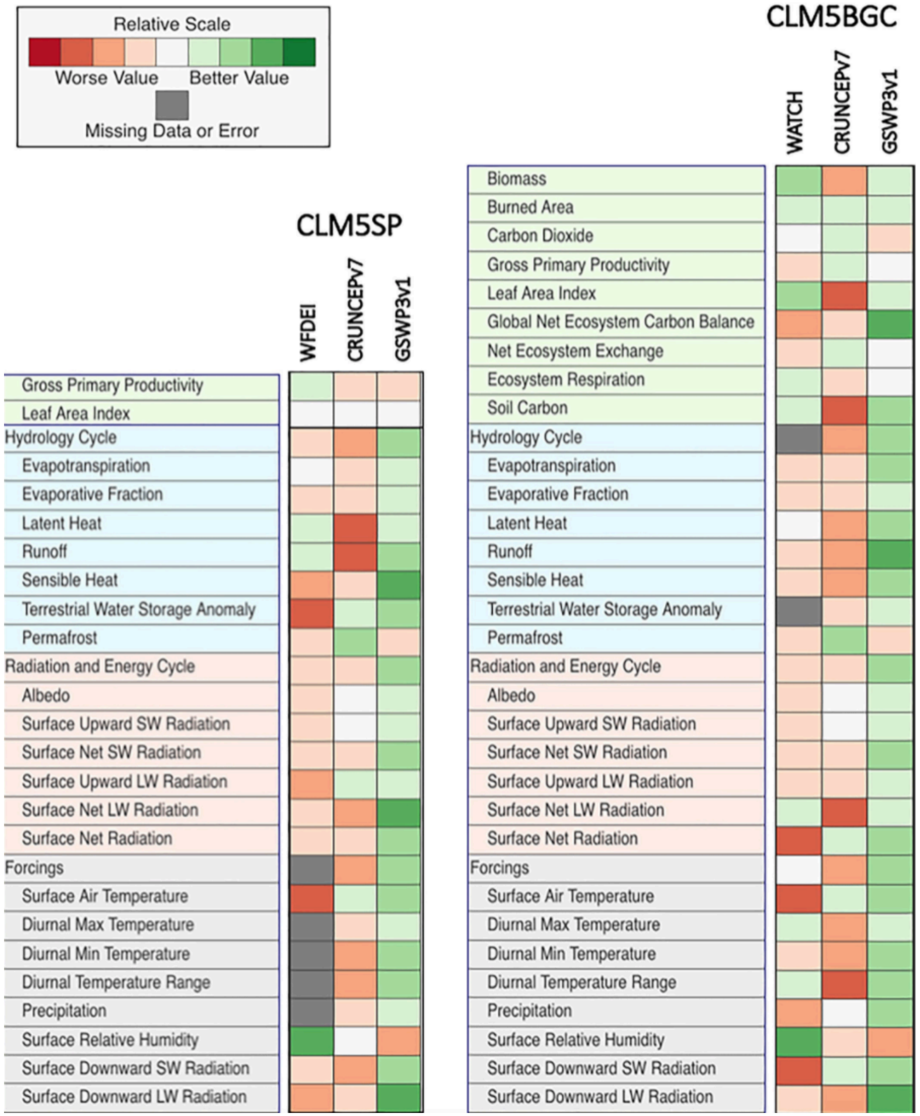
Type	Description	Example	Pros	Cons
Direct observations	Data from instrument readings with some processing	Atmospheric trace gas mixing ratios, temperature, soil respiration	Records of system states	Limited spatial and temporal coverage
Experimental results	Data at two or more levels of treatments	Response ratios of biomass and soil moisture	Effects of climate changes	Step changes in treatments, site idiosyncrasy
Data–model products	Interpolation and extrapolation of data according to some functions	Global distribution of GPP calculated from satellite and flux data	Extended spatial and temporal coverage with estimated errors	Artifacts may be introduced by the extrapolation functions, especially outside the observation ranges
Functional relationships or patterns	Derived or emerged from data	NPP vs. precipitation, soil respiration vs. temperature	Evaluation of environmental scalars and response functions	Not absolute values of the variables

Critical challenges

- How to quantify land model uncertainties from input variables vs. parameterization vs. structure?

- How to reduce the land model uncertainty without re-running models? (e.g., CMIP6 model ensembles)

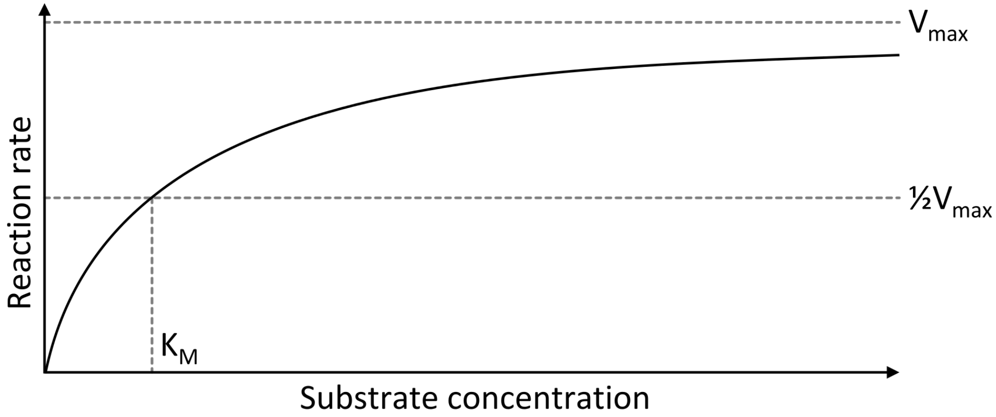
Input variables uncertainty



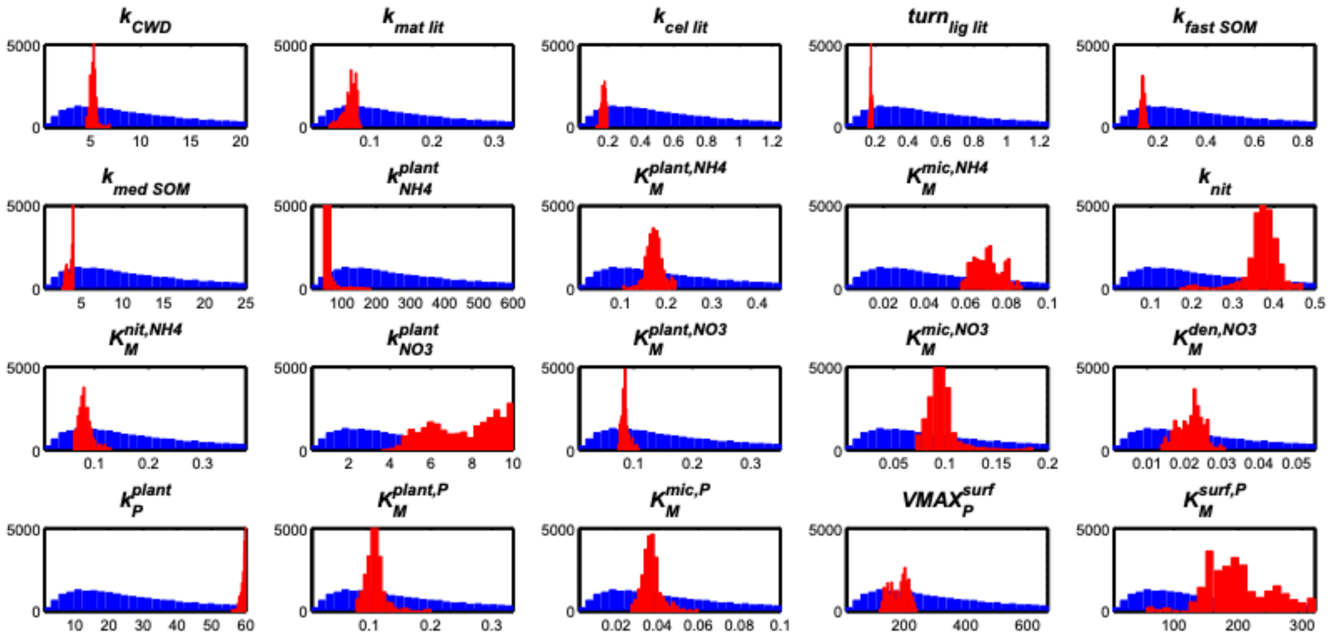
- Land model perform better with more accurate forcing (e.g. GSWP3)

Lawrence et al., 2019

Parameterization uncertainty

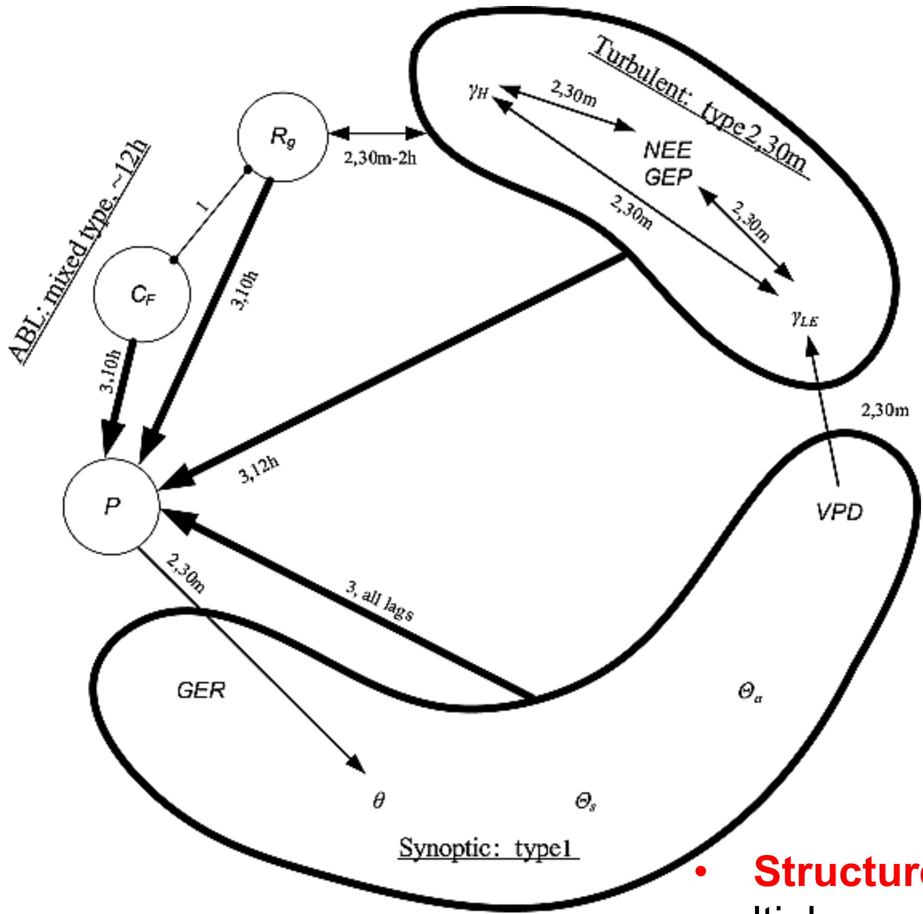


$$v = \frac{d[P]}{dt} = V_{max}\frac{[S]}{K_M + [S]}$$



Zhu et al., 2016

Emergent structure from observations

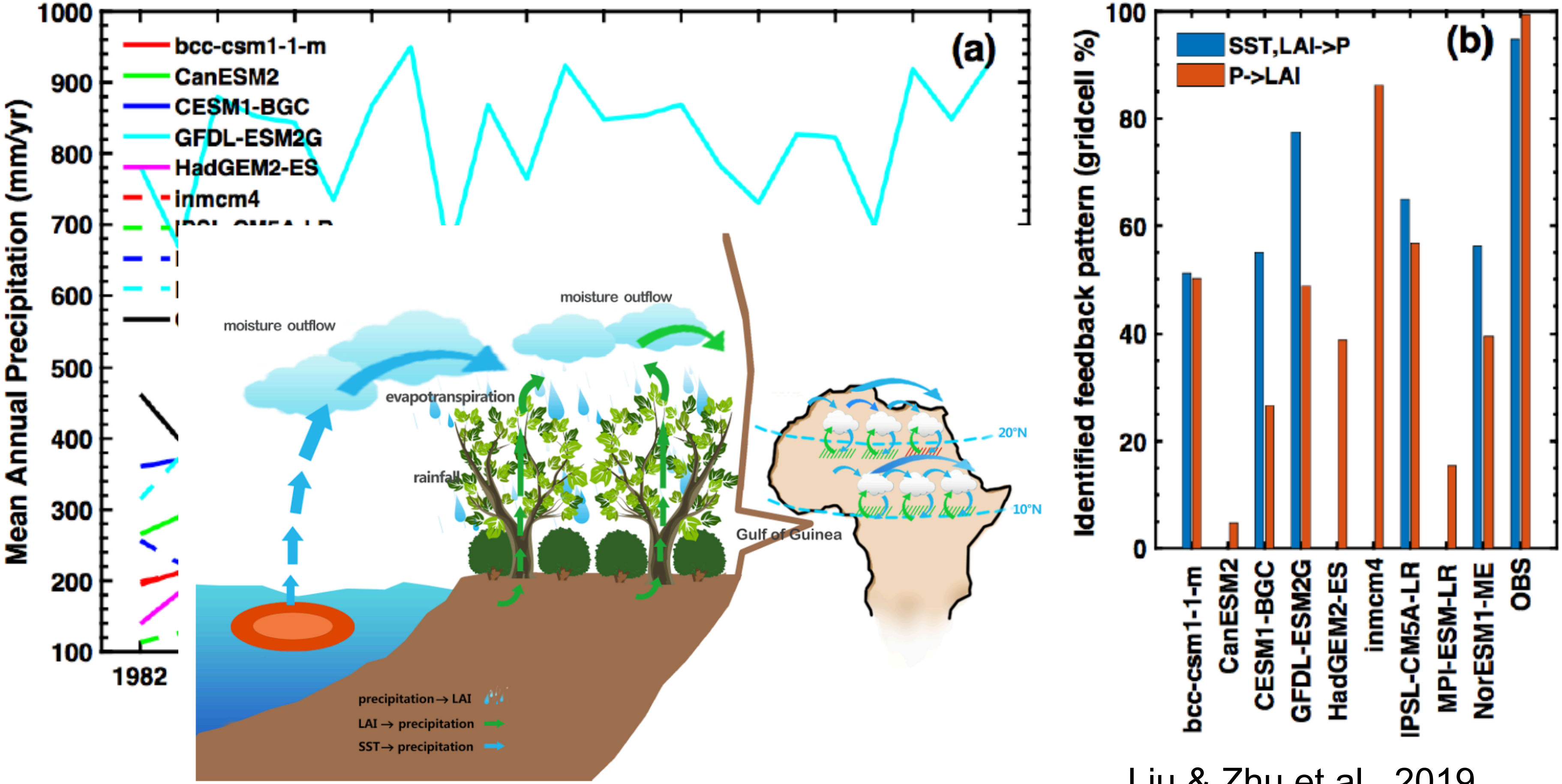


Symbol	Description	Units
R_g	total incoming shortwave radiation	W m^{-2}
Θ_a	air temperature	deg C
VPD	vapor pressure deficit	KPa
Θ_s	soil temperature (surface layer)	deg C
P	precipitation	mm
θ	soil water content (surface layer)	m^3 m^{-3}
γ_H	sensible heat flux	W m^{-2}
γ_{LE}	latent heat flux	W m^{-2}
GER	estimated gross ecosystem respiration	μmol CO_2 m^{-2} s^{-1}
NEE	net ecosystem exchange	μmol CO_2 m^{-2} s^{-1}
GEP	estimated gross ecosystem production	μmol CO_2 m^{-2} s^{-1}
C_F	cloud fraction between 12,000 feet and surface	fraction

Ruddell & Kumar 2009

- **Structure** of a system emerges when multiple processes closely interact with one another
- **Transfer entropy** (causal inference approach) effectively inform the direction & strength of process interactions

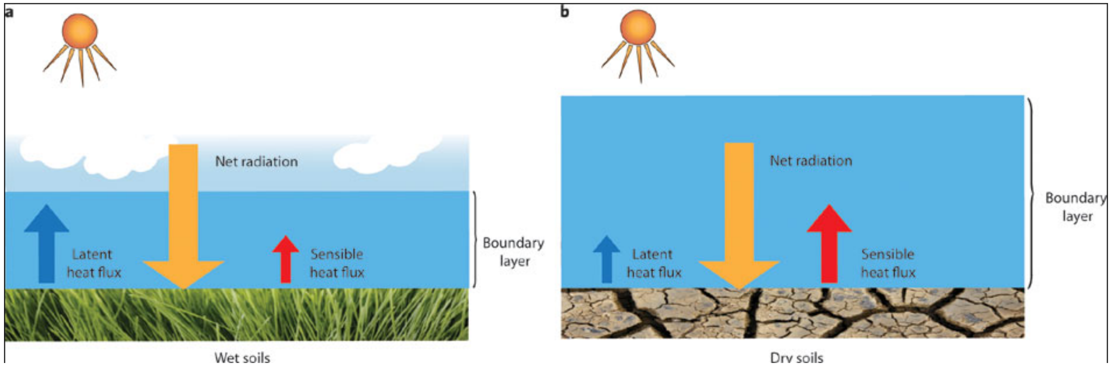
Emergent structure from land models

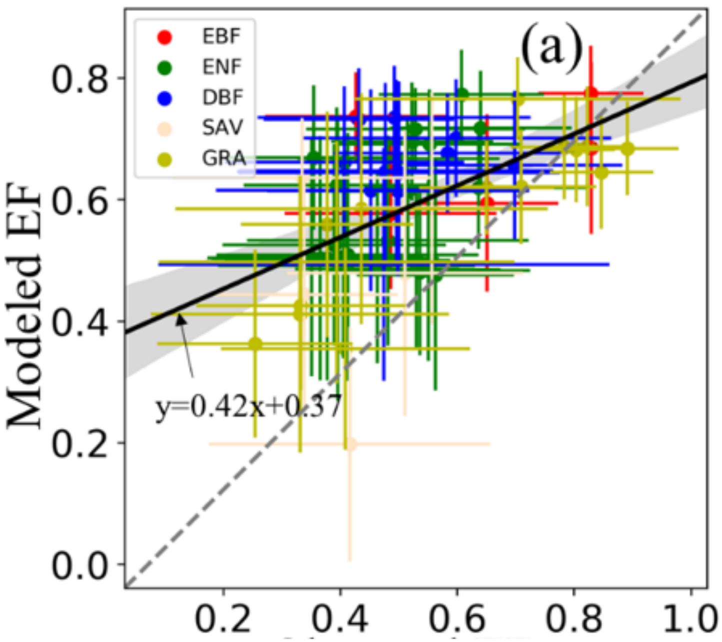


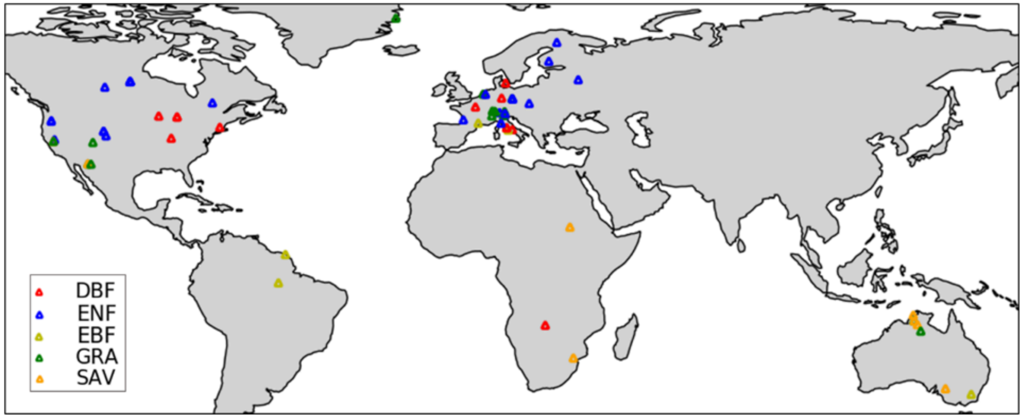
Liu & Zhu et al., 2019

- SST, LAI jointly control precipitation, precipitation has strong feedback to LAI

Case 1: CMIP6 model simulations of land surface energy partitioning







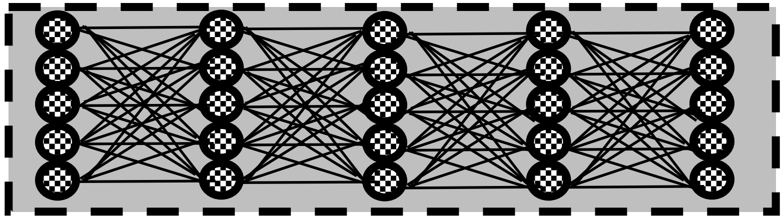
EF = LE / (LE + H)

- 64 FLUXNET sites
- 12 CMIP6 land models

Yuan & Zhu et al., under review

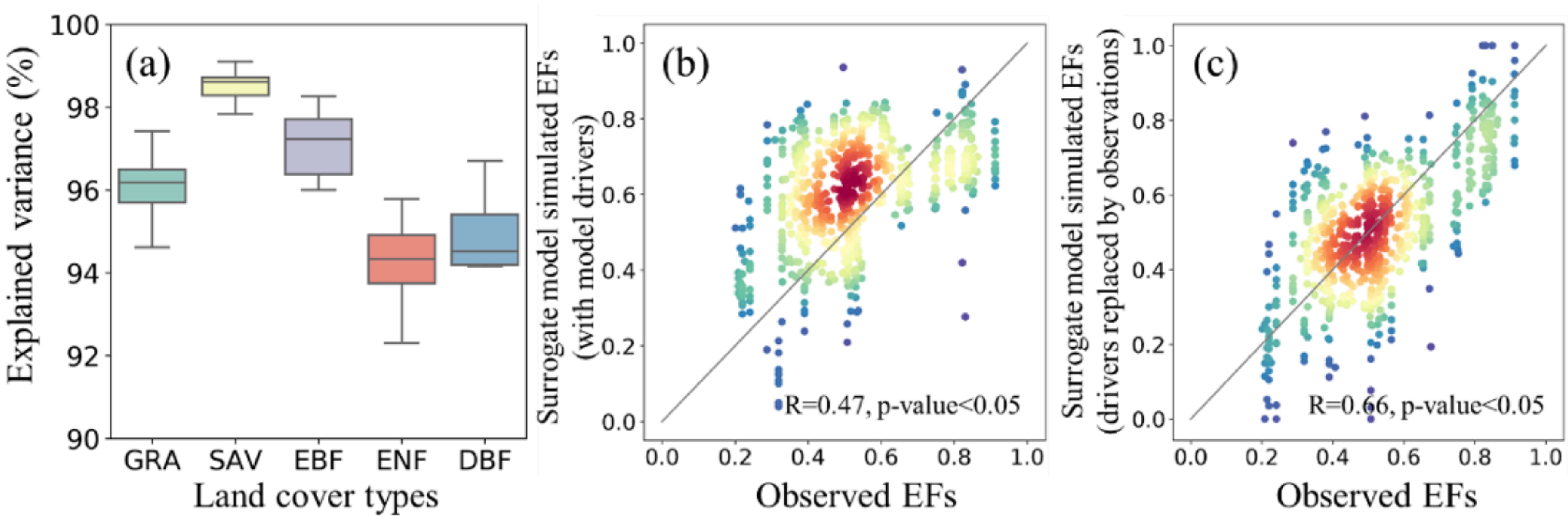
Reduce uncertainty from input variables

CMIP6
T, P, R, GPP,
LAI, VPD, SWC



Machine learning surrogate model

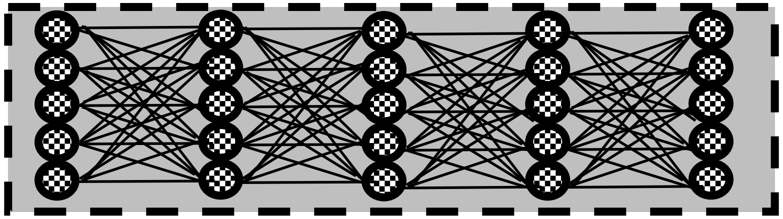
CMIP6
Evaporative
fraction



- Using FLUXNET input variables, CMIP6 multiple model ensemble simulated EF could be largely improved (R from 0.47 to 0.66)

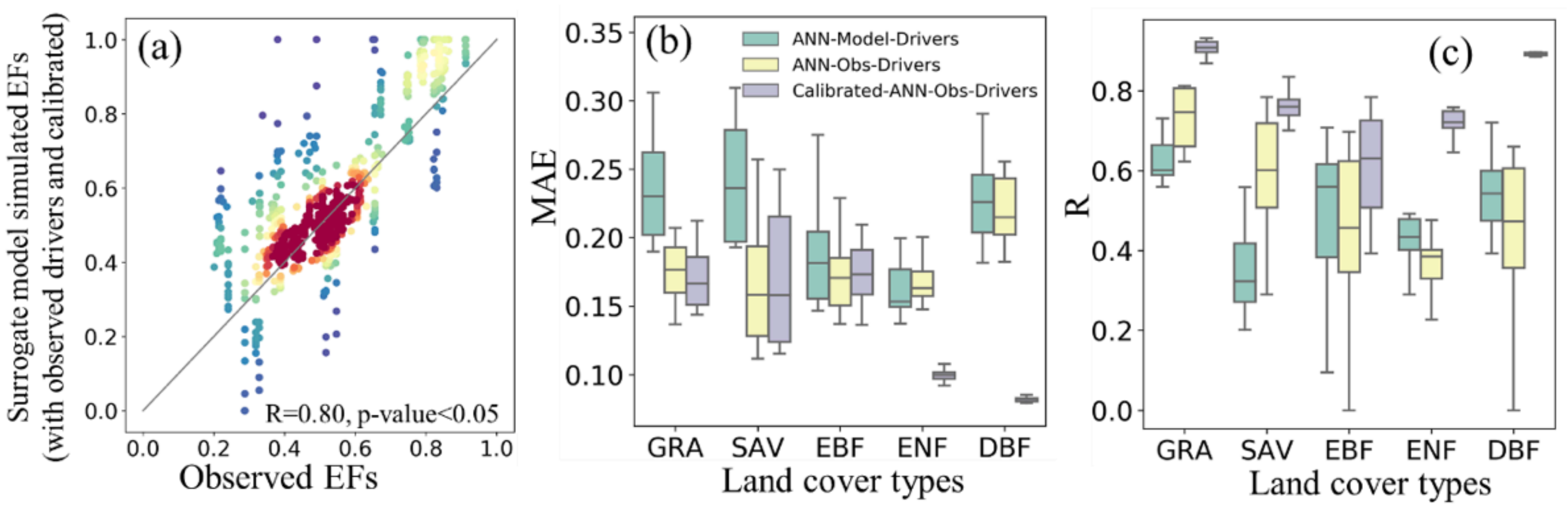
Reduce uncertainty from parameterization

FLUXNET
T, P, R, GPP,
LAI, VPD, SWC



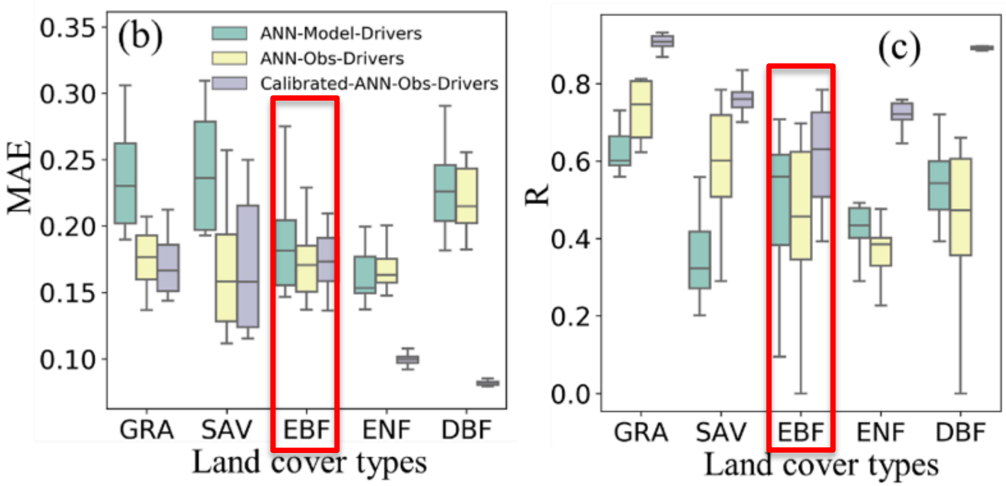
FLUXNET
Evaporative fraction

Fine tune surrogate model

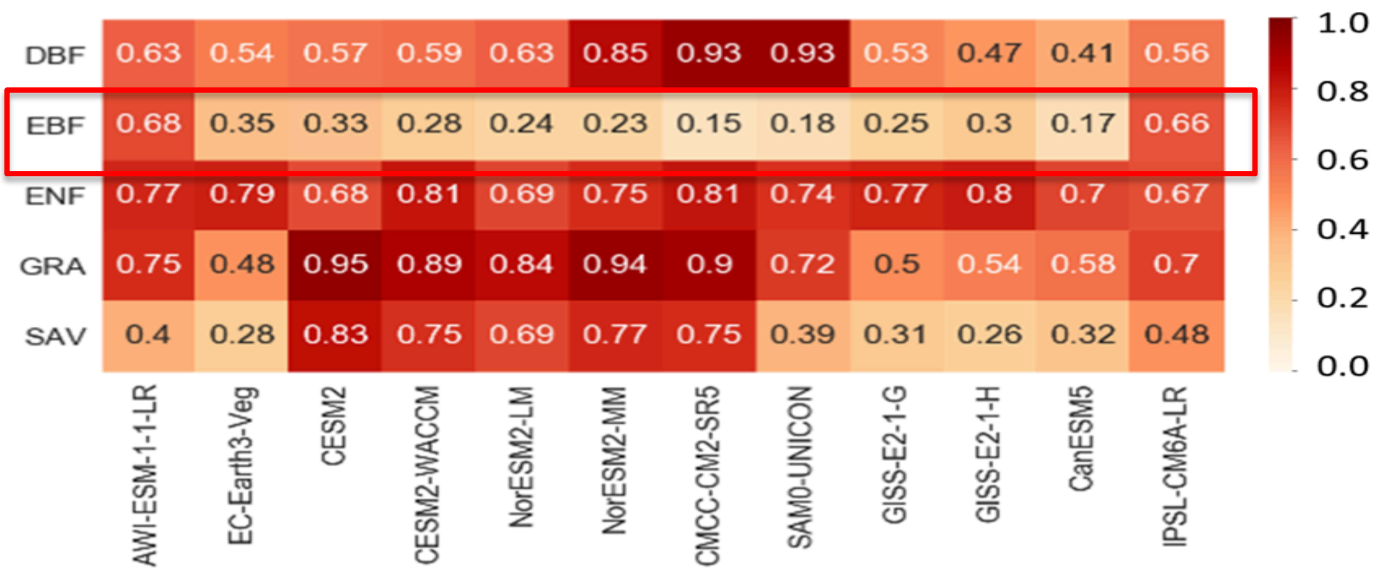


- Fine-tune of ML surrogate model against FLUXNET observed EF, continue to improve CMIP6 Performance (R from 0.66 to 0.8).

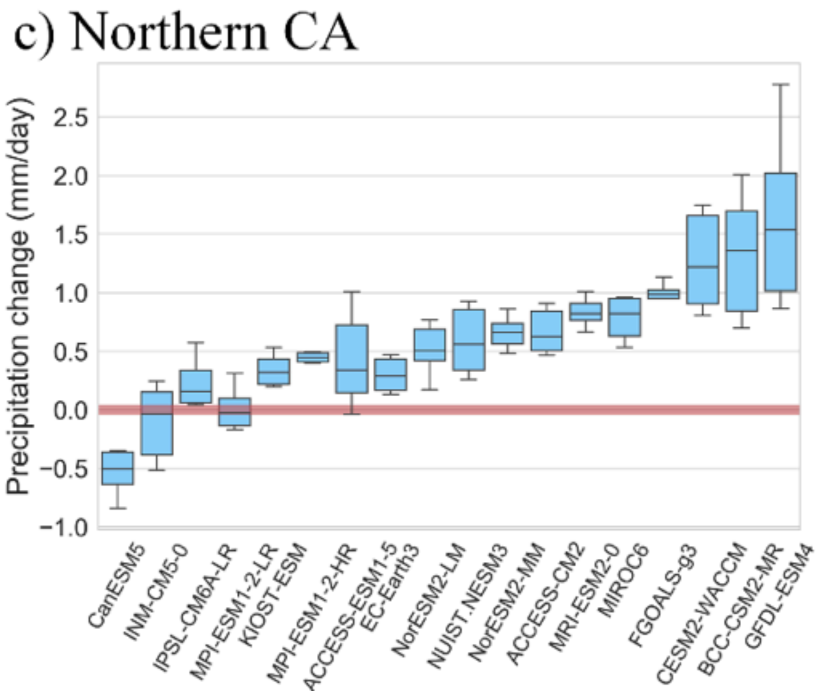
Structure uncertainty interacts with parameterization uncertainty



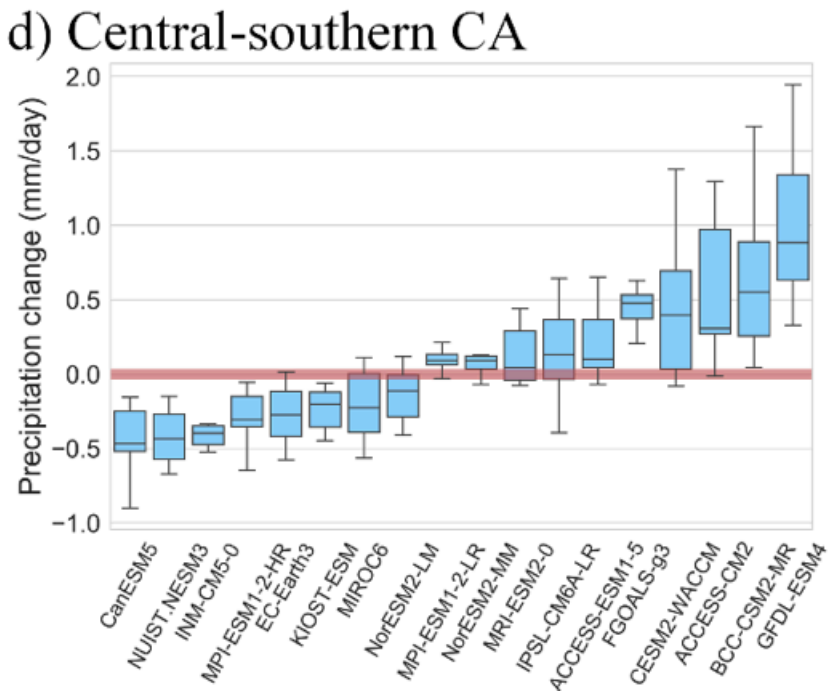
- Significant model structure uncertainty at tropical ecosystems.
- ML based parameterization is less effective due to large structure biases



Case 2: Use emergent structure to constrain CMIP6 model predictions

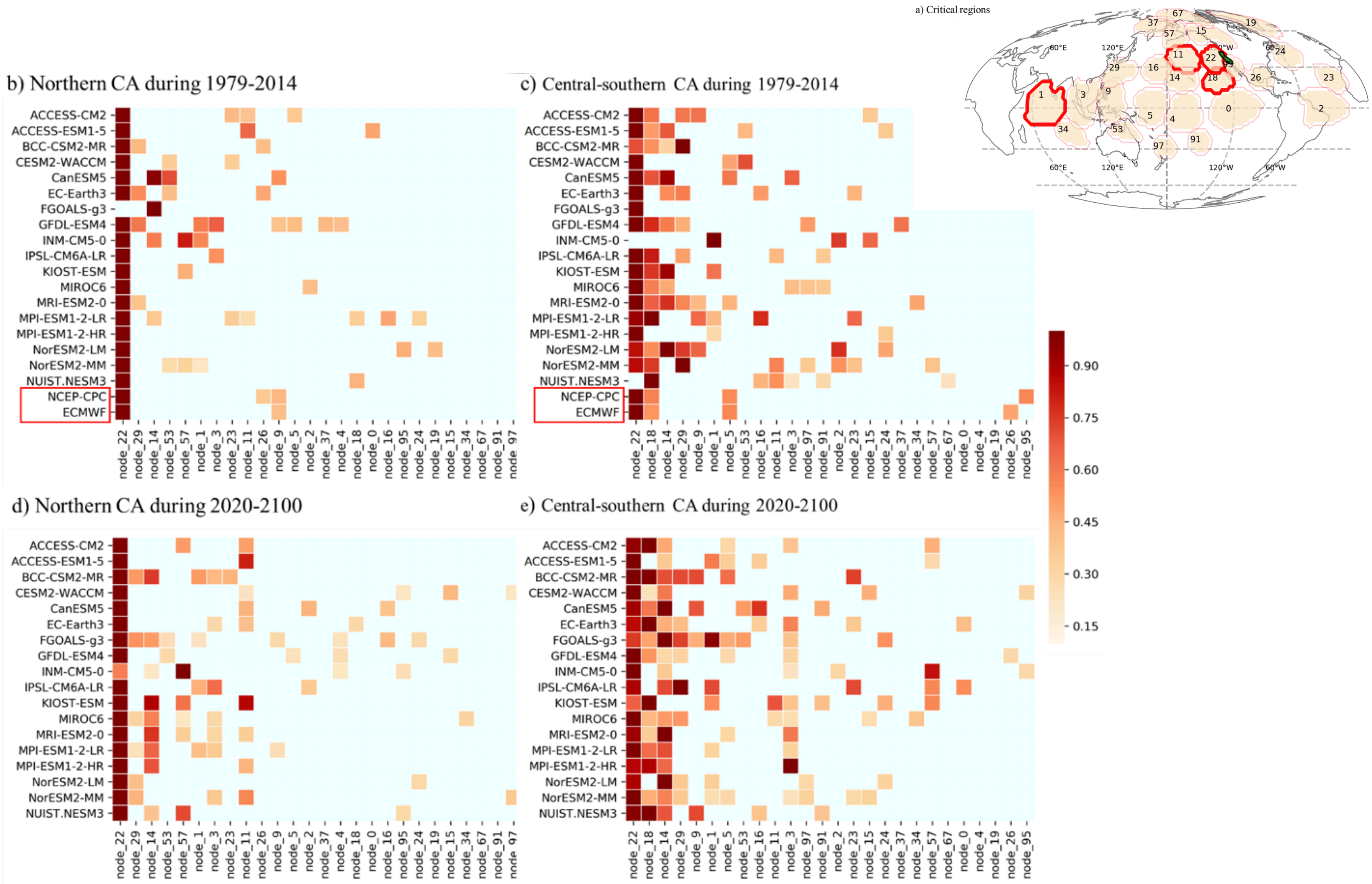


-11% to +31%



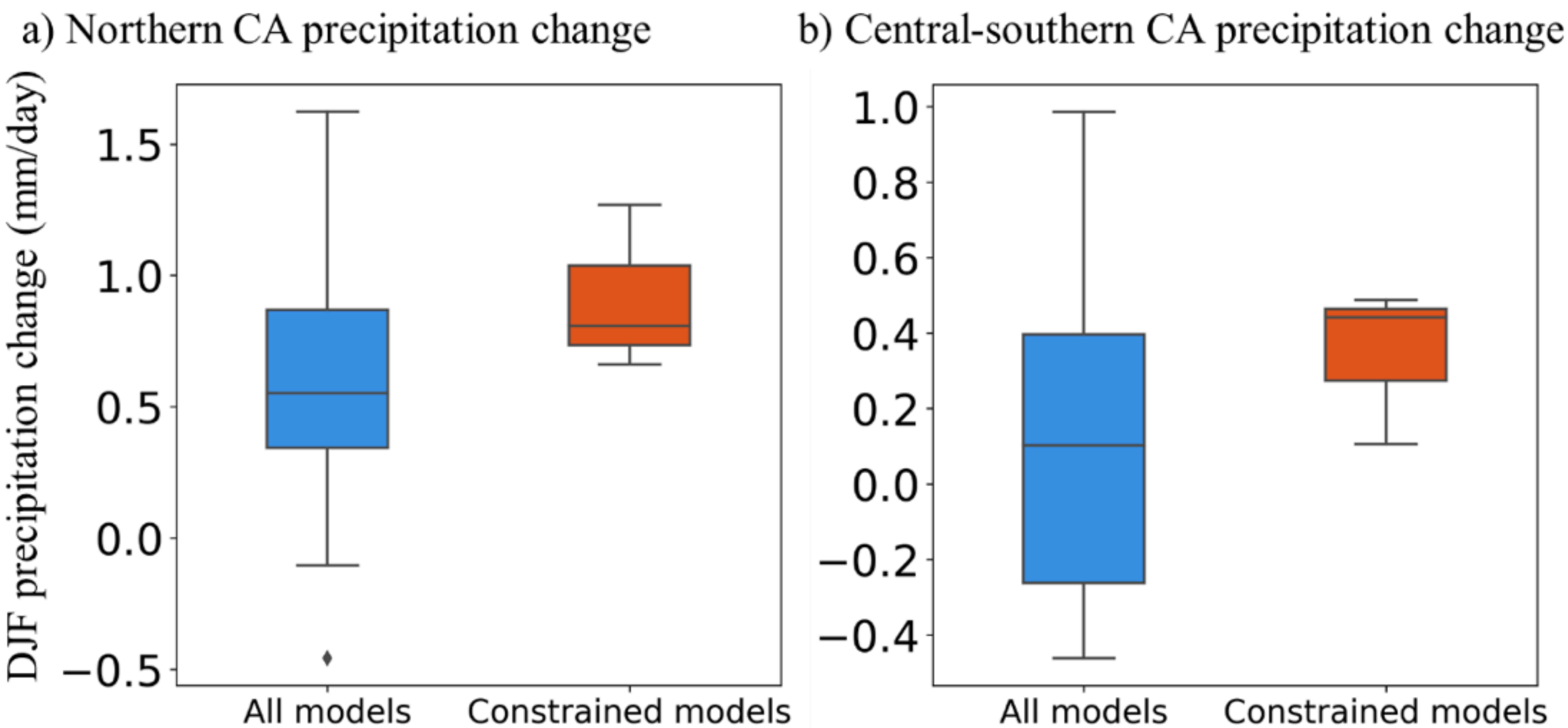
-30% to +49%

Li & Zhu et al., under review



- Emergent structure (teleconnection) highlight critical remote oceanic regions
- The structure likely preserves in the future

Uncertainty reduction using emergent structure



+18% to +34%

+6% to +31%

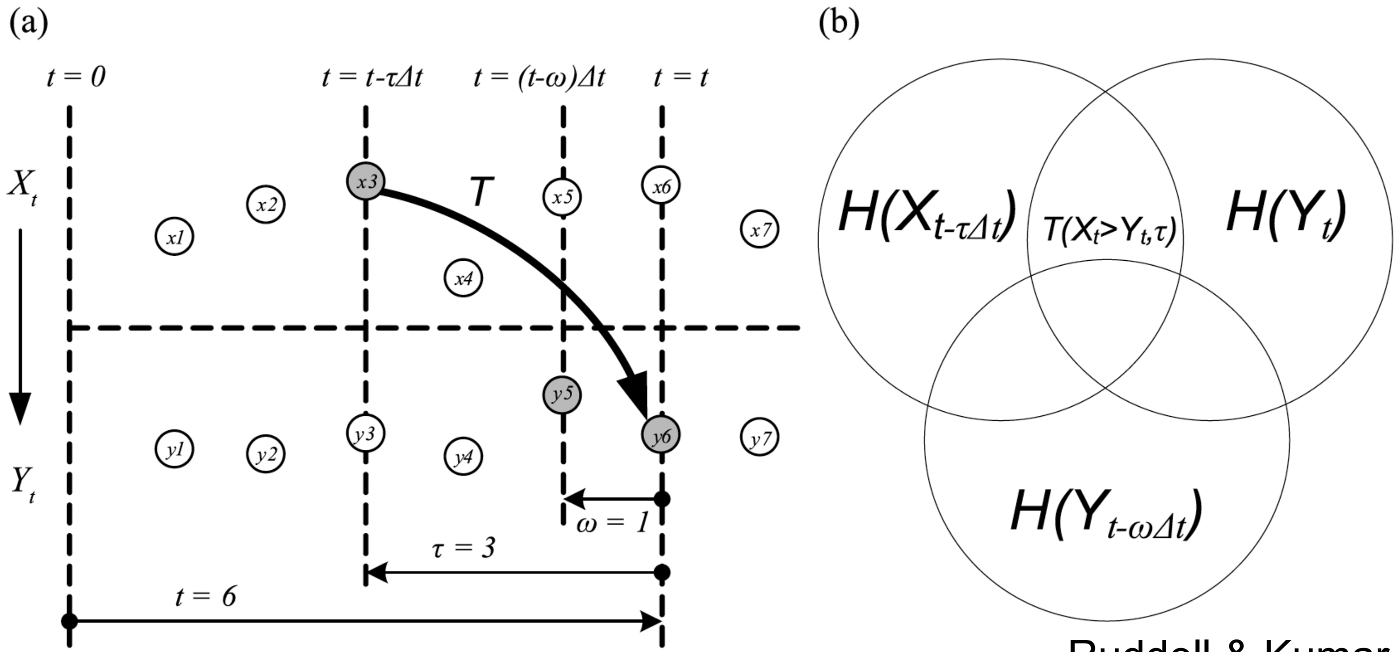
- **~70%** reduction of projection uncertainty
- Wetter CA in the future, due to strong and consistent teleconnection between North American west coast SSP and CA precipitation

summary

- Land model uncertainties from input variables, parameterization, and structure could be sequentially quantified and reduced with **machine learning** and **causal network** analysis.
- **Emergent structure** could serve as powerful constraint for land model future projections, when the structure is persistent throughout time.

Thanks!

Transfer entropy approach



Ruddell & Kumar 2009