rootwater

Oct 08, 2020

Contents:

This is the documentation for the rootwater package intended as Python toolbox for calculation of root water uptake (RWU) from measured soil moisture dynamics in the rhizosphere. The general concept is an evaluation of observed diurnal soil moisture decrease and nocturnal stagnation or capillary-driven redistribution.

For referencing to sap velocity measurements, a collection of conversion tools to estimate sap flow in the active sapwood is included.

CHAPTER 1

How to cite

If you use this package, please cite the research behind it:

Jackisch, C., Knoblauch, S., Blume, T., Zehe, E. and Hassler, S.K. (in review): Estimates of tree root water uptake from soil moisture profile dynamics. Biogeosciences Discuss., https://doi.org/10.5194/bg-2019-466

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1.1 Installation Guide

The module's development is hosted on GitHub. Please consider contributing. Moreover, we make it available through PyPI.

1.1.1 GitHub

The latest versions are available on GitHub and can be installed from a clone.

```
git clone https://github.com/cojacoo/rootwater.git
cd rootwater
pip install -r requirements.txt
pip install -e .
```

1.1.2 PyPI

We will provide stable versions through PyPI, too. They can be installed via pip.

```
pip install rootwater
```

rootwater.rootwater	The root water uptake (RWU) toolbox

1.2 The root water uptake (RWU) toolbox

Root water uptake (RWU) can be inferred from soil moisture dynamics in the rhizosphere (Feedes and van Dam, 2005; Guderle and Hildebrandt, 2015). We developped a function to evaluate the step-shaped, diurnal changes in soil moisture to derive an estimate for RWU. The science behind this function is presented in a case study by Jackisch et al. (in review)

Note: This function is by no means complete nor exhaustive. Please regard it as helper function which require throughout testing and deserve substantial extension to further application cases.

Note: For direct application (tested for TDR measurements at two beech stands) use rootwater.rootwater.dfRWUc and provide a pandas.DataFrame with measured soil moisture (in vol.%).

References

Feddes, R. A., and J. C. van Dam (2005), PLANT–SOIL–WATER RELATIONS, in Encyclopedia of Soils in the Environment, edited by D. Hillel, pp. 222–230, Elsevier, Oxford.

Guderle, M., and A. Hildebrandt (2015), Using measured soil water contents to estimate evapotranspiration and root water uptake profiles – a comparative study, Hydrol. Earth Syst. Sci., 19(1), 409–425, doi:10.5194/hess-19-409-2015.

Jackisch, C., Knoblauch, S., Blume, T., Zehe, E. and Hassler, S.K. (in review): Estimates of tree root water uptake from soil moisture profile dynamics. Submitted to Biogeosciences. DOI to be added

`rootwater.rootwater.`**`dfRWUc`**(*dummyd*, *tz='Etc/GMT-1'*, *safeRWU=True*, *lat=49.70764*, *lon=5.897638*, *elev=200.0*, *savgol=False*)

Wrapper to quickly apply rootwater.rootwater.fRWU to a dataframe with soil moisture values.

Returns three dataframes with RWU, RWU_without nocturnal correction, step shape NSE Warning: All parameters for the function rootwater.rootwater.fRWU are used as default!

Parameters

- **dummyd** (*pandas.DataFrame with time zone aware datetime index*) – input data frame of columns of soil moisture (assumes vol.%) a relatively high temporal resolution of about 30 min or smaller is assumed
- **tz** (*str*) – time zone which is required for the astral solar reference and follows its nomenclature
- **safeRWU** (*bool*) – flag if quality controls are applied when True
- **lat** (*float*) – latitude of location (degree)
- **lon** (*float*) – longitude of location (degree)
- **elev** (*float*) – elevation at location (m above msl)

Returns

- **dummx** (*pandas.DataFrame*) – data frame with time series of daily RWU estimates with applied nocturnal correction
- **dummy** (*pandas.DataFrame*) – data frame with time series of daily RWU estimates WITHOUT nocturnal correction

- **dummc** (*pandas.DataFrame*) – data frame with time series of Nash-Sutcliff-Efficiency as evaluation of the assumed step shape of the diurnal soil moisture dynamics.

References

Jackisch, C., Knoblauch, S., Blume, T., Zehe, E. and Hassler, S.K. (in review): Estimates of tree root water uptake from soil moisture profile dynamics. Submitted to Biogeosciences. DOI to be added

`rootwater.rootwater.`**`fRWU`**(*ts*, *lat=49.70764*, *lon=5.897638*, *elev=200.0*, *diffx=3*, *slope_diff=3*, *maxdiffs=0.25*, *mintime=3.5*)

Calulate a daily root water uptake estimate from a soil moisture time series

Returns a data frame with time series of daily RWU estimates and daily evaluation references after Jackisch et al. (in review)

Parameters

- **`ts`** (*`pandas.DataFrame with time zone aware datetime index`*) – time series of one soil moisture sensor (assumes vol.%) a relatively high temporal resolution of about 30 min or smaller is assumed
- **`lat`** (*`float`*) – latitude of location (degree)
- **`lon`** (*`float`*) – longitude of location (degree)
- **`elev`** (*`float`*) – elevation at location (m above msl)
- **`diffx`** (*`int`*) – number of time steps to evaluate change in moisture to (spans window)
- **`slope_diff`** (*`float`*) – minimal difference factor of slope between night and day linear regession to evaluate step shape especially in case of night decrease of soil moisture
- **`maxdiffs`** (*`float`*) – maximum of soil moistue difference to assume no significant other water transport (some sort of threshold which could be the noise of the sensed data)
- **`mintime`** (*`float`*) – minmimal time of a day or night period (in h)

Returns **RWU** – returns a data frame with time series of daily RWU estimates and daily references: rwu :: root water uptake with extrapolated night changes rwu_nonight :: neglecting nocturnal changes lm_night :: slope of linear model during night lm_day :: slope of linear model during day step_control :: control values (1111 means all criteria met) evalx :: control values for time references eval_nse :: control values for diurnal step shape as nash-sutcliffe efficiency tin :: start of previous night tout :: start of day tix :: start of next night

Return type pandas.DataFrame

References

Jackisch, C., Knoblauch, S., Blume, T., Zehe, E. and Hassler, S.K. (in review): Estimates of tree root water uptake from soil moisture profile dynamics. Submitted to Biogeosciences. DOI to be added

`rootwater.sapflow`	The Sap flow toolbox

1.3 The Sap flow toolbox

Sap velocity and sap flow is a very interesting means to monitor xylem water dynamics in higher plants (i.e. trees in our case). Since a mere flow conversion is likely to result in erroneous assumptions (Čermák et al., 2004), we have compiled a couple of sapwood-related functions to estimate active sapwood area for sap velocity conversion to sap flow.

Note: This toolbox is by no means complete nor exhaustive. Please regard it as helper functions which require throughout testing and deserve substantial extension to further application cases.

Note: To get started and for direct application (tested for beech trees) use rootwater.sapflow.sap_calc and provide a pandas.DataFrame with measured sap velocity from East30 sensors (in cm/h).

References

Čermák, J., J. Kučera, and N. Nadezhdina (2004), Sap flow measurements with some thermodynamic methods, flow integration within trees and scaling up from sample trees to entire forest stands, Trees, 18(5), 529–546, doi:10.1007/s00468-004-0339-6.

`rootwater.sapflow.`**`A_circ`**(*r, sens=[0.0, 1.1], tree='beech'*)

Calculate area of circular ring

Simple geometrical calculation of a circular ring area as reference cross-section for sap flow calculation.

Parameters

- **r** (*float*) – tree radius at breast height (in cm)
- **sens** (*list of floats*) – outer and inner point of ring (in cm)
- **tree** (*str*) – Tree name, for which to calculate and subtract bark thickness. Can be one of ['beech', 'oak'].

Returns **return** – area of ring as

Return type float

`rootwater.sapflow.`**`galvac`**(*r*)

sap-wood thickness after Galvac et al. (1990)

Calculates sap-wood thickness as a function of the tree radius at breast height.

Parameters **r** (*float*) – tree radius at breast height (in cm)

Returns **sapwood** – sapwood thickness (in cm)

Return type float

References

Glavac, V., Koenies, H. & Ebben, U. Holz als Roh- und Werkstoff (1990) 48: 437. https://doi.org/10.1007/BF02627628

`rootwater.sapflow.`**`gebauer`**(*r, tree='beech'*)

Sap-wood thickness

Calculates sap-wood thickness as published by Gebauer et al. (2008)

Parameters

- **r** (*float*) – tree radius at breast height (in cm)
- **tree** (*str*) – Tree name, for which to calculate bark and sapwood thickness. Can be one of ['beech', 'oak']

Returns **th** – sap-wood thickness (in mm)

Return type float

Raises NotImplementedError : if tree is not in ('oak', 'beech')

References

Gebauer, T., Horna, V., and Leuschner, C.: Variability in radial sap flux density patterns and sapwood area among seven co-occurring temperate broad-leaved tree species, Tree Physiol., 28, 1821–1830, 2008.

`rootwater.sapflow.`**`gebauer_act`**(*r*, *perc=0.95*, *tree='beech'*)

Active sapwood area based on percentile of Weibull distribution

Calculates the "zero" sap velocity limit as given percentile of relative flux velocity distribution as a Weibull function after Gebauer et al. (2008)

Parameters

- **r** (*float or numpy.ndarray*) – tree radius at breast height (in cm)
- **perc** (*float*) – percentile to define the "zero" sap velocity limit
- **tree** (*str*) – Tree name, for which to calculate Weibull function. Tree name has to be in gp.keys()

Returns **act_sap** – depth of "zero" sap velocity limit as active sapwood in tree (in cm)

Return type float or numpy.ndarray

References

Gebauer, T., Horna, V., and Leuschner, C.: Variability in radial sap flux density patterns and sapwood area among seven co-occurring temperate broad-leaved tree species, Tree Physiol., 28, 1821–1830, 2008.

`rootwater.sapflow.`**`gebauer_rel`**(*r*, *tree='beech'*, *n_points=50*)

relative flux density

Calculates relative flux density as a function of depth on sapwood for n_points.

Parameters

- **r** (*float*) – tree radius at breast height (in cm)
- **tree** (*str*) – Tree name, for which to calculate Weibull function. Tree name has to be in gp.keys()
- **n_points** (*int*) – Number of points for solving Weibull. This is the resolution over depth.

Returns **sv** – relative flux density at n_points

Return type numpy.ndarray

References

Gebauer, T., Horna, V., and Leuschner, C.: Variability in radial sap flux density patterns and sapwood area among seven co-occurring temperate broad-leaved tree species, Tree Physiol., 28, 1821–1830, 2008.

`rootwater.sapflow.`**`gebauer_weibull`**(*x*, *a*, *b*, *c*, *d*)

4-parameter Weibull function after Gebauer

Calls Weibull distribution function as published by Gebauer et al. (2008).

Parameters

- **x** (*float or numpy.ndarray*) – realtive sampling points for distribution function
- **b, c, d** (*a,*) – Weibull function parameters, which are tree-specific in this case

References

Gebauer, T., Horna, V., and Leuschner, C.: Variability in radial sap flux density patterns and sapwood area among seven co-occurring temperate broad-leaved tree species, Tree Physiol., 28, 1821–1830, 2008.

`rootwater.sapflow.`**`get_default_gp`**()

read default gp

Loads default Weibull distribution parameters as published by Gebauer et al. (2008). Can be used by `gebauer_weibull` to calculate sap velocity distribution in sapwood

References

Gebauer, T., Horna, V., and Leuschner, C.: Variability in radial sap flux density patterns and sapwood area among seven co-occurring temperate broad-leaved tree species, Tree Physiol., 28, 1821–1830, 2008.

`rootwater.sapflow.`**`recko`**(*r*, *hydra=False*)

sap-wood thickness after Račko et al. (2018)

Calculates sap-wood thickness as a function of the tree radius at breast height.

Parameters

- **r** (*float*) – tree radius at breast height (in cm)
- **hydra** (*bool*) – selects if only the hydrated area is returned (when True)

Returns **sapwood** – sapwood thickness (in cm)

Return type float

References

Račko, V., O. Mišíková, P. Hlaváč, and V. Deáková (2018), Can bark stripping cause red heartwood formation in beech stems? iForest - Biogeosciences and Forestry, 11(2), 251–258, doi:10.3832/ifor2147-011.

`rootwater.sapflow.`**`roessler`**(*r*, *tree='beech'*)

Estimate bark thickness

Returns the estimated bark thickness as published by Rössler (2008)

Parameters

- **r** (*float*) – tree radius at breast height (in cm)

- **tree** (*str*) – Tree name, for which to calculate bark thickness. Can be one of ['beech', 'oak']

Returns **db** – bark thickness (in mm)

Return type float

Raises NotImplementedError : if tree is not in ('oak', 'beech')

References

Rössler, G.: Rindenabzug richtig bemessen, Forstzeitung, 4, p. 21, 2008.

`rootwater.sapflow.`**`sap_calc`**(*SV*, *r*, *perc=0.95*, *tree='beech'*)

Wrapper for sap flow calculation with rootwater.sapflow.sap_volume

Calculates the sap flow after Gebauer et al. (2008) based on measured sap velocity with East30 sensors.

Parameters

- **SV** (*pandas.DataFrame*) – sap velocity (in cm/h) in three columns ordered inner, mid, outer point
- **r** (*float*) – tree radius at breast height (in cm)
- **perc** (*float*) – percentile to define the "zero" sap velocity limit
- **tree** (*str*) – Tree name, for which to calculate bark thickness and Weibull function. Tree name has to be in gp.keys()

Returns **return** – sap volume flux (cm3/h)

Return type pandas.DataFrame

`rootwater.sapflow.`**`sap_volume`**(*r*, *s1*, *s2*, *vout=False*, *perc=0.95*, *tree='beech'*)

Estimate sap flow from sap velocity in inner sapwood measured with East30 sensors

Calculates the sap flow after Gebauer et al. (2008) based on sap velocity measurements by fitting of Gebauer-Weibull function to measured sap velocity at mid and inner point through a scaling factor (but not changing the empirical, tree-specific parameters).

Parameters

- **r** (*float*) – tree radius at breast height (in cm)
- **s1** (*float or pandas.Series (datetime index is preferable)*) – sap velocity measurement at mid point of East30 sensor (cm/time)
- **s2** (*float or pandas.Series (datetime index is preferable)*) – sap velocity measurement at inner point of East30 sensor (cm/time)
- **vout** (*bool*) – True returns aggregated volume flux (cm3/time), False returns velocity distribution (cm/time)
- **perc** (*float*) – percentile to define the "zero" sap velocity limit
- **tree** (*str*) – Tree name, for which to calculate bark thickness and Weibull function. Tree name has to be in gp.keys()

Returns **return** – aggregated volume flux (cm3/time) (if vout is True), or returns velocity distribution (cm/time) (if vout is False)

Return type float or pandas.Series

References

Gebauer, T., Horna, V., and Leuschner, C.: Variability in radial sap flux density patterns and sapwood area among seven co-occurring temperate broad-leaved tree species, Tree Physiol., 28, 1821–1830, 2008.

1.4 Examples

Some examples can be found below:

1.4.1 Estimates of root water uptake from soil moisture profile dynamics

Jupyter notebook to demonstrate the development and functionality of the rootwater module. It has been developed as supplement to the forthcoming manuscript currently under review in Biogeosciences by Jackisch et al.

Jackisch, C., Knoblauch, S., Blume, T., Zehe, E. and Hassler, S.K. (in review): Estimates of tree root water uptake from soil moisture profile dynamics. *Submitted to Biogeosciences. (DOI forthcoming)*

This study is part of the CAOS project (From catchments as organised systems to models based on functional units, Zehe et al. 2014, HESS, https://doi.org/10.5194/hess-18-4635-2014).

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[1]:
```
#load required packages
%pylab inline
import pandas as pd
import numpy as np
import seaborn as sns
import scipy.stats as stats
import statsmodels.formula.api as smf
import scipy.ndimage.filters as spf
import scipy as sp
import hydroeval as he

sns.set_style('whitegrid', {'grid.linestyle': u'--'})
matplotlib.rc('pdf', fonttype=42)
```

```
Populating the interactive namespace from numpy and matplotlib
```

[2]:
```
#load/define used colour schemes

from palettable.tableau import Tableau_10
from palettable.tableau import Tableau_20
from palettable.cartocolors.qualitative import Bold_8
from palettable.colorbrewer.qualitative import Paired_12

#cm_t10 = plt.cm.get_cmap(Tableau_10.mpl_colormap)
cm_t10 = plt.cm.get_cmap(Bold_8.mpl_colormap)
cm_t20 = plt.cm.get_cmap(Tableau_20.mpl_colormap)

# These are the "Tableau 20" colors as RGB.
tableau20 = [(31, 119, 180), (174, 199, 232), (255, 127, 14), (255, 187, 120),
          (44, 160, 44), (152, 223, 138), (214, 39, 40), (255, 152, 150),
          (148, 103, 189), (197, 176, 213), (140, 86, 75), (196, 156, 148),
          (227, 119, 194), (247, 182, 210), (127, 127, 127), (199, 199, 199),
          (188, 189, 34), (219, 219, 141), (23, 190, 207), (158, 218, 229)]
```

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```
# Scale the RGB values to the [0, 1] range, which is the format matplotlib accepts.
for i in range(len(tableau20)):
    r, g, b = tableau20[i]
    tableau20[i] = (r / 255., g / 255., b / 255.)

tableau10=tableau20[0::2]
```

Load rootwater package

[3]:
```
#load rootwater package contents
import sys
sys.path.append('../../rootwater') # Adds higher directory to python modules path.

import rootwater as rw
import sapflow as sf
from gebauer_params import gp # load gebauer parameters
```

Load site data

The two sites are generally named Sand and Slate. They refer to the monitoring clusters SaD (Sand D) and SW (Slate W) of the CAOS project (From catchments as organised systems to models based on functional units, Zehe et al. 2014, HESS).

The Meteorological reference data has been provided by the "Ministère de l'Agriculture, de la Viticulture et du Développement rural, Le Gouvernement du Grand-Duché de Luxembourg" through its web service https://www.agrimeteo.lu for the stations:

Roodt: https://www.am.rlp.de/Internet/AM/NotesLUAM.nsf/luxweb/348fc27901e88eb9c1257751003632b3

Useldange: https://www.am.rlp.de/Internet/AM/NotesLUAM.nsf/luxweb/64b5f9e78c267864c12577510032b918

We only use the pyranometer data from Useldange as reference.

Precipitation data has been provided by Malte Neuper (KIT) as corrected randar-derived canopy precipitation derrived from comined data of the DWD (Deutscher Wetterdienst, Germany), ASTA (Administration des Services techniques de l'agriculture, Luxembourg) and KNMI (Koninklijk Nederlands Meteorologisch Instituut, Netherlands).

The soil water retention data has been derrived from all 250 ml soil samples of the respective subbasin and depth layer (Jackisch et al. 2019, ESSD).

[4]:
```
#load site data of soil water content
SM = pd.read_csv('soilmoisture.csv',index_col=0)
SM.index = pd.to_datetime(SM.index)

#load sap velocity data
SV = pd.read_csv('sapvelocity.csv',index_col=0)
SV.index = pd.to_datetime(SV.index)

#load cluster precipitation and solar radiation data
prec_rad = pd.read_csv('precip_radiation.csv',index_col=0)
prec_rad.index = pd.to_datetime(prec_rad.index)

#load van Genuchten parameters
VGx = pd.read_csv('vG_RWU.csv',index_col=0).T
```

Soil water retention

Load a van Genuchten pedo-transfer-model module and soil data.

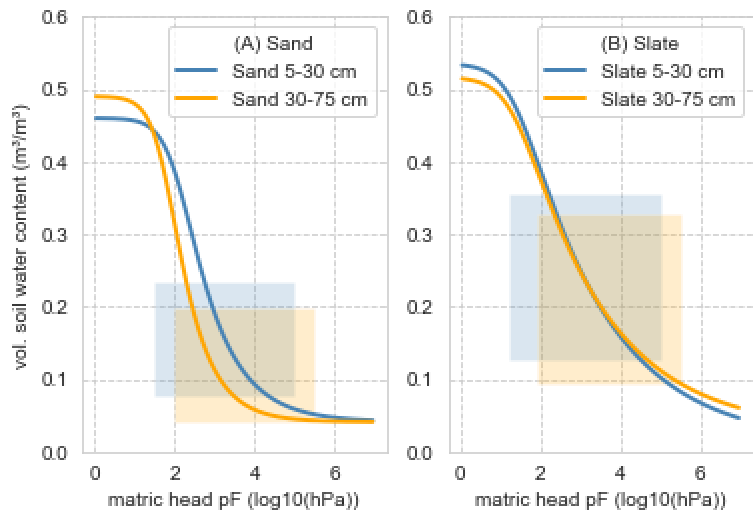
Convert the recorded soil moisture data to matric potential by application of the retention function.

[5]:
```
#show soils with given van Genuchten parameters
import vG_conv as vG

sup_dummy=np.arange(0.05,7.,0.05)
subplot(121)
lay=VGx.index[0]
thetad=vG.theta_psi((10**sup_dummy)/98.1,VGx.loc[lay,'ths'],VGx.loc[lay,'thr'],VGx.
↪loc[lay,'alpha'],VGx.loc[lay,'n'],VGx.loc[lay,'m'])
plot(sup_dummy,0.01*thetad,'-',c='steelblue',lw=2,label=lay)
lay=VGx.index[1]
thetad=vG.theta_psi((10**sup_dummy)/98.1,VGx.loc[lay,'ths'],VGx.loc[lay,'thr'],VGx.
↪loc[lay,'alpha'],VGx.loc[lay,'n'],VGx.loc[lay,'m'])
plot(sup_dummy,0.01*thetad,'-',c='orange',lw=2,label=lay)
fill_between([1.5,5],[0.0757, 0.0757],[0.2329,0.2329],facecolor='steelblue',alpha=0.2)
fill_between([2,5.5],[0.04175, 0.04175],[0.1982,0.1982],facecolor='orange',alpha=0.2)
ylim(0,0.6)
ylabel('vol. soil water content (m³/m³)')
xlabel('matric head pF (log10(hPa))')
legend(title='(A) Sand')

subplot(122)
lay=VGx.index[2]
thetad=vG.theta_psi((10**sup_dummy)/98.1,VGx.loc[lay,'ths'],VGx.loc[lay,'thr'],VGx.
↪loc[lay,'alpha'],VGx.loc[lay,'n'],VGx.loc[lay,'m'])
plot(sup_dummy,0.01*thetad,'-',c='steelblue',lw=2,label=lay)
lay=VGx.index[3]
thetad=vG.theta_psi((10**sup_dummy)/98.1,VGx.loc[lay,'ths'],VGx.loc[lay,'thr'],VGx.
↪loc[lay,'alpha'],VGx.loc[lay,'n'],VGx.loc[lay,'m'])
plot(sup_dummy,0.01*thetad,'-',c='orange',lw=2,label=lay)
fill_between([1.2,5],[0.12575,0.12575],[0.3556,0.3556],facecolor='steelblue',alpha=0.
↪2)
fill_between([1.9,5.5],[0.0921,0.0921],[0.32767,0.32767],facecolor='orange',alpha=0.2)
ylim(0,0.6)
legend(title='(B) Slate')
xlabel('matric head pF (log10(hPa))')
```

[5]:
```
Text(0.5, 0, 'matric head pF (log10(hPa))')
```



[6]:

```
#apply van Genuchten parameters to convert soil moisture to matric potential

MP = SM.copy()*np.nan
MP.columns = ['Sand_MP_10', 'Sand_MP_30', 'Sand_MP_50', 'Sand_MP_70', 'Sand_MP_90',
↪'Sand_MP_110', 'Sand_MP_130', 'Sand_MP_150', 'Sand_MP_170', 'Sand_MP_190', 'Sand_MP_
↪210', 'Sand_MP_230',
              'Slate_MP_10', 'Slate_MP_30', 'Slate_MP_50', 'Slate_MP_70', 'Slate_MP_90
↪', 'Slate_MP_110', 'Slate_MP_130', 'Slate_MP_150', 'Slate_MP_170']

lay=VGx.index[0]
for j in ['10', '30']:
    MP['Sand_MP_'+j]= vG.psi_theta(SM['Sand_SM_'+j],VGx.loc[lay,'ths'],VGx.loc[lay,
↪'thr'],VGx.loc[lay,'alpha'],VGx.loc[lay,'n'],VGx.loc[lay,'m'])

lay=VGx.index[1]
for j in ['50', '70', '90', '110', '130', '150', '170', '190', '210', '230']:
    MP['Sand_MP_'+j]= vG.psi_theta(SM['Sand_SM_'+j],VGx.loc[lay,'ths'],VGx.loc[lay,
↪'thr'],VGx.loc[lay,'alpha'],VGx.loc[lay,'n'],VGx.loc[lay,'m'])

lay=VGx.index[2]
for j in ['10', '30']:
    MP['Slate_MP_'+j]= vG.psi_theta(SM['Slate_SM_'+j],VGx.loc[lay,'ths'],VGx.loc[lay,
↪'thr'],VGx.loc[lay,'alpha'],VGx.loc[lay,'n'],VGx.loc[lay,'m'])

lay=VGx.index[3]
for j in ['50', '70', '90', '110', '130', '150', '170']:
    MP['Slate_MP_'+j]= vG.psi_theta(SM['Slate_SM_'+j],VGx.loc[lay,'ths'],VGx.loc[lay,
↪'thr'],VGx.loc[lay,'alpha'],VGx.loc[lay,'n'],VGx.loc[lay,'m'])
```

[ ]:

Root water uptake calculation

The actual algorithm is given in an external file als python function. Here some examples are given.

[7]:
```
# example time series in slate site:
start=pd.to_datetime('2017-06-12 04:00:00')
stop=pd.to_datetime('2017-06-14 04:00:00')

ts = SM.loc[start:stop,'Slate_SM_70']
ts = ts.tz_localize('Etc/GMT-1')
dif_ts = pd.Series(spf.gaussian_filter1d(ts.diff(3),1))
dif_ts.index = ts.index
```

[8]:
```
#call RWU calculation function fRWU
rwux = rw.fRWU(ts)
dif_ts = pd.Series(spf.gaussian_filter1d(ts.diff(3),1))
dif_ts.index = ts.index
dd=rwux.index[1]
```

```
/Users/cojack/miniconda3/lib/python3.7/site-packages/pandas/core/indexes/base.py:3064:
↪ FutureWarning: Converting timezone-aware DatetimeArray to timezone-naive ndarray␣
↪with 'datetime64[ns]' dtype. In the future, this will return an ndarray with 'object
↪' dtype where each element is a 'pandas.Timestamp' with the correct 'tz'.
        To accept the future behavior, pass 'dtype=object'.
        To keep the old behavior, pass 'dtype="datetime64[ns]"'.
  target = np.asarray(target)
```

[9]:
```
rwux
```

[9]:
```
                 rwu  rwu_nonight  lm_night   lm_day  step_control  evalx  \
2017-06-12       NaN          NaN       NaN      NaN           2.0    0.0
2017-06-13  0.403992        0.355   0.00081 -0.01667        1111.0    1.0
2017-06-14       NaN          NaN       NaN      NaN           NaN    NaN

            eval_nse                        tin                       tout  \
2017-06-12  0.984979  2017-06-12 04:00:00+01:00  2017-06-12 05:30:00+01:00
2017-06-13  0.949938  2017-06-12 20:00:00+01:00  2017-06-13 08:00:00+01:00
2017-06-14       NaN                        NaN                        NaN

                                  tix
2017-06-12  2017-06-12 21:30:00+01:00
2017-06-13  2017-06-13 21:00:00+01:00
2017-06-14                        NaN
```

Example of observed solar radiation, sap velocity and soil moisture during three days of the vegetation period. The example is from the sandy site dataset, soil moisture values are in 0.7 m depth.

[10]:
```
#get sunrise/sunset from astral (included in rwu function)
from astral import Location

l = Location()
l.latitude = 49.70764
l.longitude = 5.897638
l.timezone = 'Etc/GMT+1'
l.elevation = 200

#sunrise sunset
def sunr(dd):
    # give date and return time of sunrise
    sunrise = pd.to_datetime(l.sun(date=dd)['sunrise'])
    return sunrise
```

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```
def suns(dd):
    # give date and return time of sunset
    sunset = pd.to_datetime(l.sun(date=dd)['sunset'])
    return sunset
```

[11]:

```
figsize(8,3)

soil=SM.loc['2017-06-12':'2017-06-16','Sand_SM_70']
soil = soil.tz_localize('Etc/GMT+1')
ray=prec_rad.loc['2017-06-12':'2017-06-16','Rad']/100
ray = ray.tz_localize('Etc/GMT+1')
saps=SV.loc['2017-06-12':'2017-06-16','Sand_SV_inner']
saps = saps.tz_localize('Etc/GMT+1')

dif_ts = pd.Series(spf.gaussian_filter1d(soil.diff(3),1))
dif_ts.index = soil.index

fig, ax1 = plt.subplots()
ax1.plot(soil.index,soil,c='royalblue',linestyle='-',label='soil moisture ($\Theta$)')
ax1.plot(dif_ts.index,-7.5*(dif_ts)+12.2,c='royalblue',linestyle='--',lw=1,label='
↪$\Delta \Theta$')
ax1.set_ylabel('soil moisture (vol.%)')
ax1.set_ylim([12.,13.3])
ax1.set_xlim(['2017-06-14','2017-06-17 00:00:00'])

#dates to consider:
ddx = soil.resample('1d').mean().index.date

for i in np.arange(len(ddx)):
    sus = pd.to_datetime(l.sun(date=ddx[i])['sunset'])+datetime.timedelta(hours=1)
    sur = pd.to_datetime(l.sun(date=ddx[i]+datetime.timedelta(hours=24))['sunrise
↪'])+datetime.timedelta(hours=1)
    ax1.vlines(sus,12.,13.3,'k',':',alpha=0.5)
    ax1.vlines(sur,12.,13.3,'k',':',alpha=0.5)
    if i == len(ddx)-1:
        ax1.fill_betweenx([12.,13.3],[sus,sus],[sur,sur],facecolor='k',alpha=0.1)#,
↪label='astron. night')
    else:
        ax1.fill_betweenx([12.,13.3],[sus,sus],[sur,sur],facecolor='k',alpha=0.1)

ax1.legend(loc=2,ncol=2)
ax2 = ax1.twinx()
yticks(np.arange(0,17,2),np.arange(0,17,2))
leg2,=ax2.plot(ray.index,ray,c='orange',linestyle='-',lw=1,label='solar radiation')
leg3,=ax2.plot(saps.index,saps,c='y',linestyle='-',lw=1,label='sap velocity')
ax2.set_ylabel('sap velocity (cm/h) \n solar radiation (x 100 W/m²) \n $\Delta$soil␣
↪moisture (x 2/15 vol.%/1.5h)')

ax2.set_ylim([-2,11])
ax2.legend([leg2,leg3,],['solar radiation','sap velocity'],loc=1,ncol=2)
ax2.set_xlim(['2017-06-14','2017-06-17 00:00:00'])

xticks(SM.loc['2017-06-14':'2017-06-17 00:00:00'].resample('12h').mean().index,['06-
↪14\n00:00','06-14\n12:00','06-15\n00:00','06-15\n12:00','06-16\n00:00','06-16\n12:00
↪','06-17\n00:00'])
```

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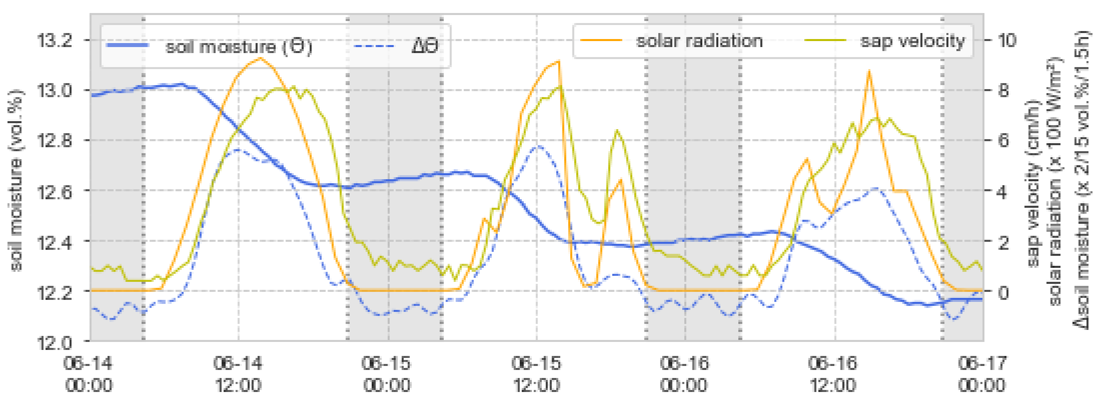
```
#
```

```
/Users/cojack/miniconda3/lib/python3.7/site-packages/pandas/plotting/_matplotlib/
↪converter.py:102: FutureWarning: Using an implicitly registered datetime converter␣
↪for a matplotlib plotting method. The converter was registered by pandas on import.␣
↪Future versions of pandas will require you to explicitly register matplotlib␣
↪converters.

To register the converters:
        >>> from pandas.plotting import register_matplotlib_converters
        >>> register_matplotlib_converters()
  warnings.warn(msg, FutureWarning)
```

[11]:
```
([<matplotlib.axis.XTick at 0x1a213a7588>,
  <matplotlib.axis.XTick at 0x1a21399c50>,
  <matplotlib.axis.XTick at 0x1a2123ec50>,
  <matplotlib.axis.XTick at 0x1a213e2b70>,
  <matplotlib.axis.XTick at 0x1a213e8630>,
  <matplotlib.axis.XTick at 0x1a213e26d8>,
  <matplotlib.axis.XTick at 0x1a213e8a58>],
 <a list of 7 Text xticklabel objects>)
```



Visualisation of calculation of root water uptake from soil moisture change of one day in one soil layer.

[12]:
```
figsize(8,4)

plot(ts,label='soilmoisture')
n=int(np.round(len(ts)/1.7))

plot(pd.date_range(rwux.loc[dd,'tin'], periods=n, freq='30min'),ts.loc[rwux.loc[dd,
↪'tin']]+rwux.loc[dd,'lm_night']*np.arange(n),'r-',label='lin. reg. night')
plot(pd.date_range(rwux.loc[dd,'tout'], periods=25, freq='30min'),ts.loc[rwux.loc[dd,
↪'tout']]+rwux.loc[dd,'lm_day']*np.arange(25),'--',c='coral',label='lin. reg. day')
plot(pd.date_range(rwux.loc[dd,'tin'], periods=n, freq='30min'),ts.loc[rwux.loc[dd,
↪'tin']]*np.ones(n),'g-',label='w/out recharge',lw=1)

#identified times
plot([rwux.loc[dd,'tin'],rwux.loc[dd,'tin']],[23.8,24.5],'r:')
text(rwux.loc[dd,'tin']+datetime.timedelta(hours=0.5),24.46,'‹‹ ---- RWU night ---- ››
↪',color='red')
text(rwux.loc[dd,'tout']+datetime.timedelta(hours=0.5),24.46,'‹‹ -----  RWU day  -----
↪ ››',color='red')
```

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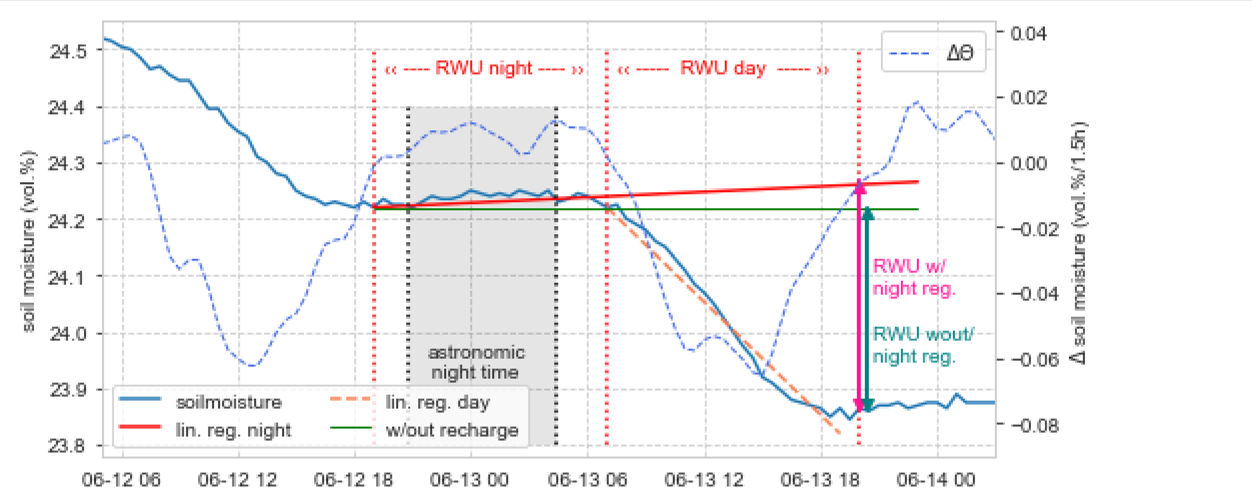
```
plot([rwux.loc[dd,'tout'],rwux.loc[dd,'tout']],[23.8,24.5],'r:')
plot([rwux.loc[dd,'tix'],rwux.loc[dd,'tix']],[23.8,24.5],'r:')

#night
sus = pd.to_datetime(l.sun(date=rwux.index[0])['sunset'])+datetime.timedelta(hours=1)
sur = pd.to_datetime(l.sun(date=dd)['sunrise'])+datetime.timedelta(hours=1)
plot([sus,sus],[23.8,24.4],'k:')
plot([sur,sur],[23.8,24.4],'k:')
fill_betweenx([23.8,24.4],[sus,sus],[sur,sur],facecolor='k',alpha=0.1)
text(sus+datetime.timedelta(hours=1),23.92,'astronomic\n night time')

plot([rwux.loc[dd,'tix'],rwux.loc[dd,'tix']],[ts.loc[rwux.loc[dd,'tix']],ts.loc[rwux.
↪loc[dd,'tix']]+rwux.loc[dd,'rwu']],'-',lw=2,c='deeppink')#,label='RWU w/ night reg.
↪')
plot(rwux.loc[dd,'tix'],ts.loc[rwux.loc[dd,'tix']]+0.007,"v",c='deeppink')
plot(rwux.loc[dd,'tix'],ts.loc[rwux.loc[dd,'tix']]+rwux.loc[dd,'rwu']-0.01,"^",c=
↪'deeppink')
plot([rwux.loc[dd,'tix']+datetime.timedelta(hours=0.4),rwux.loc[dd,'tix']+datetime.
↪timedelta(hours=0.4)],[ts.loc[rwux.loc[dd,'tix']],ts.loc[rwux.loc[dd,'tix']]+rwux.
↪loc[dd,'rwu_nonight']],'-',lw=2,c='teal')#,label='RWU wout/ night reg.')
plot(rwux.loc[dd,'tix']+datetime.timedelta(hours=0.4),ts.loc[rwux.loc[dd,'tix']]+0.
↪007,"v",c='teal')
plot(rwux.loc[dd,'tix']+datetime.timedelta(hours=0.4),ts.loc[rwux.loc[dd,'tix']]+rwux.
↪loc[dd,'rwu_nonight']-0.01,"^",c='teal')

text(rwux.loc[dd,'tix']+datetime.timedelta(hours=0.7),24.07,'RWU w/\nnight reg.',
↪color='deeppink')
text(rwux.loc[dd,'tix']+datetime.timedelta(hours=0.7),23.95,'RWU wout/\nnight reg.',
↪color='teal')

xlim(pd.to_datetime('2017-06-12 05:00:00'),pd.to_datetime('2017-06-14 03:00:00'))
ylabel('soil moisture (vol.%)')
ylim(23.78,24.55)
legend(ncol=2,loc=3)

twinx()
plot(dif_ts,c='royalblue',linestyle='--',lw=1,label='$\Delta \Theta$')
ylim(-0.09,0.043)
ylabel('$\Delta$ soil moisture (vol.%/1.5h)')
grid(False)
legend(loc=1)
```

```
[12]: <matplotlib.legend.Legend at 0x1a222a23c8>
```




```
[ ]:
```

Sap velocity to sap flow conversion

The measured sap velocity requires conversion into a flux through the rotation-symmetrical sap-wood. We use an approach considering sap-wood thickness, bark thickness and an exponential sap velocity distribution. The following functions are defined:

```
[13]: # different estimates about active sapwood area based on stem radius at brest height

figsize(5,4)
r= np.arange(70)
perc = 0.95

#East30 thermocouplers location at needles 5, 18 and 30 mm
fill_between([0,70],[0,0],[1.1,1.1],alpha=0.3,label='sap sensor1')
fill_between([0,70],[1.1,1.1],[2.4,2.4],alpha=0.3,label='sap sensor2')
fill_between([0,70],[2.4,2.4],[3.5,3.5],alpha=0.3,label='sap sensor3')

#gebauer
plot(r,sf.gebauer(r),label='Gebauer beech \ntotal sapwood')

#other
plot(r,sf.recko(r,True),':',label='Račko beech')
plot(r,0.2*r,':',label='20% ratio')
#plot(r,galvac(r),':',label='Galvac')

plot([32.1,32.1],[0,70],c='brown',alpha=0.4)
fill_between(32.+sf.gebauer_rel(32.),np.arange(50)/50.*sf.gebauer(32.),facecolor=
↪'brown',alpha=0.4)
plot([24.2,24.2],[0,70],c='brown',alpha=0.4,label='observed trees\nw/ weibull sap␣
↪\nflow estimate')
fill_between(24.+sf.gebauer_rel(24.),np.arange(50)/50.*sf.gebauer(24.),facecolor=
↪'brown',alpha=0.4)

fill_between(r,np.ones(70)*3.5,sf.gebauer_act(r,perc),alpha=0.3,facecolor='grey',
↪label='not measured')
```

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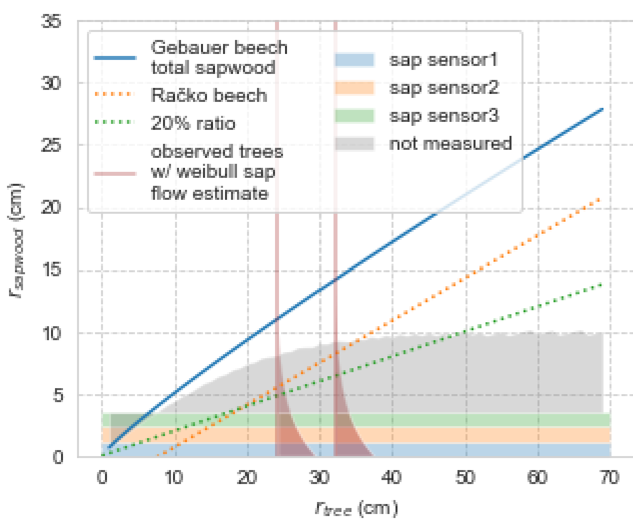
```
xlabel('$r_{tree}$ (cm)')
ylabel('$r_{sapwood}$ (cm)')#'/ $r_{tree}$')
ylim(0.,35)

legend(loc=2,ncol=2)
```

[13]: `<matplotlib.legend.Legend at 0x1a22467f28>`



[14]:
```
tst = pd.to_datetime('2017-06-14')
tnd = pd.to_datetime('2017-06-15')
```

[15]:
```
figsize(8,3)
ti = 13.
subplot(121)
plot(SV.loc[tst:tnd,['Slate_SV_inner']],label='30 mm')
plot(SV.loc[tst:tnd,['Slate_SV_mid']],label='18 mm')
plot(SV.loc[tst:tnd,['Slate_SV_outer']],label='5 mm')
plot([tst+pd.to_timedelta(ti, unit='h'),tst+pd.to_timedelta(ti, unit='h')],[0,27],'-',
↪c='grey',alpha=0.5)
plot([tst+pd.to_timedelta(ti, unit='h'),tst+pd.to_timedelta(ti, unit='h'),tst+pd.to_
↪timedelta(ti, unit='h')],SV.loc[tst+pd.to_timedelta(ti, unit='h'),['Slate_SV_outer',
↪'Slate_SV_mid','Slate_SV_inner']],'ro')
ylim(-2,30)
ylabel('Sap velocity (cm/h)')
legend(title='Sap velocity\nJune 14, 2017')

subplot(122)
r1=32.
[s2,s1,s0] = SV.loc[tst+pd.to_timedelta(ti, unit='h'),['Slate_SV_inner','Slate_SV_mid
↪','Slate_SV_outer']].values
dummyx=np.arange(50)/50.*sf.gebauer(r1)
plot(dummyx,sf.sap_volume(r1,s1,s2,True),label='Gebauer Weibull \n(scaled)')
plot(dummyx,(sf.gebauer_weibull(dummyx,a=2.14,b=3.08,c=1.27,d=2.)-0.2)*(24.),':',c=
↪'purple',label='alternative Weibull \n(scaled)')
fill_between(np.arange(2.4,sf.gebauer_act(r1),sf.gebauer(r1)/50.),sf.sap_volume(r1,s1,
↪s2,True)[(np.arange(50)/50.*sf.gebauer(r1) > 2.4) & (np.arange(50)/50.*sf.
↪gebauer(r1) <= sf.gebauer_act(r1))],label='Sap inner',alpha=0.5)
```

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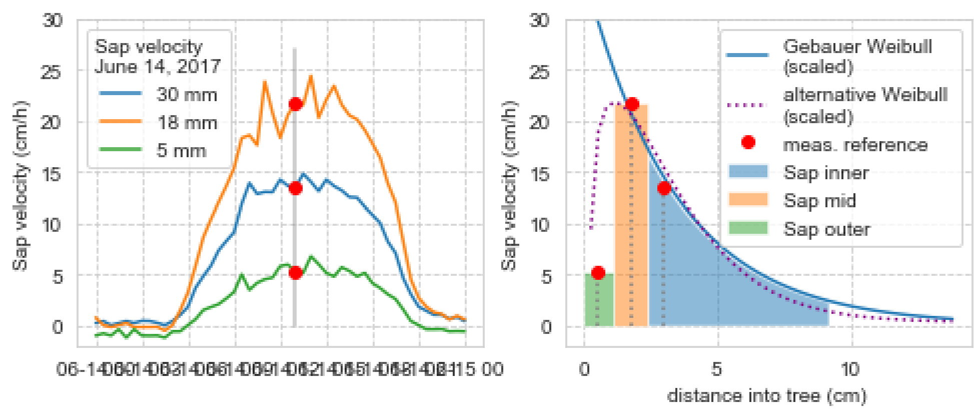
```
fill_between([1.1,2.4],[s1,s1],label='Sap mid',alpha=0.5)
fill_between([0.,1.1],[s0,s0],label='Sap outer',alpha=0.5)
plot([3.,3.],[0.,s2],':',c='grey')
plot(3.,s2,'ro',label='meas. reference')
plot([1.8,1.8],[0.,s1],':',c='grey')
plot(1.8,s1,'ro')
plot([0.5,0.5],[0.,s0],':',c='grey')
plot(0.5,s0,'ro')
ylim(-2,30)
legend()
ylabel('Sap velocity (cm/h)')
xlabel('distance into tree (cm)')
```

[15]:
```
Text(0.5, 0, 'distance into tree (cm)')
```



[16]:
```
dummydate = pd.date_range('2017-06-14',periods=5)
tst = pd.to_datetime('2017-06-14')
tnd = pd.to_datetime('2017-06-17')

r1=32. #tree radius
dummy = SV.loc[tst:tnd,['Slate_SV_inner','Slate_SV_mid','Slate_SV_outer']].copy()*np.
↪nan
for i in dummy.index:
    dummy.loc[i,'Slate_SV_inner'] = sf.sap_volume(r1,SV.loc[i,'Slate_SV_mid'],SV.
↪loc[i,'Slate_SV_inner'])
    dummy.loc[i,'Slate_SV_mid'] = SV.loc[i,'Slate_SV_mid']*sf.A_circ(r1,[1.1,2.4])
    dummy.loc[i,'Slate_SV_outer'] = SV.loc[i,'Slate_SV_outer']*sf.A_circ(r1,[0.,1.1])

figsize(5,3)
sf.stackplot(dummy/1000.)
xlim(tst,tnd)
#xlim('2017-06-17','2017-06-21')
legend(loc=1,ncol=3)
ylabel('Sap velocity (cm/h, stacked)\nSap flow (10 L/day, stacked)')
#ylim(-2,60)
for j in np.arange(4):
    tst = dummydate[j]
    tnd = dummydate[j+1]
    bar(tst+pd.Timedelta(hours=20),np.trapz(dummy.loc[tst:tnd,'Slate_SV_inner']/1000.,
↪dx=1)/20.,0.1,bottom=np.trapz(dummy.loc[tst:tnd,'Slate_SV_outer']/1000.,dx=1)/(20.
↪)+np.trapz(dummy.loc[tst:tnd,'Slate_SV_mid']/1000.,dx=1)/(20.),color='y')
```

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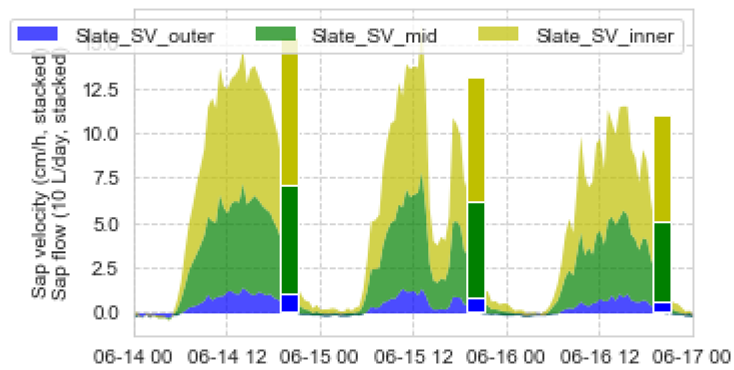
```
    bar(tst+pd.Timedelta(hours=20),np.trapz(dummy.loc[tst:tnd,'Slate_SV_mid']/1000.,
↪dx=1)/20.,0.1,bottom=np.trapz(dummy.loc[tst:tnd,'Slate_SV_outer']/1000.,dx=1)/(20.),
↪color='g')
    bar(tst+pd.Timedelta(hours=20),np.trapz(dummy.loc[tst:tnd,'Slate_SV_outer']/1000.,
↪dx=1)/20.,0.1,color='b')
```



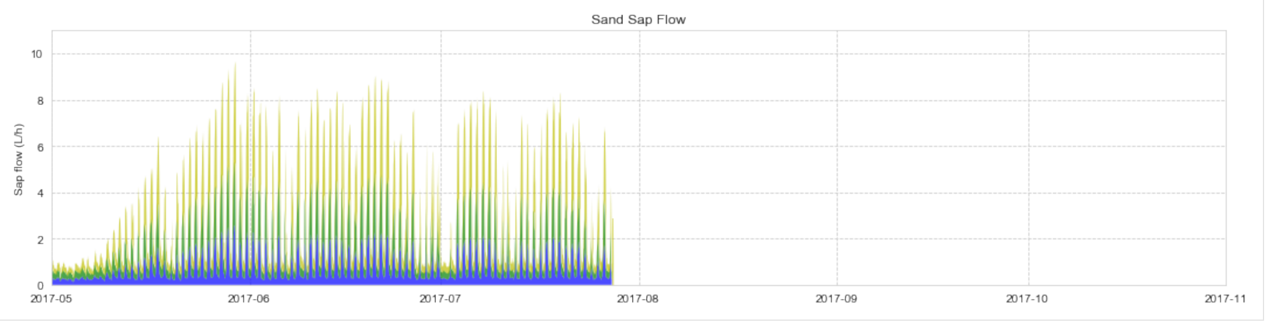
[17]:
```
#Sap flow calculation - Slate site
r1=24.
SlateSap = SV.loc[:,['Slate_SV_inner','Slate_SV_mid','Slate_SV_outer']].copy()*np.nan
for i in SlateSap.index:
    SlateSap.loc[i,'Slate_SV_inner'] = sf.sap_volume(r1,SV.loc[i,'Slate_SV_mid'],SV.
↪loc[i,'Slate_SV_inner'])
    SlateSap.loc[i,'Slate_SV_mid'] = SV.loc[i,'Slate_SV_mid']*sf.A_circ(r1,[1.1,2.4])
    SlateSap.loc[i,'Slate_SV_outer'] = SV.loc[i,'Slate_SV_outer']*sf.A_circ(r1,[0.,1.
↪1])
```

[18]:
```
#Sap flow calculation - Sand site
r1=32. #tree radius
SandSap = SV.loc[:,['Sand_SV_inner','Sand_SV_mid','Sand_SV_outer']].copy()*np.nan
for i in SandSap.index:
    SandSap.loc[i,'Sand_SV_inner'] = sf.sap_volume(r1,SV.loc[i,'Sand_SV_mid'],SV.
↪loc[i,'Sand_SV_inner'])
    SandSap.loc[i,'Sand_SV_mid'] = SV.loc[i,'Sand_SV_mid']*sf.A_circ(r1,[1.1,2.4])
    SandSap.loc[i,'Sand_SV_outer'] = SV.loc[i,'Sand_SV_outer']*sf.A_circ(r1,[0.,1.1])

SandSap.loc['2017-07-28':,'Sand_SV_inner'] = np.nan
```

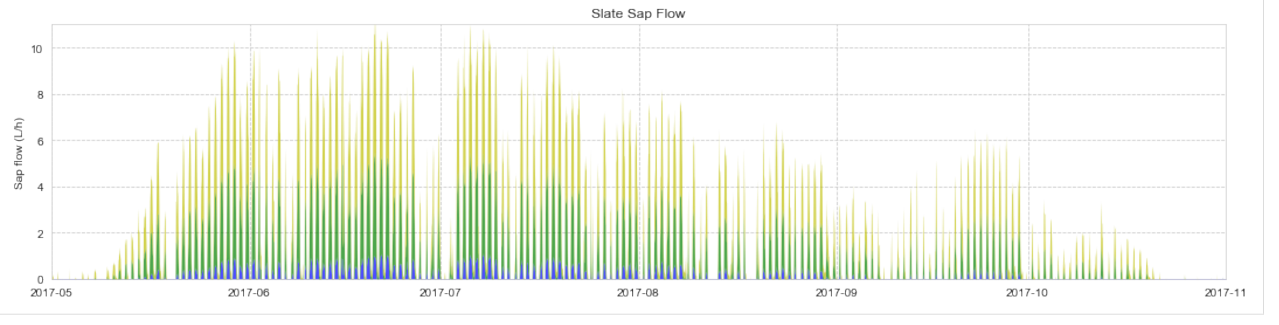
[20]:
```
figsize(18,4)
sf.stackplot(SandSap.resample('1h').mean()/1000.)
ylabel('Sap flow (L/h)')
ylim(0,11)
title('Sand Sap Flow')
xlim('2017-05-01','2017-11-01')
```

[20]:
```
(736450.0, 736634.0)
```



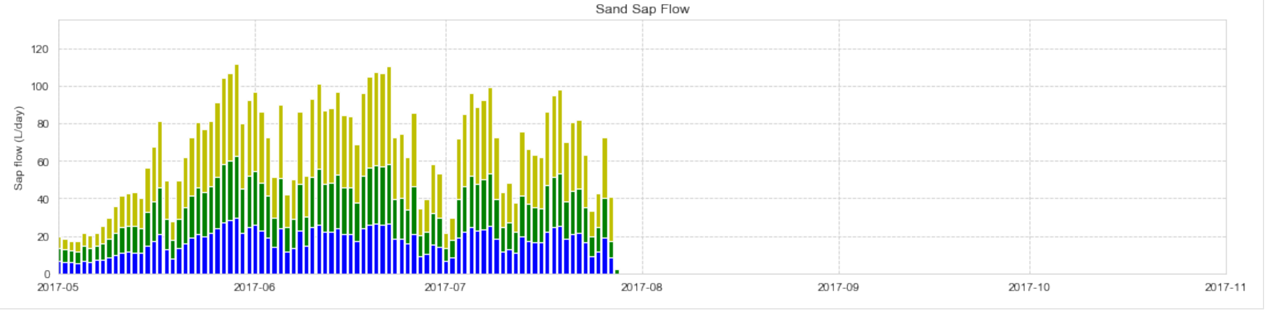
[21]:
```
figsize(18,4)
sf.stackplot(SlateSap.resample('1h').mean()/1000.)
ylabel('Sap flow (L/h)')
ylim(0,11)
title('Slate Sap Flow')
xlim('2017-05-01','2017-11-01')
```

[21]: (736450.0, 736634.0)



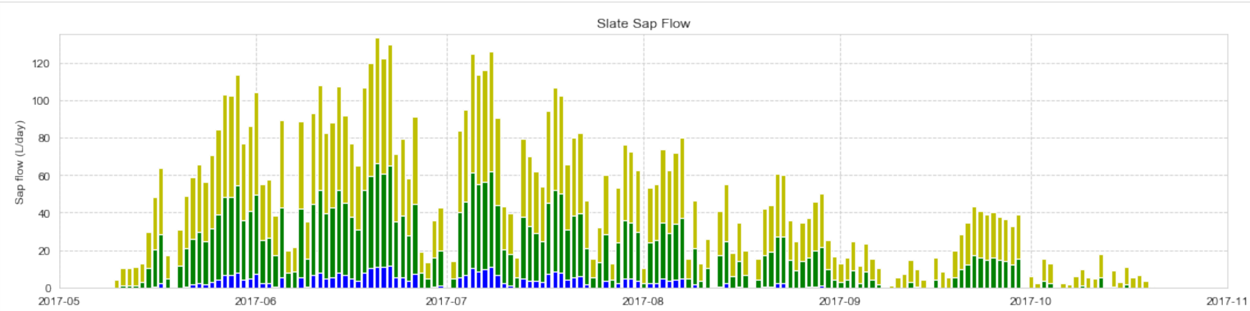
[22]:
```
figsize(18,4)
SandSap_d = SandSap.resample('1h').mean().resample('1D').sum()/1000. #daily sap␣
↪volume in L
for i in SandSap_d.index:
    bar(i,SandSap_d.loc[i,'Sand_SV_inner'],0.8,bottom=SandSap_d.loc[i,'Sand_SV_outer
↪']+SandSap_d.loc[i,'Sand_SV_mid'],color='y')
    bar(i,SandSap_d.loc[i,'Sand_SV_mid'],0.8,bottom=SandSap_d.loc[i,'Sand_SV_outer'],
↪color='g')
    bar(i,SandSap_d.loc[i,'Sand_SV_outer'],0.8,color='b')
xlim('2017-05-01','2017-11-01')
ylim(0,135)
ylabel('Sap flow (L/day)')
title('Sand Sap Flow')
```

[22]: Text(0.5, 1.0, 'Sand Sap Flow')



```
[23]: SlateSap_d = SlateSap.resample('1h').mean().resample('1D').sum()/1000. #daily sap␣
↪volume in L
for i in SlateSap_d.index:
    bar(i,SlateSap_d.loc[i,'Slate_SV_inner'],0.8,bottom=SlateSap_d.loc[i,'Slate_SV_
↪outer']+SlateSap_d.loc[i,'Slate_SV_mid'],color='y')
    bar(i,SlateSap_d.loc[i,'Slate_SV_mid'],0.8,bottom=SlateSap_d.loc[i,'Slate_SV_outer
↪'],color='g')
    bar(i,SlateSap_d.loc[i,'Slate_SV_outer'],0.8,color='b')
xlim('2017-05-01','2017-11-01')
ylim(0,135)
ylabel('Sap flow (L/day)')
title('Slate Sap Flow')
```

```
[23]: Text(0.5, 1.0, 'Slate Sap Flow')
```




```
[ ]:
```

RWU and sap reference time series plot

Functions calling the RWU detection algorithm (fRWU) and building a result array are included in rootwater

Call RWU detection for soil moisture data at both sites

```
[24]: [Sand_rwu,Sand_rwunn,Sand_nse] = rw.dfRWUc(SM.loc[:,SM.columns[:12]])
```

```
/Users/cojack/miniconda3/lib/python3.7/site-packages/numpy/core/fromnumeric.py:3118:␣
↪RuntimeWarning: Mean of empty slice.
  out=out, **kwargs)
```

```
[25]: [Slate_rwu,Slate_rwunn,Slate_nse] = rw.dfRWUc(SM.loc[:,SM.columns[12:]])
```

```
[ ]:
```

```
[26]: figsize(15,6)
fig, ax1 = plt.subplots(1,1)
ax1.set_ylim([-140,140])
ax1.set_ylabel('         RWU (mm/day)                        Sap-Flow (L/day)')

ax2 = ax1.twinx()

for i in SlateSap_d.index:
    x=np.max([0.,SlateSap_d.loc[i,'Slate_SV_inner']])
    y=np.max([0.,SlateSap_d.loc[i,'Slate_SV_mid']])
    z=np.max([0.,SlateSap_d.loc[i,'Slate_SV_outer']])
```

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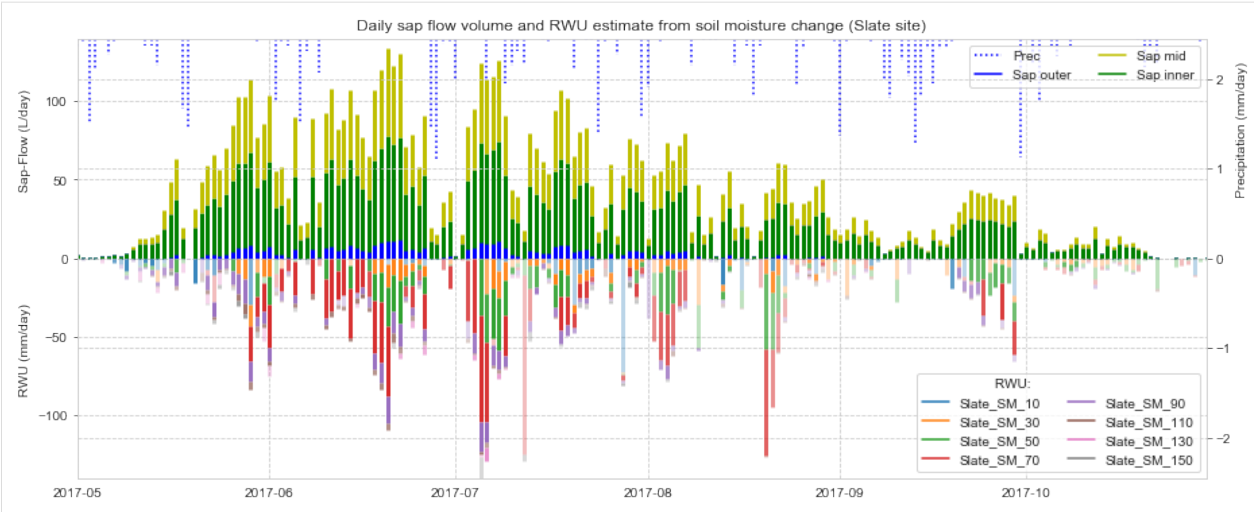
```
    ax1.plot([i,i],[0,x],'b-',label='',linewidth=3,solid_capstyle='butt')
    ax1.plot([i,i],[z,x+z],'g-',label='',linewidth=3,solid_capstyle='butt')
    ax1.plot([i,i],[x+z,z+y+x],'y-',label='',linewidth=3,solid_capstyle='butt')

    ax1.plot([i,i],[140,(140-(prec_rad.loc[i:i+pd.Timedelta(hours=24),'Slate_Precip'].
↪sum())*4.)],c='blue',linestyle=':')

    count=0
    for l in np.arange(8):
        rwud=Slate_rwu.loc[i,Slate_rwu.columns[l]]

        rwuc=np.min([np.max([0.3,Slate_nse.loc[i,Slate_rwu.columns[l]]]),1])
        if np.isnan(rwuc):
            rwuc=0.1
        ax2.plot([i,i],[count,count-rwud],c=tableau10[l],linestyle='-',linewidth=3,
↪solid_capstyle='butt',alpha=rwuc)
        if isnan(rwud)==False:
            count=count-rwud

###legend
for l in np.arange(8):
    ax2.plot(i,0,c=tableau10[l],label=Slate_rwu.columns[l])
ax1.plot([i],[0],c='blue',linestyle=':',label='Prec')

ax1.plot([i],[0],'b-',label='Sap outer')
ax1.plot([i],[0],'y-',label='Sap mid')
ax1.plot([i],[0],'g-',label='Sap inner')


ax1.legend(loc=1,ncol=2)
ax2.legend(loc=4,ncol=2,title='RWU:                              ')

ax2.set_ylim([-2.45,2.45])
ax2.set_ylabel('                                                                        ␣
↪ Precipitation (mm/day) ')

ax2.set_xlim(['2017-05-01','2017-10-30'])
title('Daily sap flow volume and RWU estimate from soil moisture change (Slate site)')
#fig.savefig('slate_summary_nse.pdf',bbox_inches='tight')
```

```
[26]: Text(0.5, 1.0, 'Daily sap flow volume and RWU estimate from soil moisture change␣
↪(Slate site)')
```



[45]:

```python
figsize(15,6)
fig, ax1 = plt.subplots(1,1)
ax1.set_ylim([-140,140])
ax1.set_ylabel('         RWU (mm/day)                                   Sap-Flow (L/day)')
ax2 = ax1.twinx()


for i in SandSap_d.index:
    x=np.max([0.,SandSap_d.loc[i,'Sand_SV_inner']])
    y=np.max([0.,SandSap_d.loc[i,'Sand_SV_mid']])
    z=np.max([0.,SandSap_d.loc[i,'Sand_SV_outer']])

    ax1.plot([i,i],[0,z],'b-',label='',linewidth=3,solid_capstyle='butt')
    ax1.plot([i,i],[z,x+z],'g-',label='',linewidth=3,solid_capstyle='butt')
    ax1.plot([i,i],[x+z,z+y+x],'y-',label='',linewidth=3,solid_capstyle='butt')

    ax1.plot([i,i],[140,(140-(prec_rad.loc[i:i+pd.Timedelta(hours=24),'Sand_Precip'].
↪sum())*4.)],c='blue',linestyle=':')

    count=0
    for l in np.arange(10):
        rwud=Sand_rwu.loc[i,Sand_rwu.columns[l]]
        #rwud=SaDrwunn.loc[i,SaD.columns[l]]
        rwuc=np.min([np.max([0.3,Sand_nse.loc[i,Sand_rwu.columns[l]]]),1])
        if np.isnan(rwuc):
            rwuc=0.1
        ax2.plot([i,i],[count,count-rwud],c=tableau10[l],linestyle='-',linewidth=3,
↪solid_capstyle='butt',alpha=rwuc)
        if isnan(rwud)==False:
            count=count-rwud

###legende
for l in np.arange(10):
    ax2.plot(i,0,c=tableau10[l],label=Sand_rwu.columns[l])
ax1.plot([i],[0],c='blue',linestyle=':',label='Prec')

ax1.plot([i],[0],'b-',label='Sap outer')
ax1.plot([i],[0],'y-',label='Sap mid')
ax1.plot([i],[0],'g-',label='Sap inner')
```

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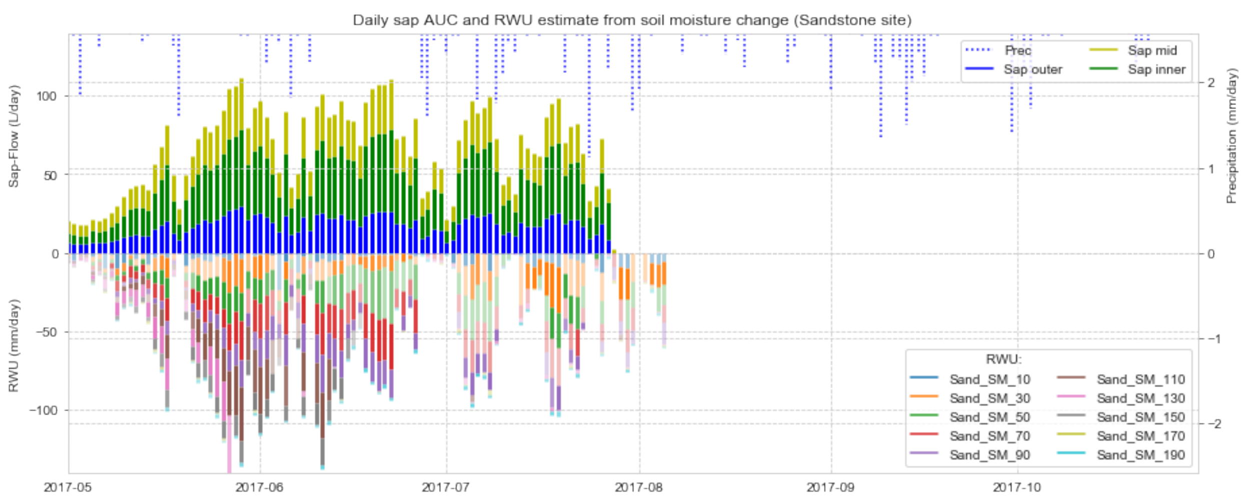
```
ax2.set_ylim([-2.58,2.58])

ax1.legend(loc=1,ncol=2)
ax2.legend(loc=4,ncol=2,title='RWU:                        ')

ax2.set_xlim(['2017-05-01','2017-10-30'])
ax1.set_xlim('2017-05-01','2017-10-30')
ax2.set_ylabel('                                                                    ␣
↪Precipitation (mm/day)   ')

title('Daily sap AUC and RWU estimate from soil moisture change (Sandstone site)')
#savefig('sand_summary_nse.pdf',bbox_inches='tight')
```

[45]:
```
Text(0.5, 1.0, 'Daily sap AUC and RWU estimate from soil moisture change (Sandstone␣
↪site)')
```



[27]:
```
Slatecom = pd.concat([Slate_rwu.sum(axis=1),Slate_rwunn.sum(axis=1),SlateSap_d.
↪sum(axis=1)],axis=1)
Slatecom.columns = ['rwu','rwu_nonight','sap']

Sandcom = pd.concat([Sand_rwu.sum(axis=1),Sand_rwunn.sum(axis=1),SandSap_d.
↪sum(axis=1)],axis=1)
Sandcom.columns = ['rwu','rwu_nonight','sap']

SWcomc=Slatecom.loc['2017-05-01':'2017-10-30']
SWcomc=SWcomc[SWcomc>0].dropna()

SaDcomc=Sandcom.loc['2017-05-01':'2017-07-28']
SaDcomc=SaDcomc[SaDcomc>0].dropna()
```

[28]:
```
def linfit(df,c1='rwu',c2='sap',zeroi=True,pltx=True,applymod=False):
    # linear regression function returning all results (result,x_pred,y_pred,lower,
↪upper,conf) as required for plotting
    import statsmodels.formula.api as smf
```

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```
    from statsmodels.sandbox.regression.predstd import wls_prediction_std
    #import statsmodels.api as sm
    from scipy import stats
    df = df.sort_values(by=c2)[[c1,c2]].reset_index()
    if zeroi: #zero intercept
        result = smf.ols(formula=c1+' ~ '+c2+' - 1', data=df).fit()
    else:
        result = smf.ols(formula=c1+' ~ '+c2, data=df).fit()
    y_hat = result.predict(df[c2])
    y_err = df[c1].values - y_hat
    s_err = np.sum(np.power(y_err, 2))
    mean_x = df[c2].mean()

    #confidence intervals
    n = len(df)
    x_pred = np.linspace(df[c2].min(), df[c2].max(), 50)
    y_pred = result.predict(pd.Series(x_pred,name=c2))
    dof = n - result.df_model - 1
    t = stats.t.ppf(1-0.05, df=dof)
    conf = t * np.sqrt((s_err/(n-2))*(1.0/n + (np.power((x_pred-mean_x),2) / ((np.
↪sum(np.power(x_pred,2))) - n*(np.power(mean_x,2))))))
    upper = y_pred + abs(conf)
    lower = y_pred - abs(conf)

    #prediction interval
    #sdev, lower2, upper2 = wls_prediction_std(result, exog=sm.add_constant(x_pred),␣
↪alpha=0.05)

    if pltx & applymod:
        ax = plt.subplot(gs[0, 0])
        ax.scatter(df[c2], df[c1]/result.params[0], alpha=0.5)
        ax.plot(x_pred, y_pred/result.params[0], '-', linewidth=2)
        ax.fill_between(x_pred, lower/result.params[0], upper/result.params[0], color=
↪'#888888', alpha=0.4)
        #ax.fill_between(x_pred, lower2, uppe2, color='#888888', alpha=0.1)

        return result
    elif pltx & ~applymod:
        ax = plt.subplot(gs[0, 0])
        ax.scatter(df[c2], df[c1], alpha=0.5)
        ax.plot(x_pred, y_pred, '-', linewidth=2)
        ax.fill_between(x_pred, lower, upper, color='#888888', alpha=0.4)
        return result
    else:
        return result,x_pred,y_pred,lower,upper,conf
```

[29]:

```
fig = plt.figure(figsize=(8,4))
import matplotlib.gridspec as gridspec
gs = gridspec.GridSpec(1, 2)

ax = plt.subplot(gs[0, 0])

result,x_pred,y_pred,lower,upper,conf = linfit(SaDcomc,c1='rwu_nonight',c2='sap',
↪pltx=False)
#sc2 = ax.scatter(SaDcomc.sap,SaDcomc.rwu_nonight/result.params[0],c='skyblue',marker=
↪'.')
```

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```
sc2 = ax.scatter(SaDcomc.sap,SaDcomc.rwu_nonight,c='skyblue',marker='.')
result2=result

result,x_pred,y_pred,lower,upper,conf = linfit(SaDcomc,c1='rwu',c2='sap',pltx=False)
#ax.fill_between(np.sort(SaDcomc.sap.values),result.get_prediction().summary_
↪frame(alpha=0.05).obs_ci_upper/result.params[0],result.get_prediction().summary_
↪frame(alpha=0.05).obs_ci_lower/result.params[0],color='#888888',alpha=0.1)
#ax.fill_between(np.sort(SaDcomc.sap.values),result.get_prediction().summary_
↪frame(alpha=0.05).mean_ci_upper/result.params[0],result.get_prediction().summary_
↪frame(alpha=0.05).mean_ci_lower/result.params[0],color='#888888',alpha=0.3)
#sc = ax.scatter(SaDcomc.sap,SaDcomc.rwu/result.params[0],c=SaDcomc.index.dayofyear,
↪cmap='plasma',vmin=100,vmax=270)
ax.fill_between(np.sort(SaDcomc.sap.values),result.get_prediction().summary_
↪frame(alpha=0.05).obs_ci_upper,result.get_prediction().summary_frame(alpha=0.05).
↪obs_ci_lower,color='#888888',alpha=0.1)
ax.fill_between(np.sort(SaDcomc.sap.values),result.get_prediction().summary_
↪frame(alpha=0.05).mean_ci_upper,result.get_prediction().summary_frame(alpha=0.05).
↪mean_ci_lower,color='#888888',alpha=0.3)
sc = ax.scatter(SaDcomc.sap,SaDcomc.rwu,c=SaDcomc.index.dayofyear,cmap='plasma',
↪vmin=100,vmax=270)


ax.plot(x_pred,y_pred,'r:',label='R² = %s, \nA = %s m², \nr = %s m'%(round(result.
↪rsquared,3),round(1./result.params[0],1),round(np.sqrt((1./result.params[0])/np.pi),
↪1)))
ax.plot([SaDcomc.sap.min(),SaDcomc.sap.max()],[result2.predict().min(),result2.
↪predict().max()],':',c='skyblue',lw=2,label='no nocturnal \ncorrection: \nR² = %s,␣
↪\nA = %s m², \nr = %s m'%(round(result2.rsquared,3),round(1./result2.params[0],1),
↪round(np.sqrt((1./result2.params[0])/np.pi),1)))


result1=result



ax.set_xlim(0,128)
#ax.set_ylim(0,128)
ax.set_ylim(-0.4,3.5)
ax.set_ylabel('est. RWU (mm/day)')
ax.set_xlabel('Sap (L/day)')
#ax.set_title('Sandstone Site')
ax.legend(loc=2)

ax = plt.subplot(gs[0, 1])

result,x_pred,y_pred,lower,upper,conf = linfit(SWcomc,c1='rwu_nonight',c2='sap',
↪pltx=False)
#sc2 = ax.scatter(SWcomc.sap,SWcomc.rwu_nonight/result.params[0],c='skyblue',marker='.
↪')
sc2 = ax.scatter(SWcomc.sap,SWcomc.rwu_nonight,c='skyblue',marker='.')
result4=result

result,x_pred,y_pred,lower,upper,conf = linfit(SWcomc,c1='rwu',c2='sap',pltx=False)
#ax.fill_between(np.sort(SWcomc.sap.values),result.get_prediction().summary_
↪frame(alpha=0.05).obs_ci_upper/result.params[0],result.get_prediction().summary_
↪frame(alpha=0.05).obs_ci_lower/result.params[0],color='#888888',alpha=0.1)
#ax.fill_between(np.sort(SWcomc.sap.values),result.get_prediction().summary_
↪frame(alpha=0.05).mean_ci_upper/result.params[0],result.get_prediction().summary_
↪frame(alpha=0.05).mean_ci_lower/result.params[0],color='#888888',alpha=0.3)
```

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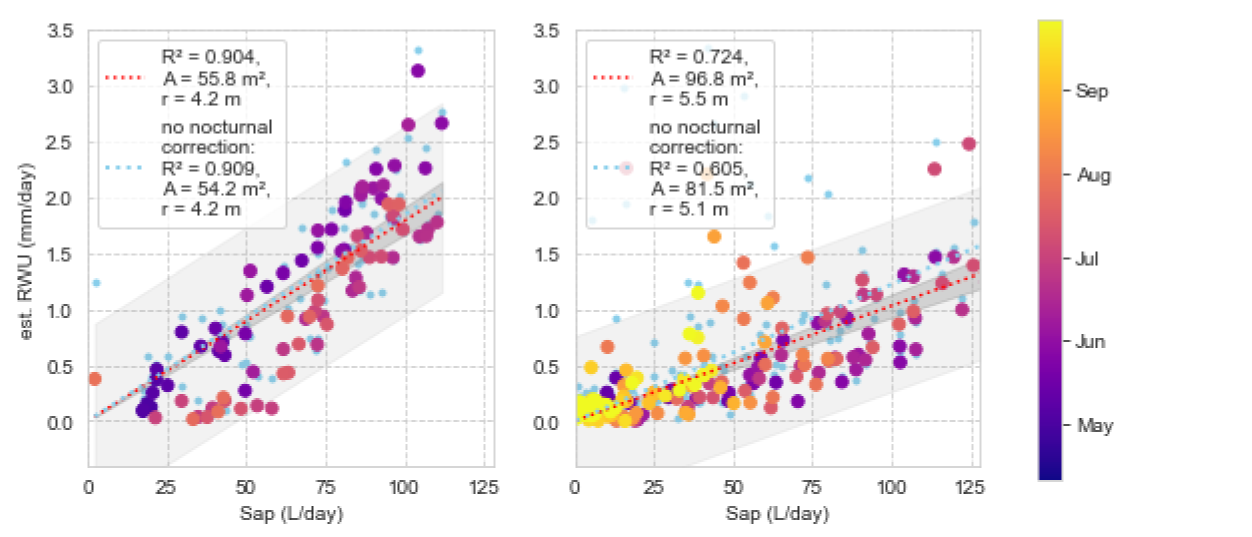
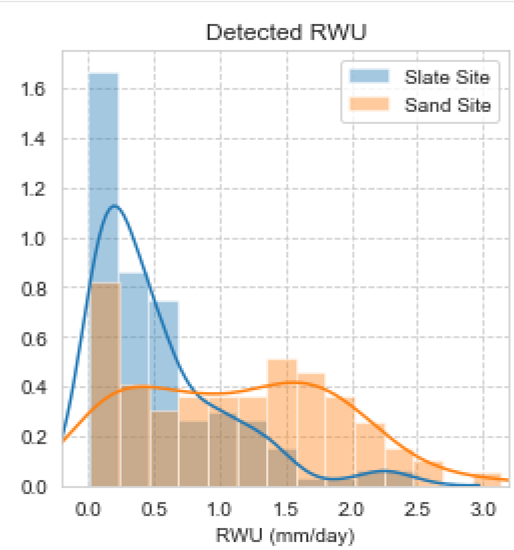
```
#ax.plot([SWcomc.sap.min(),SWcomc.sap.max()],[result.predict().min()/result.params[0],
↪result.predict().max()/result.params[0]],'r:',label='R$^2$ = %s, \nA = %s m$^2$, \nr = %s m
↪'%(round(result.rsquared,3),round(1/result.params[0],1),round(np.sqrt((1./result.
↪params[0])/np.pi),1)))
#ax.plot([SWcomc.sap.min(),SWcomc.sap.max()],[result4.predict().min()/result4.
↪params[0],result4.predict().max()/result4.params[0]],':',c='skyblue',lw=2,label='no␣
↪nocturnal \ncorrection: \nR$^2$ = %s, \nA = %s m$^2$, \nr = %s m'%(round(result4.rsquared,
↪3),round(1./result4.params[0],1),round(np.sqrt((1./result4.params[0])/np.pi),1)))

#sc = ax.scatter(SWcomc.sap,SWcomc.rwu/result.params[0],c=SWcomc.index.dayofyear,cmap=
↪'plasma',vmin=100,vmax=270)
ax.fill_between(np.sort(SWcomc.sap.values),result.get_prediction().summary_
↪frame(alpha=0.05).obs_ci_upper,result.get_prediction().summary_frame(alpha=0.05).
↪obs_ci_lower,color='#888888',alpha=0.1)
ax.fill_between(np.sort(SWcomc.sap.values),result.get_prediction().summary_
↪frame(alpha=0.05).mean_ci_upper,result.get_prediction().summary_frame(alpha=0.05).
↪mean_ci_lower,color='#888888',alpha=0.3)

ax.plot([SWcomc.sap.min(),SWcomc.sap.max()],[result.predict().min(),result.predict().
↪max()],'r:',label='R$^2$ = %s, \nA = %s m$^2$, \nr = %s m'%(round(result.rsquared,3),
↪round(1/result.params[0],1),round(np.sqrt((1./result.params[0])/np.pi),1)))
ax.plot([SWcomc.sap.min(),SWcomc.sap.max()],[result4.predict().min(),result4.
↪predict().max()],':',c='skyblue',lw=2,label='no nocturnal \ncorrection: \nR$^2$ = %s,␣
↪\nA = %s m$^2$, \nr = %s m'%(round(result4.rsquared,3),round(1./result4.params[0],1),
↪round(np.sqrt((1./result4.params[0])/np.pi),1)))


sc = ax.scatter(SWcomc.sap,SWcomc.rwu,c=SWcomc.index.dayofyear,cmap='plasma',vmin=100,
↪vmax=270)


result3=result


ax.set_xlim(0,128)
ax.set_ylim(-0.4,3.5)
ax.set_xlabel('Sap (L/day)')
#ax.set_title('Slate Site')
ax.legend(loc=2)

cb_ax = fig.add_axes([0.95, 0.1, 0.02, 0.8])
cbar = fig.colorbar(sc, cax=cb_ax,label='',ticks=(121,152,182,213,244))
cbar.set_ticklabels(['May','Jun','Jul','Aug','Sep'])

#savefig('RWU_reg2.pdf',bbox_inches='tight')
```



RWU and sap flow evaluation

[30]:
```
figsize(4,4)
sns.distplot((SWcomc.rwu),bins=11,label='Slate Site')
sns.distplot((SaDcomc.rwu),bins=14,label='Sand Site')
xlim(-0.2,3.2)
xlabel('RWU (mm/day)')
legend()
title('Detected RWU')
```

[30]:
```
Text(0.5, 1.0, 'Detected RWU')
```



[31]:
```
figsize(4,4)
sns.distplot((SWcomc.sap),bins=8,label='Slate Site')
sns.distplot((SaDcomc.sap),bins=6,label='Sand Site')
xlim(-5,150)
xlabel('Sap (L/day)')
```

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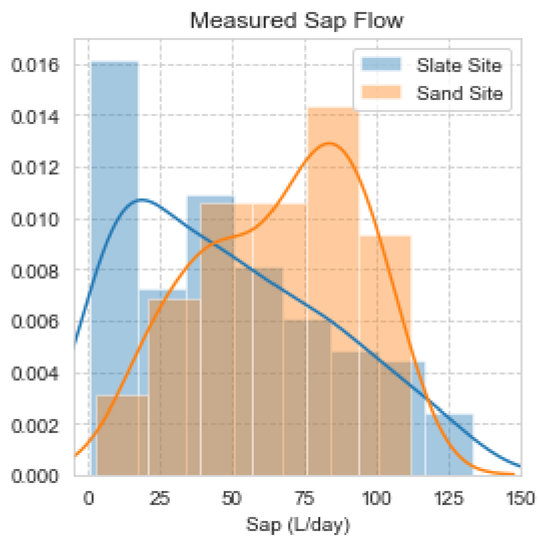
```
legend()
title('Measured Sap Flow')
```

[31]:
```
Text(0.5, 1.0, 'Measured Sap Flow')
```



[33]:
```
figsize(13,4.5)

ax1 = plt.subplot(122)
#Slate
ax1.bar(Slate_rwu.columns,(~np.isnan(Slate_rwu.loc[SWcomc.index[0]:SWcomc.index[-
↪1]])).astype(int).sum(axis=0),label='all detected',facecolor='steelblue')
ax1.bar(Slate_rwu.columns,((Slate_nse.loc[(~np.isnan(Slate_rwu.loc[SWcomc.index[0]:
↪SWcomc.index[-1]])).index]>0.25) & (~np.isnan(Slate_rwu.loc[SWcomc.index[0]:SWcomc.
↪index[-1]]))).astype(int).sum(axis=0),width=0.45,alpha=1,facecolor='lightsteelblue',
↪label='KGE(step) > 0.25')
ax1.bar(Slate_rwu.columns,((Slate_nse.loc[(~np.isnan(Slate_rwu.loc[SWcomc.index[0]:
↪SWcomc.index[-1]])).index]>0.5) & (~np.isnan(Slate_rwu.loc[SWcomc.index[0]:SWcomc.
↪index[-1]]))).astype(int).sum(axis=0),width=0.45,alpha=1,facecolor='lightblue',
↪label='KGE(step) > 0.5')
ax1.bar(Slate_rwu.columns,((Slate_nse.loc[(~np.isnan(Slate_rwu.loc[SWcomc.index[0]:
↪SWcomc.index[-1]])).index]>0.75) & (~np.isnan(Slate_rwu.loc[SWcomc.index[0]:SWcomc.
↪index[-1]]))).astype(int).sum(axis=0),width=0.45,alpha=1,facecolor='lightskyblue',
↪label='KGE(step) > 0.75')
ax1.text(-0.5,93.5,'(B) Slate, \n       n='+str((SWcomc['sap']>0.1).astype(int).sum()),
↪fontsize=14)
ax1.bar(0,0,facecolor='orangered',width=0.1,label='total $\Sigma$ RWU')
xlabel('depth layer (cm)')
ax1.legend(loc=1)

ax2 = ax1.twinx()
ax2.bar(np.arange(len(Slate_rwu.columns))+0.4,Slate_rwu.loc[SWcomc.index[0]:SWcomc.
↪index[-1]].sum(axis=0),facecolor='orangered',width=0.1)
ax2.set_ylim(0,27.5)
ax1.set_ylim(0,110)
ax1.set_xlim(-0.8,11.8)

ax2.set_ylabel('$\Sigma$ detected RWU in layer (mm)')
```

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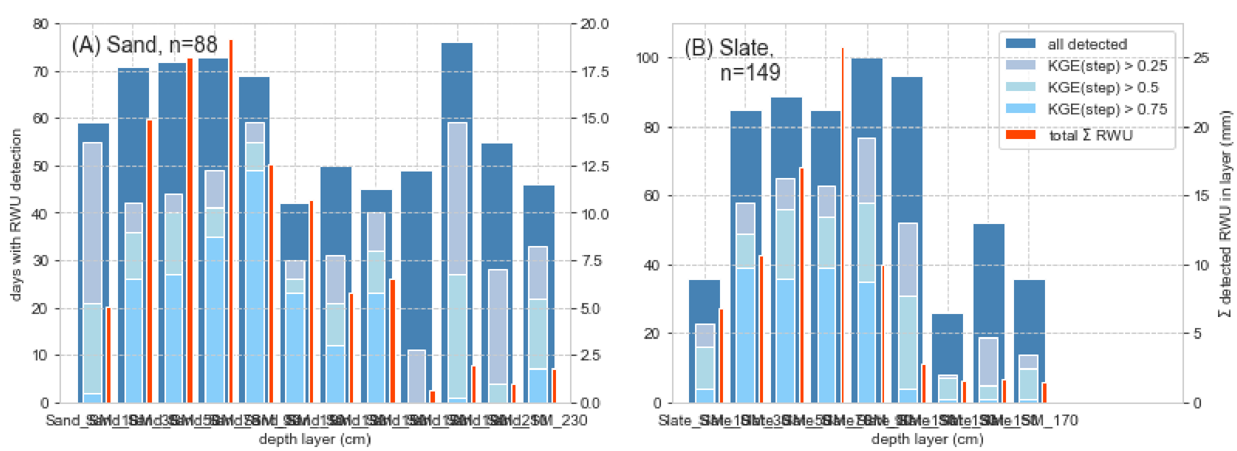
```
ax1 = plt.subplot(121)
#Sand
ax1.bar(Sand_rwu.columns,(~np.isnan(Sand_rwu.loc[SaDcomc.index[0]:SaDcomc.index[-
↪1]])).astype(int).sum(axis=0),facecolor='steelblue')
ax1.bar(Sand_rwu.columns,((Sand_nse.loc[(~np.isnan(Sand_rwu.loc[SaDcomc.index[0]:
↪SaDcomc.index[-1]])).index]>0.25) & (~np.isnan(Sand_rwu.loc[SaDcomc.index[0]:
↪SaDcomc.index[-1]]))).astype(int).sum(axis=0),width=0.45,alpha=1,facecolor=
↪'lightsteelblue',label='KGE > 0.25')
ax1.bar(Sand_rwu.columns,((Sand_nse.loc[(~np.isnan(Sand_rwu.loc[SaDcomc.index[0]:
↪SaDcomc.index[-1]])).index]>0.5) & (~np.isnan(Sand_rwu.loc[SaDcomc.index[0]:SaDcomc.
↪index[-1]]))).astype(int).sum(axis=0),width=0.45,alpha=1,facecolor='lightblue',
↪label='KGE > 0.5')
ax1.bar(Sand_rwu.columns,((Sand_nse.loc[(~np.isnan(Sand_rwu.loc[SaDcomc.index[0]:
↪SaDcomc.index[-1]])).index]>0.75) & (~np.isnan(Sand_rwu.loc[SaDcomc.index[0]:
↪SaDcomc.index[-1]]))).astype(int).sum(axis=0),width=0.45,alpha=1,facecolor=
↪'lightskyblue',label='KGE > 0.75')
ax1.text(-0.5,73.9,'(A) Sand, n='+str((SaDcomc['sap']>0.1).astype(int).sum()),
↪fontsize=14)
ax1.bar(0,0,facecolor='orangered',width=0.1,label='total $\Sigma$ RWU')
xlabel('depth layer (cm)')
ax1.set_ylabel('days with RWU detection')

ax2 = ax1.twinx()
ax2.bar(np.arange(len(Sand_rwu.columns))+0.4,Sand_rwu.loc[SaDcomc.index[0]:SaDcomc.
↪index[-1]].sum(axis=0),facecolor='orangered',width=0.13)
ax1.set_ylim(0,80)
ax2.set_ylim(0,20)
ax1.set_xlim(-0.8,11.8)

#savefig('RWUdetect_new.pdf',bbox_inches='tight')
```

[33]: (-0.8, 11.8)




```
[35]: h = sns.jointplot((Slate_nse[Slate_rwu>0.05]).values[~np.isnan((Slate_nse[Slate_rwu>0.
↪05]).values)],np.log((Slate_rwu[Slate_rwu>0.05]).values[~np.isnan((Slate_rwu[Slate_
↪rwu>0.05]).values)]),marginal_kws=dict(bins=15))
h.set_axis_labels('RWU step NSE','log(RWU)')
title('(B)\nSlate',fontsize=16)
```

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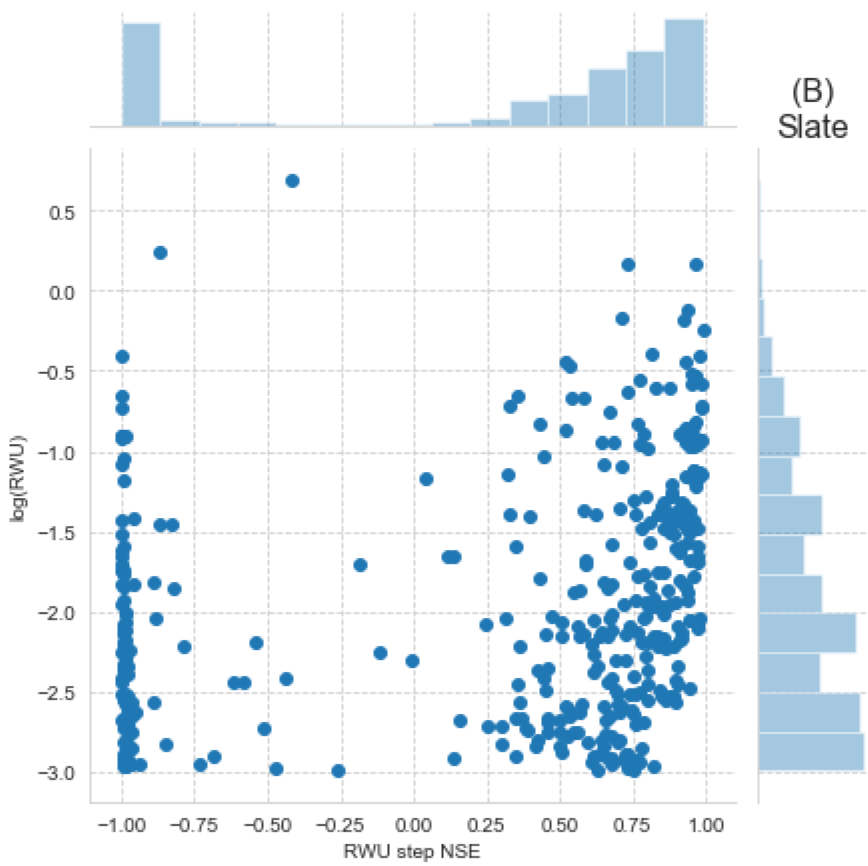
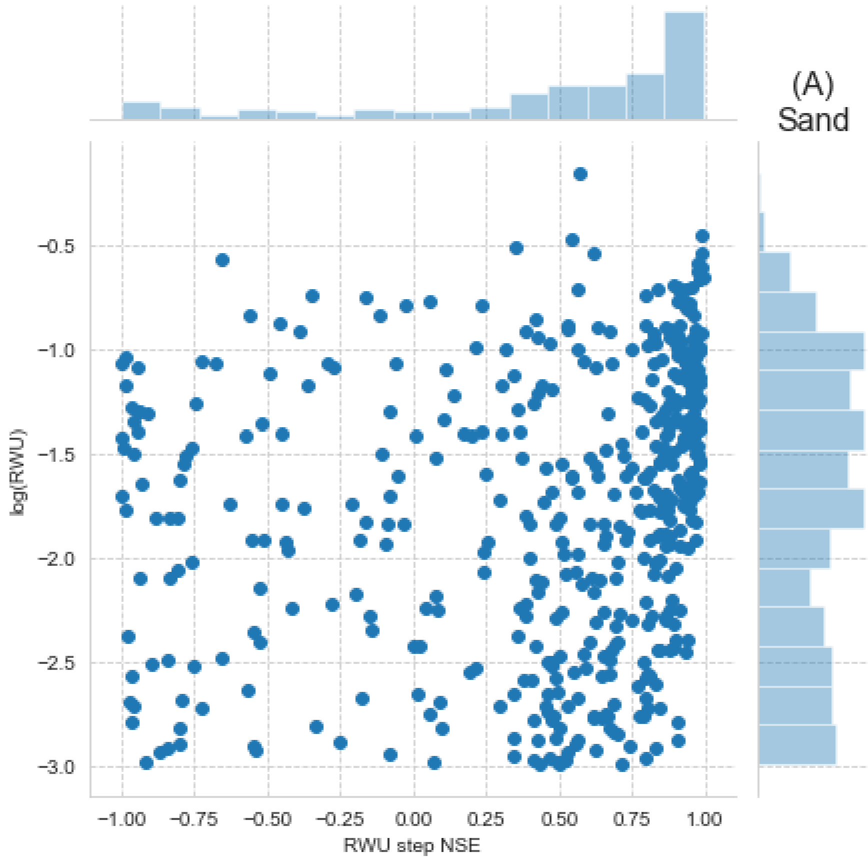
```
#savefig('RWU_SWnse.pdf',bbox_inches='tight')
```

[35]:
```
Text(0.5, 1, '(B)\nSlate')
```



[36]:
```
h = sns.jointplot((Sand_nse[Sand_rwu>0.05]).values[~np.isnan((Sand_nse[Sand_rwu>0.
↪05]).values)],np.log((Sand_rwu[Sand_rwu>0.05]).values[~np.isnan((Sand_rwu[Sand_rwu>
↪0.05]).values)]),marginal_kws=dict(bins=15))
h.set_axis_labels('RWU step NSE','log(RWU)')
title('(A)\nSand',fontsize=16)
#savefig('RWU_SaDnse.pdf',bbox_inches='tight')
```

[36]:
```
Text(0.5, 1, '(A)\nSand')
```



Correlation of RWU and Sap time series

[37]:
```
#rolling functions of Spearman rho and KGE
def spear_roll(ts,win=21,rf1='rwu',rf2='sapAUC'):
    if len(ts.columns)==2:
        rf1,rf2 = ts.columns

    if win == 0:
        xs = ts[rf1].copy()*0
        xs += sp.stats.mstats.spearmanr(ts.loc[:,rf2],ts.loc[:,rf1])[0]
    else:
        xs = ts[rf1].copy()*np.nan
        win2 = int(np.floor(win/2)) #use center of moving window
        for i in np.arange(len(ts))[win2:-(win2+1)]:
            xs.loc[ts.index[i]] = sp.stats.mstats.spearmanr(ts.loc[ts.index[i-win2]:
↪ts.index[i+win2],rf2],ts.loc[ts.index[i-win2]:ts.index[i+win2],rf1])[0]
    return xs

def kge_roll(ts,win=21,rf1='rwu',rf2='sapAUC',linreg=False):
    if len(ts.columns)==2:
        rf1,rf2 = ts.columns

    if win==0:
        xs = ts[rf1].copy()*0
        if linreg:
```

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```
            result = smf.ols(formula=rf1+' ~ '+rf2+' -1', data=ts).fit()
            xs += he.kge(ts.loc[:,rf1].values,(ts.loc[:,rf2]*result.params[0]).
↪values)[0]
        else:
            xs += he.kge(ts.loc[:,rf1].values,ts.loc[:,rf2].values)[0]
    else:
        xs = ts[rf1].copy()*np.nan
        win2 = int(np.floor(win/2)) #use center of moving window
        for i in np.arange(len(ts))[win2:-(win2+1)]:
            if linreg:
                result = smf.ols(formula=rf1+' ~ '+rf2+' -1', data=ts.loc[ts.index[i-
↪win2]:ts.index[i+win2]]).fit()
                xs.loc[ts.index[i]] = he.kge(ts.loc[ts.index[i-win2]:ts.index[i+win2],
↪rf1].values,(ts.loc[ts.index[i-win2]:ts.index[i+win2],rf2]*result.params[0]).
↪values)[0]
            else:
                xs.loc[ts.index[i]] = he.kge(ts.loc[ts.index[i-win2]:ts.index[i+win2],
↪rf1].values,ts.loc[ts.index[i-win2]:ts.index[i+win2],rf2].values)[0]
    return xs
```

[38]:

```
#convert RWU to volume flux by assuming a cylindrical rhizosphere and water balance␣
↪with sap flow
result = smf.ols(formula='rwu ~ sap - 1', data=SWcomc).fit()
SWcomc['rwu_V'] = SWcomc.rwu/result.params[0]

result = smf.ols(formula='rwu ~ sap - 1', data=SaDcomc).fit()
SaDcomc['rwu_V'] = SaDcomc.rwu/result.params[0]
```

[39]:

```
result = smf.ols(formula='rwu_nonight ~ sap - 1', data=SWcomc).fit()
SWcomc['rwuNN_V'] = SWcomc.rwu_nonight/result.params[0]

result = smf.ols(formula='rwu_nonight ~ sap - 1', data=SaDcomc).fit()
SaDcomc['rwuNN_V'] = SaDcomc.rwu_nonight/result.params[0]
```

[40]:

```
figsize(6,4)
subplot(211)
SaDcomc['sap'].plot(c=tableau20[2],label='Sand Sap')
SaDcomc['rwu_V'].plot(c=tableau20[3],label='Sand RWU')


#SWcomc_V['sapAUC'].plot(c=tableau20[0],label='Slate Sap')
#SWcomc_V['rwu'].plot(c=tableau20[1],label='Slate RWU')

#ylim(0,70)
xlim(SWcomc.index[0],SWcomc.index[-1])
legend()
ylabel('Volume flux (L/day)')

subplot(212)
SaDcomc[['sap','rwu_V']].pipe(kge_roll).plot(c=tableau20[4],label='Sand (21 days)')
plot([SaDcomc.index[0],SaDcomc.index[-1]],[he.kge(SaDcomc['sap'].values,SaDcomc['rwu_V
↪'].values)[0],he.kge(SaDcomc['sap'].values,SaDcomc['rwu_V'].values)[0]],':',
↪c=tableau20[4],label='Sand')
ylim(-0.33,1)
yticks([0.,0.33,0.66,1])
```

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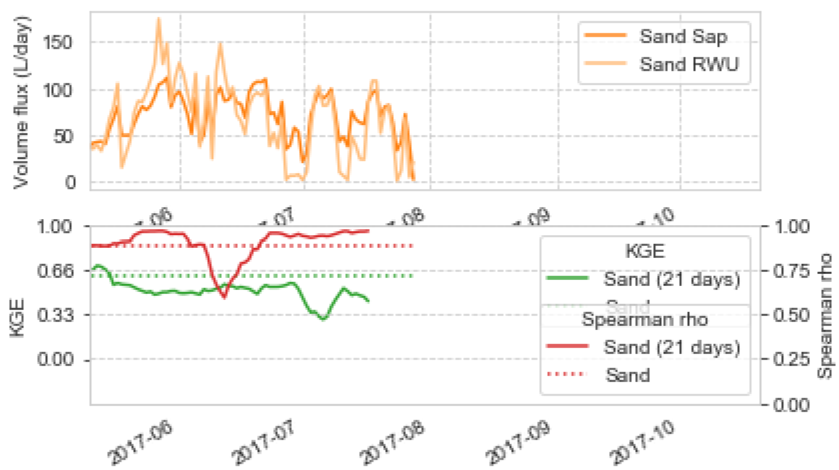
```
legend(title='KGE')
ylabel('KGE')

SaDcomc[['sap','rwu_V']].pipe(spear_roll).plot(secondary_y=True,c=tableau20[6],label=
↪'Sand (21 days)')
plot([SaDcomc.index[0],SaDcomc.index[-1]],[sp.stats.mstats.spearmanr(SaDcomc['sap'],
↪SaDcomc['rwu_V'])[0],sp.stats.mstats.spearmanr(SaDcomc['sap'],SaDcomc['rwu_V'])[0]],
↪':',c=tableau20[6],label='Sand')

legend(title='Spearman rho',loc=4)
ylim(0,1)
xlim(SWcomc.index[0],SWcomc.index[-1])
ylabel('Spearman rho')

#savefig('sand_cor_raw.pdf',bbox_inches='tight')
```

[40]:
```
Text(0, 0.5, 'Spearman rho')
```



[41]:
```
#gof rs and KGE :: Sand SF vs. RWU
sp.stats.mstats.spearmanr(SaDcomc['sap'],SaDcomc['rwu_V'])[0],he.kge(SaDcomc['sap'].
↪values,SaDcomc['rwu_V'].values)[0][0]
```

[41]:
```
(0.8862139410376528, 0.6196591567251213)
```

[42]:
```
#gof rs and KGE :: Sand SF vs. RWU no nocturnal correction
sp.stats.mstats.spearmanr(SaDcomc['sap'],SaDcomc['rwuNN_V'])[0],he.kge(SaDcomc['sap'].
↪values,SaDcomc['rwuNN_V'].values)[0][0]
```

[42]:
```
(0.8496002254235497, 0.6565935747093112)
```

[43]:
```
figsize(6,4)
subplot(211)

SWcomc['sap'].plot(c=tableau20[0],label='Slate Sap')
SWcomc['rwu_V'].plot(c=tableau20[1],label='Slate RWU')

xlim(SWcomc.index[0],SWcomc.index[-1])
legend()
ylabel('Volume flux (L/day)')
```

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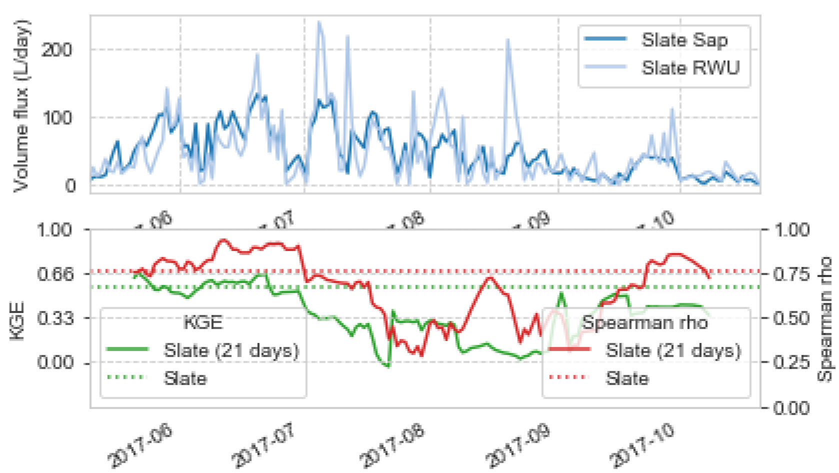
```
subplot(212)
SWcomc[['sap','rwu_V']].pipe(kge_roll).plot(c=tableau20[4],label='Slate (21 days)')
plot([SWcomc.index[0],SWcomc.index[-1]],[he.kge(SWcomc['sap'].values,SWcomc['rwu_V'].
↪values)[0],he.kge(SWcomc['sap'].values,SWcomc['rwu_V'].values)[0]],':',
↪c=tableau20[4],label='Slate')
ylim(-0.33,1)
yticks([0.,0.33,0.66,1])
legend(title='KGE')
ylabel('KGE')

SWcomc[['sap','rwu_V']].pipe(spear_roll).plot(secondary_y=True,c=tableau20[6],label=
↪'Slate (21 days)')
plot([SWcomc.index[0],SWcomc.index[-1]],[sp.stats.mstats.spearmanr(SWcomc['sap'],
↪SWcomc['rwu_V'])[0],sp.stats.mstats.spearmanr(SWcomc['sap'],SWcomc['rwu_V'])[0]],':
↪',c=tableau20[6],label='Slate')

legend(title='Spearman rho',loc=4)
ylim(0,1)
xlim(SWcomc.index[0],SWcomc.index[-1])
ylabel('Spearman rho')

#savefig('slate_cor_raw.pdf',bbox_inches='tight')
```

[43]:

```
Text(0, 0.5, 'Spearman rho')
```



[44]:

```
#gof rs and KGE :: Slate SF vs. RWU
sp.stats.mstats.spearmanr(SWcomc['sap'],SWcomc['rwu_V'])[0],he.kge(SWcomc['sap'].
↪values,SWcomc['rwu_V'].values)[0][0]
```

[44]:

```
(0.7591547251949937, 0.5565136803470871)
```

[45]:

```
#gof rs and KGE :: Sand SF vs. RWU no nocturnal correction
sp.stats.mstats.spearmanr(SWcomc['sap'],SWcomc['rwuNN_V'])[0],he.kge(SWcomc['sap'].
↪values,SWcomc['rwuNN_V'].values)[0][0]
```

[45]:

```
(0.6742796092176031, 0.37863838836851427)
```

[46]:
```
figsize(6,4)
subplot(221)
SaDcomc['sap'].plot(c=tableau20[2],label='Sand Sap')
SWcomc['sap'].plot(c=tableau20[0],label='Slate Sap')

ylim(0,210)
xlim(SaDcomc.index[0],SaDcomc.index[-1])
legend(ncol=2,loc=1)
ylabel('Volume flux (L/day)')

subplot(222)
SaDcomc['rwu_V'].plot(c=tableau20[2],label='Sand RWU')
SWcomc['rwu_V'].plot(c=tableau20[0],label='Slate RWU')

ylim(0,210)
xlim(SaDcomc.index[0],SaDcomc.index[-1])


subplot(223)
c_dummy = pd.concat([SaDcomc['sap'],SWcomc['sap']],axis=1,join='inner')
c_dummy.columns = ['sap','rwu']
c_dummy.pipe(kge_roll).plot(c=tableau20[4],label='sap (21 days)')
plot([c_dummy.index[0],c_dummy.index[-1]],[he.kge(c_dummy['sap'].values,c_dummy['rwu
↪'].values)[0],he.kge(c_dummy['sap'].values,c_dummy['rwu'].values)[0]],':',
↪c=tableau20[4],label='sap')
ylim(-0.33,1)
yticks([0.,0.33,0.66,1])
legend(title='KGE')
ylabel('KGE')

c_dummy[['sap','rwu']].pipe(spear_roll).plot(secondary_y=True,c=tableau20[6],label=
↪'sap (21 days)')
plot([c_dummy.index[0],c_dummy.index[-1]],[sp.stats.mstats.spearmanr(c_dummy['sap'],c_
↪dummy['rwu'])[0],sp.stats.mstats.spearmanr(c_dummy['sap'],c_dummy['rwu'])[0]],':',
↪c=tableau20[6],label='sap')

legend(title='Spearman rho',loc=4)
ylim(0,1)
xlim(SaDcomc.index[0],SaDcomc.index[-1])
ylabel('Spearman rho')


subplot(224)
c1_dummy = pd.concat([SaDcomc['rwu_V'],SWcomc['rwu_V']],axis=1,join='inner')
c1_dummy.columns = ['sapAUC','rwu']
c1_dummy.pipe(kge_roll).plot(c=tableau20[4],label='rwu (21 days)')
plot([c1_dummy.index[0],c1_dummy.index[-1]],[he.kge(c1_dummy['sapAUC'].values,c1_
↪dummy['rwu'].values)[0],he.kge(c1_dummy['sapAUC'].values,c1_dummy['rwu'].
↪values)[0]],':',c=tableau20[4],label='rwu')
ylim(-0.33,1)
yticks([0.,0.33,0.66,1])
ylabel('KGE')

c1_dummy[['sapAUC','rwu']].pipe(spear_roll).plot(secondary_y=True,c=tableau20[6],
↪label='rwu (21 days)')
plot([c1_dummy.index[0],c1_dummy.index[-1]],[sp.stats.mstats.spearmanr(c1_dummy[
↪'sapAUC'],c1_dummy['rwu'])[0],sp.stats.mstats.spearmanr(c1_dummy['sapAUC'],c1_dummy[
↪'rwu'])[0]],':',c=tableau20[6],label='rwu')
```

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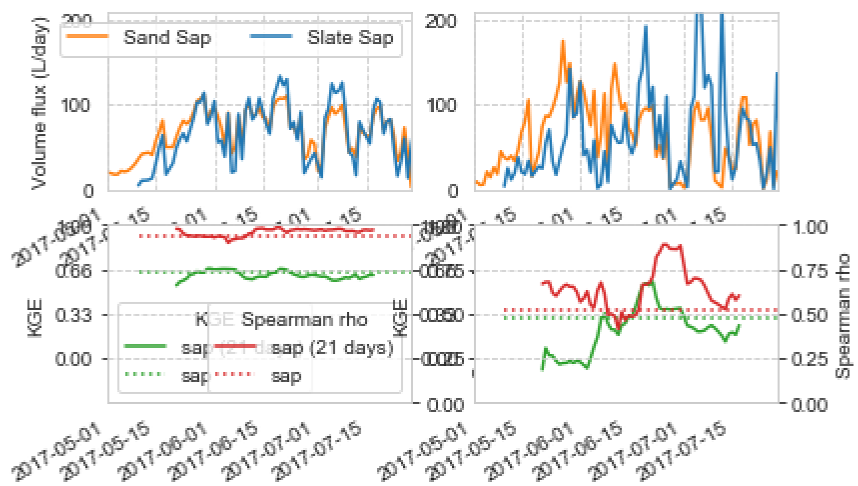
```
ylim(0,1)
xlim(SaDcomc.index[0],SaDcomc.index[-1])
ylabel('Spearman rho')

#savefig('spatial_cor_raw.pdf',bbox_inches='tight')
```

[46]:
```
Text(0, 0.5, 'Spearman rho')
```



[47]:
```
#gof rs and KGE :: Sand SF vs. Slate SF
sp.stats.mstats.spearmanr(c_dummy['sap'],c_dummy['rwu'])[0],he.kge(c_dummy['sap'].
↪values,c_dummy['rwu'].values)[0][0]
```

[47]:
```
(0.9410326515589673, 0.649790149119509)
```

[48]:
```
#gof rs and KGE :: Sand RWU vs. Slate RWU
sp.stats.mstats.spearmanr(c1_dummy['sapAUC'],c1_dummy['rwu'])[0],he.kge(c1_dummy[
↪'sapAUC'].values,c1_dummy['rwu'].values)[0][0]
```

[48]:
```
(0.5175876754824124, 0.30311623610738714)
```

[49]:
```
#check effect of nocturnal correction
c2_dummy = pd.concat([SaDcomc['rwu_V'],SWcomc['rwuNN_V']],axis=1,join='inner')
c3_dummy = pd.concat([SaDcomc['rwuNN_V'],SWcomc['rwu_V']],axis=1,join='inner')
c4_dummy = pd.concat([SaDcomc['rwuNN_V'],SWcomc['rwuNN_V']],axis=1,join='inner')
c5_dummy = pd.concat([SaDcomc['rwu_V'],SWcomc['rwu_V']],axis=1,join='inner')
```

[50]:
```
[sp.stats.mstats.spearmanr(c2_dummy.iloc[:,0],c2_dummy.iloc[:,1])[0],
sp.stats.mstats.spearmanr(c3_dummy.iloc[:,0],c3_dummy.iloc[:,1])[0],
sp.stats.mstats.spearmanr(c4_dummy.iloc[:,0],c4_dummy.iloc[:,1])[0],
sp.stats.mstats.spearmanr(c5_dummy.iloc[:,0],c5_dummy.iloc[:,1])[0]]
```

[50]:
```
[0.46122905031917727,
 0.4907986750092013,
 0.4167203418039945,
 0.5175876754824124]
```

[51]:
```
[he.kge(c2_dummy.iloc[:,0].values,c2_dummy.iloc[:,1].values)[0],
he.kge(c3_dummy.iloc[:,0].values,c3_dummy.iloc[:,1].values)[0],
he.kge(c4_dummy.iloc[:,0].values,c4_dummy.iloc[:,1].values)[0],
he.kge(c5_dummy.iloc[:,0].values,c5_dummy.iloc[:,1].values)[0]]
```

[51]:
```
[array([0.3241462]),
 array([0.23824204]),
 array([0.26613051]),
 array([0.30311624])]
```

RWU sourcing

[52]:
```
SWcom3 = pd.concat([Slate_rwu,MP[['Slate_MP_10', 'Slate_MP_30', 'Slate_MP_50', 'Slate_
↪MP_70', 'Slate_MP_90','Slate_MP_110', 'Slate_MP_130', 'Slate_MP_150', 'Slate_MP_170
↪']].resample('1D').mean(),SlateSap_d.sum(axis=1)],axis=1)
SWcom3.columns = ['10',   '30',   '50',   '70',   '90',   '110',   '130',   '150',   '170
↪', 'p10',  'p30',  'p50',  'p70',  'p90', 'p110', 'p130', 'p150', 'p170','sap']
```

[53]:
```
SaDcom3 = pd.concat([Sand_rwu,MP[['Sand_MP_10', 'Sand_MP_30', 'Sand_MP_50', 'Sand_MP_
↪70', 'Sand_MP_90','Sand_MP_110', 'Sand_MP_130', 'Sand_MP_150', 'Sand_MP_170', 'Sand_
↪MP_190', 'Sand_MP_210', 'Sand_MP_230']].resample('1D').mean(),SandSap_d.
↪sum(axis=1)],axis=1)
SaDcom3.columns = ['10',   '30',   '50',   '70',   '90',   '110',   '130',   '150',   '170
↪', '190', '210', '230', 'p10',  'p30',  'p50',  'p70',  'p90', 'p110', 'p130', 'p150
↪', 'p170','p190', 'p210', 'p230','sap']
```

[54]:
```
fig = plt.figure(figsize=(8,3.5))
import matplotlib.gridspec as gridspec
gs = gridspec.GridSpec(1, 2)

ax = plt.subplot(gs[0, 0])
cmapx = cm.get_cmap('YlGnBu',12)
for i in Sand_rwu.columns:
    cl = 'p'+i.split('_')[-1]
    ci = i.split('_')[-1]
    sc = ax.scatter(-1.*(SaDcom3[cl]),SaDcom3[ci],c=np.repeat((float(ci))/100.,
↪len(SaDcom3[ci])),s=SaDcom3.sap/3.,cmap=cmapx,vmin=0,vmax=2.4)

ax.scatter(0,0,c='k',s=10/3.,label='10',alpha=0.3)
ax.scatter(0,0,c='k',s=20/3.,label='20',alpha=0.3)
ax.scatter(0,0,c='k',s=40/3.,label='40',alpha=0.3)
ax.scatter(0,0,c='k',s=80/3.,label='80',alpha=0.3)

ax.set_ylabel('RWU in layer (mm/day)')
ax.set_xlabel('Matric Potential (m)')
ax.legend(title='sap flow\n(L/day):')
ax.set_xlim(2,3000)
ax.set_ylim(0.01,1.2)
ax.set_title('Sand site')
ax.set_xscale('log')

ax = plt.subplot(gs[0, 1])

for i in Slate_rwu.columns:
    cl = 'p'+i.split('_')[-1]
```

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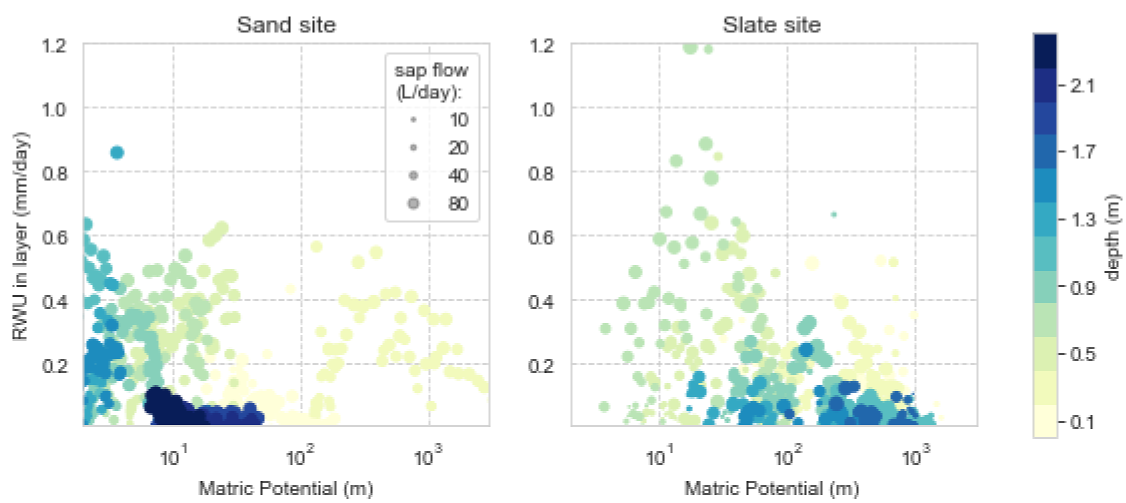
```
    ci = i.split('_')[-1]
    sc = ax.scatter(-1.*(SWcom3[cl]),SWcom3[ci],c=np.repeat((float(ci))/100.,
↪len(SWcom3[ci])),s=SWcom3.sap/3.,cmap=cmapx,vmin=0,vmax=2.4)

ax.set_xlabel('Matric Potential (m)')
ax.set_xlim(2,3000)
ax.set_ylim(0.01,1.2)
ax.set_title('Slate site')
ax.set_xscale('log')
cb_ax = fig.add_axes([0.95, 0.1, 0.02, 0.8])
cbar = fig.colorbar(sc, cax=cb_ax,label='depth (m)',ticks=[0.1, 0.5, 0.9,1.3,1.7,2.1])

#savefig('RWUsourcing_new.pdf',bbox_inches='tight')
```



Site event soil water balance

[55]:
```
def cumplot(dummy,rain,dpth):
    dummy = dummy.iloc[:,:]-dummy.iloc[0,:]
    dum_sum= dummy.cumsum(axis=1)
    dum2 = dum_sum.iloc[:,0]*0.
    dum2.name='0'
    dum_sum=pd.concat([dum2,dum_sum],axis=1)

    for i in np.arange(len(dpth)):
        if i<10:
            ci=tableau10[i]
        if i>=10:
            ci=tableau20[(i-10)*2+1]
        fill_between(dum_sum.index, dum_sum.iloc[:,i], dum_sum.iloc[:,i+1], color=ci,
↪alpha=0.6,label=dpth[i]+' cm')
        plot(dum_sum.index,dum_sum.iloc[:,i+1],c=ci,alpha=0.8,label='')

    plot(rain, label='Precip')
    ylabel(' water (mm)' )
    legend(ncol=2)
```

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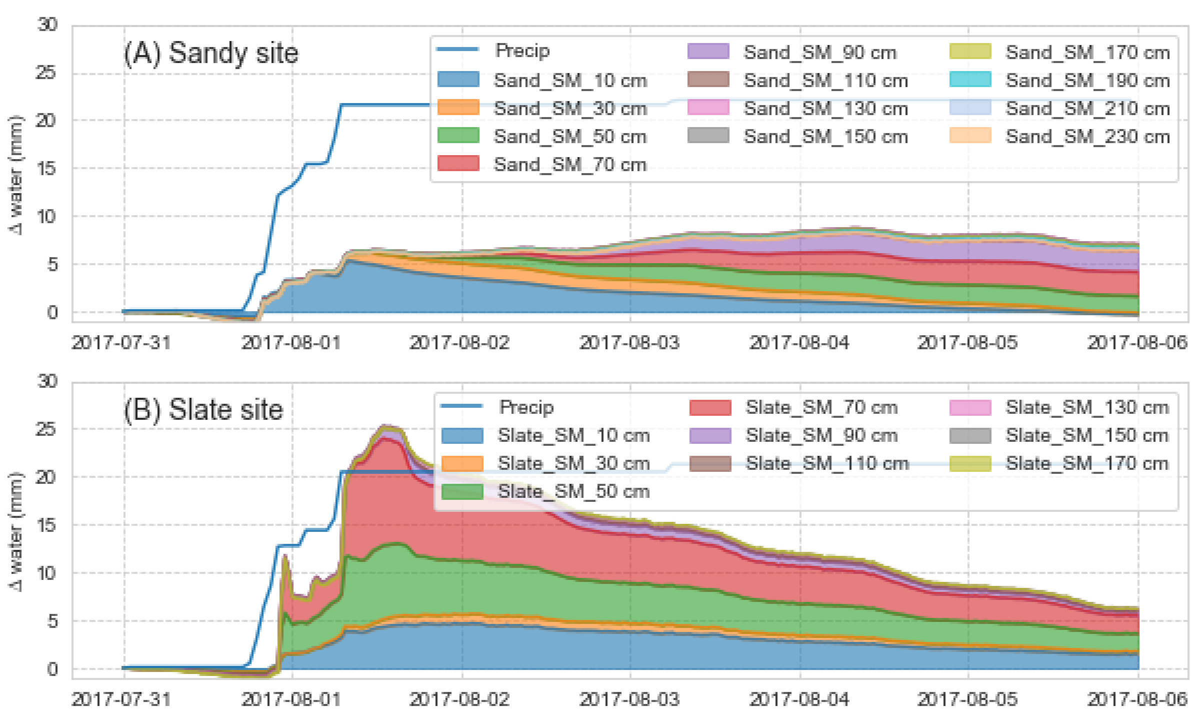
```
    return
```

```
[56]: t_start = pd.to_datetime('2017-07-31')
t_end = pd.to_datetime('2017-8-6')

figsize(10,6)

subplot(211)
dpth = ['Sand_SM_10', 'Sand_SM_30', 'Sand_SM_50', 'Sand_SM_70', 'Sand_SM_90',
        'Sand_SM_110', 'Sand_SM_130', 'Sand_SM_150', 'Sand_SM_170',
        'Sand_SM_190', 'Sand_SM_210', 'Sand_SM_230']
cumplot(SM.loc[t_start:t_end,dpth],prec_rad.loc[t_start:t_end,'Sand_Precip'].resample(
↪'1h').max().cumsum(),dpth)
text(t_start,26,'(A) Sandy site',fontsize=14)
ylim([-1,30])
legend(loc=1,ncol=3)
#xticklabel('')
#title('Sandstone site')

subplot(212)
dpth = ['Slate_SM_10', 'Slate_SM_30', 'Slate_SM_50', 'Slate_SM_70', 'Slate_SM_90',
        'Slate_SM_110', 'Slate_SM_130', 'Slate_SM_150', 'Slate_SM_170']
cumplot(SM.loc[t_start:t_end,dpth],prec_rad.loc[t_start:t_end,'Slate_Precip'].
↪resample('1h').max().cumsum(),dpth)
text(t_start,26,'(B) Slate site',fontsize=14)
ylim([-1,30])
legend(loc=1,ncol=3)
#title('Slate site')

#savefig('WB_0817.pdf',bbox_inches='tight')
```

```
[56]: <matplotlib.legend.Legend at 0x1a280b7a20>
```



```
[ ]:
```

CHAPTER 2

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