THIS PRESENTATION IS MEANT TO BE VIEWED AS AN INTERACTIVE WEBPAGE:

http://bgc-jena.mpg.de/~jnelson/EGU2020/index.html

WATER FLUX PARTITIONING FOR EDDY COVARIANCE DATA

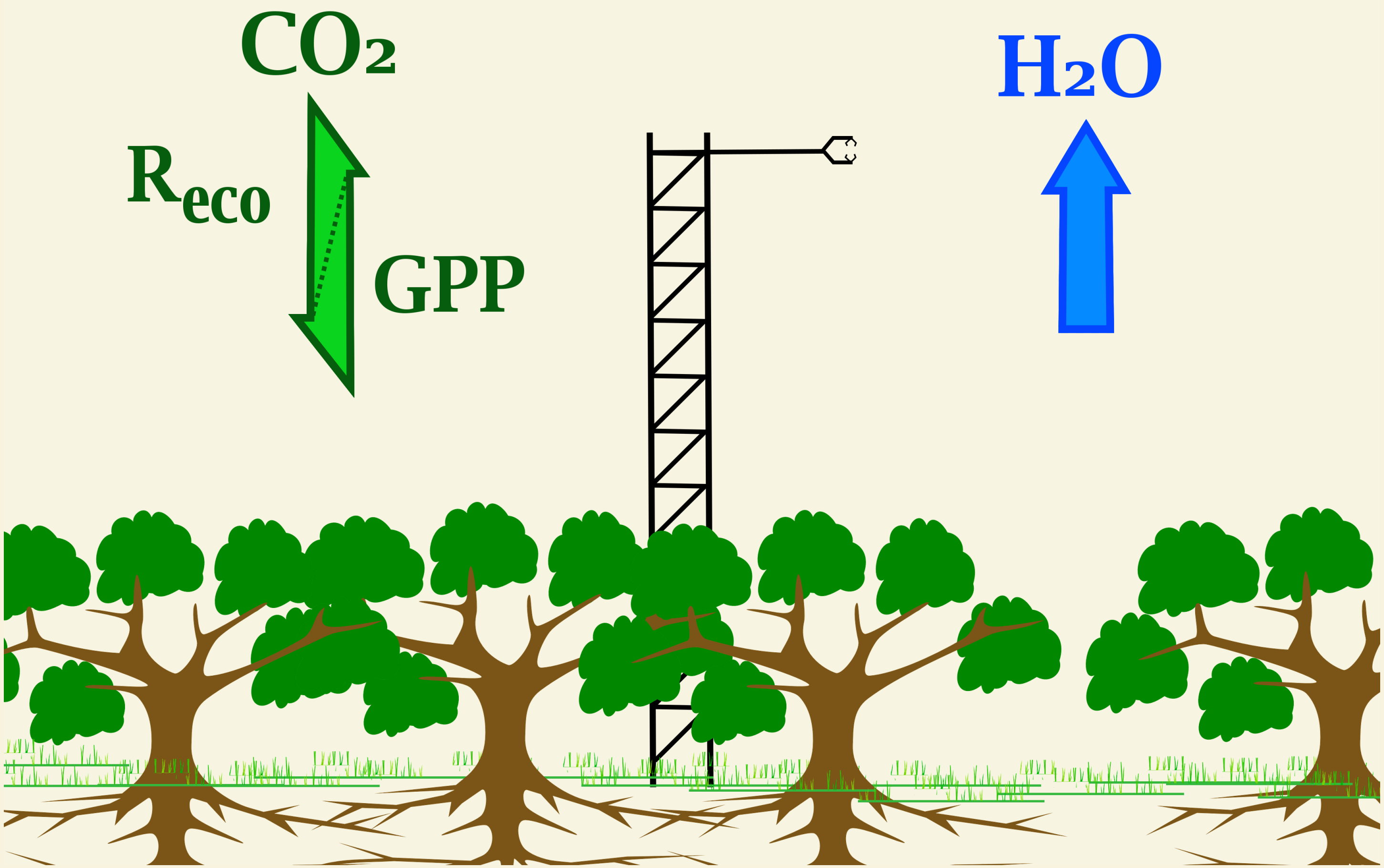
Speaker notes

- Click the arrows on the presentation or use your left/right keys to advance slides.
- Information about the slides can be found here in the Speaker notes.
- Note that some slides are interactive.
- References are links: hover over to see the citation, click to open the reference.
- Feel free to direct questions to: jnelson@bgc-jena.mpg.de
- This presentation is part of EGU 2020

TABLE OF CONTENTS:

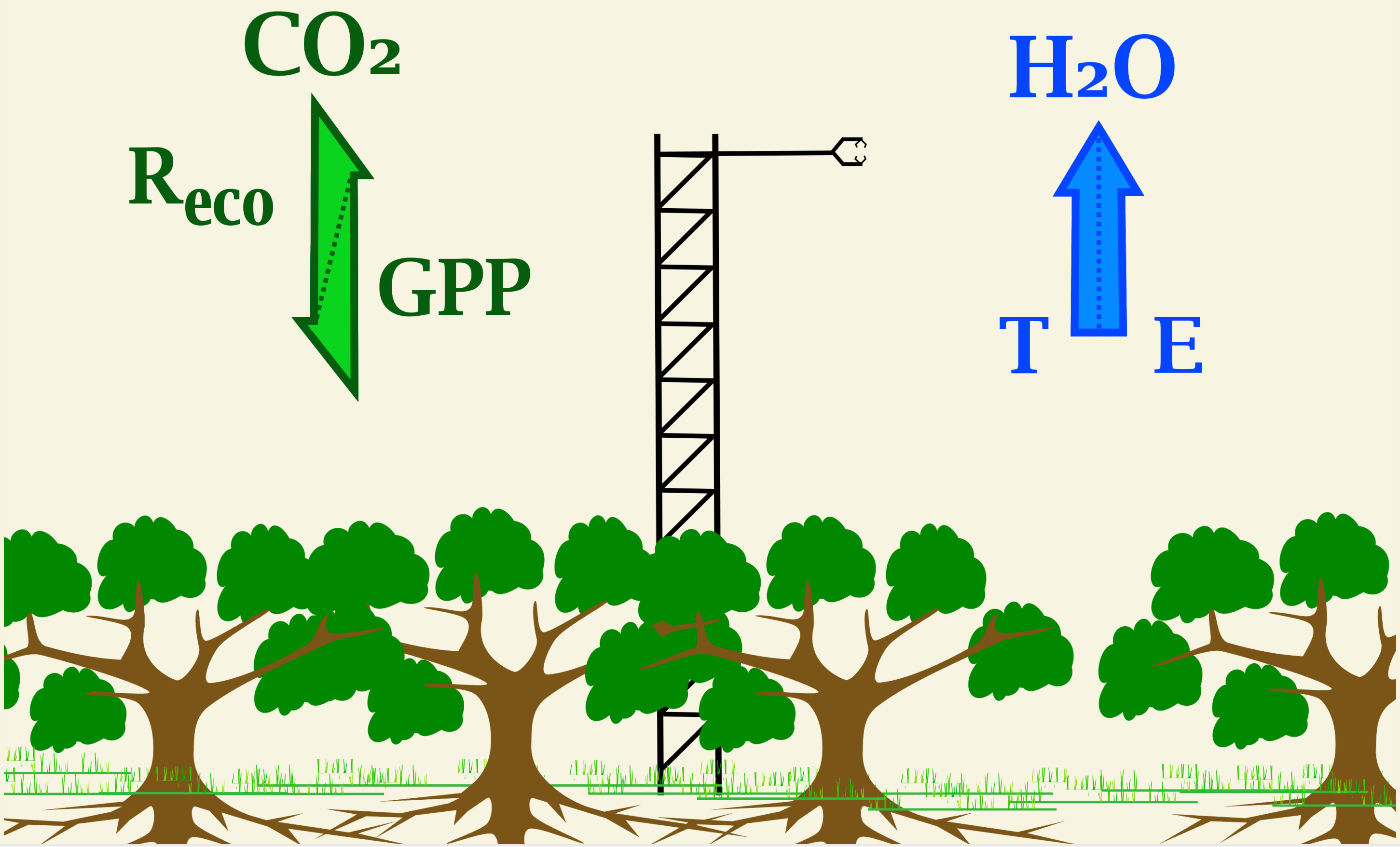
Speaker notes

Click on the section title to skip to that slide.



Speaker notes

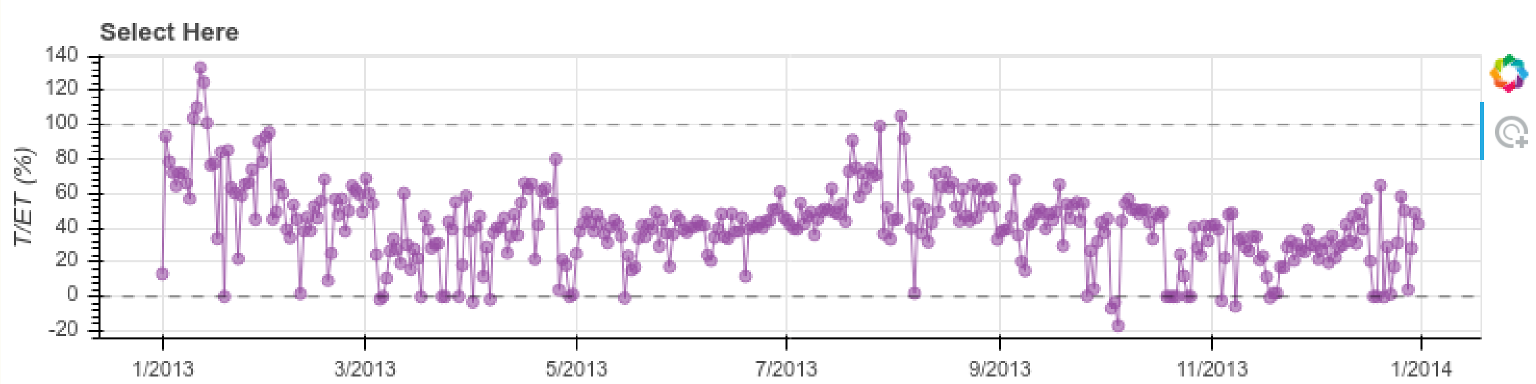
- Eddy covariance measures net or aggregate fluxes of CO_2, heat, and water.
- Methods have existed for over 15 years for separating net ecosystem exchange of CO_2 (NEE) into the photosynthesis part (Gross Primary Productivity, GPP) and the respiration part (ecosystem respiration, R_{eco}).
- next slide...

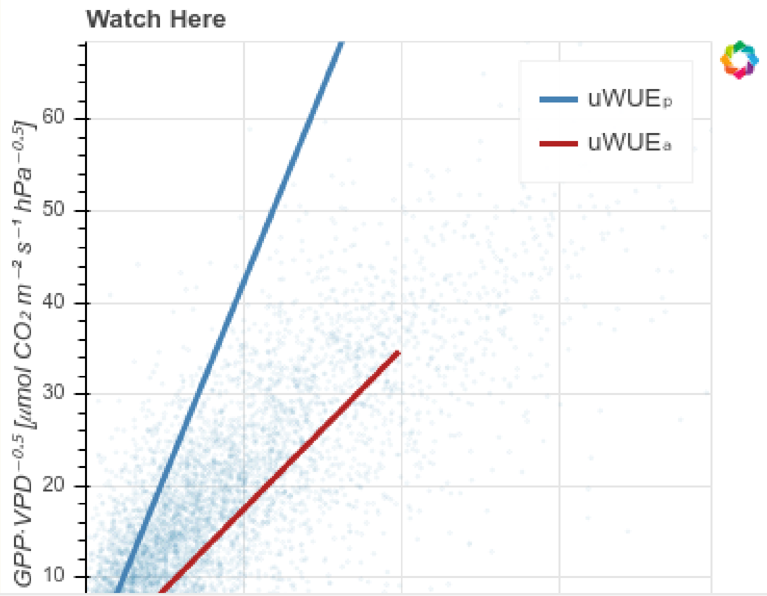


Speaker notes

- Eddy covariance measures net or aggregate fluxes of CO_2, heat, and water.
- Methods have existed for over 15 years for separating net ecosystem exchange of CO_2 (NEE) into the photosynthesis part (Gross Primary Productivity, GPP) and the respiration part (ecosystem respiration, R_{eco}).
- In the last few years, methods have come out to replicate the success of NEE partitioning with the water fluxes by partitioning evapotranspiration (ET) into transpiration (T) and evaporation (E).

- Description and application of three ET partitioning methods:
  - underlying water use efficiency (uWUE)
  - Pérez-Priego
  - TEA





The uWUE method relies on estimates of the underlying water use efficiency (uWUE):

$$uWUE = \frac{GPP \cdot \sqrt{VPD}}{ET},$$

Two uWUE variants are calculated from half-hourly data:

1. the potential uWUE ($uWUE_p$) is calculated at an annual scale using a 95th percentile regression between $GPP \cdot \sqrt{VPD}$ and ET, representing conditions with the highest carbon gain to water loss and thus where T≈ET
2. the apparent uWUE ($uWUE_a$) is estimated as the linear regression slope from a daily or 8 daily window.

T/ET is then calculated as:

Speaker notes

HERE IS A BRIEF OVERVIEW OF THE UWUE METHOD.

- See the paper here.
- Navigate ↓down↓ to see a tutorial of how to apply this method to a FLUXNET2015 dataset.
- Or go directly to the →next→ method.

introduction

Here we will go through application of the uWUE partitioning algorithm to eddy covariance data. The script is designed to run on FLUXNET2015 (https://fluxnet.fluxdata.org/data/fluxnet2015-dataset/) .csv files directly, which ensures consistent variable names, processing and units. The tutorial will use data from the Hyytiälä forest (http://sites.fluxdata.org/FI-Hyy/) in Finland, but can be applied to any FLUXNET2015 dataset.

Some experience in Python will make things easy, but I will try to explain the process step by step so as to be accessible to all backgrounds.

first things first

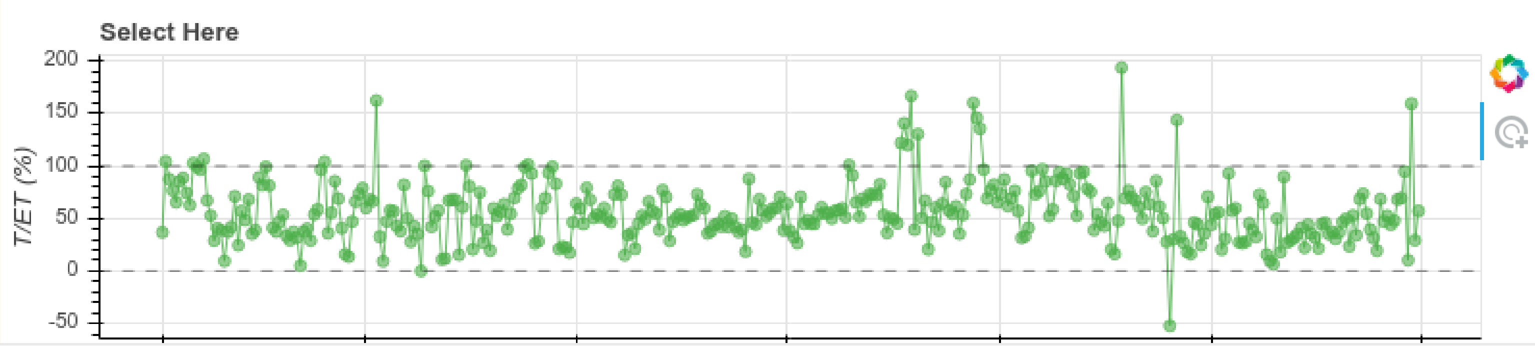
The firs step is to import all needed packages:

In [15]:
```
import xarray as xr # labelled multi-dimensional arrays that are compatable with netcdf formats
import numpy as np # numerical python for working with basic n-dimensional array
import warnings # standard library for suppressing warnings
```

Speaker notes

UWUE

- An interactive tutorial can be found here: launch binder



Speaker notes

HERE IS A BRIEF OVERVIEW OF THE PÉREZ-PRIEGO METHOD.

- See the paper here.
- Navigate ↓down↓ to see a tutorial of how to apply this method to a FLUXNET2015 dataset.
- Or go directly to the →next→ method.

symbol	description
a_1, a_2, a_3, β	fit model parameters
TA	ambient air temperature
VPD	vapor pressure deficit
PPFD	photosynthetic photon flux density
GPP_{max}	ninetieth percentile of GPP in 5 day window
C_a	ambient CO_2 mixing ratio
χ	Internal to ambient CO_2 concentration
χ_0	Long-term effective χ
g_c	canopy stomatal conductance

introduction

Here we will go through application of the Pérez-Priego partitioning algorithm to eddy covariance data. The script is designed to run on FLUXNET2015 (https://fluxnet.fluxdata.org/data/fluxnet2015-dataset/) .csv files directly, which ensures consistent variable names, processing and units. The tutorial will use data from the Hyytiälä forest (http://sites.fluxdata.org/FI-Hyy/) in Finland, but can be applied to any FLUXNET2015 dataset.

Some experience in R will make things easy, but I will try to explain the process step by step so as to be accessible to all backgrounds.

This example has been adapted from the original example:

https://github.com/oscarperezpriego/ETpartitioning/blob/master/inst/main_ETpartitioning.r (https://github.com/oscarperezpriego/ETpartitioning/blob/master/inst/main_ETpartitioning.r)

first things first

The firs step is to import all needed packages:

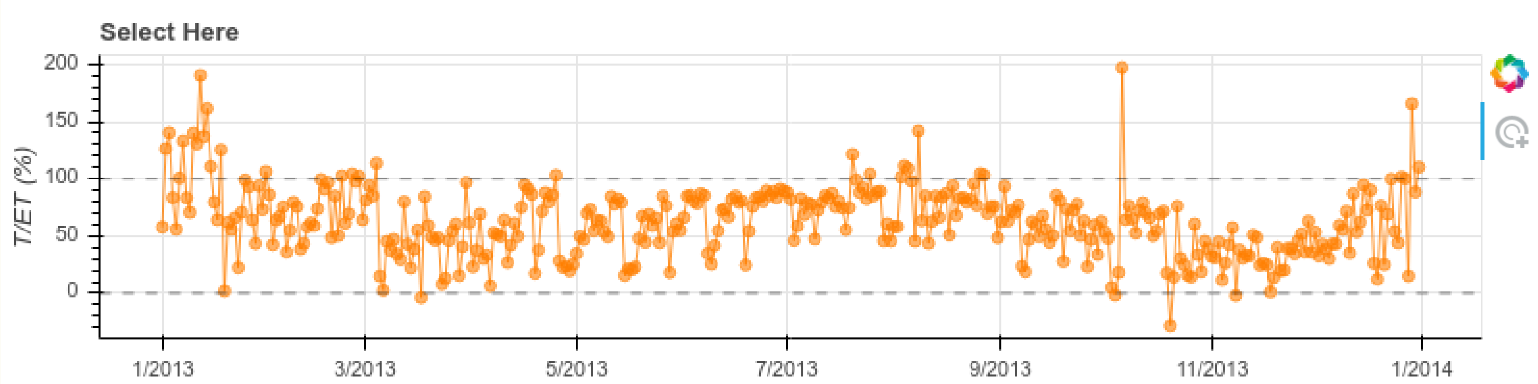
Speaker notes

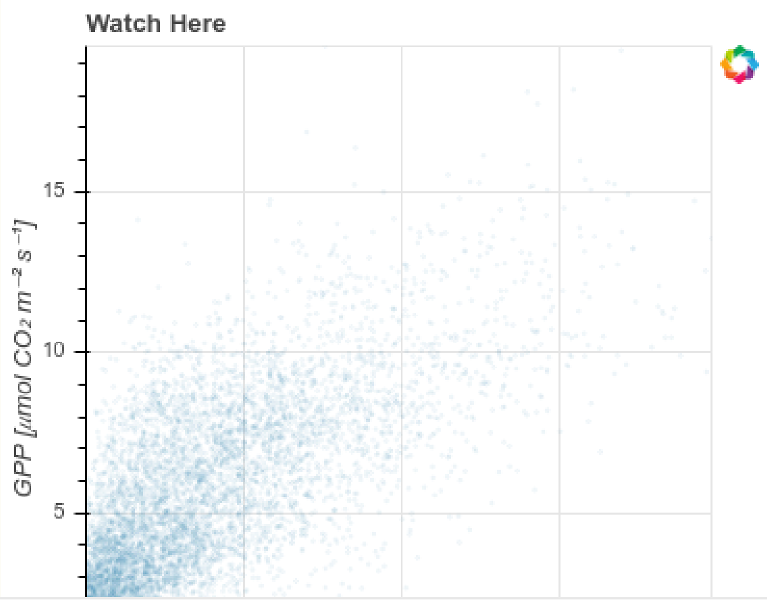
PÉREZ-PRIEGO

launch binder

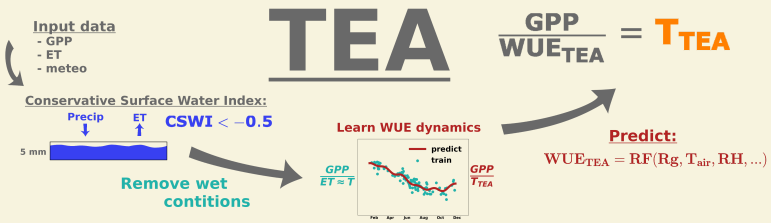
- An interactive tutorial can be found here:

loading the dataset





The TEA method utilizes a version of Random Forest (RF), to predict water use efficiency $WUE = GPP/ET$). The model is trained on the ecosystem water use efficiency ($WUE_{eco} = GPP/ET$) during periods in the growing season and when surfaces are likely to be dry, i.e where E/ET should be minimal. The RF, trained on WUE_{eco} from the filtered periods, then predicts WUE (now GPP/T) for the full time series.



Click on a point of T/ET from the plot above to see the predicted

Speaker notes

HERE IS A BRIEF OVERVIEW OF THE TEA METHOD.

- See the paper here.
- Navigate ↓down↓ to see a tutorial of how to apply this method to a FLUXNET2015 dataset.
- Or go directly to the →next→ method.

introduction

Here we will go through application of the TEA algorithm to eddy covariance data. The script is designed to run on FLUXNET2015 (https://fluxnet.fluxdata.org/data/fluxnet2015-dataset/) .csv files directly, which ensures consistent variable names, processing and units. The tutorial will use data from the Hyytiälä forest (http://sites.fluxdata.org/FI-Hyy/) in Finland, but can be applied to any FLUXNET2015 dataset.

Some experience in Python will make things easy, but I will try to explain the process step by step so as to be accessible to all backgrounds.

resource usage

Note that processing large dataset can take some time and memory use. This script only processes six years worth of data. Processing the original 18 year dataset with one processor takes approximately 10 minutes and 0.75 GiB of RAM. If you have access to a multi-core processor, the speed can be increased considerably. Here are the maximum memory usage and run times when using different number of processors on my laptop:

processors	max memory	time

Speaker notes

TEA

- An interactive tutorial can be found here:

uWUE	· $T \propto GPP \cdot \sqrt{VPD}$ · $T \approx ET$ during some periods · easiest to calculate
Pérez-Priego	· big leaf model with optimality · no $T \approx ET$ assumption · expensive parameter estimation
TEA	· models WUE via machine learning · $T \approx ET$ during some periods

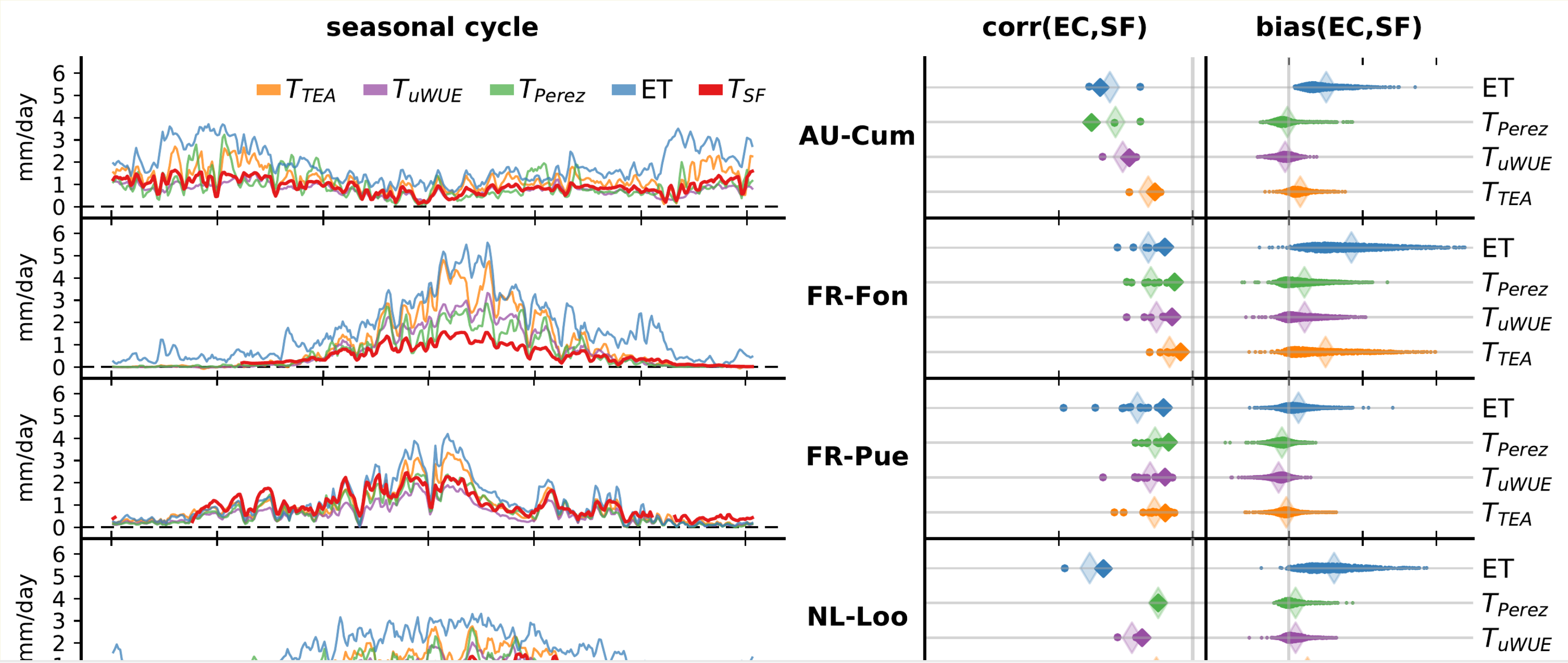
Speaker notes

- The table above summarizes some key aspects of the three methods related to:
  - core functionality
  - whether the method assumes $T \approx ET$ during some periods
  - unique aspects of the method

- Comparison of the partitioning methods to:
    - Canopy T estimates from SAPFLUXNET
    - LAI
    - VPD
    - Dry down events

Speaker notes

Click on the section title to skip to that slide.

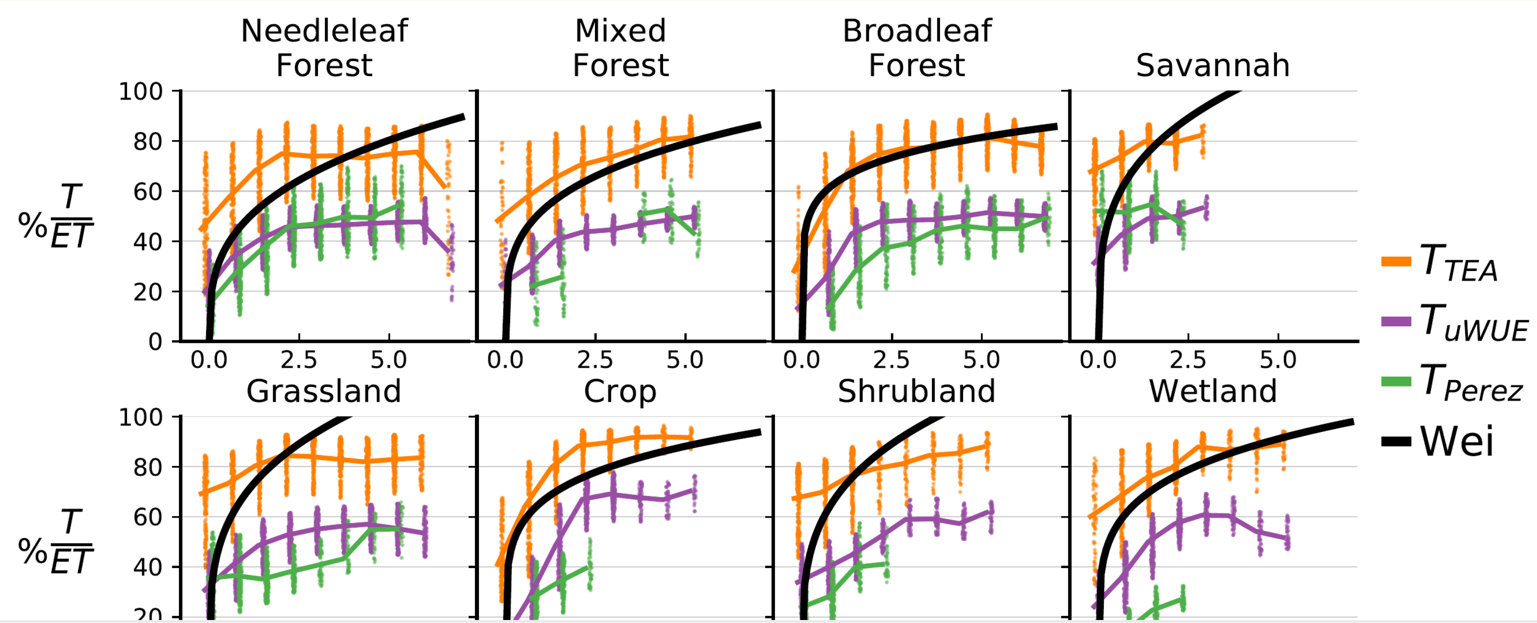


Speaker notes

Comparison of sap flow based estimates of transpiration (T_{SF}) against estimated transpiration (T) and measured evapotranspiration (ET) from eddy covariance (EC). Note the three different sizes of markers in the correlation plots (corr(EC,SF)), where the largest markers represents the mean correlation, the smallest markers represent the correlations from each available year, and the medium sized markers represent the selected year shown (time series in the left column of sub-figures).

Sap flow data from SAPFLUXNET

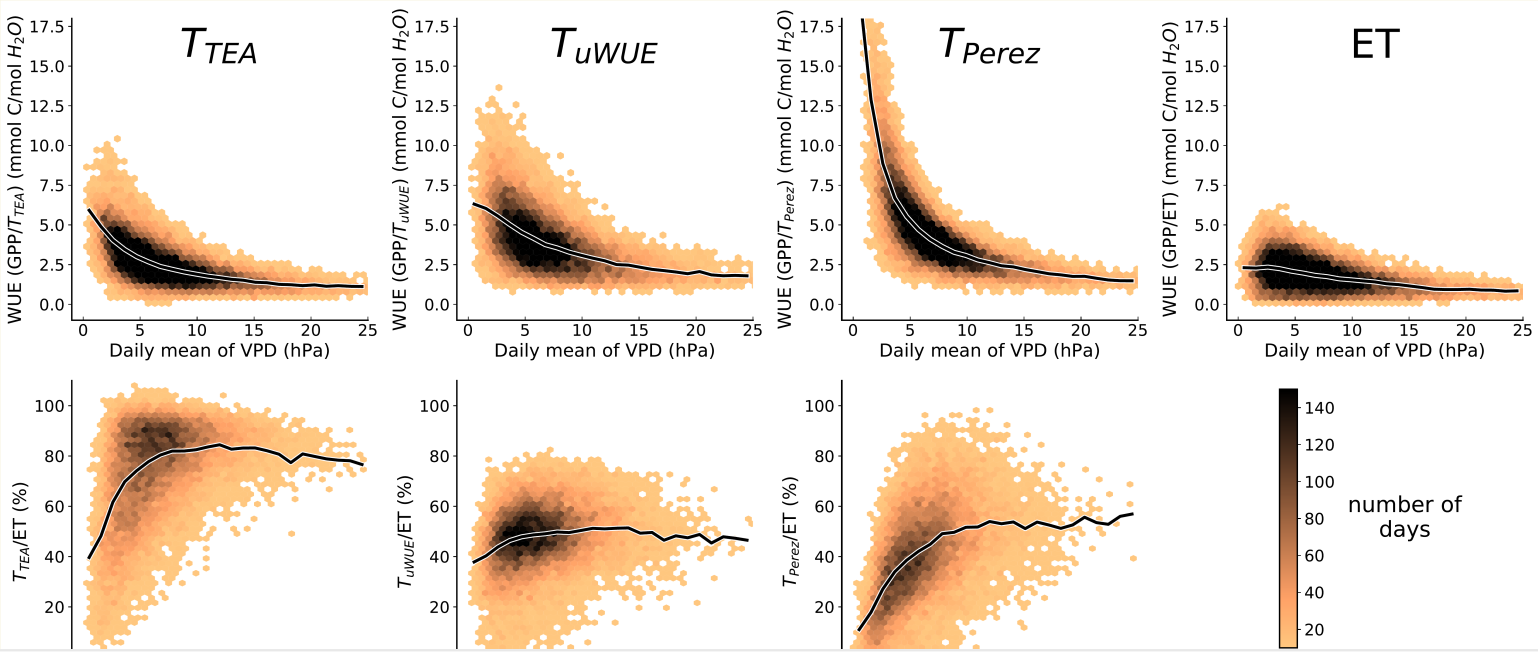
Figure from: Nelson, et al (2020). Ecosystem transpiration and evaporation: insights from three water flux partitioning methods across FLUXNET sites. Manuscript submitted for publication



Speaker notes

Daily T/ET from each EC based method as a function of MODIS LAI. For each PFT, the associated relationship derived from Wei et al (2017) is shown in black, which was derived from site level T/ET estimates. Points show the distribution within the given LAI bin, truncated to the 25^{th} and 75^{th} percentiles. PFTs were grouped to match those found in Wei, Z. et al (2017) and are slightly different compared to subsequent figures.

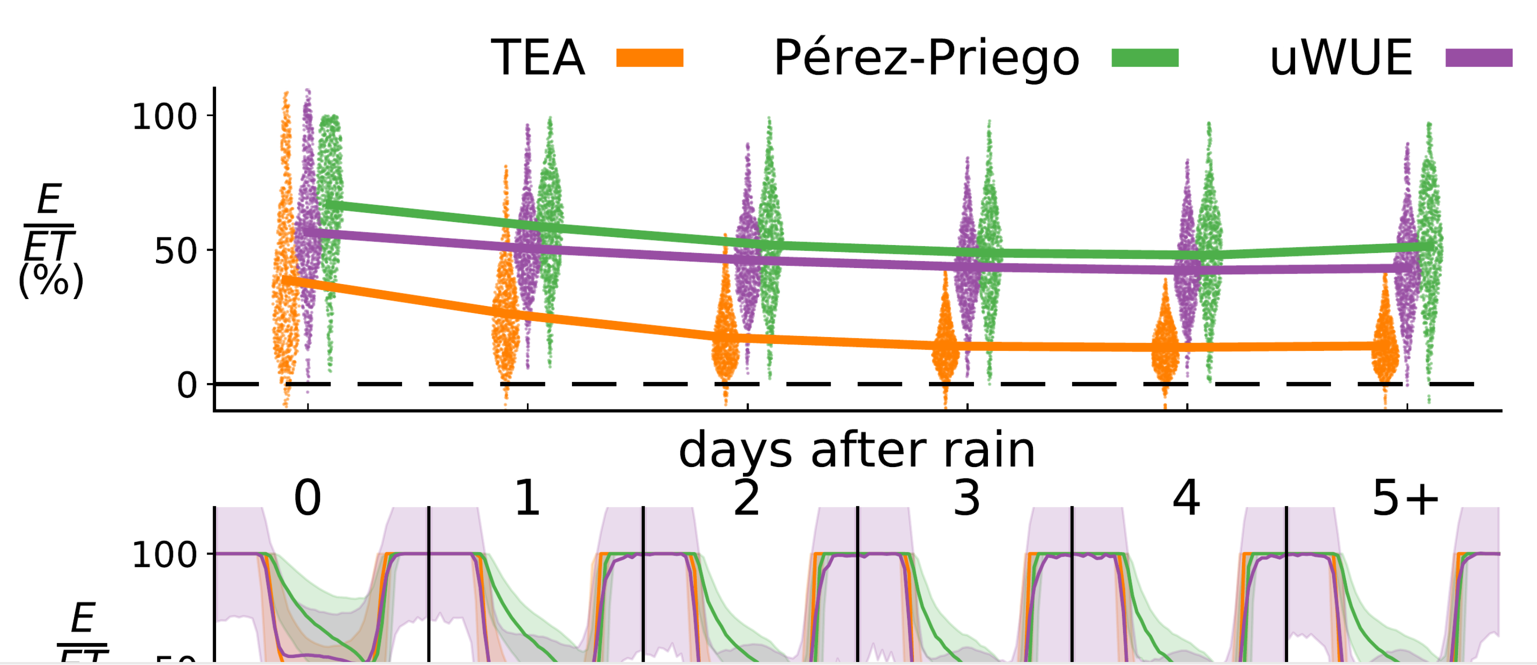
Figure from: Nelson, et al (2020). Ecosystem transpiration and evaporation: insights from three water flux partitioning methods across FLUXNET sites. Manuscript submitted for publication



Speaker notes

Relationship of both WUE (top row) and T/ET (bottom row) to VPD at daily scale across 124 sites. Lines indicate the median value from one hPa wide bins. Only days with a mean temperature above 5° C, at least 1 mm, day^{-1} of ET, and where all three partitioning methods could be applied were included.

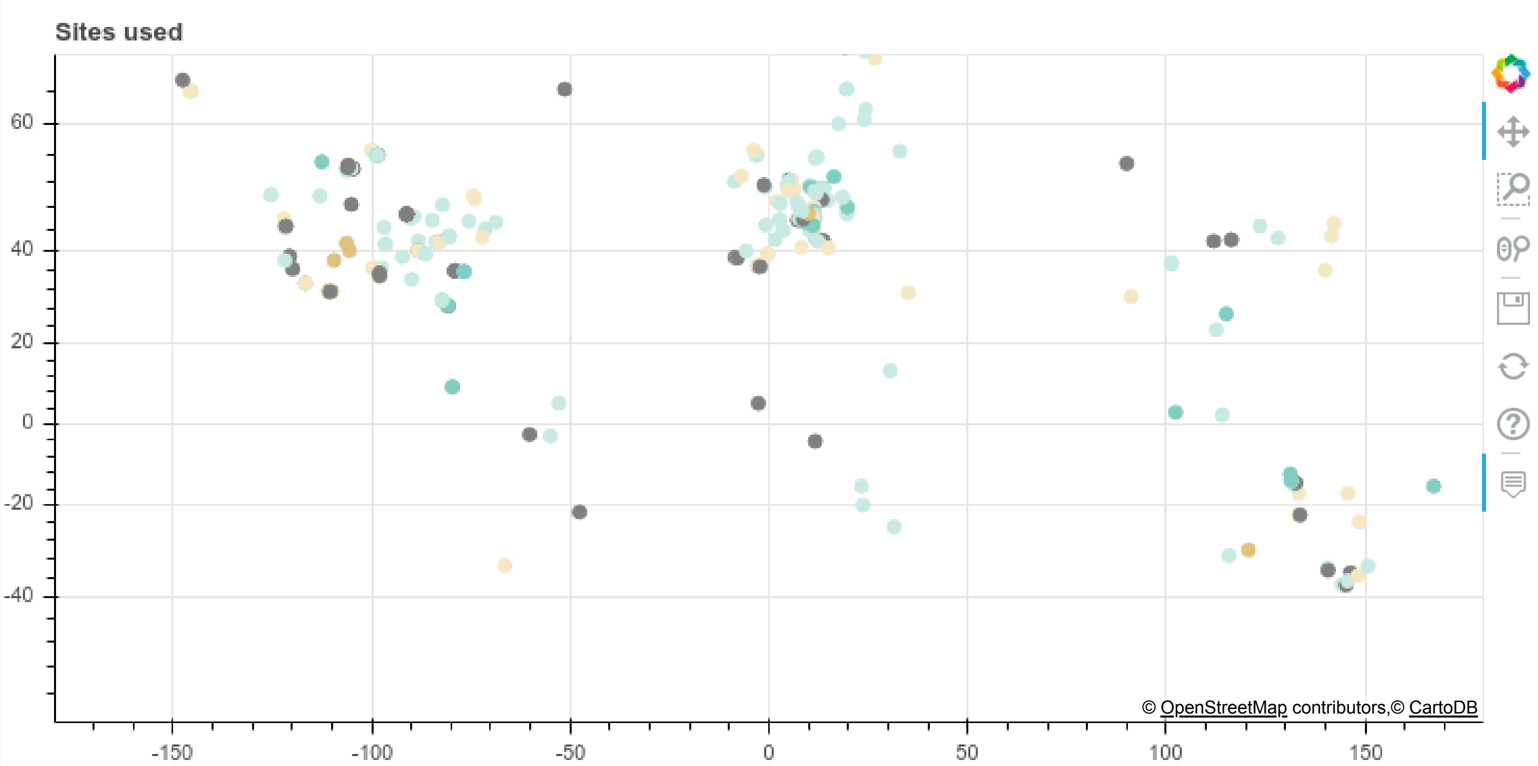
Figure from: Nelson, et al (2020). Ecosystem transpiration and evaporation: insights from three water flux partitioning methods across FLUXNET sites. Manuscript submitted for publication



Speaker notes

Percentage of evaporation (E/ET) estimated using the TEA, uWUE, and Pérez-Priego methods for progressive days after rain (rainy days defined as receiving > 0.1 mm in one day). Upper and lower panels show daily aggregated and diurnal cycles of E/ET, respectively. Diurnal cycles are estimated as the median for each half hour, with the interquartile range shown as shading. Only days with a mean temperature above 5° C, at least 1 mm, day^{-1} of ET, and where all partitioning methods could be applied for all half hours in a day were included.

Figure from: Nelson, et al (2020). Ecosystem transpiration and evaporation: insights from three water flux partitioning methods across FLUXNET sites. Manuscript submitted for publication



#	Site ID	Site Name	Citation	Dataset	PI	TEA T/ET (%)	uWUE T/ET (%)
0	AR-SLu	San Luis	10.18140/FLX/14401	FLUXNET 2015	Gabriela Posse	56.7	22.4
1	AT-Neu	Neustift	10.18140/FLX/14401	FLUXNET 2015	Georg Wohlfahrt	78	51.2
2	AU-ASM	Alice Springs	10.18140/FLX/14401	FLUXNET 2015	Derek Eamus	51.4	26.2
3	AU-Cpr	Calperum	10.18140/FLX/14401	FLUXNET 2015	Georgia Koerber	62.4	38.8
4	AU-Cum	Cumberland Plain	10.18140/FLX/14401	FLUXNET 2015	Elise Pendall	64.4	40.3
5	AU-DaP	Daly River Savanna	10.18140/FLX/14401	FLUXNET 2015	Jason Beringer	75.2	52.1
11	AU-How	Howard Springs	10.18140/FLX/14401	FLUXNET 2015	Jason Beringer	77.9	54

Speaker notes

OVERVIEW OF FLUXNET SITES USED HERE

- Hover over points on the map to see more information.

Many thanks to my co-authors:

Oscar Pérez-Priego, Sha Zhou, Rafael Poyatos, Yao Zhang, Peter D. Blanken, Teresa E. Gimeno, Georg Wohlfahrt, Ankur R. Desai, Beniamino Gioli, Jean-Marc Limousin, Damien Bonal, Eugénie Paul-Limoges, Russell L. Scott, Andrej Varlagin, Kathrin Fuchs, Leonardo Montagnani, Sebastian Wolf, Nicolas Delpierre, Daniel Berveiller, Mana Gharun, Luca Belelli Marchesini, Damiano Gianelle, Ladislav Šigut, Ivan Mammarella, Lukas Siebicke, T. Andrew Black, Alexander Knohl, Lukas Hörtnagl, Vincenzo Magliulo, Nuno Carvalhais, Mirco Migliavacca, Markus Reichstein, and Martin Jung

And all the FLUXNET/SAPFLUXNET PIs and support personnel.