An Assessment of Remote Sensing Methods to Monitor Spatio-Temporal Variations in Annual GPP

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Overview & Summary of Results

- **Objective**: To compare and assess 9 different methods for monitoring spatio-temporal variations in annual GPP in different biomes using satellite observations
- **Methods:** We employed 489 site years of data from 168 sites in the LaThuile dataset to examine the agreement between
  - (i) mean annual GPP from tower fluxes and satellite models and proxies[1], and
  - (ii) annual anomalies in GPP from tower fluxes and satellite models and proxies.
- **Key findings**:
  - **Spatial variation in mean annual GPP**
    - In cropland and deciduous broadleaf forests none of the proxies or models performed well.
    - In the remaining biomes, the simplest model, which combined mean growing season EVI with biome-dependent mean annual climate variables had the best agreement (R^2 ~0.6 - 0.8) and low bias.
  - **Variation in annual anomalies**
    - In cropland and deciduous broadleaf forests none of the proxies or models were able to explain interannual variation in GPP.
    - In the remaining biomes, a neural network model estimated at daily time scale using PAR, air temperature, vapor pressure deficit and FPAR as inputs explained the most variance, with R^2 ranging from 0.4 to 0.75.

[1] We define a proxy in this context as an index derived from seasonal time series of remotely sensed observations (e.g., mean growing season EVI).

Background & Justification

- Terrestrial gross primary productivity (GPP) is the largest carbon flux (Beer et al., 2010).
- Regular monitoring of terrestrial GPP is required to understand the global carbon cycle, future climate, availability of food (Bunn et al., 2006) and to evaluate climate mitigation programs such as United Nations Reducing Emissions from Degradation and deforestation (UN-REDD).
- Different methods that use satellite data have been proposed to compute temporally continuous and spatially extensive estimates of GPP.

Background & Justification

These methods can be divided into two broad approaches:

- In the first approach, satellite based metrics including the mean growing season VI (NDVI or EVI), the integral of growing season VI (EVI-area), or the growing period length (GPL) are assumed to reflect spatio-temporal patterns in ecosystem productivity (Myneni et al., 1998; Zhou et al., 2001; Angert et al., 2005; Goetz et al., 2005) because of their relationship with vegetation phenology and total leaf area (Tucker at al., 2001; Slayback et al., 2003). Throughout this presentation we will refer to these metrics as 'proxies'.

- In the second approach, satellite data is combined with meteorological variables to model daily or 8-day estimates of GPP. Three types of models have been used in this context : (i) light use efficiency models (Running et al., 2004), (ii) simpler models based on EVI and land surface temperature (Sims et al., 2008), and (iii) nonlinear, data dependent models based on machine learning algorithms (Xiao et al., 2010).

Background & Justification

- Here we examine the suitability of 9 different satellite based proxies and models to capture the variability in annual GPP in two main dimensions (Richardson et al., 2010).
  - *Spatial variation in mean annual GPP*: This mode of variance lets us answer questions related to variations in GPP over space (e.g. Which *area* was most productive in the last five years?).
  - *Temporal (inter-annual) variation in GPP*: This mode of variance on the other hand helps us investigate variations in GPP over time (e.g. Which *year* was most productive in the last five years?).

Motivating Questions

- While photosynthesis at leaf and canopy level is well understood, a great deal of uncertainty remains about drivers of and controls on spatio-temporal variations in ecosystem level productivity (Beer et al., 2010).
- It would therefore be useful to understand how different satellite-based proxies and models (which represent different hypotheses and are calculated at different time scales) vary in their ability to capture variation in annual GPP in space and time in different biomes. In particular we posed the following questions:
  - Are satellite based models or proxies more successful in tracking spatial versus temporal variance in GPP at annual time scales?
  - Are satellite-derived metrics calculated at high temporal resolution better than annual metrics in capturing variability in annual GPP?
  - Are more complex models better than simpler models and proxies in capturing spatial and temporal variance in annual GPP?

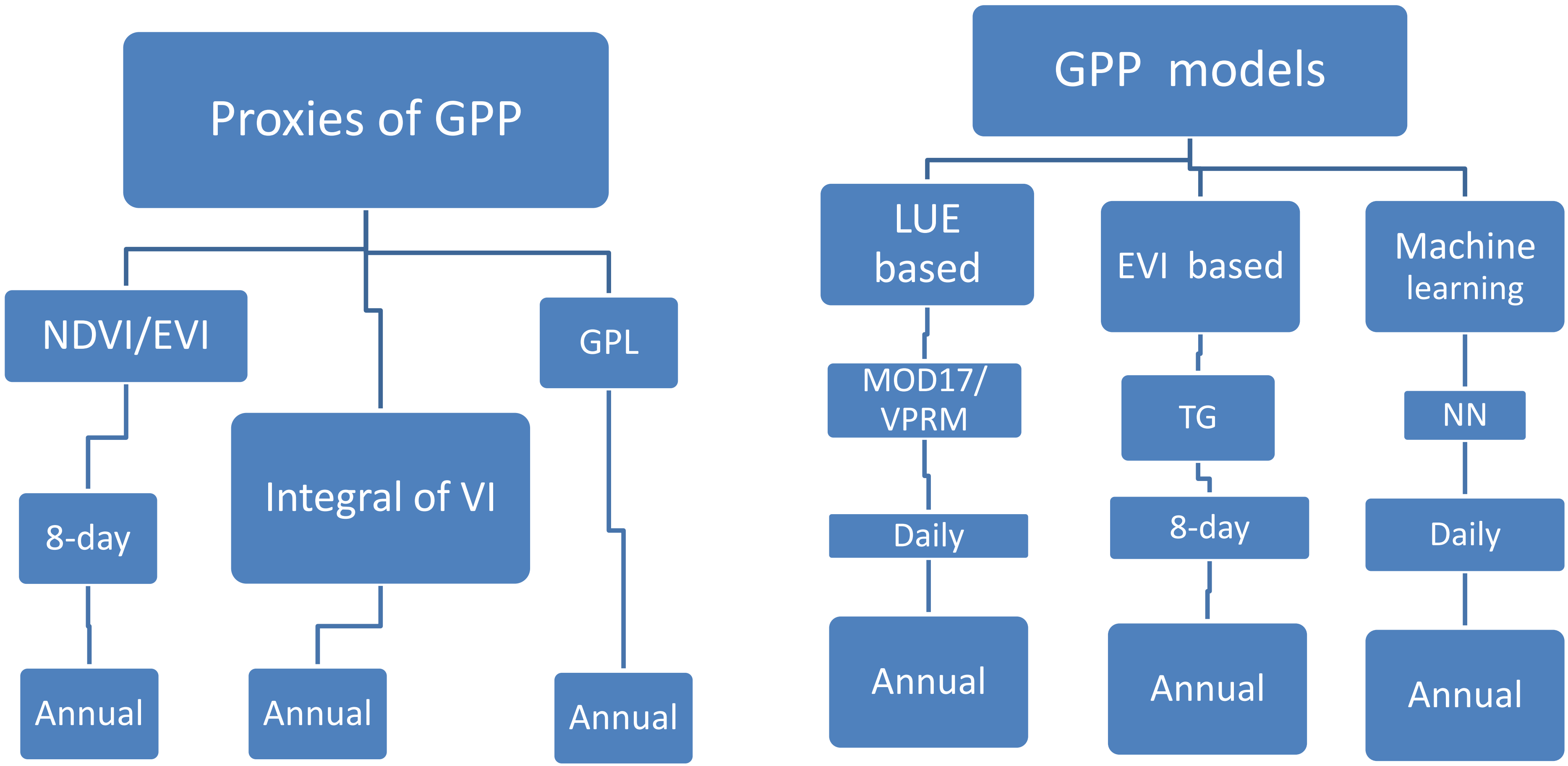
Objectives

The goal of this work is to use GPP and meteorological data from the La Thuile data set in association with satellite-derived observations to assess how well different remote sensing proxies and model are able to capture spatial and temporal variation in annual GPP. To do this we focused on the two different approaches described on slide 4. Specifically, we evaluated how well spatial and temporal variation in annual tower GPP in different biomes is captured by:

1. Four different MODIS-based proxies:
   - mean growing season EVI & NDVI, growing period length (GPL) & growing season EVI-area.
2. GPP models based on MODIS and different combinations of met forcing data:
   - The temperature-greenness (TG) model (Sims et al., 2008);
   - The vegetation photosynthesis & respiration model (VPRM) (Mahadevan et al., 2008),
   - MODIS GPP (MOD17; Running et al., 2004);
   - A neural network model ;
   - MOD17 recalibrated and estimated using tower data (Heinsch et al., 2006; referred to as ‘MOD17-Tower’).
   - In addition, we also developed and evaluated a simple regression model using mean EVI and mean climatic covariates (temperature or precipitation depending on biome) as predictors.

Analysis Framework

Two satellite data based approaches – an schematic representation



Analysis Framework

Different models and proxies require different data and number of parameters

Increasing complexity	Proxy/Model	Input variables	Parameters	Output
	Mean growing season NDVI/EVI.	8-day NDVI/EVI	None	It is assumed that proxies are highly correlated with GPP and thus variations in proxies indicate variations in GPP.
	EVI-area/ GPL	8-day EVI	None	
	TG	8-day EVI, day and night land surface temperature.	2 parameters for deciduous and evergreen biomes	8-day GPP
	VPRM	8-day EVI, LSWI, Daily PAR, air temperature	3 biome specific parameters.	Daily GPP.
	MOD17	Daily PAR, minimum temperature and VPD 8-day FPAR.	5 biome specific parameters	Daily GPP
	Neural network	Daily PAR, minimum temperature, VPD 8-day FPAR	Non-parametric .	Daily GPP.

Analysis Framework

They also represent different hypotheses about the underlying drivers of GPP.

	Proxy/ Model	**Underlying hypothesis about spatio-temporal variation in ecosystem level GPP**	**Assumptions about unrepresented processes and parameters**
Increasing complexity	Mean EVI/NDVI	Variations in GPP arise because of the difference in amount of green material (and hence absorbed PAR)	Other variables , known to affect photosynthesis, either co-vary with the selected variable or become insignificant at coarse temporal and spatial resolution.
	GPL	Growing period length controls GPP.	
	Integral of NDVI/EVI	Variations in GPP are controlled by amount of greenness and GPL.	
	TG model	Variations in GPP are controlled by greenness modulated by temperature.	Other meteorological variables are not important at 8-day time scale. Model parameter vary across space (but not time) and depends on mean annual night temperature.
	MOD17/ VPRM	Ecosystem level GPP at daily time scale is controlled by the same processes as instantaneous leaf or canopy level GPP.	Parameters are biome specific and remain constant over time and space.
	NN	Ecosystem level GPP is controlled by the same variables as are used in MOD17, but they interact in a complex, nonlinear way.	No constraint about spatial and temporal variability is imposed on weights.

Analysis Framework

Modes and drivers of variability in annual GPP along space and time are different

Modes of GPP variability	Magnitude of Variability	Main drivers	Comment
Site to site (spatial) variability in mean annual GPP	Large variability in every biome – typically ranges from 400 to 2500 gC/m2/year (higher for EBF).	Difference in phenology, absorbed PAR and temperature and/or moisture availability	From biome to biome the dominant meteorological constraint may be different.
Interannual (temporal) variability in GPP.	Usually 10-15% of mean annual GPP. An order of magnitude smaller than spatial variations.	May differ from site to site and biotic factors may also play an important role.	Uncertainty in satellite based estimates may be of the same order as inter-annual variations.

Structure of Study

- We examined the ability of different proxies & models to capture variation in annual GPP over space and time. Along each dimension (space and time), we performed the following analysis:
  1. We first compared variations in annual tower GPP with the corresponding variations in four remotely sensed proxies (mean NDVI and EVI, GPL and EVI area). This step let us examine how strongly simple variables such as phenology and leaf area control annual GPP along the two dimensions in different biomes.
  2. Next we compared GPP predicted from six different models with tower GPP (slide 7). Of the six models, the TG model was based entirely on MODIS data (EVI +LST). MOD17 is available as a product and is based on MODIS FAPAR and coarse resolution meteorological data. The remaining four models – VPRM, NN, MOD17-Tower and EVI+Met – were calibrated to tower GPP using meteorological data from flux towers and MODIS FAPAR data. This analysis allowed us to evaluate how models of different complexity and resolution compare against each other in capturing variations in GPP.
- All analyses were stratified by biome type. We pooled in data from the biomes that had less than 10 sites (savannas, woody savannas, open shrubland, closed shrubland and mixed forest) and labeled the group as OTH (OTHER) .

FLUXNET Data

Following Richardson et al. (2010), working with daily files from La Thuile dataset we selected the site years that satisfied the following two conditions :

(i) Less than 5% of the days in the year had missing data.

(ii) Mean annual QC was at least 0.75

Biome wise daily FLUXNET data used in the study that satisfied the above two conditions

Vegetation Type	CRO	DBF	ENF	EBF	GRA	OTHER	TOTAL
No. of site	21	25	49	16	29	24	164
Total site years	43	79	177	43	85	59	486

Where

CRO – Cropland; DBF – Deciduous broadleaf forests

ENF – Evergreen needleleaf forests; EBF – Evergreen broadleaf forests

GRA – Grassland; OTH ER– Mix of savannas, shrubland and mixed forest.

We used daily GPP, PAR, temperature and precipitation data from the LaThuile dataset.

MODIS Data and Model Calibration

We used the following MODIS data in this study:

- BRDF corrected surface reflectance from MCD43A4.
- Land surface phenology and EVI-area from MCD12.
- Day and night land surface temperature (LST) from MOD11A2.
- Fraction of absorbed PAR from MOD15.
- GPP from MOD17.

- The TG model was estimated following Sims et al. (2008).
- VPRM and MOD17-Tower were calibrated to daily tower GPP by minimizing the sum of squares for observed versus predicted daily GPP. The neural network model was calibrated by minimizing the difference between daily modeled and observed values.
- Estimates of the TG model for evergreen broadleaf forests (EBF) were not computed. Similarly, GPL and EVI-area were not extracted for EBF.
- Following earlier studies (Sims et al, 2008); we used a 3 by 3 kilometer window centered on each FLUXNET site. Thus, we averaged 1 km data (e.g. MOD17) in 3-by-3 windows and 500 m (e.g. EVI) in 7-by-7 windows.

Analysis I: Spatial Variation in Mean Annual GPP

- We first examined correlation of mean annual tower GPP with the four remotely sensed proxies - mean growing season NDVI and EVI; growing period length, and integral of growing season EVI.

- Based on results from the first step and the fact that site to site variation in annual productivity in many biomes is often limited by a single variable (Garbulsky et al., 2010; Beer et al., 2010), we developed a regression model combining mean EVI and climatic covariates (temperature or precipitation) as predictors of annual GPP. This model is referred to as 'EVI+Met'.

- We then examined the agreement between mean annual GPP from six models (TG, MOD17, NN, VPRM, MOD17-Tower and EVI+Met) and tower fluxes. We used R^2, root mean square error (RMSE), mean bias error (MBE) and regression slopes to assess the agreement. MBE was calculated as a simple mean of observed minus predicted values.

- We used a leave-one-site-out cross-validation strategy for all comparisons.

Analysis II: Inter-Annual Variation in GPP

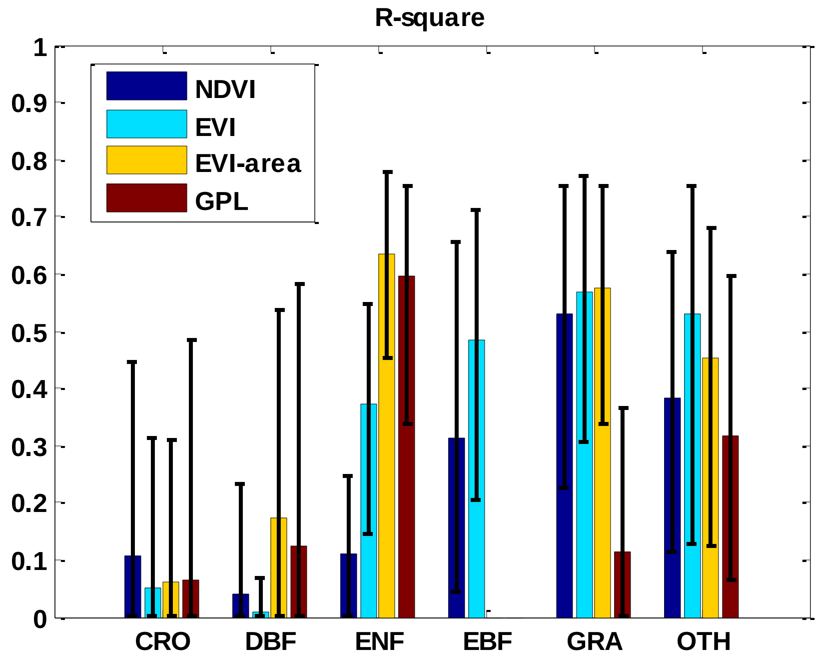
- We followed the same steps that we used in Analysis I, focusing on whether the proxies or models captured interannual variation in annual GPP.
- We first estimated R^2 between annual anomalies of the four proxies and tower GPP.
- Next, we examined the agreement between annual anomalies from the five models and tower fluxes. The EVI+Met model was not used in this analysis because the two predictors (mean EVI and mean minimum temperature or precipitation) did not explain statistically significant variance in annual anomalies of tower GPP.
- As in the previous step, we used cross-validation, but only used sites that had 3 or more years of data.

Results I

Spatial variation in mean annual GPP

Result – Proxies

R^2 between mean annual tower GPP and the four MODIS proxies

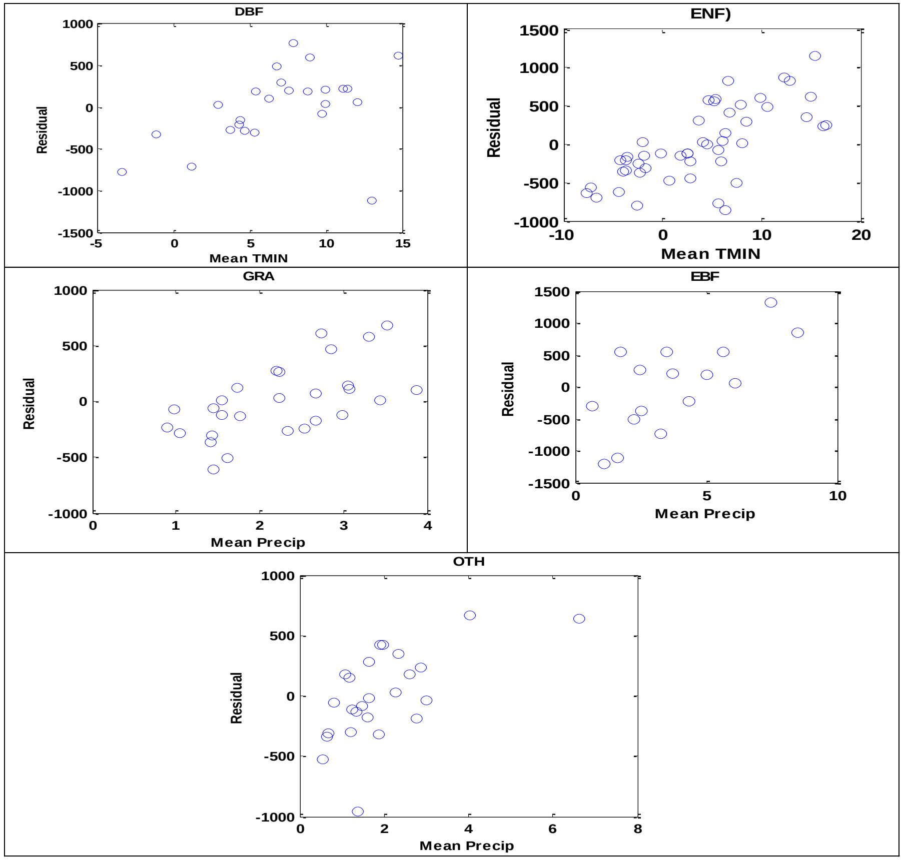


Vegetation type	Sample size
CRO	21
DBF	25
ENF	49
EBF	16
GRA	29
OTH	24

1. None of the proxies was able to capture variations in CRO and DBF.
2. In the remaining four biomes, mean EVI and/or EVI-area were able to capture approximately half the total variance in annual GPP.
3. Mean NDVI, which has been used in several studies, had weaker correlation than mean EVI and EVI-area.

Modeling Annual GPP Using Mean EVI and Climatic Covariates

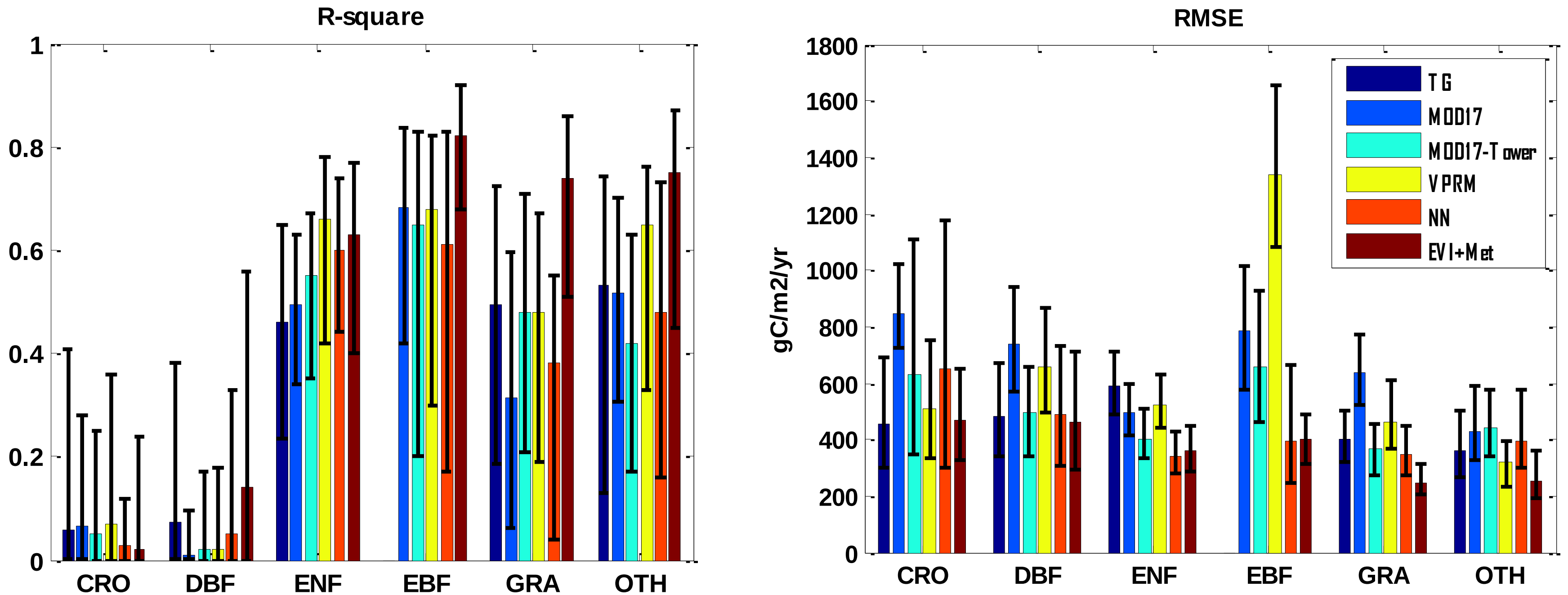
We regressed mean EVI with annual GPP and examined the relationship of model residuals with mean minimum temperature (TMIN used in MOD17 algorithm) and precipitation.



1. Residuals show significant correlation with TMIN or precipitation. There is a tendency for residuals to be negatively correlated with temperature after about 10 degree Celsius. Similarly, precipitation dependence seems to be asymptotic.
2. However, to keep the model simple within the range of data used here, we used linear regression to combine mean EVI with mean minimum temperature (DBF and ENF) or precipitation (EBF, GRA and OTH) to model mean annual GPP. This model is labeled EVI+Met.

Result – Models

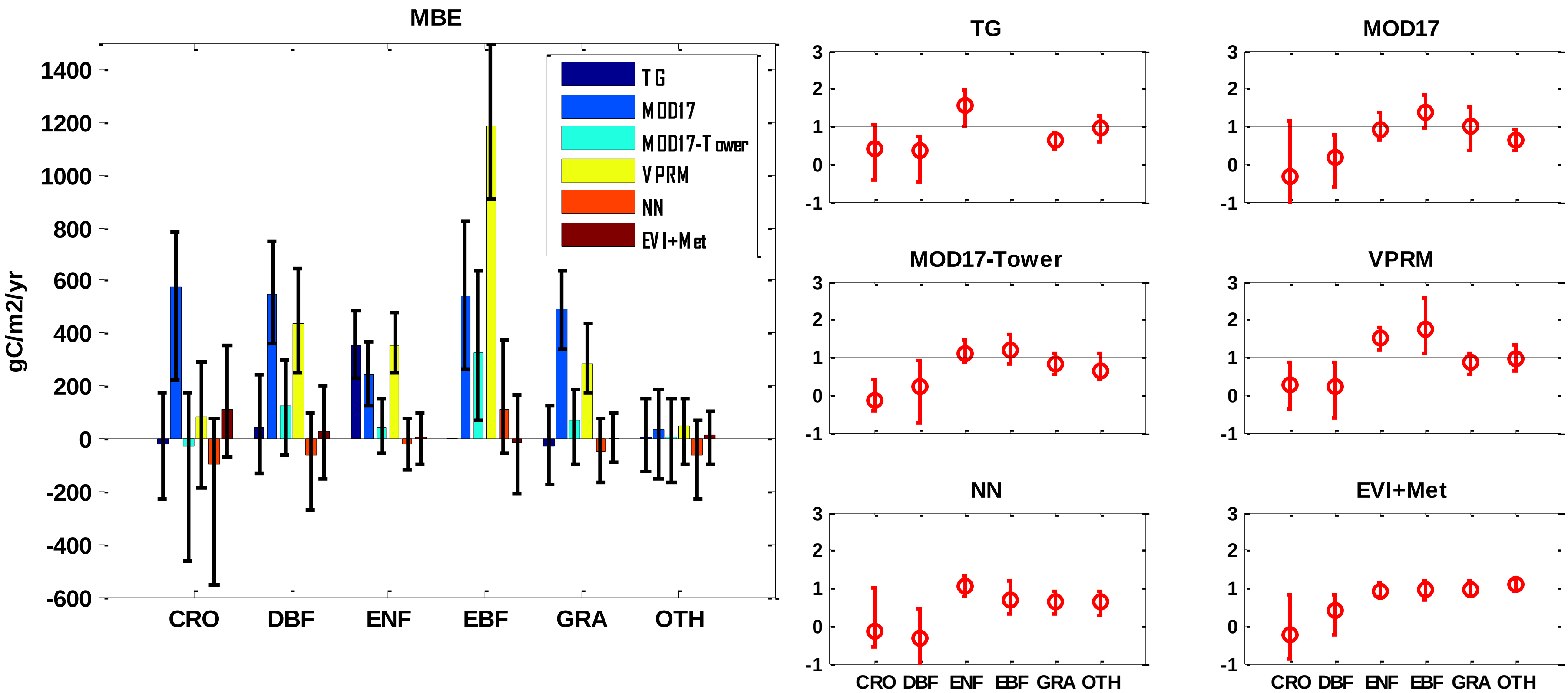
Cross-validated R^2 and RMSE between mean annual tower GPP and the corresponding values from the six models



1. None of the models, including the four that were calibrated to tower GPP using high quality meteorological data from tower, was able to explain variance for CRO and DBF.
2. In the remaining biomes, the linear model that uses mean growing season EVI and mean daily minimum temperature or precipitation as predictors performed better than any of the other models and proxies.

Result– Models

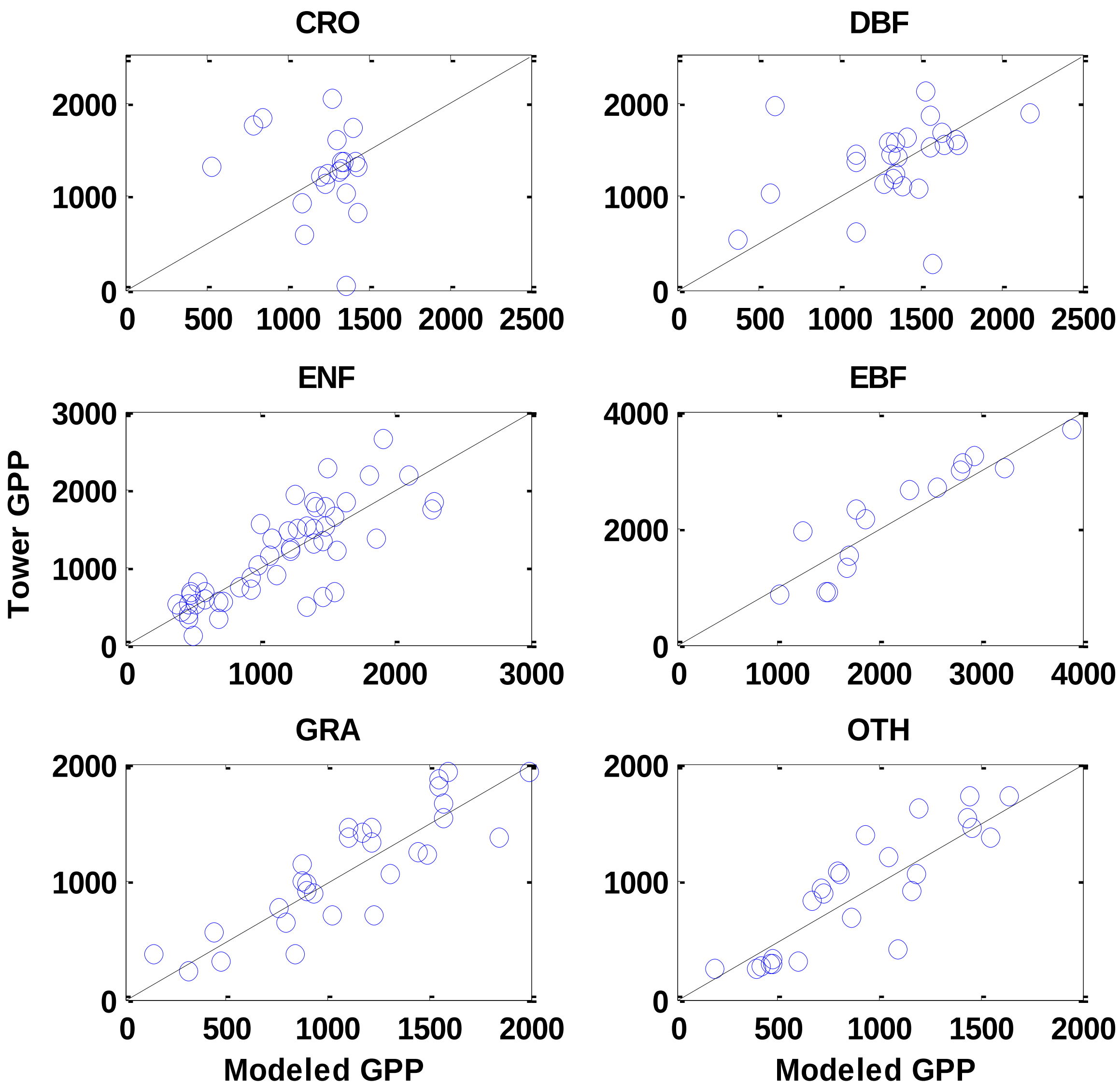
Cross-Validated MBE and slope between mean annual tower GPP and corresponding values from the six models



1. Except MOD17 and VPRM, all other models had near zero mean bias. Of these, only the EVI+Met model had a slope close to 1.0. For the other models, low bias was spurious - systematic under and over-estimation leading to compensating errors.

Result– Models

Scatter plot of mean annual tower GPP and corresponding values predicted by the regression model based on mean EVI and minimum *temperature or precipitation*



1. Model results do not exhibit systematic bias and are randomly distributed around the 1:1 line.

Part I - Conclusions

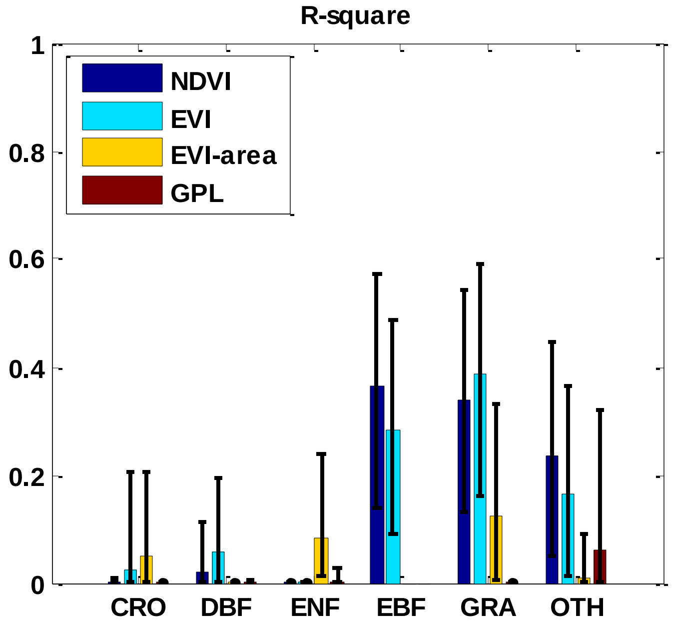
- None of the four proxies and six models could capture variations in mean annual GPP in CRO and DBF.
- In the remaining four biomes, the remotely sensed proxies captured significant spatial variation in mean annual GPP.
- The EVI+Met model was significantly better in all four criteria (R^2 , RMSE, MBE and slope) than all the other models and proxies, including NN, VPRM and MOD17-Tower, which were calculated at daily time step using high quality tower data.
- The remaining models did not have significantly different R^2 (except in EBF) than EVI-area and/or mean EVI, the two simple proxies.

Results II

Inter-annual variation in GPP

Results – Proxies

*Cross-validated R^2 between anomalies of annual tower GPP and corresponding values from the proxies**



Vegetation type	Sample size
CRO	18
DBF	61
ENF	147
EBF	28
GRA	61
OTH	38

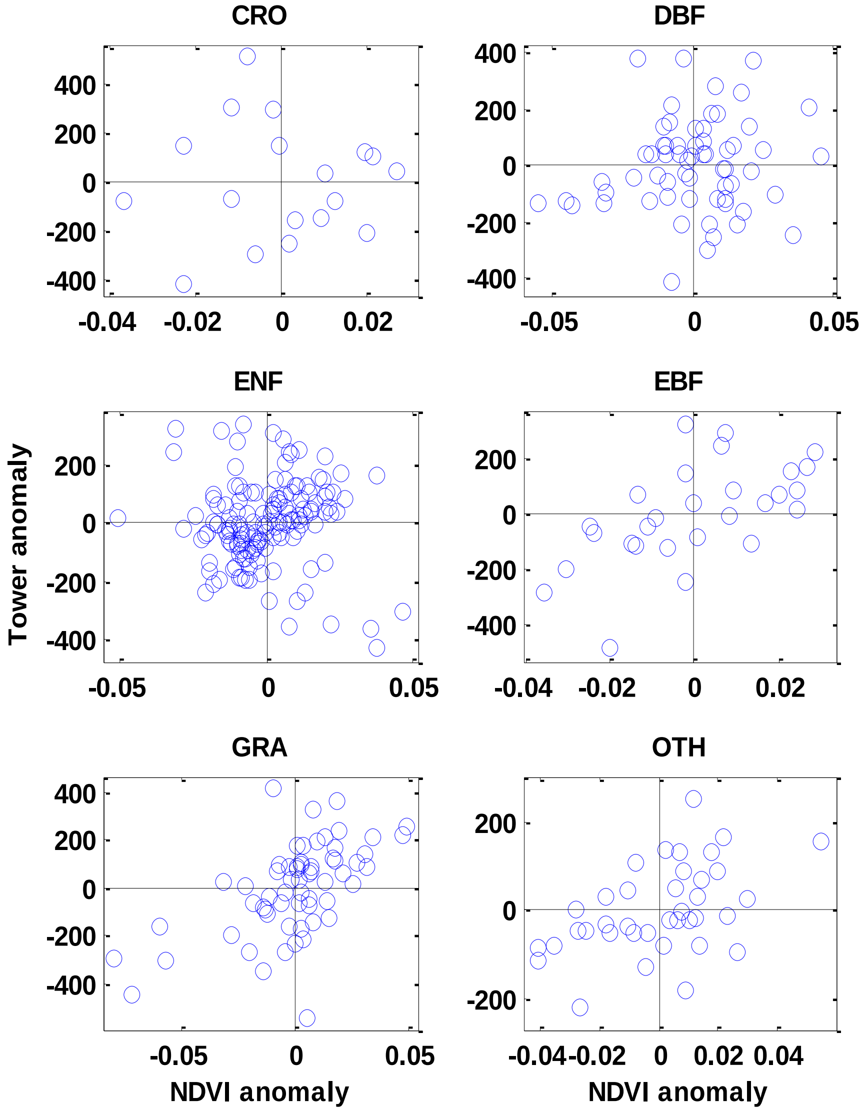
1. None of the proxies explained inter-annual variation in tower GPP in CRO, DBF, ENF and OTH.
2. In GRA and EBF, mean NDVI and EVI were moderately successful in explaining variance in tower GPP (R^2 of ~0.4). But for two anomalous values, R^2 in GRA could be significantly higher (see the next slide).

**sites with 3 or more years of data.*

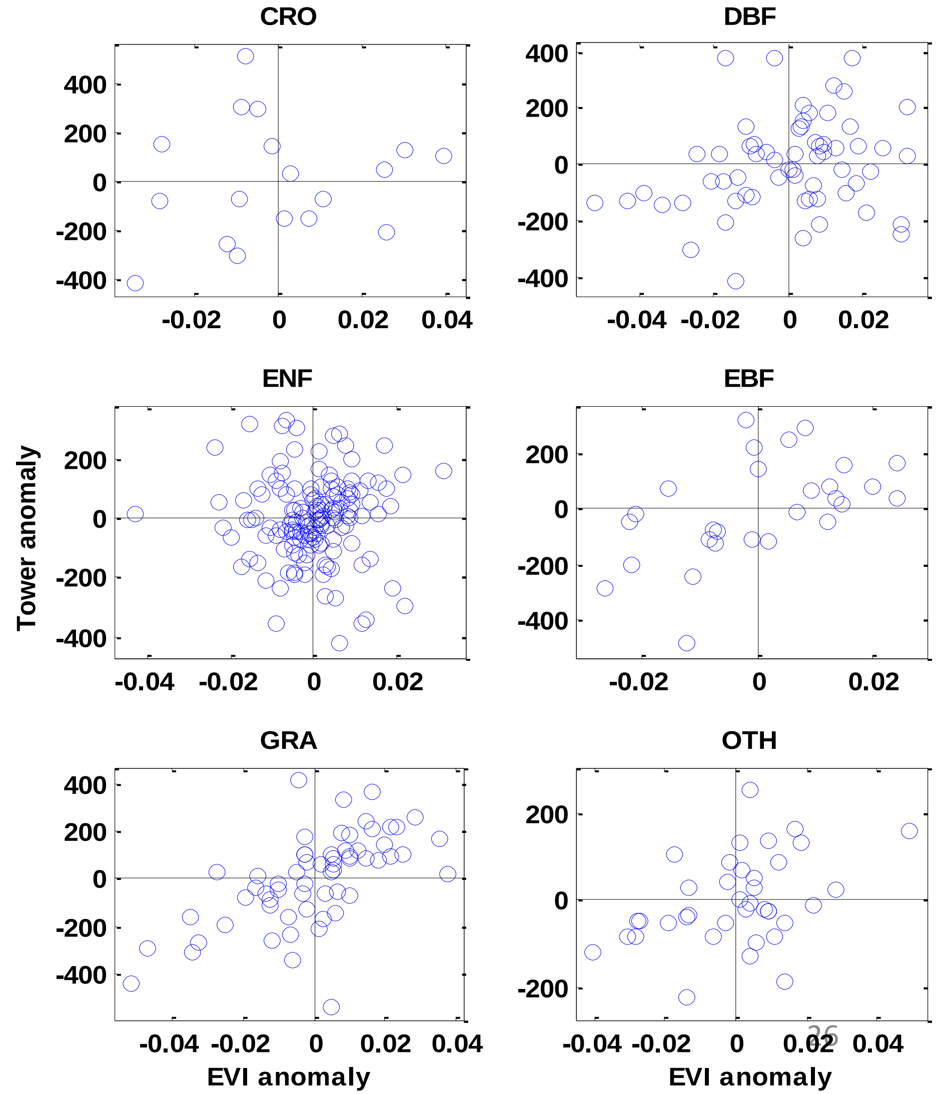
Result– Proxies

Scatter plot of anomalies of annual tower GPP with anomalies of NDVI and EVI (for sites with 3 or more years of data)

NDVI

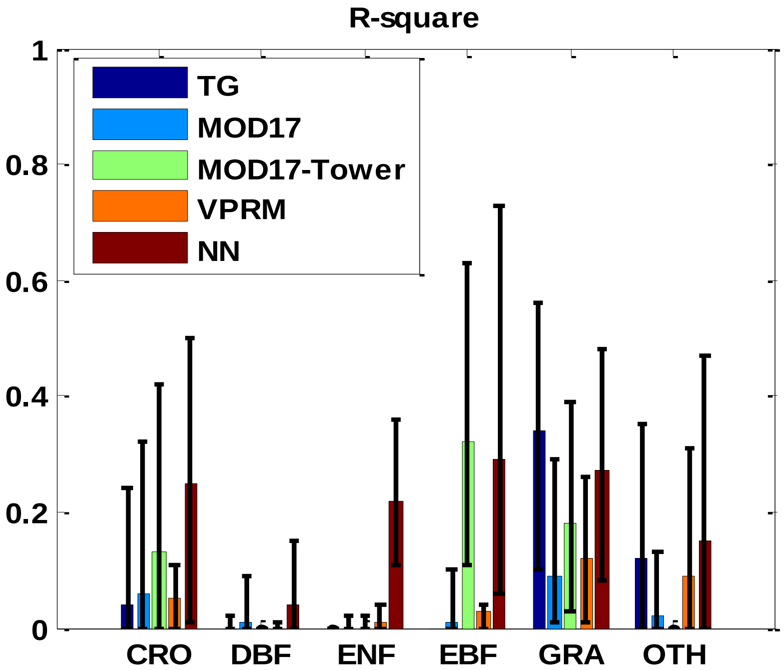


EVI

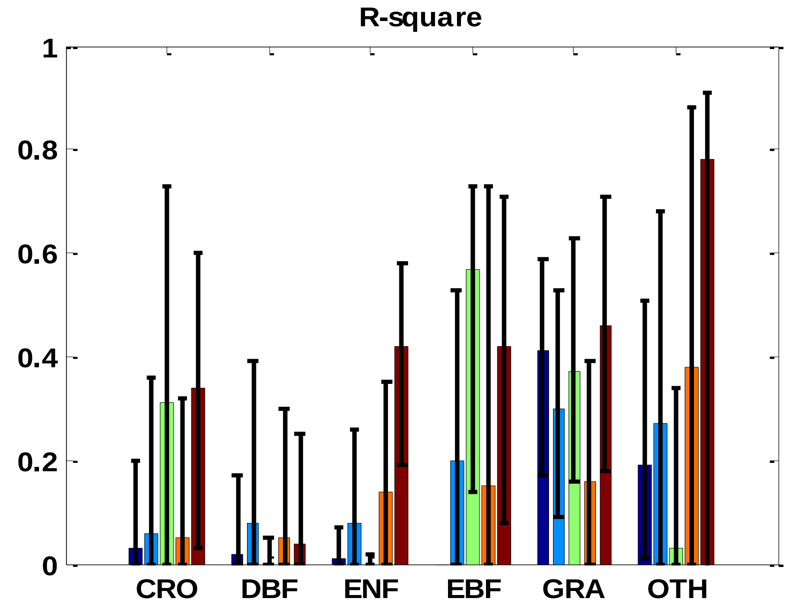


Results – Models

*Cross-validated R^2 between annual anomalies of tower and modeled GPP**



After removing the anomalies that were less than 10% of mean site GPP.



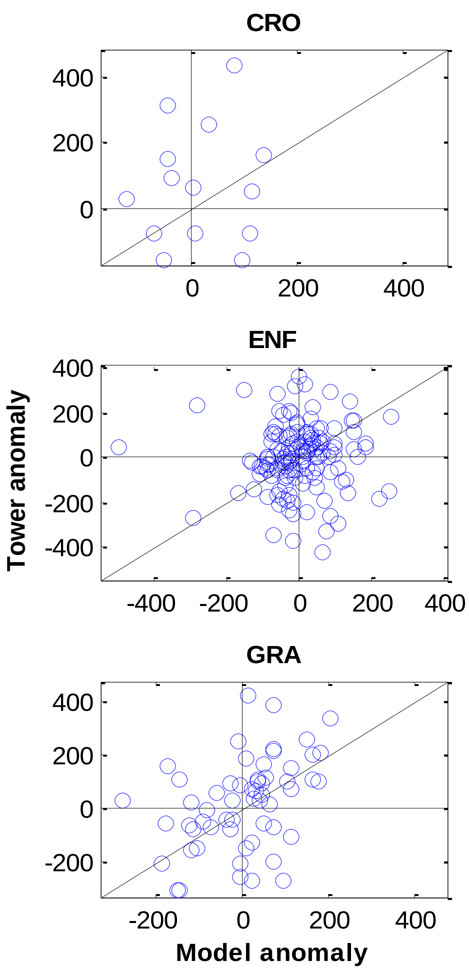
1. None of the models was able to explain inter-annual variation in CRO and DBF.
2. In the remaining 4 biomes, NN had an R^2 ranging from 0.4 to 0.75 after removing anomalies that were less than 10% of mean site GPP.

**for sites with 3 or more years of data*

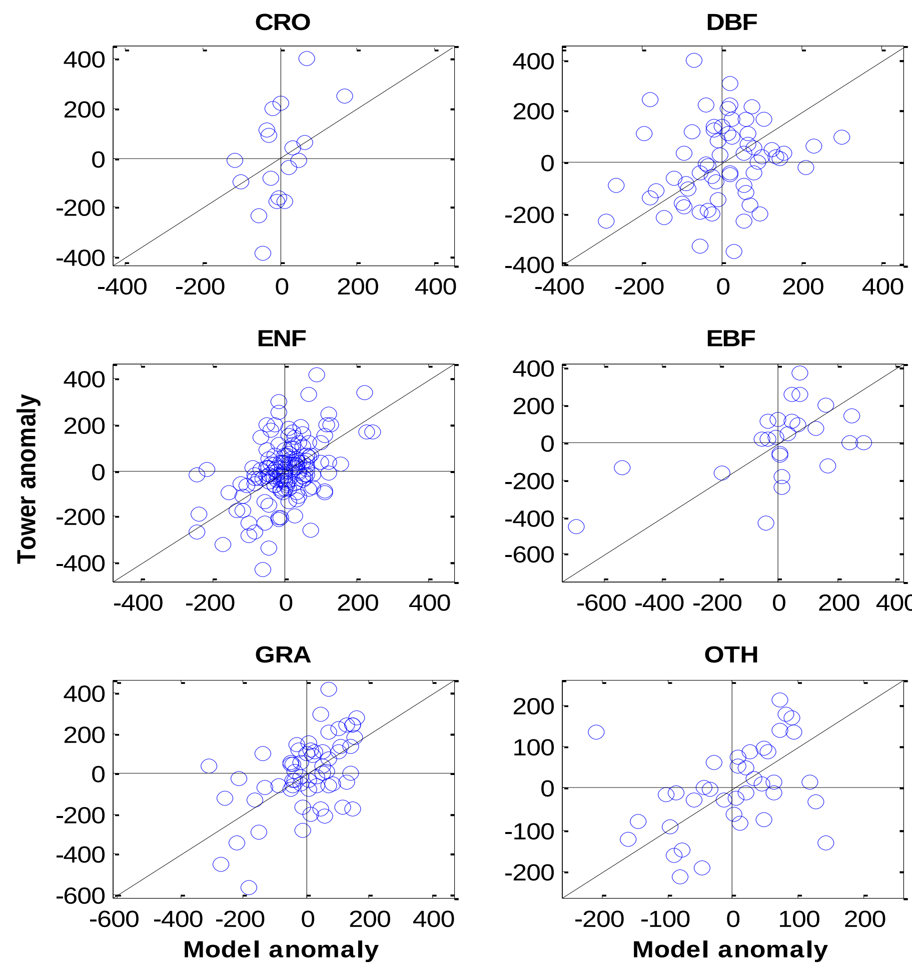
Results– Models

Scatter plots of annual anomalies for tower and two models: NN and MOD17-Tower.

MOD17-Tower



Neural Network



Part II – Conclusions

1. The four satellite proxies did not explain inter-annual variations in CRO, DBF, ENF and OTH. In the remaining two biomes mean NDVI and EVI captured about 40% of the total variance.

2. None of the models captured inter-annual variations in CRO and DBF. For the remaining four biomes, the neural network was moderately successful in explaining variance (R^2 ~ 0.45-0.75), probably because it captured seasonal scale anomalies in forcing data or non-linear responses of GPP to (and interactions among) climate forcing and remotely sensed proxies.

3. In CRO and DBF, models and proxies of different complexity and resolution could not capture spatial or temporal variations in annual GPP.

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