# Footprint-Aware Approaches for Model-Data Benchmarking across AmeriFlux Sites

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# Acknowledgements

## AmeriFlux Sites

We acknowledge 200+ participated sites for sharing data and metadata with the AmeriFlux network.

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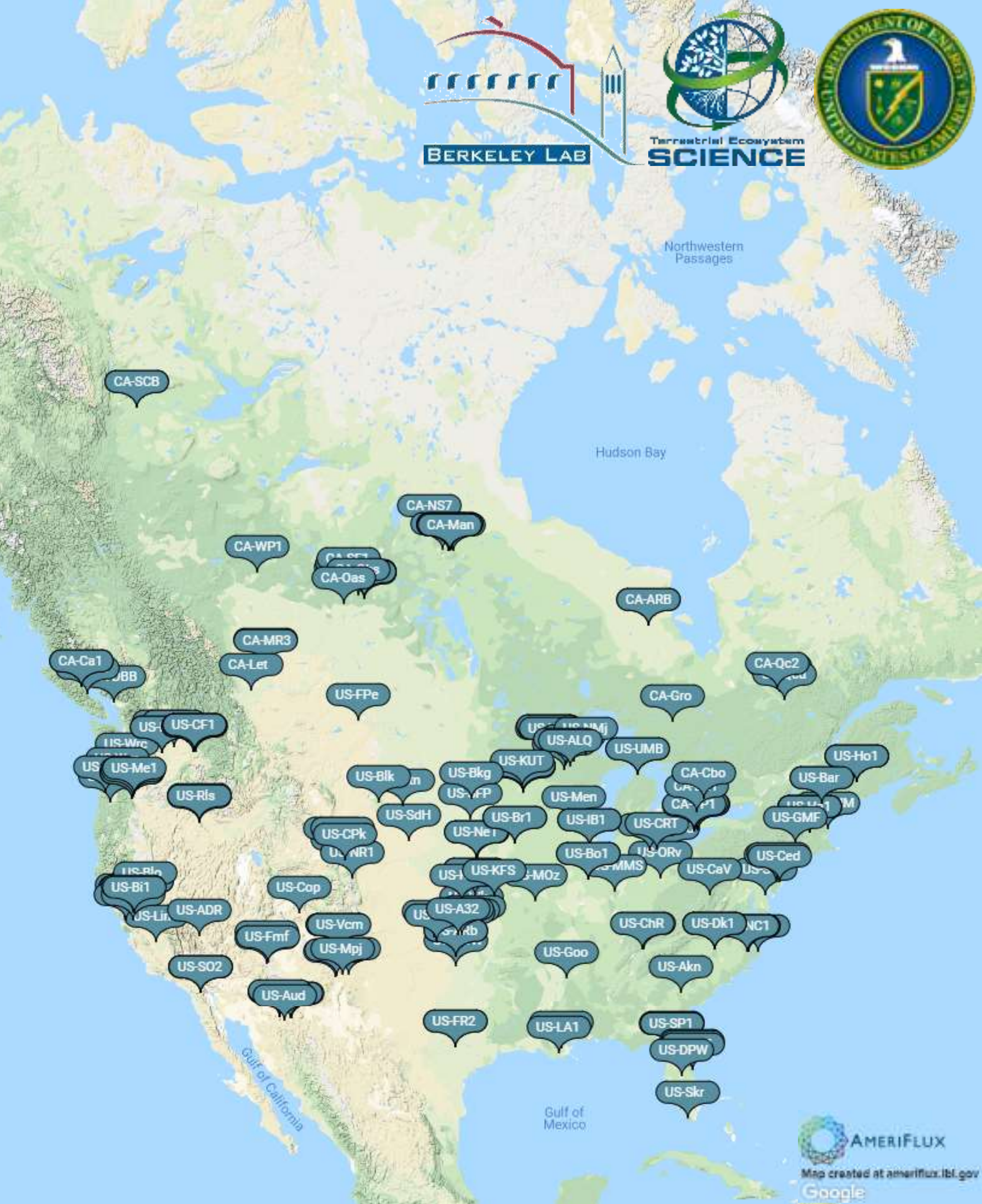
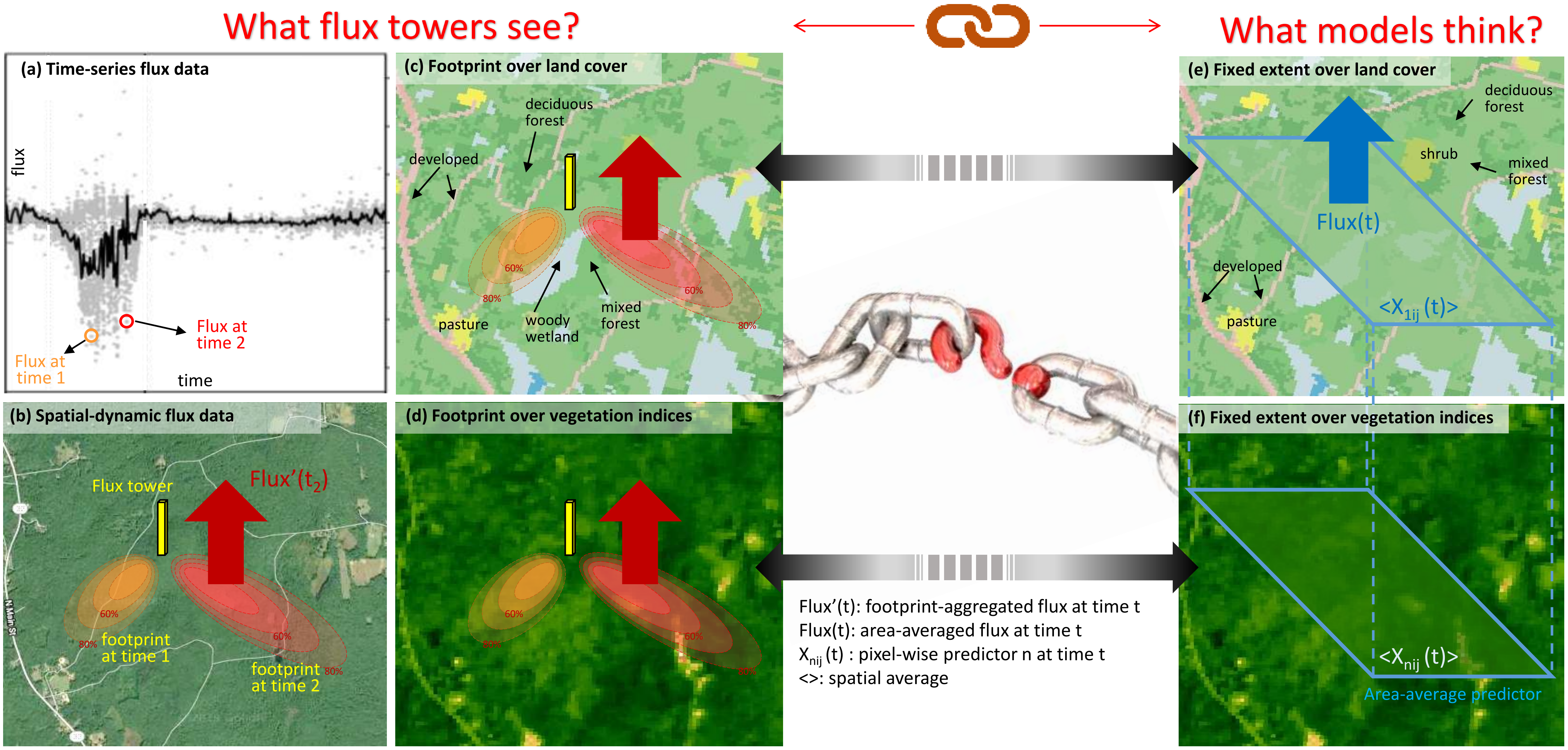


# Background




Flux'(t): footprint-aggregated flux at time t

Flux(t): area-averaged flux at time t

$X_{nij}$ (t) : pixel-wise predictor n at time t

<>: spatial average

*(Chen et al., 2012; Gockede et al., 2008; Rebmann et al., 2005; Wang et al., 2016)*

# Objectives

- Evaluate representativeness of flux footprints to target areas – flux surrogates
- Representativeness indices for footprint-to-target-area representativeness

## Footprint climatology

- Flux Footprint Prediction model (Kljun et al 2015)
  - zm: effective measurement height
  - $z_0$: roughness length
  - V_SIGMA: std of lateral wind velocity
  - WS: wind speed
  - PBL: boundary layer height
    - Nieuwstadt 1981; Batchvarova & Gryning 1991
  - MO_LENGTH: Obukhov length
  - USTAR: friction velocity
  - WD: wind direction
- 214 AmeriFlux sites
  - 1-8 years per site, 712 years in total
- Monthly day/night climatology

## Land surface characteristics

- Land cover type
  - NLCD (US): 2001-2016
  - Land Cover of Canada: 2010
  - 30 m resolution
- Enhanced Vegetation Index (EVI)
  - Landsat 5: 1985-2013
  - Landsat 8: 2013-2019
  - Cloud-free (<1%)
  - 30 m resolution
- Google Earth Engine
  - Preprocessed/quality-controlled
  - Site-specific cutouts
    - 200+ land cover maps
    - 3000+ EVI maps

## Representativeness analysis

- Target area
  - 250m, 500m, 1000m, 1500m, 2000m, 3000m radius around tower
- **Representativeness Index**
  - Footprint-weighted vs Target-area
    - Land cover composition
    - EVI (Enhanced Vegetation Index)

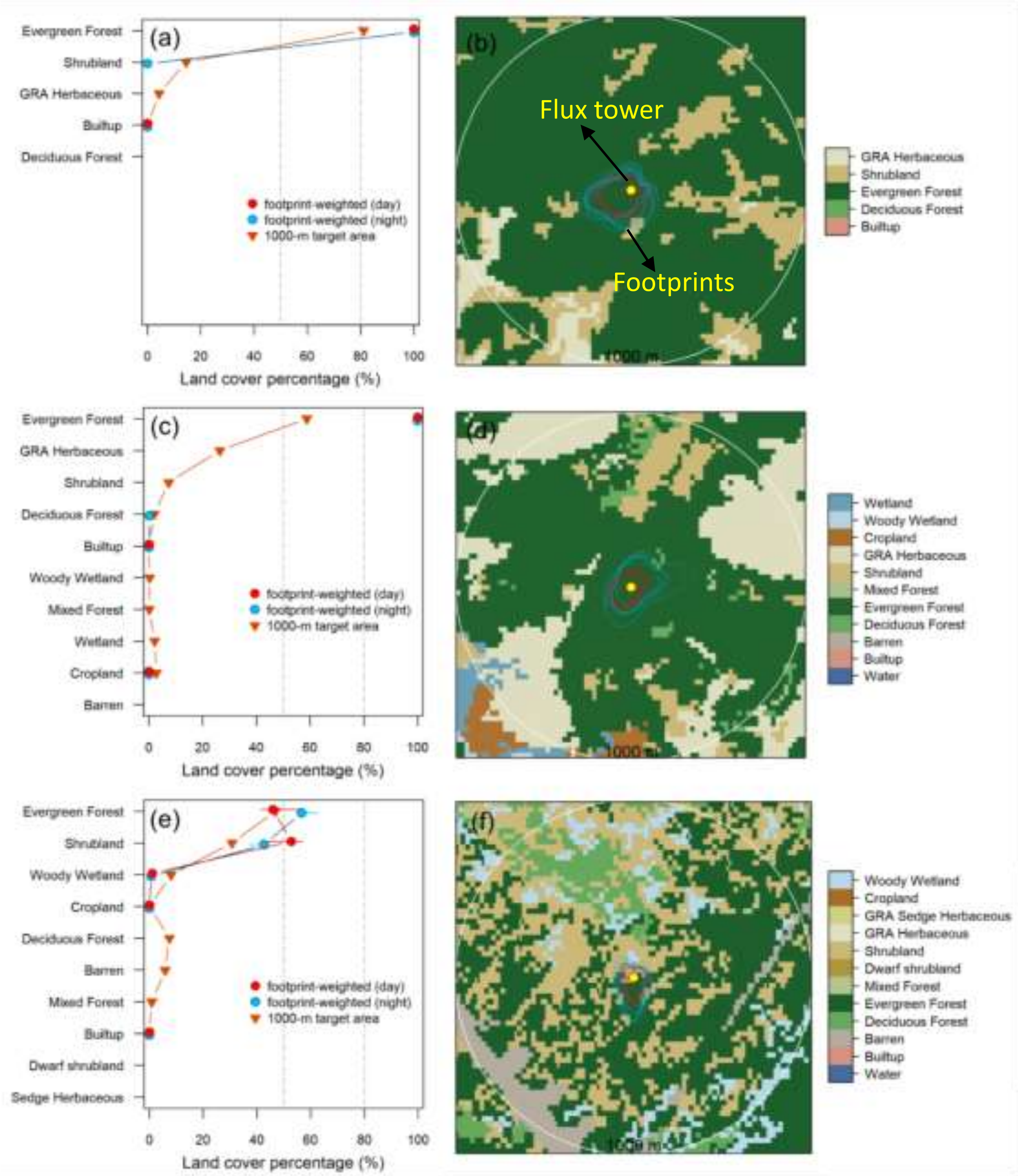
*(Chu et al. 2021)*

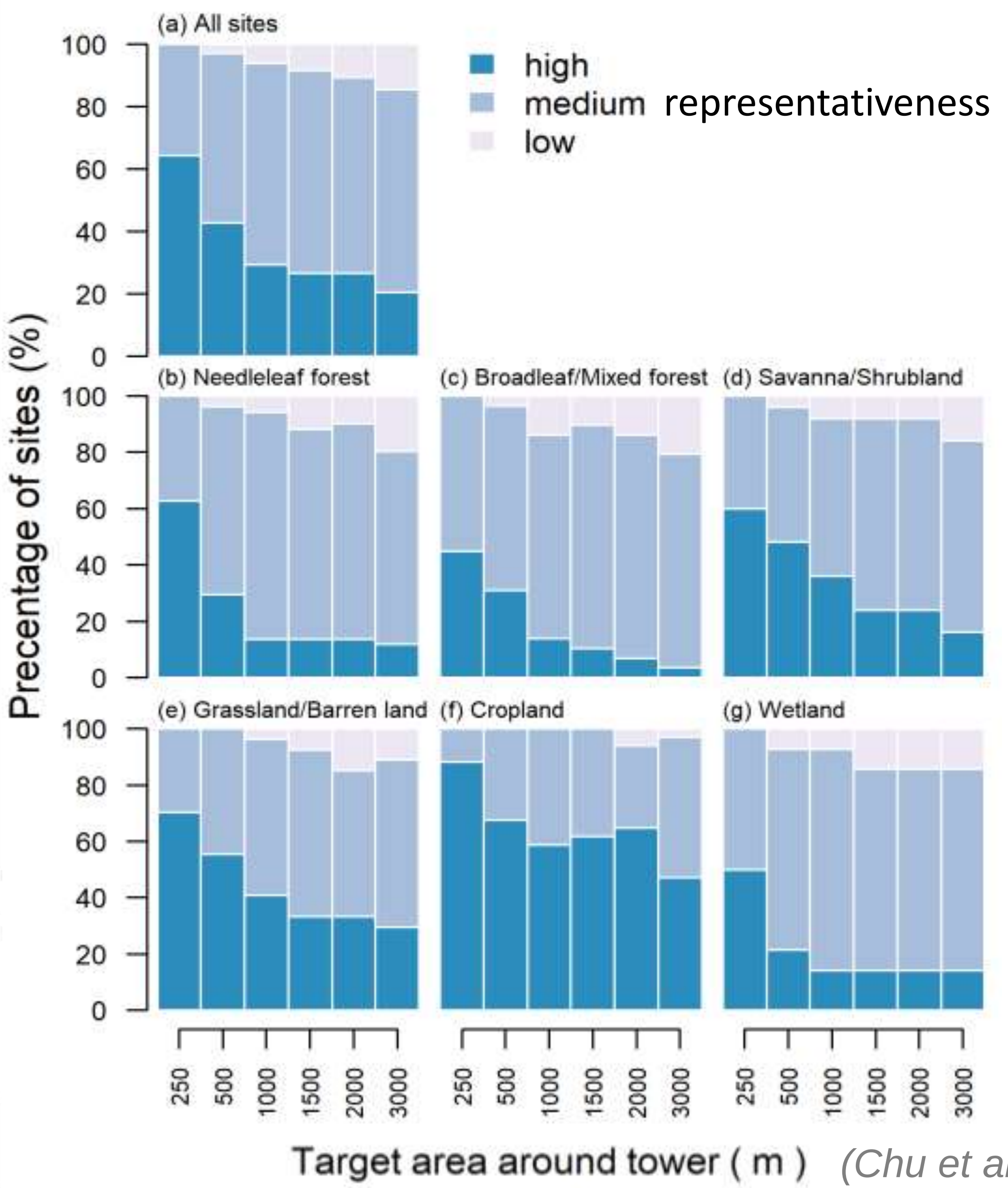
# Representativeness based on land cover composition

High

Medium

Low



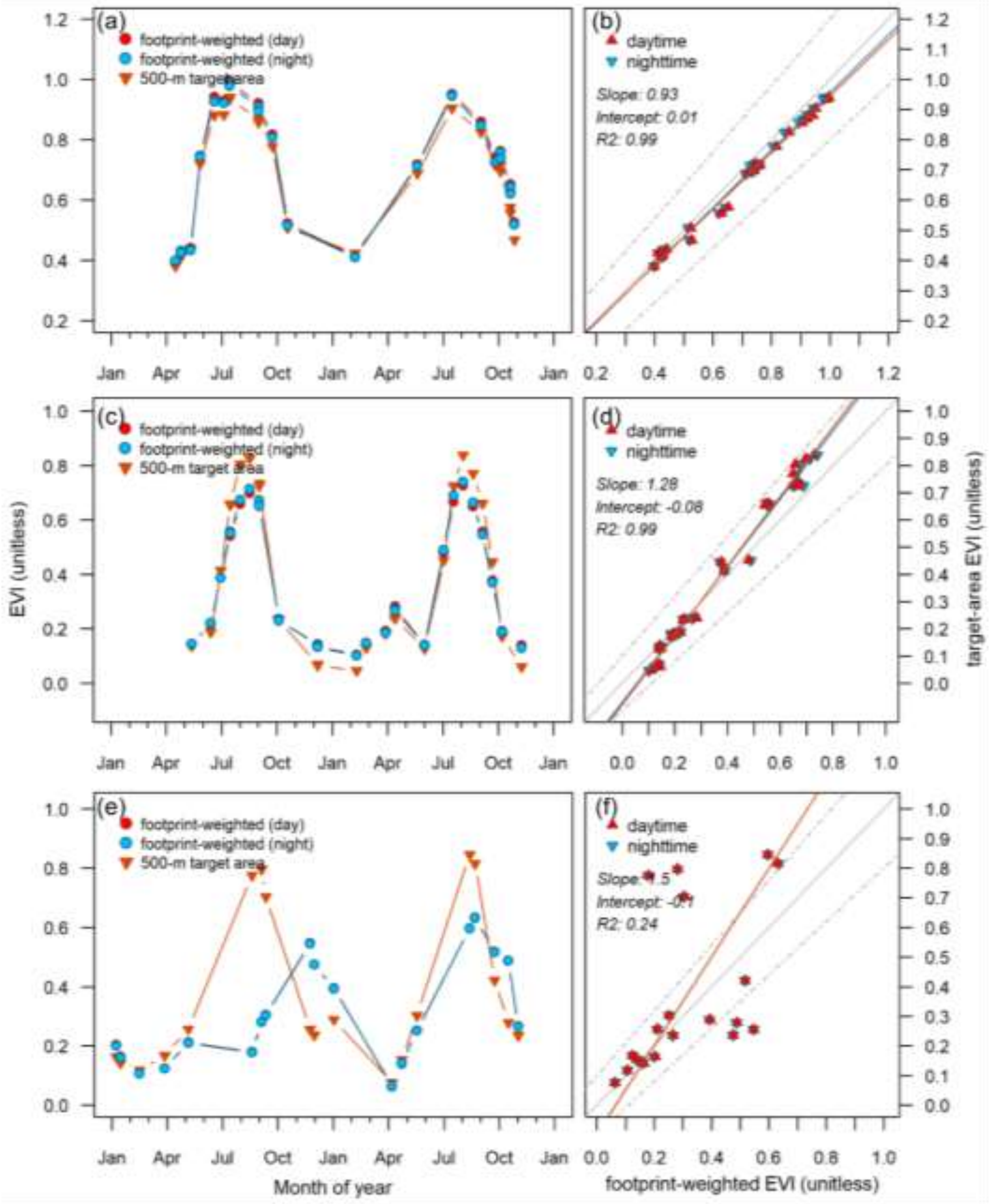

(Chu et al. 2021)

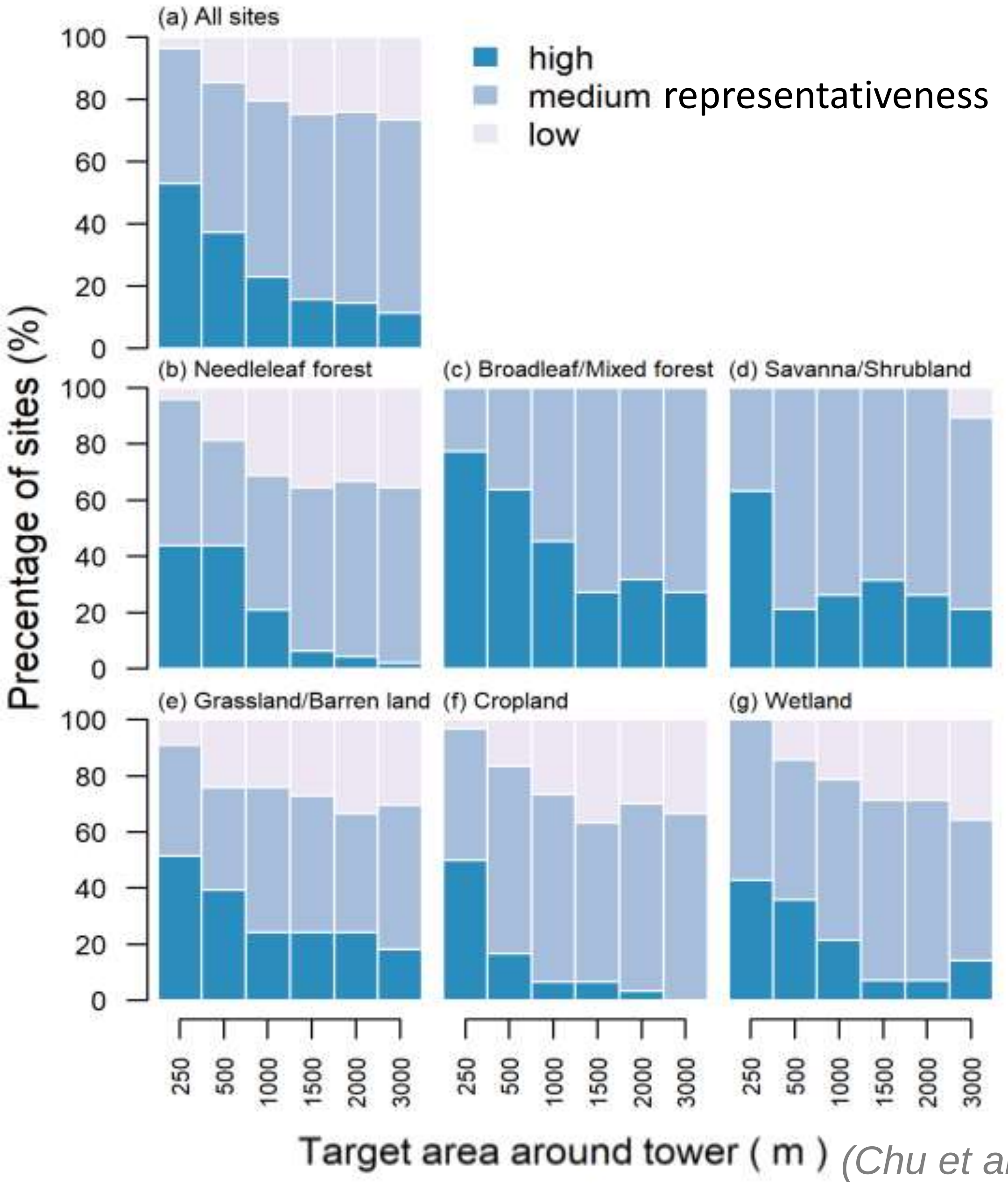
# Representativeness based on EVI

High

Medium

Low



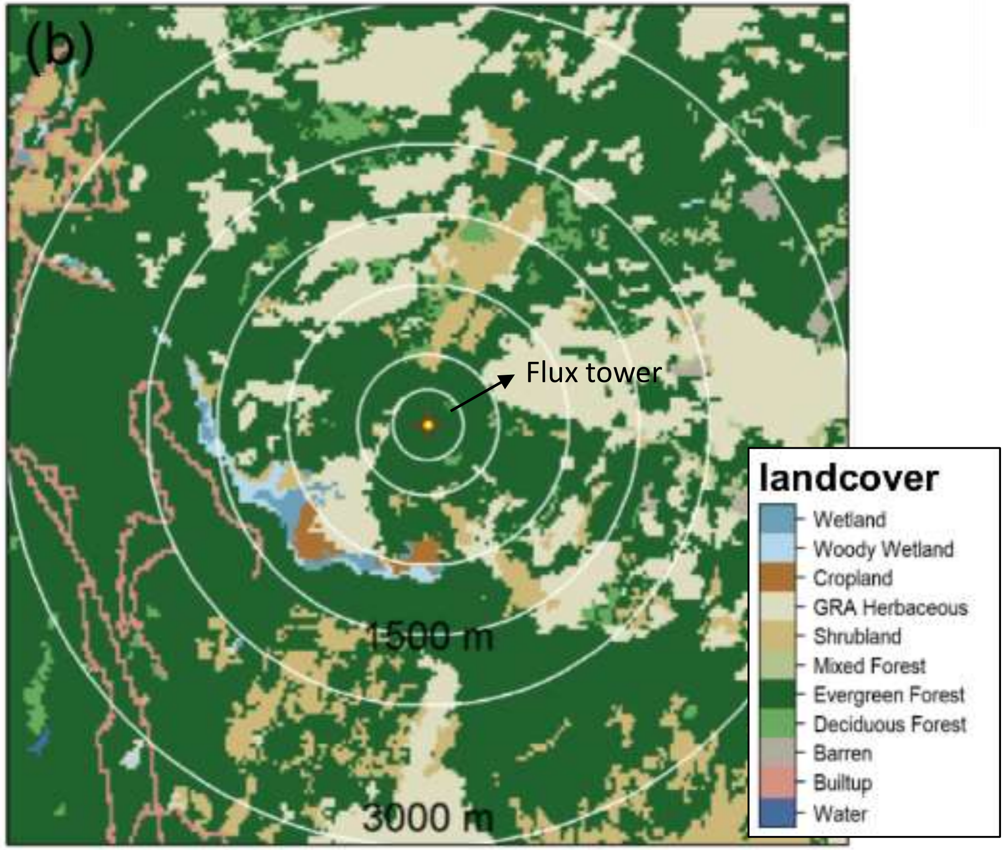



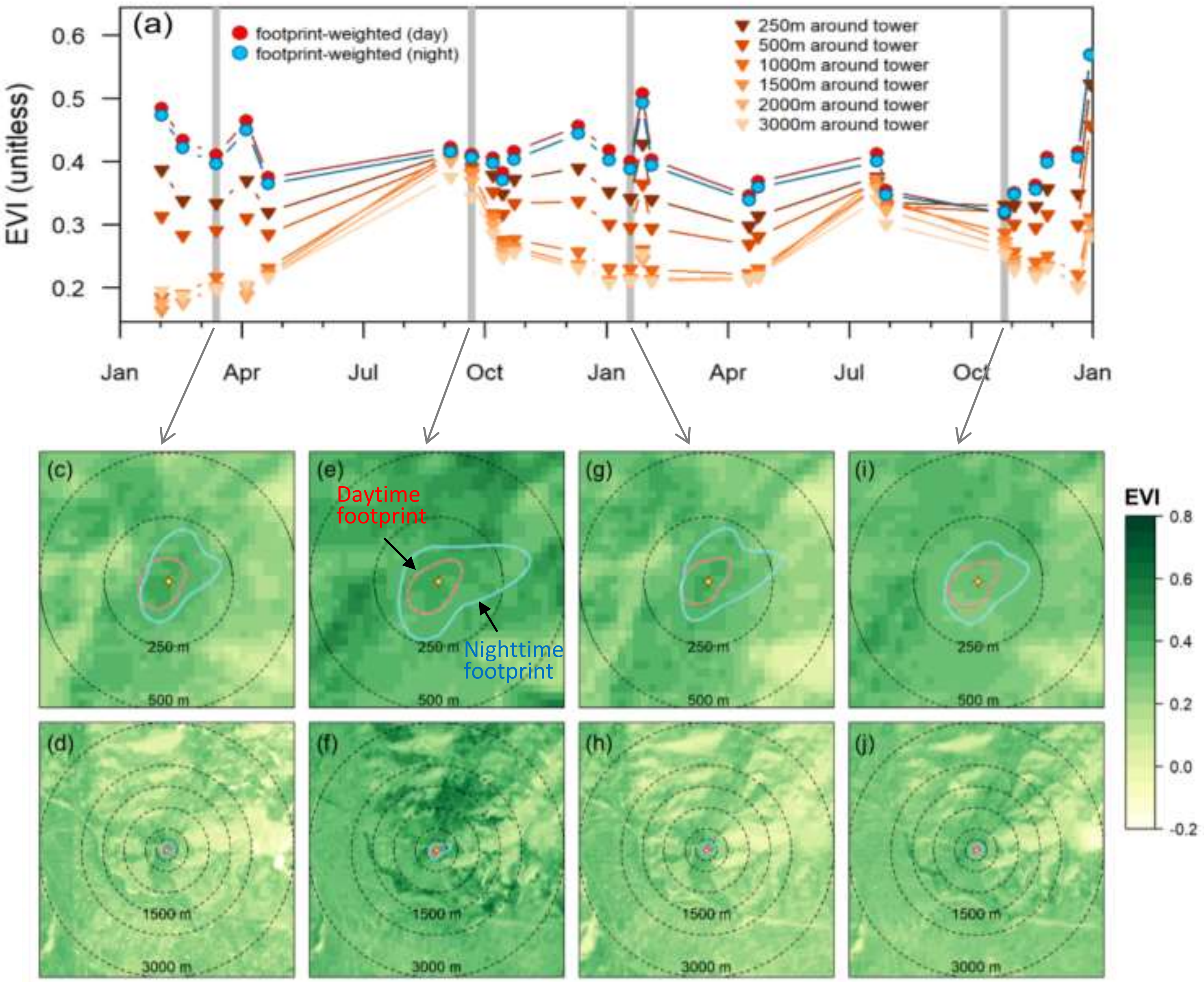

*(Chu et al. 2021)*

# Example case – limited representativeness

## US-Vcp site

An evergreen forest located within a forest-shrub-grassland landscape

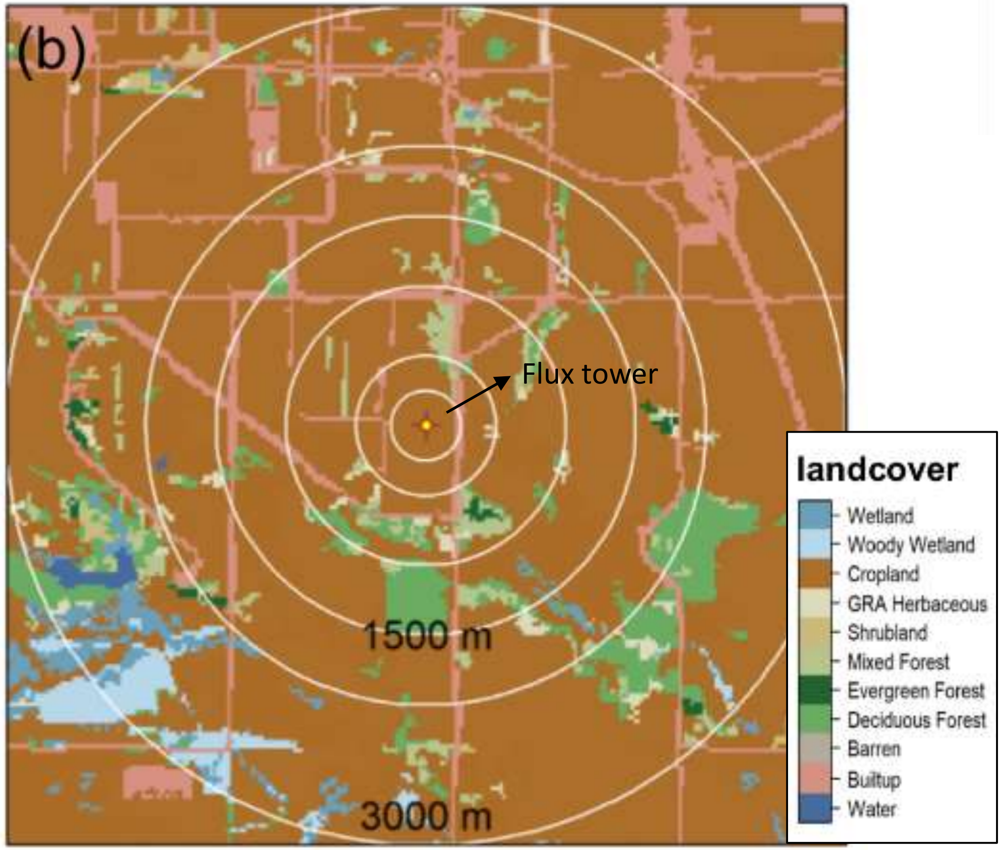


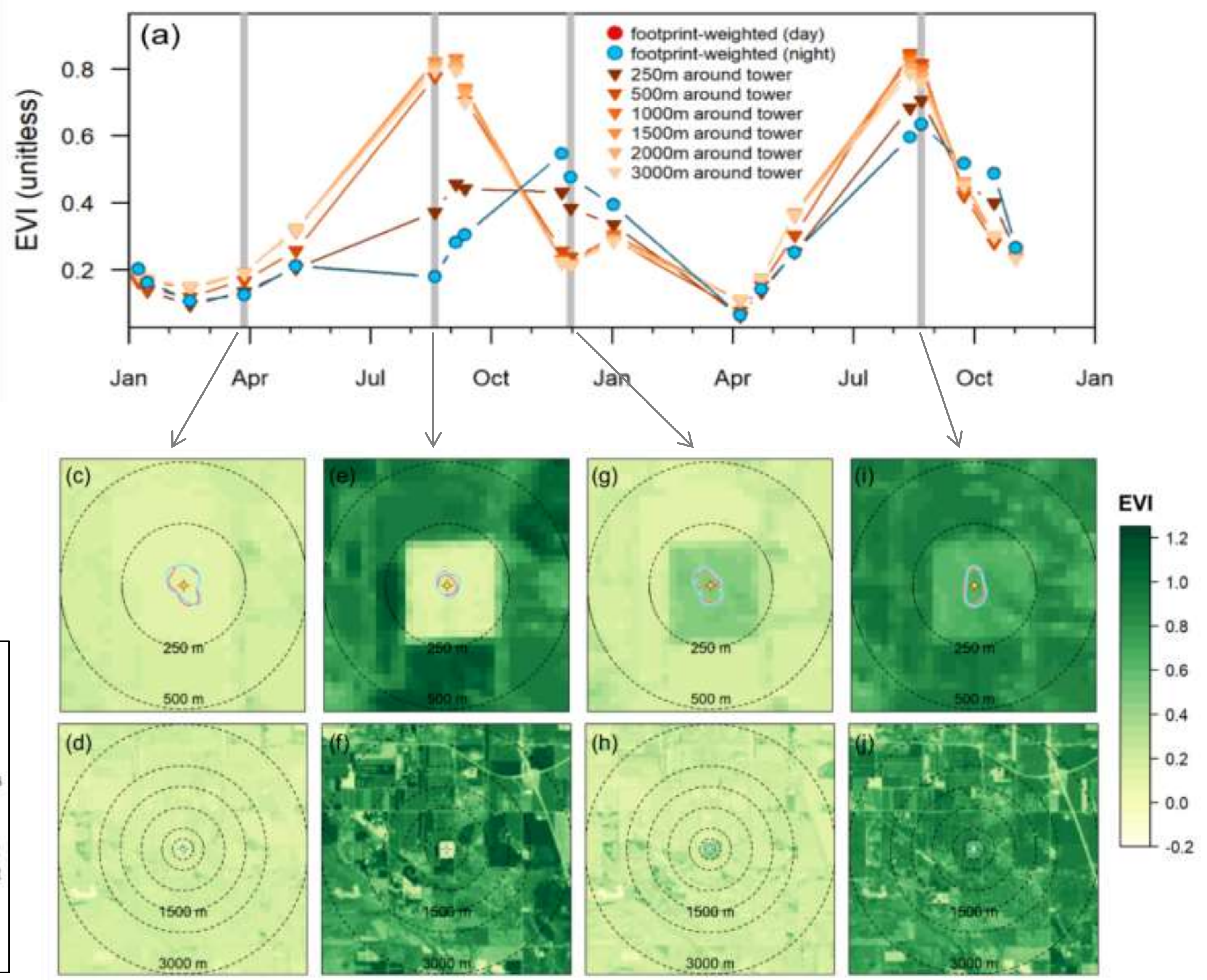



# Example case - contrasting representativeness

## US-Ro6 site

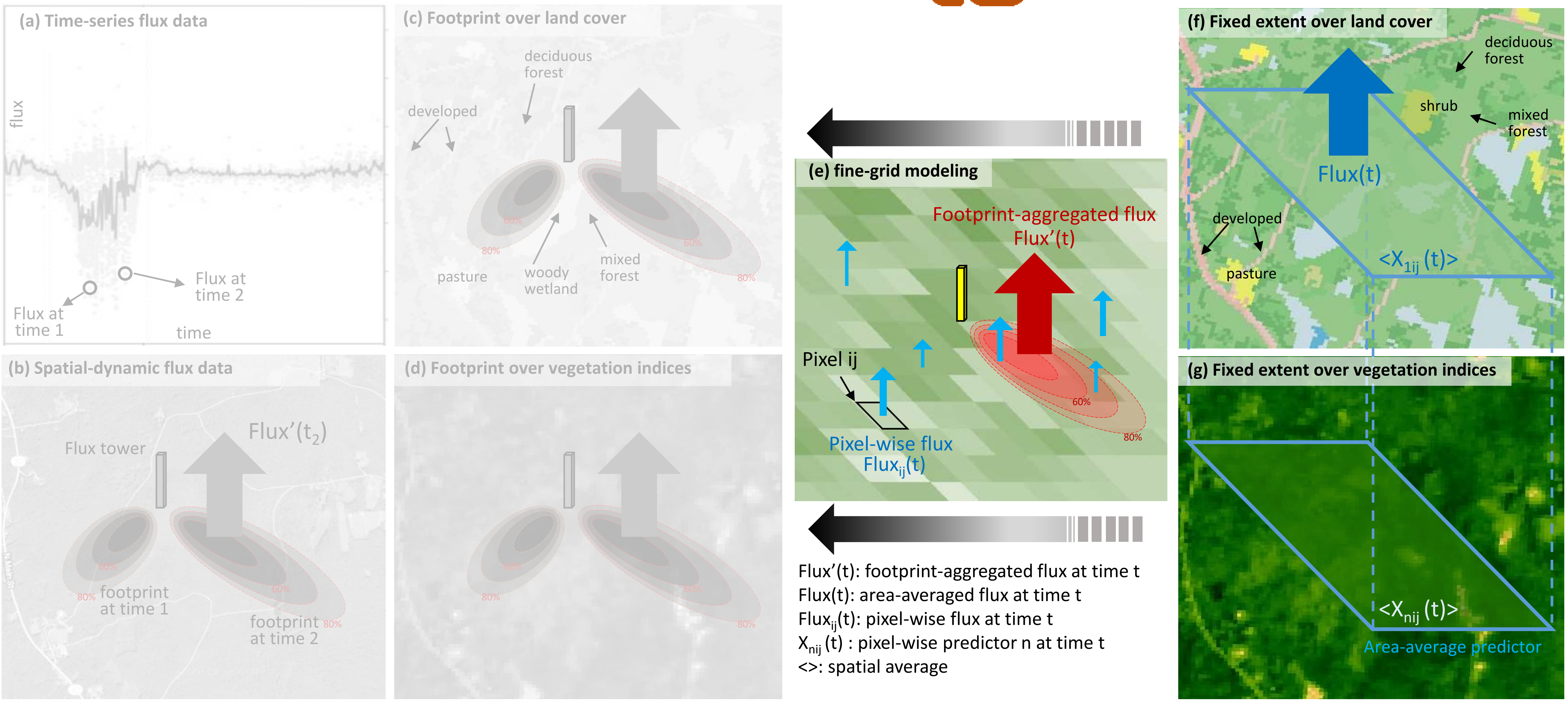
A cropland located in an agricultural landscape dominated with corn/soybean rotation — was planted with wheat, clover, and corn



# A fine-grid modeling approach

## What flux towers see? What models think?




*(Chen et al., 2010; Fu et al., 2014; Ran et al., 2016)*

# Objectives

- ➢ Evaluate representativeness of flux footprints to target areas – modeled fluxes
- ➢ Test a footprint-aware data-model benchmarking framework

## Footprint climatology

- Flux Footprint Prediction model (Kljun et al 2015)
  - zm: effective measurement height
  - $z_0$: roughness length
  - V_SIGMA: std of lateral wind velocity
  - WS: wind speed
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    - Nieuwstadt 1981; Batchvarova & Gryning 1991
  - MO_LENGTH: Obukhov length
  - USTAR: friction velocity
  - WD: wind direction
- 58 AmeriFlux sites
  - 403 years in total
- Daily daytime climatology

## Land surface characteristics

- Land cover type
  - NLCD (US): 2001-2016
  - Land Cover of Canada: 2010
  - 30 m resolution
- Vegetation Indices
  - EVI, LSWI, LAI, fPAR, NDVI
  - Landsat 5: 1985-2013
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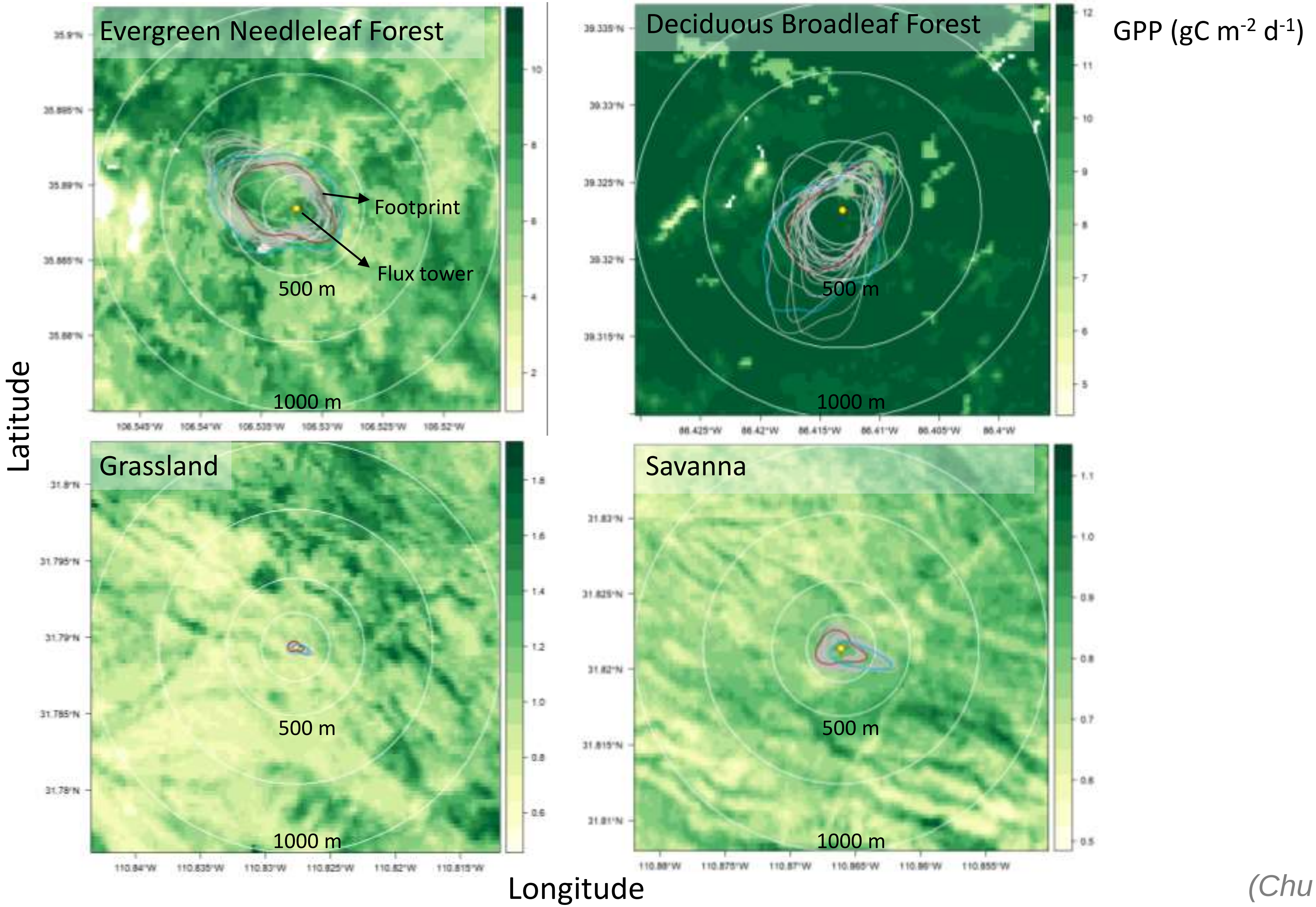
  - Cloud-free (<1%)
  - 30 m resolution
- Google Earth Engine
  - Preprocessed/quality-controlled
  - Site-specific cutouts
    - 1900+ VI stack maps

## Representativeness analysis

- Target area
  - 250m, 500m, 1000m, 1500m, 2000m, 3000m radius around tower
- **Gridded GPP modeling**
  - MODIS GPP model (Running et al., 2004)
    - fPAR, land cover type, met
  - VPM (Xiao et al. 2010)
    - EVI, LSWI, land cover type, met
  - P-model (Stocker et al. 2020)
    - fPAR, land cover, met
  - Tower meteorological variables
  - Daily GPP +/- 3 days VI retrieval

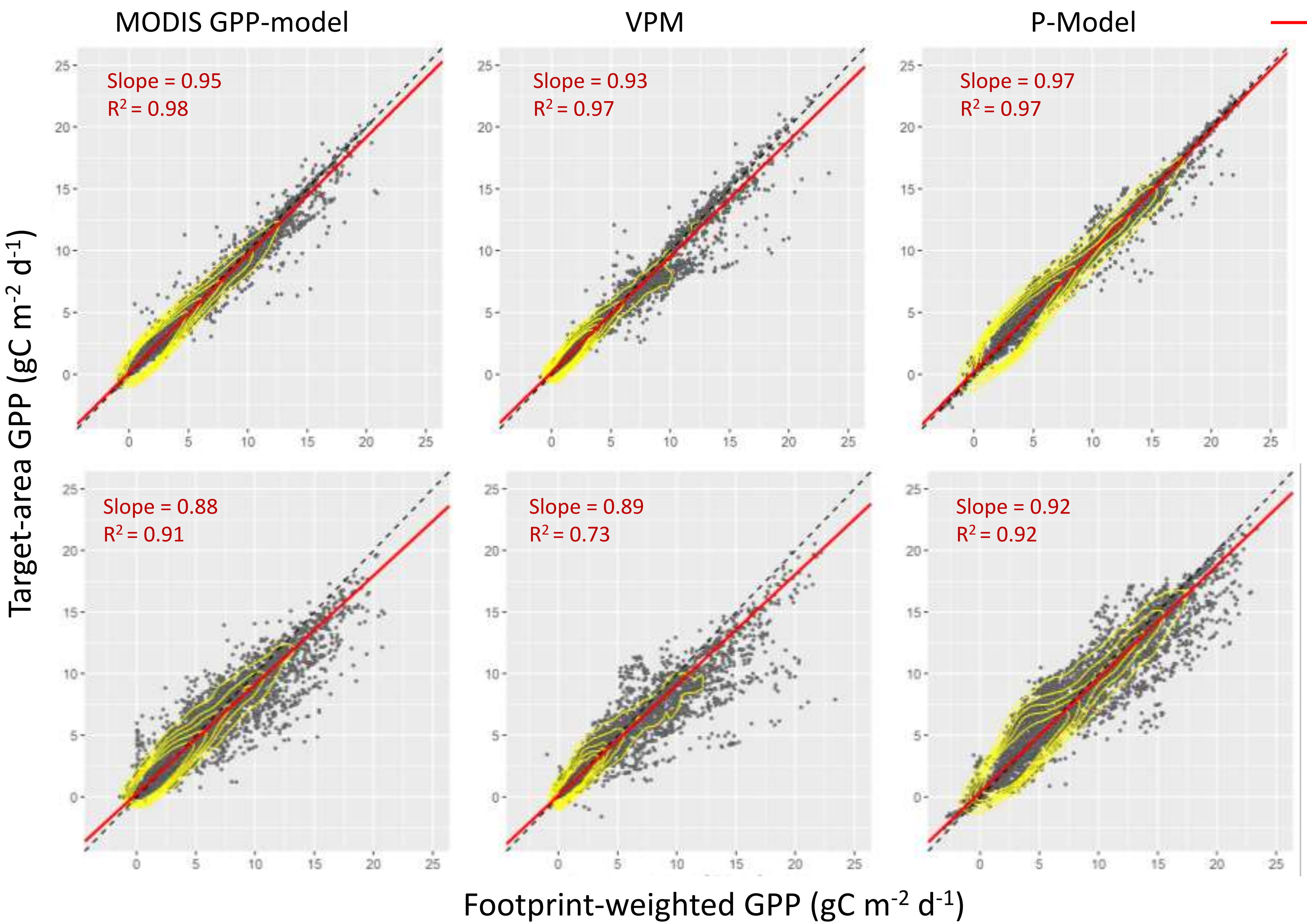
*(Chu et al. in prep)*

# Example GPP maps + footprints



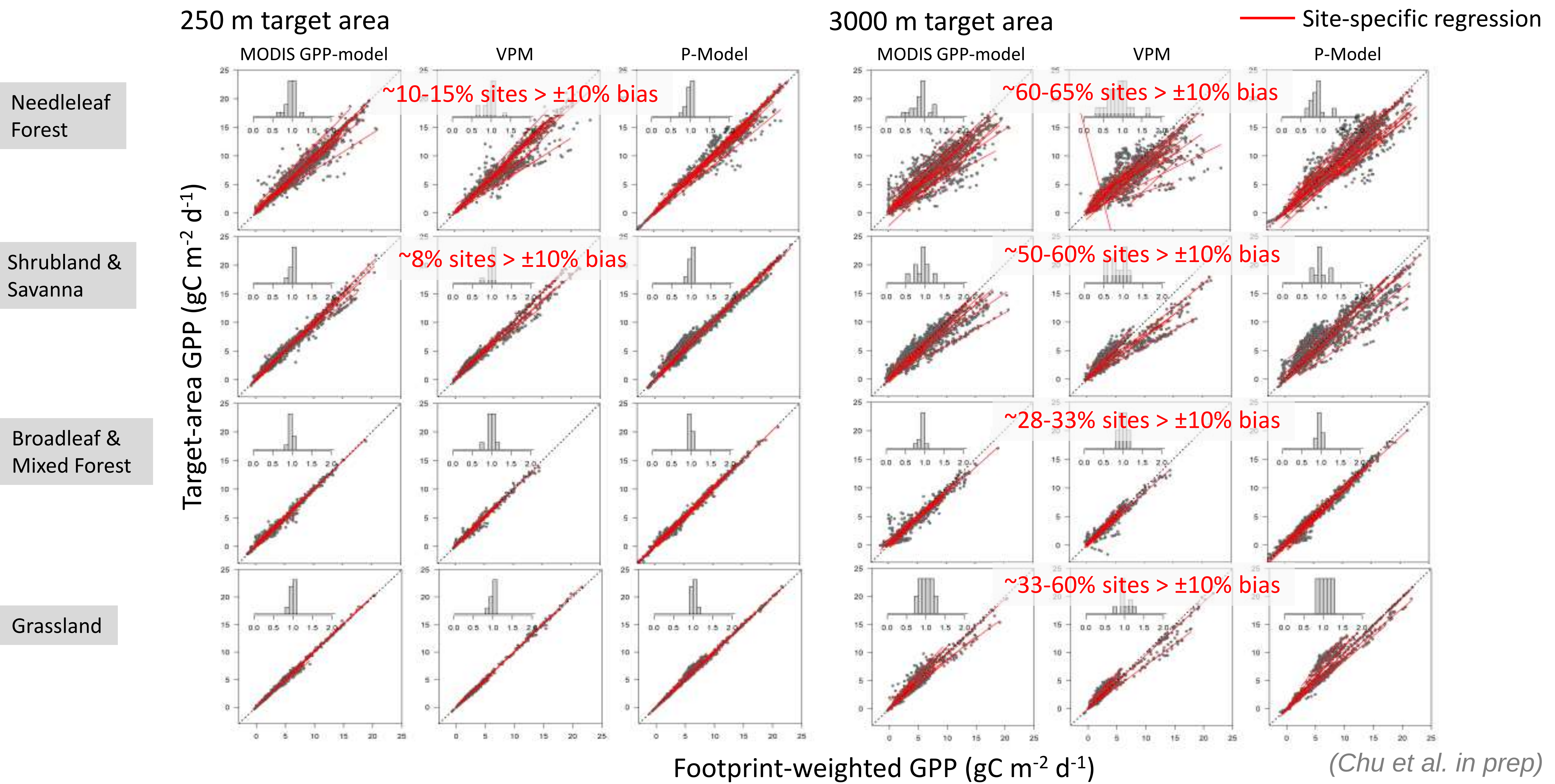

*(Chu et al. in prep)*

# Footprint-weighted vs Target-area GPP (all sites)



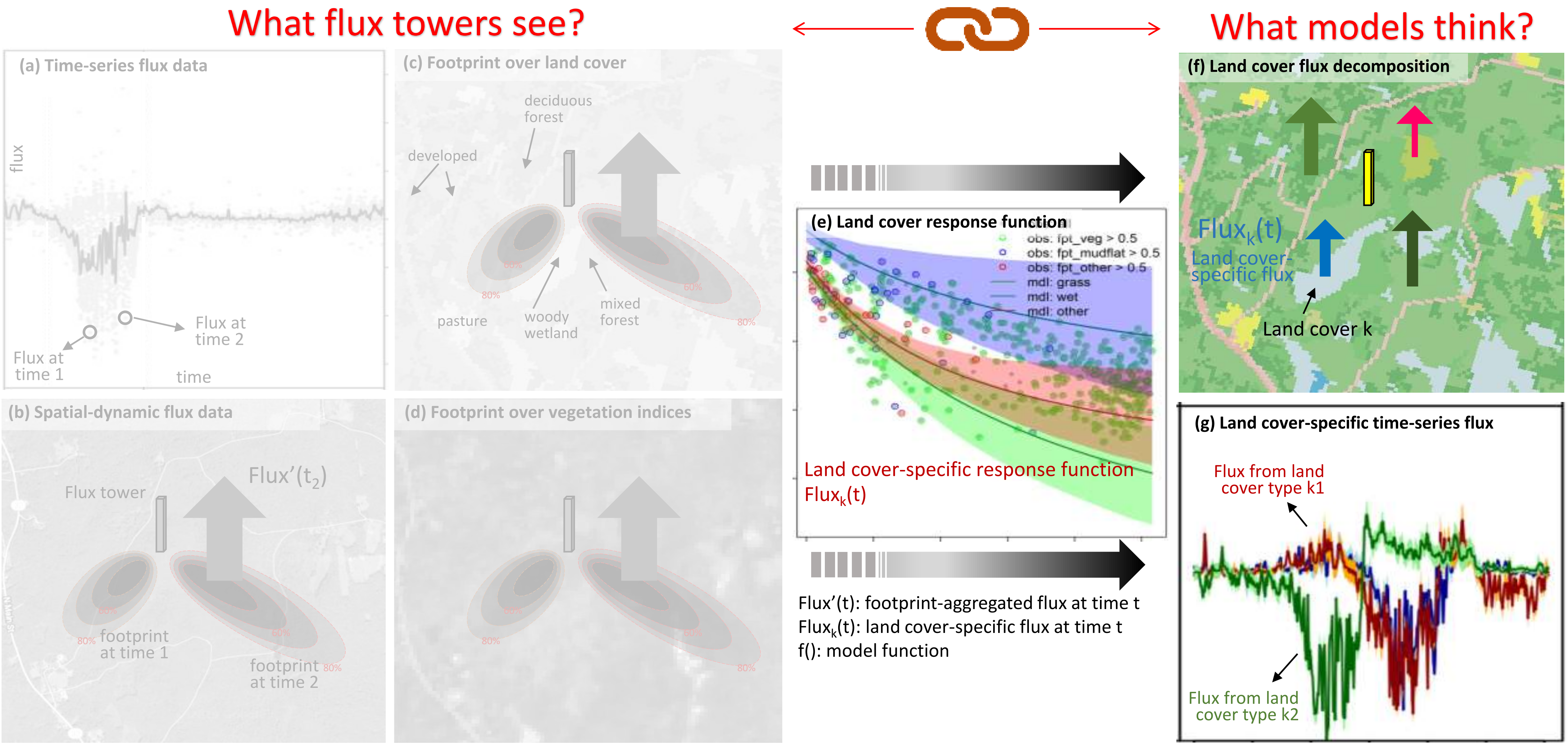

*(Chu et al. in prep)*

# Footprint-weighted vs Target-area GPP (by ecosystem types)




(Chu et al. in prep)

# A footprint-informed decomposition approach




*(Wang et al., 2006; Xu et al., 2017; Duman et al. 2018; Levy et al., 2020)*

# Footprint-informed flux decomposition

## Bayesian Hierarchical Model

$$\boldsymbol{F_x} \sim N(\mu_x, \sigma_x^2)$$

*x: flux variable*
*k: land cover type*

Footprint weights

$$\boldsymbol{\mu_{FC}} = \sum_{k=1}^{K} \boldsymbol{\varphi_k} \cdot (\mathrm{Reco}_k - I(day/night) \cdot GPP_k)$$

$$Reco_k = \boldsymbol{R_{ref\_k}} \cdot \exp\left[\boldsymbol{E_{0\_k}} \left(\frac{1}{T_{ref} - T_0} - \frac{1}{\boldsymbol{T_a} - T_0}\right)\right]$$

$$GPP_k = \boldsymbol{A_{max\_k}} \cdot \frac{\boldsymbol{Rg}}{\boldsymbol{Rg} + \boldsymbol{K_{m\_k}}}$$

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$$\boldsymbol{\mu_{LE}} = \sum_{k=1}^{K} \boldsymbol{\varphi_k} \cdot \frac{\Delta \cdot \boldsymbol{A} + \rho \cdot C_p \cdot \boldsymbol{VPD} \cdot \boldsymbol{g_a}}{\gamma \frac{\boldsymbol{g_a}}{G_{s_k}} + \Delta + \gamma} = \sum \boldsymbol{\varphi_k} \cdot f(G_{s_k}) \cdot LE_{pot}(\boldsymbol{A}, \boldsymbol{VPD}, \boldsymbol{g_a})$$

Potential LE

$$G_{s\_k} = \boldsymbol{G_{s\_ref\_k}}(1 - \boldsymbol{m_k} \cdot ln(\boldsymbol{VPD}))$$

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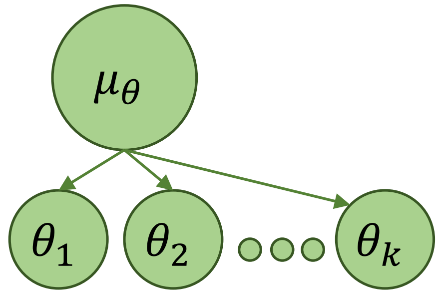
$$\boldsymbol{\mu_H} = \sum_{k=1}^{K} \boldsymbol{\varphi_k} \cdot (\boldsymbol{\beta_{0\_k}} + \boldsymbol{\beta_{1\_k}} \cdot \boldsymbol{Rg})$$



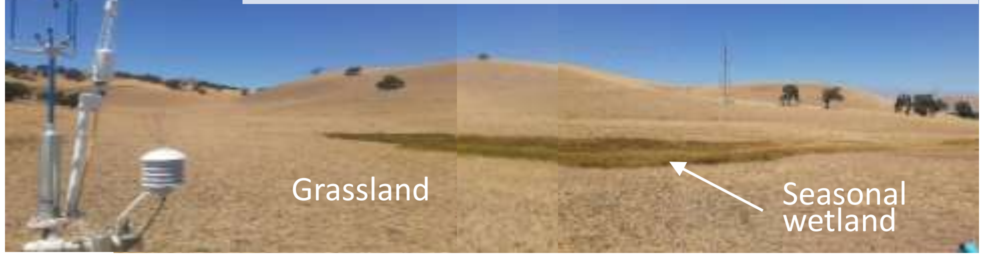

$$\theta_k \sim N(\mu_\theta, \sigma_\theta^2);\ \theta_k \in [L_\theta, U_\theta]$$

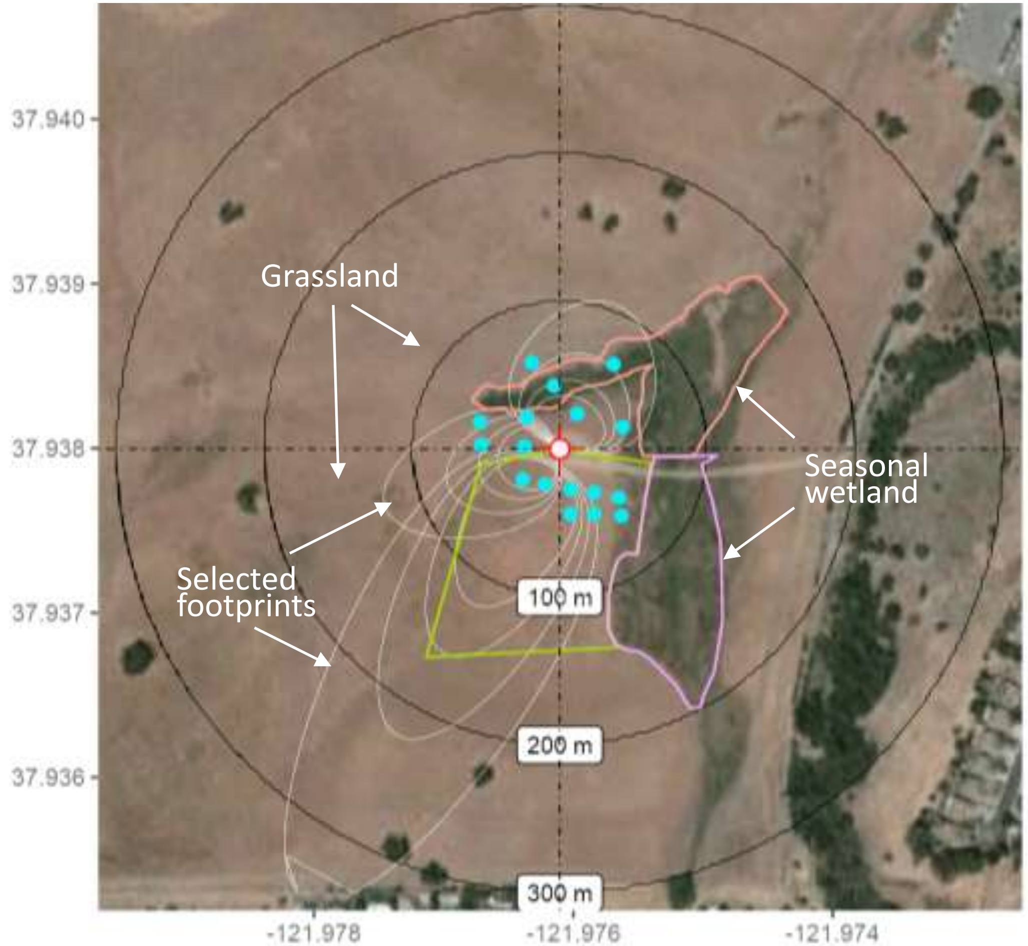
*k: land cover type*
*θ: parameter*

$$\left.\begin{array}{l} \boldsymbol{E_{0\_k}} \\ \boldsymbol{K_{m\_k}} \\ \boldsymbol{R_{ref\_k}} \\ \boldsymbol{A_{max\_k}} \\ \boldsymbol{G_{s\_ref\_k}} \\ \boldsymbol{M_k} \\ \boldsymbol{\beta_{0\_k}} \\ \boldsymbol{\beta_{1\_k}} \end{array}\right\} \text{land cover specific parameters}$$

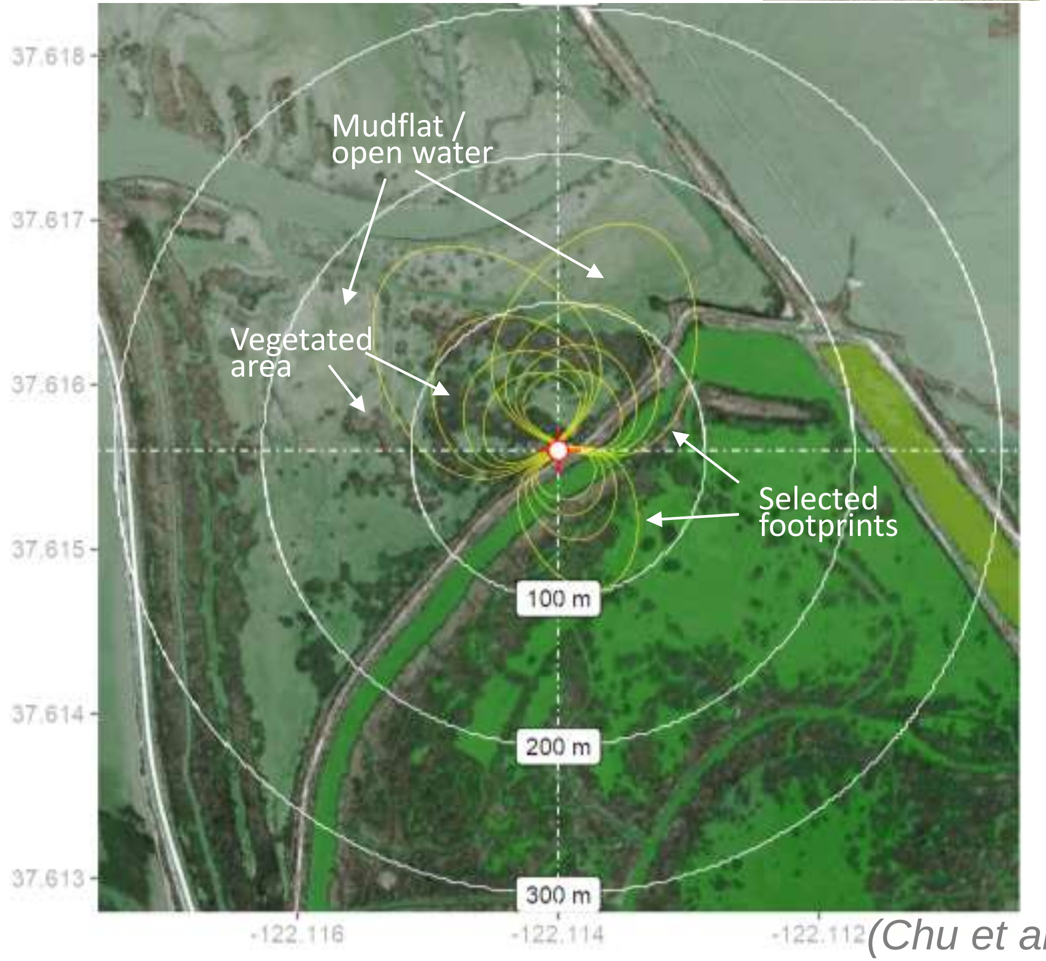
# Testing cases

## Concord grazed grassland (US-CGG)




## Eden Landing tidal wetland (US-EDN)

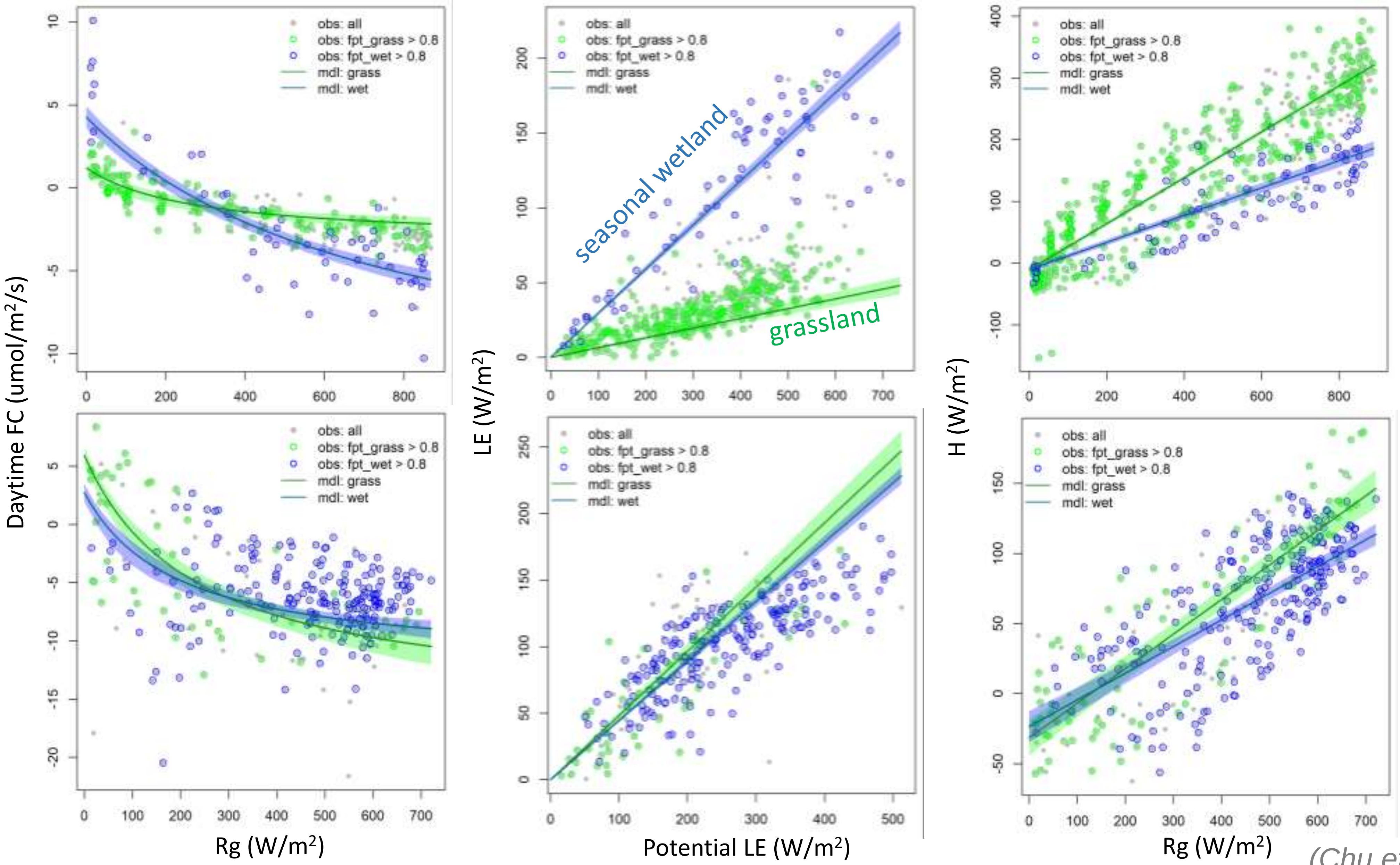




*(Chu et al. in prep)*

# Land cover-specific response functions (Concord grassland)

Dry season

Wet season

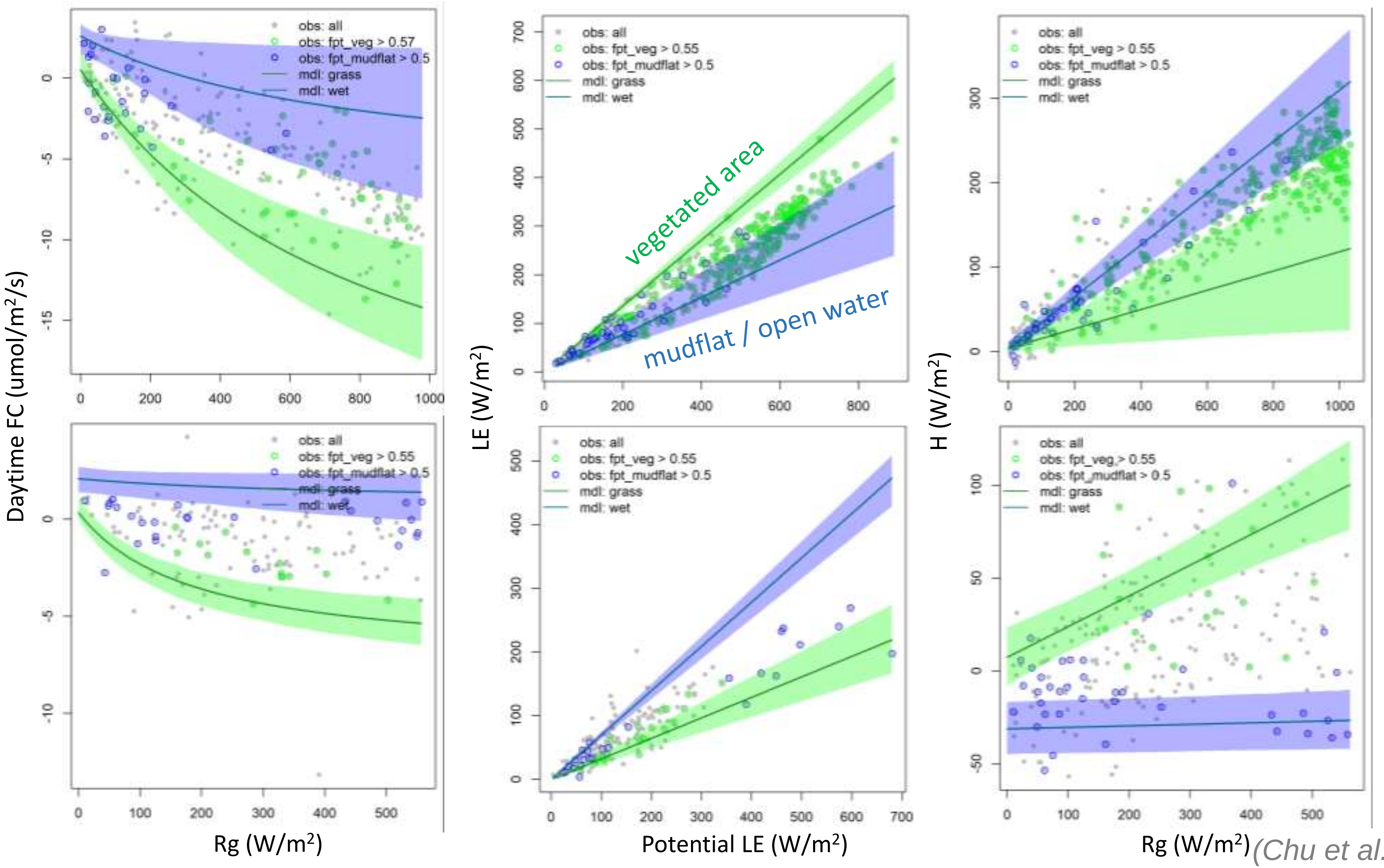



(Chu et al. in prep)

# Land cover-specific response functions (Eden Landing wetland)

Growing season

Dormant season




(Chu et al. in prep)

# Summary

- Footprint representativeness of AmeriFlux sites
  - Large-scale eddy-covariance flux datasets need to be used with footprint-awareness
  - Using a fixed-extent target area across sites can bias model-data integration
  - Most sites do not represent the dominant land-cover type at a larger spatial extent
  - A representativeness index provides general guidance for site selection and data use

  *Chu et al. (2021) Agric. For. Meteorol. 301-302, 108350, DOI:10.1016/j.agrformet.2021.108350*
  *Supplementary Dataset at Zenodo https://doi.org/10.5281/zenodo.4015350*

- Future work – footprint-informed flux decomposition
  - Improve model structures, MCMC settings
  - Expand tests to sites with degrees of patchiness & heterogeneity
  - Sensitivity tests of footprint models

@chuhousen