# Assesing uncertanties related to satellite remote sensing indices to estimate Gross Primary Production

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# Preface

*If you can keep your leaves when all about you, are losing theirs and blaming it on drought; If you can photosynthesize when others shut their stomates and stop transpiring; yours will be the canopy and all beneath it and -which is more-you'll be a tree, my seed.*

# Abstract

Methods to quantify Gross Primary Production (GPP) are classified into two categories: Eddy Covariance techniques (EC) and satellite data-driven. EC techniques can measure carbon fluxes directly, albeit of spatial constraints. Satellite data-driven methods are promising because they overcome spatial constraints associated with EC techniques. However, there are challenges associated with an increase in uncertainty when estimating GPP from satellite-driven products such as mixed pixels, cloud cover, and the ability of the sensor to retrieve vegetation under saturation conditions in high biomass environments. Therefore an effort to analyze and quantify the uncertainty of GPP products derived from satellite platforms is needed. Here we present how commonly used satellite vegetation indices (NDVI, EVI, fPAR, and NIRv) with different spatial resolutions can impact the uncertainty in the GPP estimation compared with direct methods such as eddy covariance measurements. We conduct this study on three different sites: Santa Rosa National Park flux-site (Costa Rica), the Borden Forest Research Station flux-site (Canada) and Chamela Biological Station (México).

# Dedication

# Acknowledgements

# 1 Introduction

# 2 Assesing uncertanties related to satellite remote sensing indices to estimate Gross Primary Production

## 2.1 Introduction

Gross Primary Production (GPP) is the total amount of carbon fixation by plants through photosynthesis (Badgley et al. 2019). Quantifying GPP is essential for understanding land-atmosphere carbon exchange (Köhler et al. 2018), ecosystem function, and ecosystem responses to climate change (Guan et al. 2022; Brown et al. 2021; Myneni and Williams 1994). With recent advances in technology for remote sensing and more computational power available with lower costs (Gorelick et al. 2017), global mapping of photosynthesis is being done by more scientists (Ryu, Berry, and Baldocchi 2019). Given that GPP cannot be directly estimated from satellite remote sensing techniques, the use of vegetation indices has been a widely used method to approximate and quantify GPP (Ryu, Berry, and Baldocchi 2019). However, estimates remain with high uncertainties and validation efforts are required to characterize these and improve accuracy. (Anav et al. 2015; Brown et al. 2021)

There are several methods to calculate GPP that can be grouped into two broad categories: eddy covariance techniques, and satellite data-driven (Guan et al. 2022; Xie et al. 2020) Eddy Covariance (EC) techniques are methods that allowed scientists to directly measure the carbon, water, and energy fluxes between vegetation canopies and the atmosphere since the 1990s (Baldocchi 2020; Ryu, Berry, and Baldocchi 2019). This method to measure terrestrial fluxes, is the principal approach for quantifying the exchange of CO2 between the land and atmosphere using advanced field instrumentation (Badgley et al. 2019; Tramontana et al. 2016). Measurements provided using EC have a limited spatial resolution of less than $<$ 1km2 , which bring spatial constraints to estimations of ecosystem carbon and water fluxes at regional to global scales. (Badgley, Field, and Berry 2017).

The second category of methods to estimate GPP is the satellite data-driven models. Because of their dependency on earth observation platforms, they are not spatially constrained but can have more uncertainties than the EC techniques (Ryu, Berry, and Baldocchi 2019; Wang et al. 2011). Satellite data-driven models can be classified into Vegetation Index models (VI), Light Use Efficiency models (LUE), and process-based models (Xie et al. 2020).

LUE models are based on the concept of radiation conversion efficiency, and take into consideration ecological processes (Liu et al. 1997). The radiation conversion efficiency explains the amount of carbon that a specific type of vegetation can fix per unit of solar radiation (Monteith 1972). MODIS GPP product uses an algorithm based on this radiation conversion efficiency concept, relating the absorbed photosynthetically active radiation (APAR) with the LUE term (Heinsch et al. 2006).

GPP = PAR * fAPAR * LUE

Where PAR is the incident photosynthetically active radiation and fAPAR is the fraction of the PAR that is effectively absorbed by plants. fAPAR can be used to assess the primary productivity of canopies [GCOS, 2011; Running et al. (2004)]. LUE is the radiation use conversion efficiency term of the vegetation [heinsch_evaluation_2006]

VI's are a summary of satellite obtained spectral data (Myneni and Williams 1994) derived from optical sensors that are combined with climate variables to calculate GPP (Wu, Chen, and Huang 2011). This is usually done with some form of regression and physical methods that associate interactions between vegetation and incoming radiation (Fernández-Martínez et al. 2019)

Well known VI's used to estimate GPP are normalized difference vegetation index (NDVI), enhanced vegetation index (EVI), leaf area index (LAI), and fraction of photosynthetically active radiation (fPAR) among others (Balzarolo et al., 2019; Rahman et al 2005; Xie et al., 2019; Badgley et al., 2019; Zhang et al., 2020, Sellers et al., 1997).

Nonetheless, even when estimating GPP from satellite remote sensing methods is promising to overcome limitations as temporal and spatial scale, there are some challenges involved in the process. The first constraint is the use of images needed to address the problem of mixed-pixels, which requires determining the fraction of the vegetated surface and its attributable signal (Badgley et al., 2017). A second challenge is that photosynthesis regulation can occur with no major changes in canopy structure or leaf pigments that can undergo without being detected with reflectance data (Pabon-Moreno et al., 2022; Pierrat et al., 2022).

The accuracy of GPP estimation through the use of VI's can be affected due to their limitation to predict spatial, temporal, interannual variability and trends. (Fernández-Martínez et al., 2019) An index such as NDVI is good for detecting changes in seasonal variability, but it becomes saturated with high biomass conditions (Badgley et al., 2017). Other indices such as EVI can overcome this problem and be better suited for predicting GPP in large biomass forests (Badgley et al., 2017) but it has been evaluated in a narrow range of ecosystems and needs inputs of start and end dates of the growing seasons which can increase uncertainties (Shi et al., 2017).

To overcome these problems, other indices have been formulated in recent years. One of these VIs is near-infrared reflectance index (NIRv) (Badgley et al., 2019) NIRv is defined as the fraction of reflected NIR light that originates from vegetation. NIRv was originally proposed as a replacement for fPAR in LUE models in that the NIR and PAR reflectance of vegetation are correlated and the scaling by NDVI corrects for soil contributions in the signal (Badgley et al., 2019) NIRv has been shown to have a stronger correlation to GPP at flux towers and on a regional basis than fAPAR notwithstanding the fact that GPP is fAPAR driven. NIRv has been extended to include a weighting with PAR (Dechant et al., 2022) and replacing the NIR reflectance with NIRv radiance (Wu et al., 2020) Both of these approaches have been shown to have even stronger correlations with GPP than NIRv as could be expected since they either directly or indirectly weight the NIRv with PAR.

The stronger correlation between the NIR indices to GPP versus indices based on fAPAR seemingly contradicts the hypotheses in the LUE model that GPP should be linearly related to fAPAR. There are two explanations: i. Many of the reported comparative studies use fAPAR based on VIs and not APAR. We hypothesize that the NIR indices are simply better estimators of APAR than these VI approximations due to lower measurement error for the NIR indices or a stronger physical relationship between them and APAR versus the historical VIs. The strength of correlation between APAR and GPP depends on LUE having a linear relationship to observed APAR. While this may hold in some circumstances (e.g. early seasonal measurements for vegetation such as crops where leaf chlorophyll concentration increases during the growth phase) it is not the case in general and definitely during stress conditions (Monteith 1972).

Despite these efforts, relying solely on these remote satellite indices is a problem. Efforts to validate and quantify their accuracy are needed (Brown et al., 2021). In-situ eddy-covariance flux measurements represent a solution given that they represent site-level observations. With the calculation of the flux footprint, the area from the flux tower can serve as a reference point in which satellite images can be linked to a specific set of pixels and calculate the accuracy of the estimations provided by the indices. (Chu et al., 2020)

As such, the main objective of my M.Sc. thesis is the analysis of uncertainty associated with the VI/LUE models since they offer the potential for GPP estimation without requiring knowledge regarding canopy and soil properties other than measurements of reflected light and possibly a correction for soil contribution. We aim to quantify the uncertainty from some of the most used satellite vegetation indices with in-situ GPP data from the Santa Rosa National Park flux-site (Costa Rica), the Borden Forest Research Station flux-site (Canada), Chamela Biological Station (México) and a corn/soybean site from Dechant et al. 2022.

## 2.2 Methods

Sites links:

- https://ameriflux.lbl.gov/sites/siteinfo/US-Ton#data-citation
- https://ameriflux.lbl.gov/sites/siteinfo/US-CMW#data-citation
-

## 2.3 Results

## 2.4 Discussion

## 2.5 References


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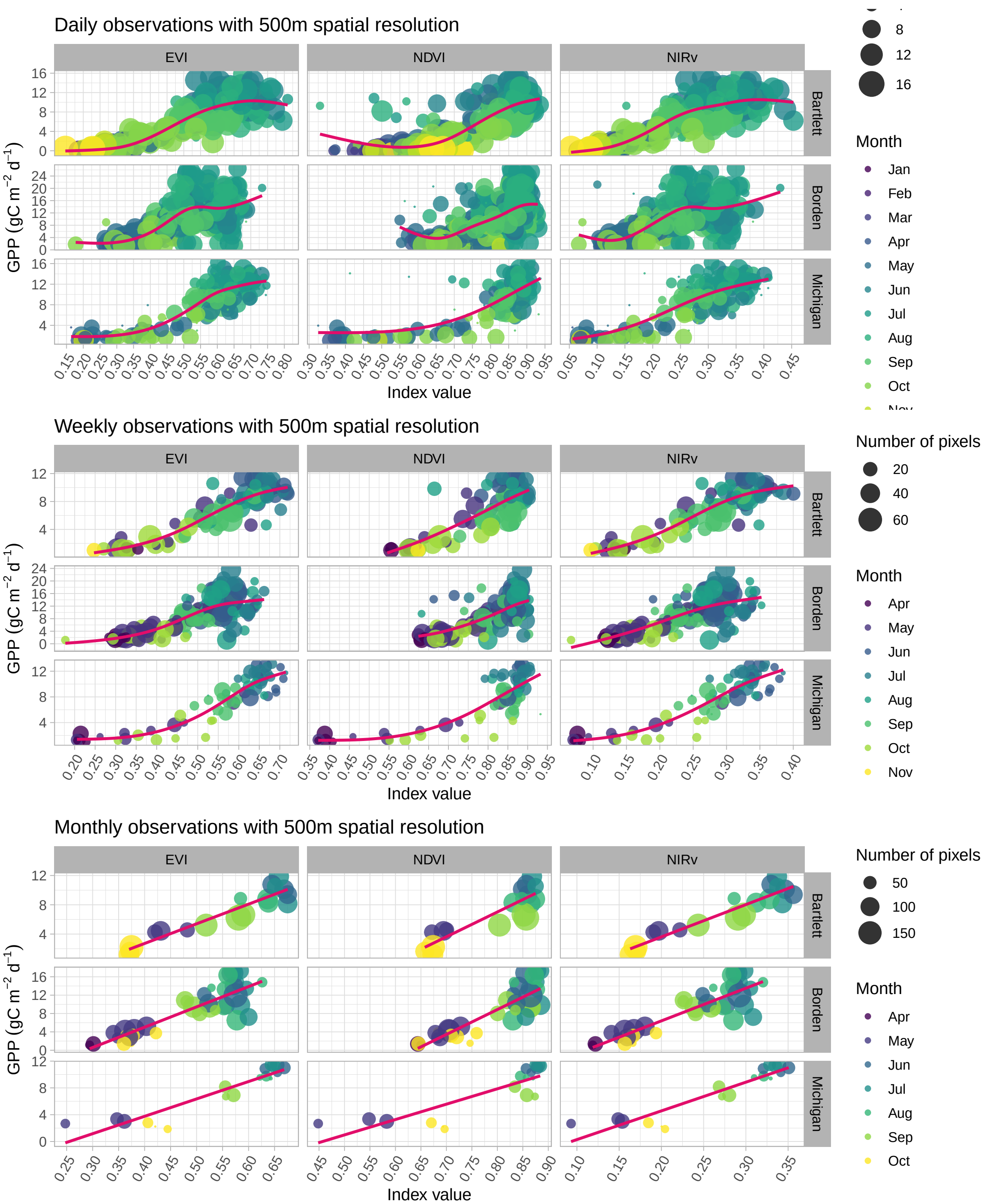
## 2.6 Figures



Daily observations with 500m spatial resolution
EVI
NDVI
NIRv
Bartlett
Borden
Michigan
GPP (gC m-2 d-1)
Index value
8
12
16
Month
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Weekly observations with 500m spatial resolution
EVI
NDVI
NIRv
Bartlett
Borden
Michigan
GPP (gC m-2 d-1)
Index value
Number of pixels
20
40
60
Month
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Monthly observations with 500m spatial resolution
EVI
NDVI
NIRv
Bartlett
Borden
Michigan
GPP (gC m-2 d-1)
Index value
Number of pixels
50
100
150
Month
Apr
May
Jun
Jul
Aug
Sep
Oct

## 2.7 Tables

# 3 Conclusions and Future Work

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# 4 Appendices