The impact of weather conditions on cycling counts in Auckland, New Zealand

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In [1]:
```
!date
```

```
Wed Sep 12 13:57:19 NZST 2018
```

Introduction

Auckland (https://en.wikipedia.org/wiki/Auckland) is the largest city in New Zealand, with a population exceeding 1.5 million people, accounting for more than 1/3 of the country's population. Since 2006, Auckland has also accounted for more than 50% of the country's population growth, adding about 110,000 residents over this period. This has been placing pressure notably on housing and the transportation infrastructure, with congestion being a common occurence during peak hours. Auckland Transport (https://at.govt.nz/) is the Auckland council-controlled organisation responsible for transport projects and services. Over the past few years it has developed a strategy to actively promote and enable cycling as an alternative to individual automobile, and has built a number of cycle paths across the city. The Auckland Transport cycling and walking research and monitoring (https://at.govt.nz/cycling-walking/research-monitoring/) department is tasked with conducting research and monitoring on sustainable transportation solutions including cycling and walking. It has installed a total of 39 dedicated cycling (as of June 2018) counters accross the city (see interactive map below).

This **Jupyter notebook** (http://jupyter.org/) presents an **analysis of cycling counts** along a dedicated cycle lane popular with commuters and recreational cyclists alike (Tamaki Drive (https://en.wikipedia.org/wiki/Tamaki_Drive), in Auckland central) and examines how **weather conditions** (rainfall, temperature, wind, sunshine fraction) influence the number of cyclists on a day to day basis.

It makes use of the fbprophet (https://facebook.github.io/prophet/) library. **Fbprophet** implements a Generalized Additive Model (https://en.wikipedia.org/wiki/Generalized_additive_model), and - in a nutshell - models a time-series as the **sum of different components** (non-linear trend, periodic components and holidays or special events) and allows to incorporate **extra-regressors** (categorical or continuous). The reference is Taylor and Letham, 2017 (https://peerj.com/preprints/3190.pdf), see also this blog post from Facebook research announcing the package (https://research.fb.com/prophet-forecasting-at-scale/).

In this notebook, we first explore some characteristics of the hourly and daily cycling counts over Tamaki drive, then build a model first without, then with the weather extra-regressors.

The cycling counts data (initially available at the hourly interval) are provided by Auckland Transport (https://at.govt.nz/) (see the Auckland Transport cycling and walking research and monitoring website (https://at.govt.nz/cycling-walking/research-monitoring/)) and the hourly weather data are provided by the National Institute for Water and Atmospheric research (http://www.niwa.co.nz) (NIWA Ltd) CliFlo (https://cliflo.niwa.co.nz/) database. We used the Mangere Electronic Weather Station (EWS) station in this particular case.

Note that an extended and edited version of this work is to be submitted to **Weather and Climate**, the journal of the Meteorological Society of New Zealand (https://www.metsoc.org.nz/) as a collaboration between NIWA and Auckland Transport.

---

imports and settings

disable the sdout logging of fbprophet

In [2]:
```
import logging
logging.getLogger('fbprophet').setLevel(logging.ERROR)
```

ignore the pystan DeprecationWarning

In [3]:
```
import warnings
warnings.simplefilter("ignore", DeprecationWarning)
warnings.simplefilter("ignore", FutureWarning, )
```

In [4]:
```
%matplotlib inline
```

In [5]:
```
import os
import sys
from glob import glob
```

In [6]:
```
import numpy as np
```

In [7]:
```
np.random.seed(42)
```

In [8]:
```
import pandas as pd
from matplotlib import pyplot as plt
import seaborn as sns
```

folium for interactive mapping of the counters location

In [9]:
```
import folium
from folium.plugins import MarkerCluster
```

some metrics and stats

In [10]:
```
from sklearn.metrics import mean_absolute_error as MAE
from scipy.stats import skew
```

some utilities from the calendar package

In [11]:
```
from calendar import day_abbr, month_abbr, mdays
```

we use the convenient holiday package (https://github.com/dr-prodigy/python-holidays) from Maurizio Montel (https://github.com/dr-prodigy) to build a DataFrame of national and regional (Auckland region) holidays

In [12]:
```
import holidays
```

fbprophet itself, we use here the version 0.3, release on the 3rd of June 2018

In [13]:
```
import fbprophet
```

In [14]:
```
fbprophet.__version__
```

Out[14]:
```
'0.3'
```

In [15]:
```
Prophet = fbprophet.Prophet
```

import some utility functions for data munging and plotting

In [16]:
```
sys.path.append('../code/')
```

In [17]:
```
import utils
```

reads the counter locations

we read the counters locations, and display these locations on an interactive map powered by Folium ()

In [18]:
```
loc_counters = pd.read_csv('../data/cycling_Auckland/cycling_counters.csv')
```

In [19]:
```
loc_counters = loc_counters.query("user_type == 'Cyclists'")
```

In [37]:
```
len(loc_counters)
```

Out[37]: 39

In [38]:
```
loc_counters.loc[loc_counters.name.str.contains("Tamaki"),:]
```

Out[38]:

	name	id	Name.1	latitude	longitude	site_code	setup_date	user_type
44	Tamaki Drive EB	100000827	Tamaki Drive EB	-36.847782	174.78935	ECO08011685	12/11/2009	Cyclists
45	Tamaki Drive WB	100003810	Tamaki Drive WB	-36.847942	174.78903	U15G2011813	26/03/2012	Cyclists

In [39]:
```
center_lat = loc_counters.query("name == 'Tamaki Drive EB'").latitude.values[0]
center_lon = loc_counters.query("name == 'Tamaki Drive EB'").longitude.values[0]
```

In [40]:
```
m = folium.Map(
    location=[center_lat, center_lon],
    zoom_start=14,
    tiles='OpenStreetMap',
    width='80%',
)

m.add_child(folium.LatLngPopup())

marker_cluster = MarkerCluster().add_to(m)

for i, row in loc_counters.iterrows():
    name = row['name']
    lat = row.latitude
    lon = row.longitude
    opened = row.setup_date

    # HTML here in the pop up
    popup = '<b>{}</b></br><i>setup date = {}</i>'.format(name, opened)

    folium.Marker([lat, lon], popup=popup, tooltip=name).add_to(marker_cluster)
```

In [41]:
```
m
```

Out[41]:

read the actual counter data, and extract the time-series for the Tamaki drive counters

In [42]:
```
lfiles = glob('../data/cycling_Auckland/cycling_counts_????.csv')
```

In [43]:
```
lfiles.sort()
```

In [44]:
```
lfiles
```

Out[44]:
```
['../data/cycling_Auckland/cycling_counts_2010.csv',
 '../data/cycling_Auckland/cycling_counts_2011.csv',
 '../data/cycling_Auckland/cycling_counts_2012.csv',
 '../data/cycling_Auckland/cycling_counts_2013.csv',
 '../data/cycling_Auckland/cycling_counts_2014.csv',
 '../data/cycling_Auckland/cycling_counts_2015.csv',
 '../data/cycling_Auckland/cycling_counts_2016.csv',
 '../data/cycling_Auckland/cycling_counts_2017.csv',
 '../data/cycling_Auckland/cycling_counts_2018.csv']
```

In [45]:
```
l = []
for f in lfiles:
    d = pd.read_csv(f, index_col=0, parse_dates=True)
    l.append(d)
```

In [46]:
```
df = pd.concat(l, axis=0)
```

In [47]:
```
df = df.loc[:,['Tamaki Drive EB', 'Tamaki Drive WB']]
```

In [48]:
```
df.head()
```

Out[48]:

datetime	Tamaki Drive EB	Tamaki Drive WB
2010-07-01 00:00:00	2.0	NaN
2010-07-01 01:00:00	3.0	NaN
2010-07-01 02:00:00	1.0	NaN
2010-07-01 03:00:00	1.0	NaN
2010-07-01 04:00:00	2.0	NaN

In [49]:
```
df.tail()
```

Out[49]:

datetime	Tamaki Drive EB	Tamaki Drive WB
2018-07-31 19:00:00	26.0	8.0
2018-07-31 20:00:00	15.0	6.0
2018-07-31 21:00:00	6.0	3.0
2018-07-31 22:00:00	7.0	2.0
2018-07-31 23:00:00	1.0	1.0

adds Tamaki drive eastern bound and western bound together

In [50]:
```
Tamaki = df.loc[:,'Tamaki Drive WB'] +  df.loc[:,'Tamaki Drive EB']
```

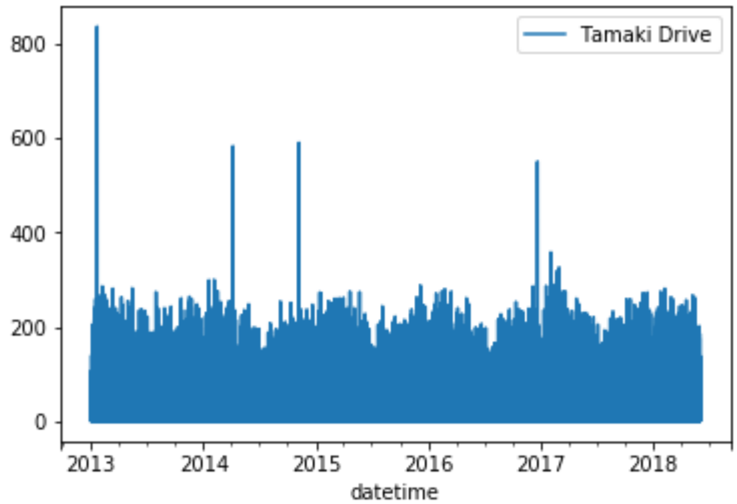
restrict to the period where the hourly weather data is available

In [51]:
```
Tamaki = Tamaki.loc['2013':'2018-06-01',]
```

In [52]:
```
Tamaki = Tamaki.to_frame(name='Tamaki Drive')
```

In [53]:
```
Tamaki.plot()
```

Out[53]: <matplotlib.axes._subplots.AxesSubplot at 0x1a22cd26d8>



there seems to be a few pretty large outliers, we're going to try and filter these out

getting rid of the outliers using a median filter

In [54]:
```
utils.median_filter?
```

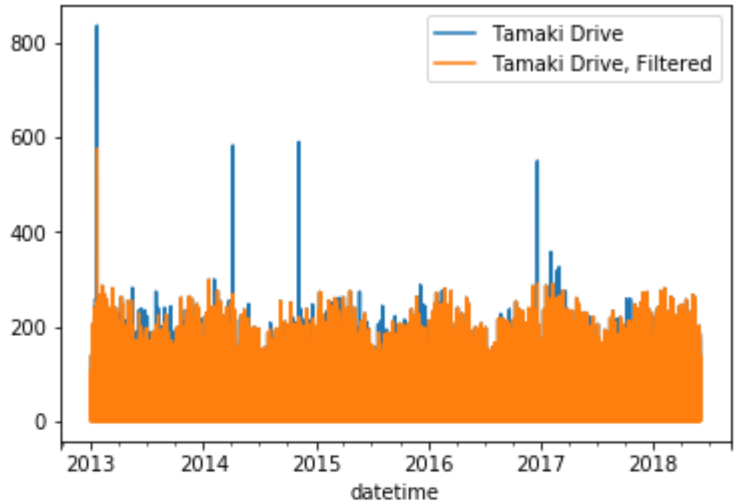
```
Signature: utils.median_filter(df, varname=None, window=24, std=3)
Docstring:
A simple median filter, removes (i.e. replace by np.nan) observations that exceed N
(default = 3)
tandard deviation from the median over window of length P (default = 24) centered a
round
each observation.

Parameters
----------
df : pandas.DataFrame
    The pandas.DataFrame containing the column to filter.
varname : string
    Column to filter in the pandas.DataFrame. No default.
window : integer
    Size of the window around each observation for the calculation
    of the median and std. Default is 24 (time-steps).
std : integer
    Threshold for the number of std around the median to replace
    by `np.nan`. Default is 3 (greater / less or equal).

Returns
-------
dfc : pandas.Dataframe
    A copy of the pandas.DataFrame `df` with the new, filtered column `varname`
File:      ~/research/NIWA/Auckland_Cycling/code/utils.py
Type:      function
```

In [55]:
```
dfc = Tamaki.copy()
```

In [56]:
```
dfc.loc[:,'Tamaki Drive, Filtered'] = utils.median_filter(dfc, varname='Tamaki Drive
```

In [57]:
```
dfc.plot()
```

Out[57]: <matplotlib.axes._subplots.AxesSubplot at 0x1a23ea1c50>



In [58]:
```
dfc.isnull().sum()
```

Out[58]:
```
Tamaki Drive                 6
Tamaki Drive, Filtered     229
dtype: int64
```

plots the seasonal cycle (average and inter-quartile range)

In [59]:
```
seas_cycl = dfc.loc[:,'Tamaki Drive, Filtered'].rolling(window=30*24, center=True, m
```

In [60]:
```
q25 = dfc.loc[:,'Tamaki Drive, Filtered'].rolling(window=30*24, center=True, min_per
q75 = dfc.loc[:,'Tamaki Drive, Filtered'].rolling(window=30*24, center=True, min_per
```

the following cells build the ticks and tick labels for the seasonal cycle plot

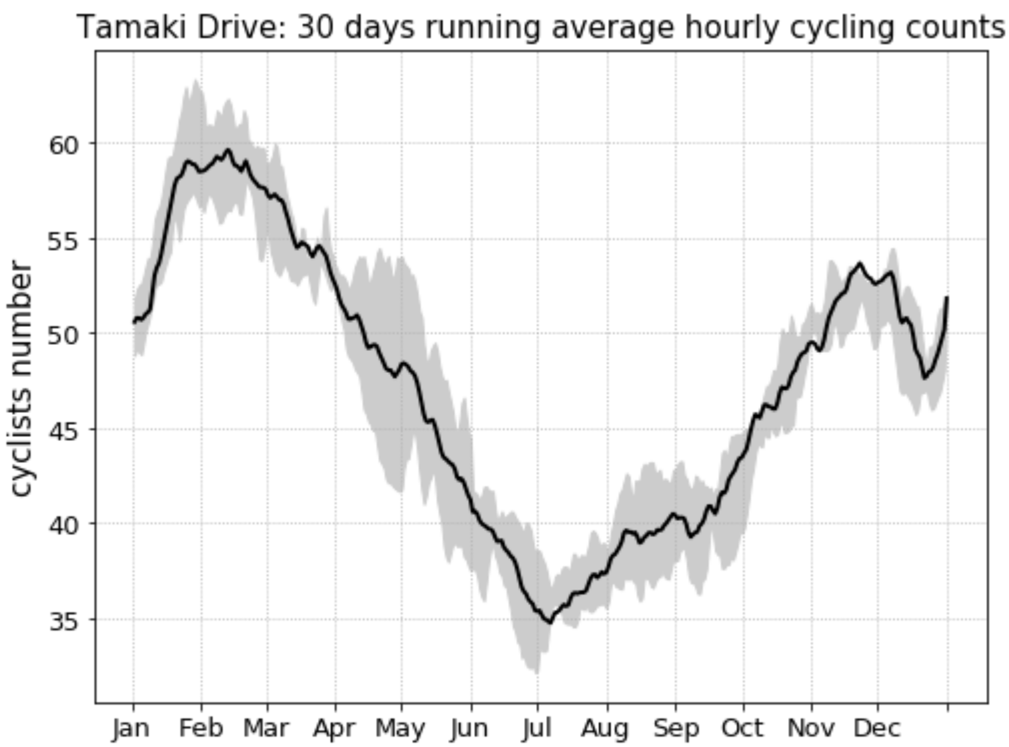
In [61]:
```
ndays_m = mdays.copy()
```

In [62]:
```
ndays_m[2] = 29
```

In [63]:
```
ndays_m = np.cumsum(ndays_m)
```

In [64]:
```
month_abbr = month_abbr[1:]
```

In [65]:
```
f, ax = plt.subplots(figsize=(8,6))

seas_cycl.plot(ax=ax, lw=2, color='k', legend=False)

ax.fill_between(seas_cycl.index, q25.values.ravel(), q75.values.ravel(), color='0.8'

ax.set_xticks(ndays_m)
ax.set_xticklabels(month_abbr)

ax.grid(ls=':')

ax.set_xlabel('', fontsize=15)

ax.set_ylabel('cyclists number', fontsize=15);

[l.set_fontsize(13) for l in ax.xaxis.get_ticklabels()]
[l.set_fontsize(13) for l in ax.yaxis.get_ticklabels()]

ax.set_title('Tamaki Drive: 30 days running average hourly cycling counts', fontsize

for ext in ['png','jpeg','pdf']:
    f.savefig(f'../figures/paper/seasonal_cycle.{ext}', dpi=200)
```



cyclists per day of week and hour of the day

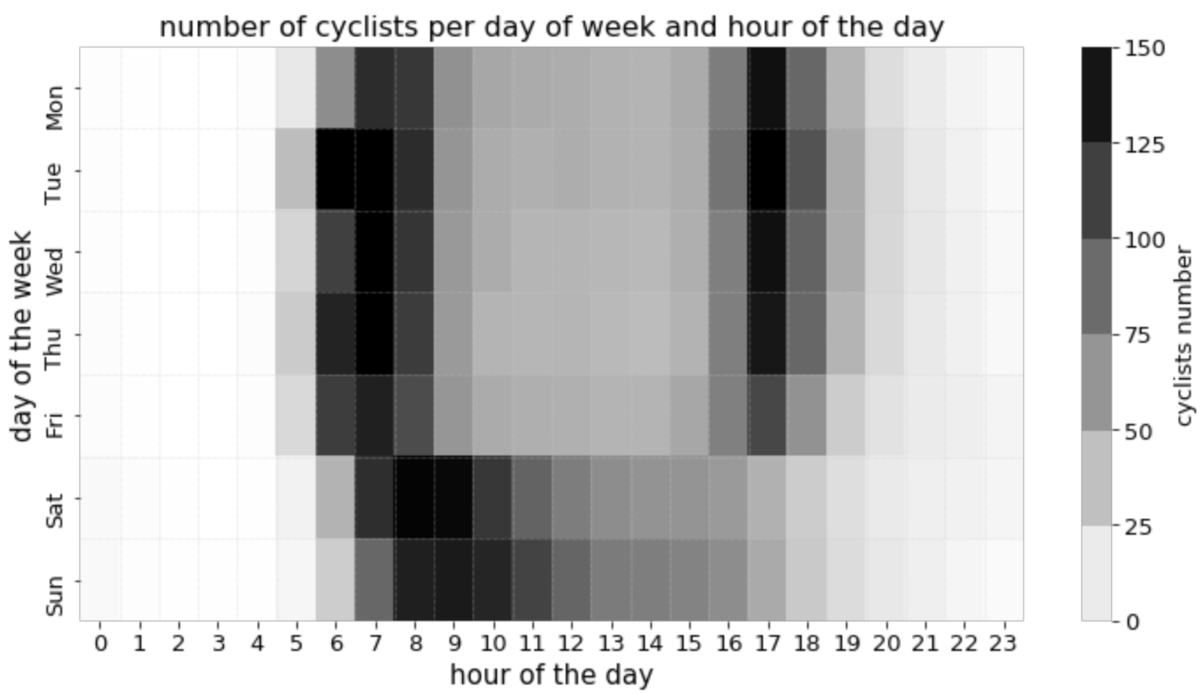
In [66]:
```
hour_week = dfc.loc[:,['Tamaki Drive, Filtered']].copy()
```

In [67]:
```
hour_week.loc[:,'day_of_week'] = hour_week.index.dayofweek
hour_week.loc[:,'hour'] = hour_week.index.hour
```

In [68]:
```
hour_week = hour_week.groupby(['day_of_week','hour']).mean().unstack()
```

In [69]:
```
hour_week.columns = hour_week.columns.droplevel(0)
```

In [70]:
```
f, ax = plt.subplots(figsize=(12,6))

sns.heatmap(hour_week, ax = ax, cmap=plt.cm.gray_r, vmax=150, cbar_kws={'boundaries'

cbax = f.axes[1]
[l.set_fontsize(13) for l in cbax.yaxis.get_ticklabels()]
cbax.set_ylabel('cyclists number', fontsize=13)

[ax.axhline(x, ls=':', lw=0.5, color='0.8') for x in np.arange(1, 7)]
[ax.axvline(x, ls=':', lw=0.5, color='0.8') for x in np.arange(1, 24)];

ax.set_title('number of cyclists per day of week and hour of the day', fontsize=16)

[l.set_fontsize(13) for l in ax.xaxis.get_ticklabels()]
[l.set_fontsize(13) for l in ax.yaxis.get_ticklabels()]

ax.set_xlabel('hour of the day', fontsize=15)
ax.set_ylabel('day of the week', fontsize=15)
ax.set_yticklabels(day_abbr[0:7]);

for ext in ['png','jpeg','pdf']:
    f.savefig(f'../figures/paper/cyclists_dayofweek_hourofday.{ext}', dpi=200)
```



looking at week days versus week-ends

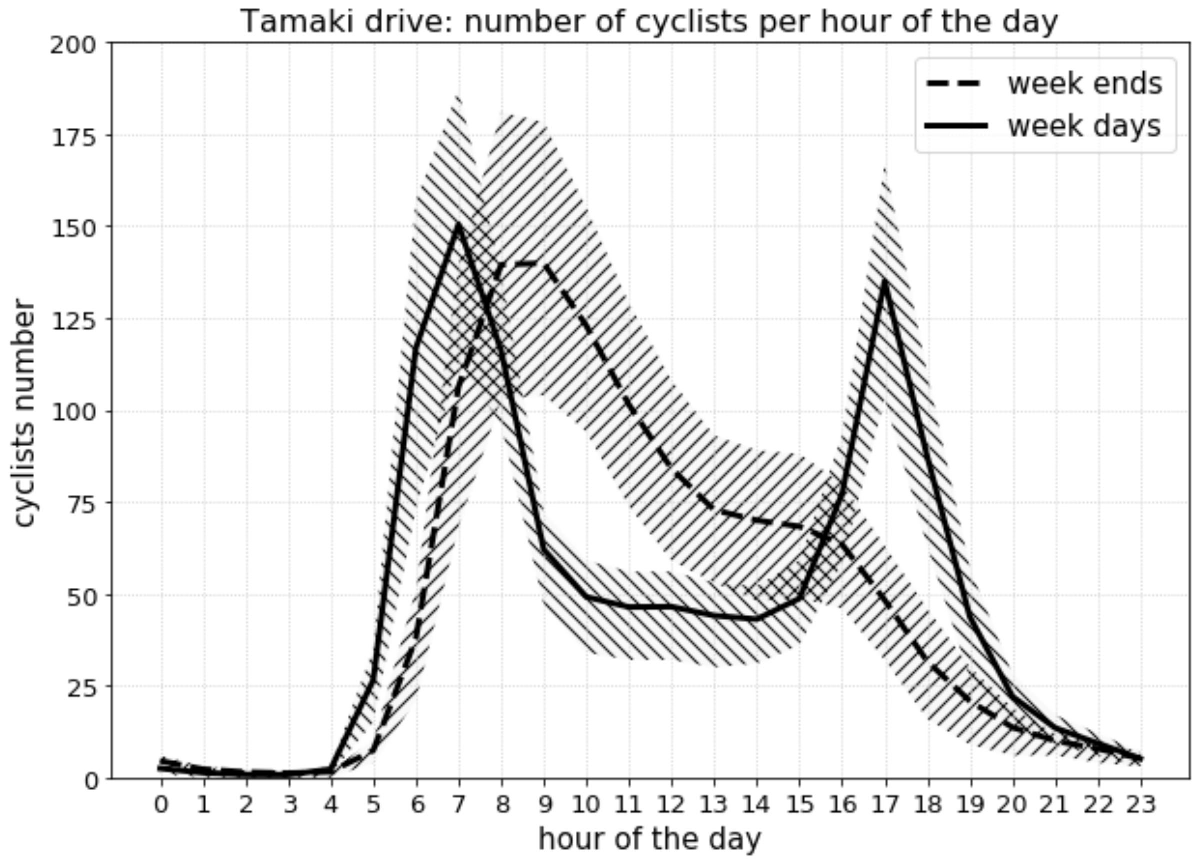
In [108…
```
weekdays = dfc.loc[dfc.index.weekday_name.isin(['Monday','Tuesday','Wednesday','Thur
weekends = dfc.loc[dfc.index.weekday_name.isin(['Sunday','Saturday']), 'Tamaki Drive
```

In [109…

```
summary_hour_weekdays = weekdays.groupby(weekdays.index.hour).describe()
summary_hour_weekends = weekends.groupby(weekends.index.hour).describe()
```

In [111…

```
f, ax = plt.subplots(figsize=(10,7))

ax.plot(summary_hour_weekends.index, summary_hour_weekends.loc[:,'mean'], color='k',

ax.fill_between(summary_hour_weekends.index, summary_hour_weekends.loc[:,'25%'], \
                summary_hour_weekends.loc[:,'75%'], hatch='///', facecolor='0.8', al

ax.set_xticks(range(24));

ax.grid(ls=':', color='0.8')

# ax.set_title('week-ends', fontsize=16)

ax.plot(summary_hour_weekdays.index, summary_hour_weekdays.loc[:,'mean'], color='k',

ax.fill_between(summary_hour_weekdays.index, summary_hour_weekdays.loc[:,'25%'], \
                summary_hour_weekdays.loc[:,'75%'], hatch='\\\\\\', facecolor='0.8',

ax.legend(loc=1 , fontsize=15)

ax.set_xticks(range(24));

ax.grid(ls=':', color='0.8')

ax.set_ylim([0, 200])

ax.set_xlabel('hour of the day', fontsize=15)

ax.set_ylabel('cyclists number', fontsize=15);

[l.set_fontsize(13) for l in ax.xaxis.get_ticklabels()]
[l.set_fontsize(13) for l in ax.yaxis.get_ticklabels()]

ax.set_title('Tamaki drive: number of cyclists per hour of the day', fontsize=16)

for ext in ['png','jpeg','pdf']:
    f.savefig(f'../figures/paper/daily_cycle.{ext}', dpi=200)
```



calculates the daily totals from the hourly data

In [112…

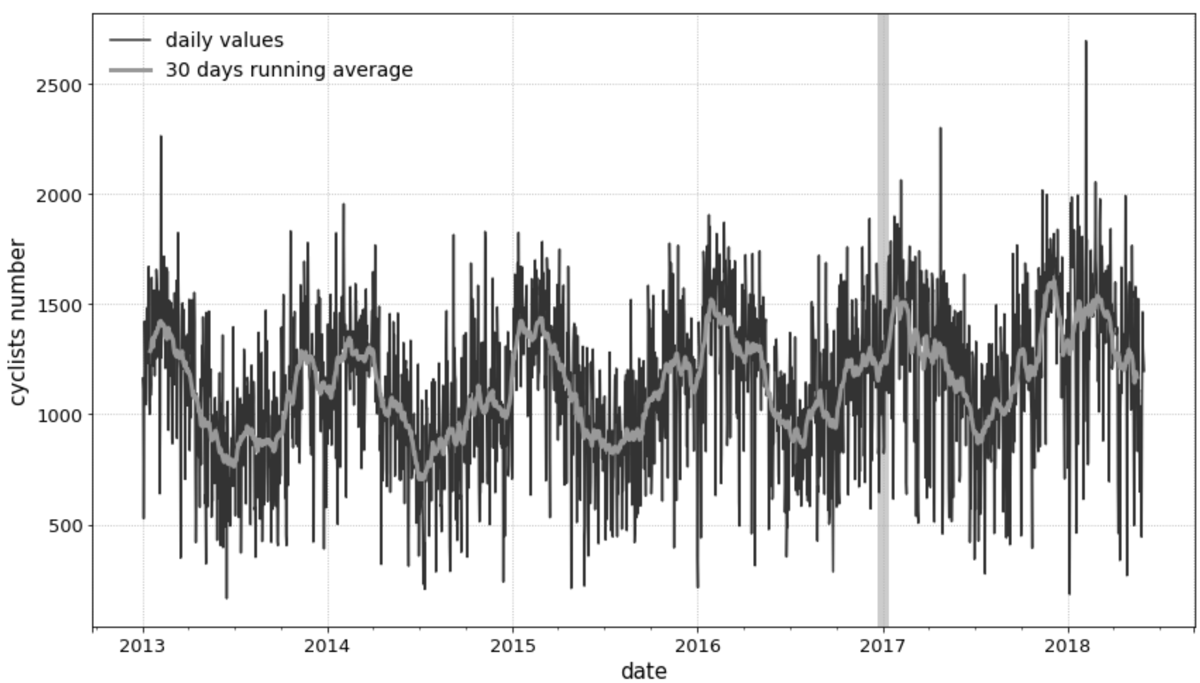
```
data = dfc.loc['2013':,['Tamaki Drive, Filtered']].resample('1D').sum()
```

plots the time series

We are separating the time-series into a **training set** (the period 2013 to 2016 included, i.e. 1461 days) and a **test set** (the period ranging from the 1st January 2017 to the 1st of June 2018, i.e. 517 days). The model will be fitted on the training set, and evaluated on the test set (out of sample prediction), to ensure a fair evaluation of the performance of the model. The grey vertical bar on the figure below marks the separation between the training and test set.

In [113…

```python
f, ax = plt.subplots(figsize=(14,8))

data.plot(ax=ax, color='0.2')

data.rolling(window=30, center=True).mean().plot(ax=ax, ls='-', lw=3, color='0.6')

ax.grid(ls=':')
ax.legend(['daily values','30 days running average'], frameon=False, fontsize=14)

[l.set_fontsize(13) for l in ax.xaxis.get_ticklabels()]
[l.set_fontsize(13) for l in ax.yaxis.get_ticklabels()]

ax.set_xlabel('date', fontsize=15)

ax.set_ylabel('cyclists number', fontsize=15);

ax.axvline('2017', color='0.8', lw=8, zorder=-1)

for ext in ['png','jpeg','pdf']:
    f.savefig(f'../figures/paper/cycling_counts_Tamaki_drive.{ext}', dpi=200)
```



creates a pandas dataframe holding the dates of the holidays (both national holidays and the Auckland regions' specific holidays)

see holiday (https://github.com/dr-prodigy/python-holidays)

In [114…

```python
holidays_df = pd.DataFrame([], columns = ['ds','holiday'])
```

In [115…

```
ldates = []
lnames = []
for date, name in sorted(holidays.NZ(prov='AUK', years=np.arange(2013, 2018 + 1)).it
    ldates.append(date)
    lnames.append(name)
```

In [116…

```
ldates = np.array(ldates)
lnames = np.array(lnames)
```

In [117…

```
holidays_df.loc[:,'ds'] = ldates
```

In [118…

```
holidays_df.loc[:,'holiday'] = lnames
```

In [119…

```
holidays_df.holiday.unique()
```

Out[119]:

```
array(["New Year's Day", "Day after New Year's Day",
       'Auckland Anniversary Day', 'Waitangi Day', 'Good Friday',
       'Easter Monday', 'Anzac Day', "Queen's Birthday", 'Labour Day',
       'Christmas Day', 'Boxing Day', 'Anzac Day (Observed)',
       'Boxing Day (Observed)', "Day after New Year's Day (Observed)",
       'Waitangi Day (Observed)', 'Christmas Day (Observed)',
       "New Year's Day (Observed)"], dtype=object)
```

we conflate the actual holidays and the 'observed' ones to reduce the number of categories

In [120…

```
holidays_df.loc[:,'holiday'] = holidays_df.loc[:,'holiday'].apply(lambda x : x.repla
```

In [121…

```
holidays_df.holiday.unique()
```

Out[121]:

```
array(["New Year's Day", "Day after New Year's Day",
       'Auckland Anniversary Day', 'Waitangi Day', 'Good Friday',
       'Easter Monday', 'Anzac Day', "Queen's Birthday", 'Labour Day',
       'Christmas Day', 'Boxing Day'], dtype=object)
```

prepares the cycling count ndata for ingesting in fbprophet

In [122…

```
data = data.rename({'Tamaki Drive, Filtered':'y'}, axis=1)
```

In [123…

```
data.head()
```

Out[123]:

	y
datetime	
2013-01-01	1163.0
2013-01-02	1112.0
2013-01-03	527.0
2013-01-04	1045.0
2013-01-05	1422.0

Splits the data into a training and test set, and returns these data frames in a format **fbprophet** can understand

In [124…
```
data_train, data_test = utils.prepare_data(data, 2017)
```

In [125…
```
data_train.tail()
```

Out[125]:

	ds	y
1456	2016-12-27	1515.0
1457	2016-12-28	998.0
1458	2016-12-29	999.0
1459	2016-12-30	1333.0
1460	2016-12-31	1239.0

In [126…
```
data_test.head()
```

Out[126]:

	ds	y
0	2017-01-01	1245.0
1	2017-01-02	956.0
2	2017-01-03	823.0
3	2017-01-04	853.0
4	2017-01-05	1476.0

Instantiate, then fit the model to the training data

The first step in **fbprophet** is to instantiate the model, it is there that you can set the `prior scales` for each component of your time-series, as well as the number of Fourier series to use to model the cyclic components.

A general rule is that larger prior scales and larger number of Fourier series will make the model more flexible, but at the potential cost of generalisation: i.e. the model might overfit (https://en.wikipedia.org/wiki/Overfitting), learning the noise (rather than the signal) in the training data, but giving poor results when applied to yet unseen data (the test data)… setting these hyperparameters (https://en.wikipedia.org/wiki/Hyperparameter_(machine_learning)) can be more an art than a science …

In [127…
```
m = Prophet(mcmc_samples=300, holidays=holidays_df, holidays_prior_scale=0.25, chang
            yearly_seasonality=10, \
            weekly_seasonality=True, \
            daily_seasonality=False)
```

In [128…
```
m.fit(data_train)
```

```
/Users/nicolasf/anaconda3/envs/PANGEO/lib/python3.6/site-packages/pystan/misc.py:45
6: DeprecationWarning: inspect.getargspec() is deprecated, use inspect.signature()
or inspect.getfullargspec()
  if "chain_id" in inspect.getargspec(init).args:
```

Out[128]: <fbprophet.forecaster.Prophet at 0x1a2727e438>

make the `future` dataframe

In [129…
```
future = m.make_future_dataframe(periods=len(data_test), freq='1D')
```

In [130…
```
future.head()
```

Out[130]:

	ds
0	2013-01-01
1	2013-01-02
2	2013-01-03
3	2013-01-04
4	2013-01-05

In [131…
```
future.tail()
```

Out[131]:

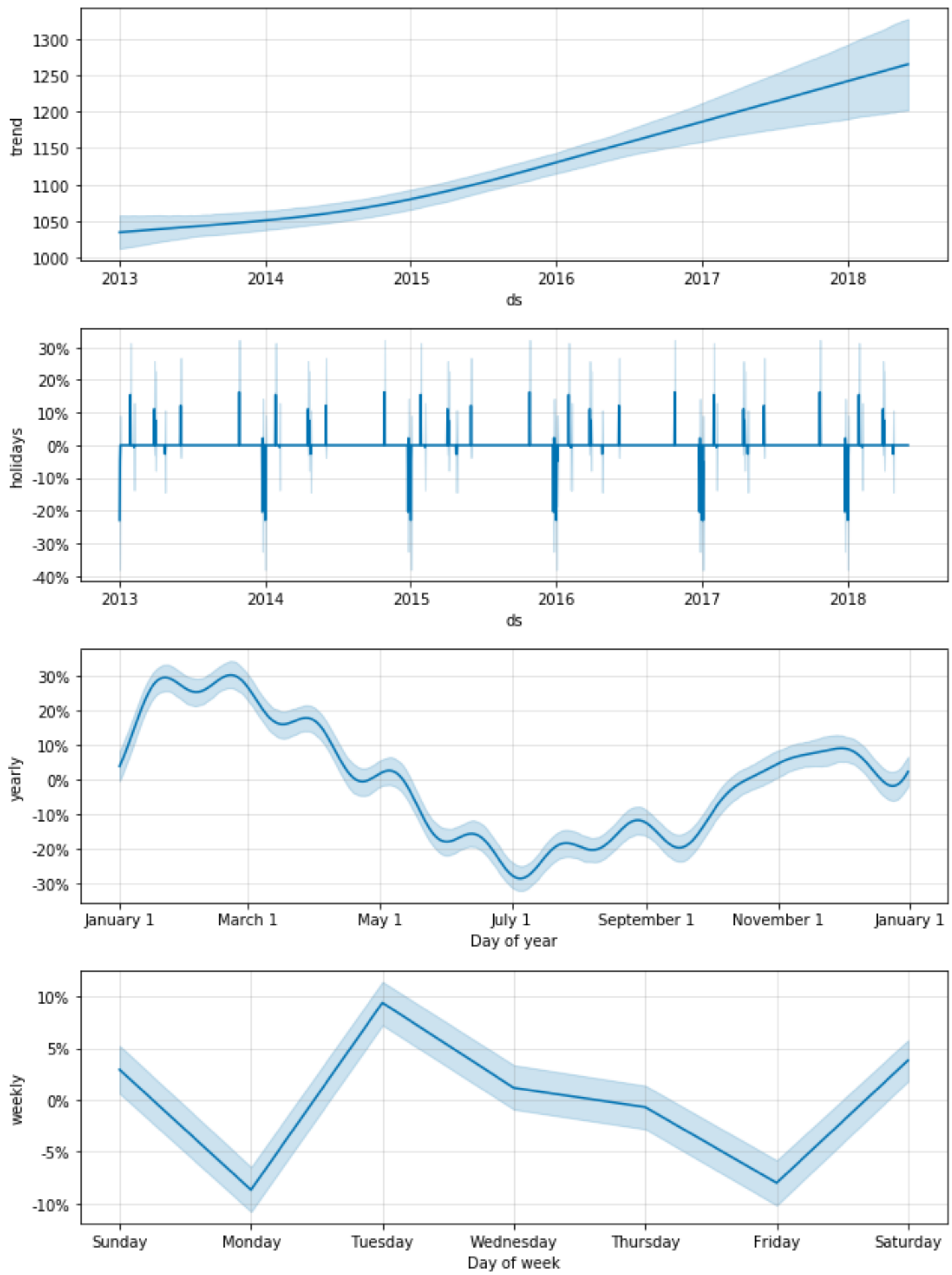
	ds
1973	2018-05-28
1974	2018-05-29
1975	2018-05-30
1976	2018-05-31
1977	2018-06-01

forecast

In [132…
```
forecast = m.predict(future)
```

plots the `components` of the forecast (trend + cyclic component [yearly seasonality, weekly seasonality] and effects of the holidays at this stage)

In [133…
```
f = m.plot_components(forecast)
```



put it all together with the actual observations

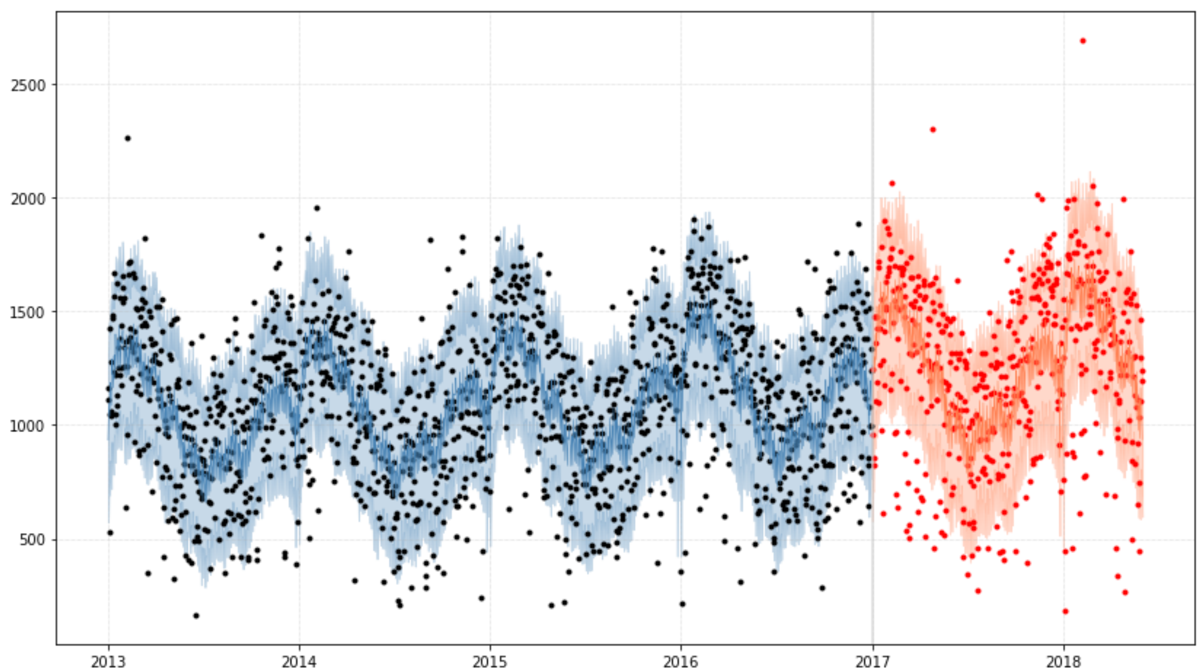
In [134…

```
utils.make_verif?
```

```
Signature: utils.make_verif(forecast, data_train, data_test)
Docstring:
Put together the forecast (coming from fbprophet)
and the overved data, and set the index to be a proper datetime index,
for plotting

Parameters
----------
forecast : pandas.DataFrame
    The pandas.DataFrame coming from the `forecast` method of a fbprophet
    model.

data_train : pandas.DataFrame
    The training set, pandas.DataFrame

data_test : pandas.DataFrame
    The training set, pandas.DataFrame

Returns
-------
forecast :
    The forecast DataFrane including the original observed data.
File:      ~/research/NIWA/Auckland_Cycling/code/utils.py
Type:      function
```

In [135…
```
verif = utils.make_verif(forecast, data_train, data_test)
```

In [136…
```
f = utils.plot_verif(verif)
```

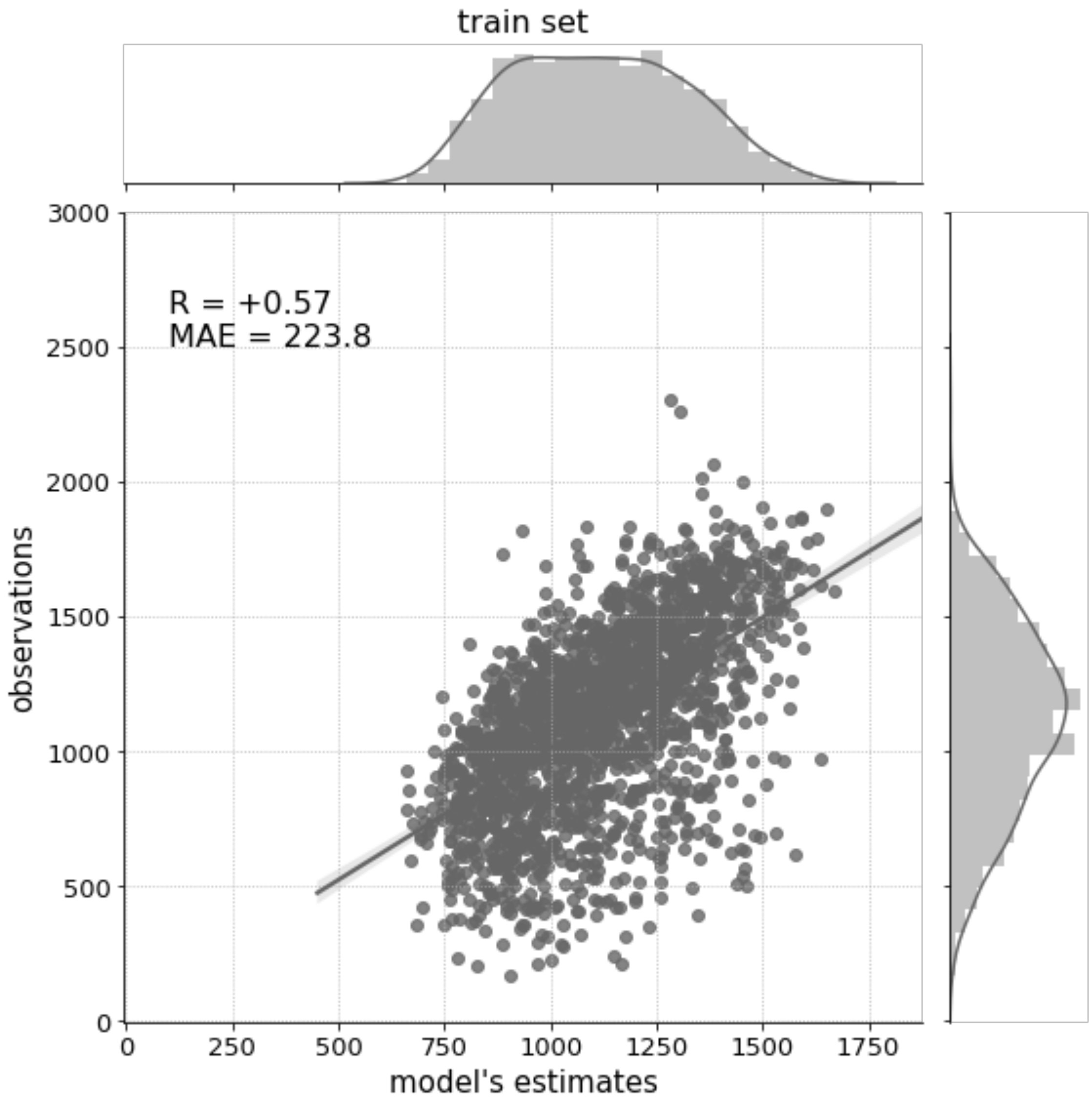


scatter plot, marginal distribution and correlation between observations and modelled / predicted values

train set

In [137…

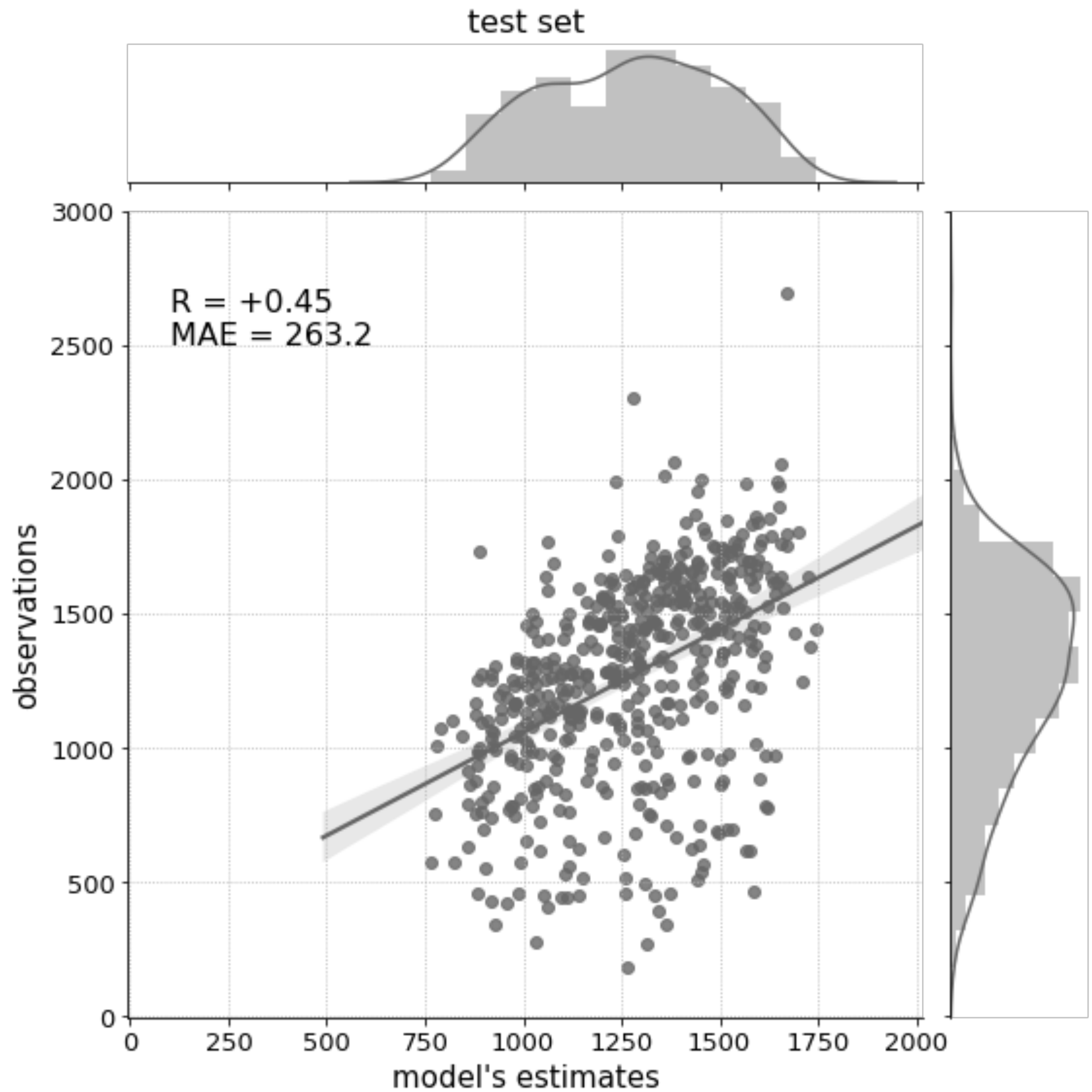
```
utils.plot_joint_plot(verif.loc[:'2017',:], title='train set', fname='train_set_join
```



test set

In [138…

```
utils.plot_joint_plot(verif.loc['2017':,:], title='test set', fname='test_set_joint_
```



In [139…

```
verif.loc['2017':,['y','yhat']].corr()
```

Out[139]:

	y	yhat
y	1.000000	0.453109
yhat	0.453109	1.000000

Mean Absolute Error (in number of cyclists)

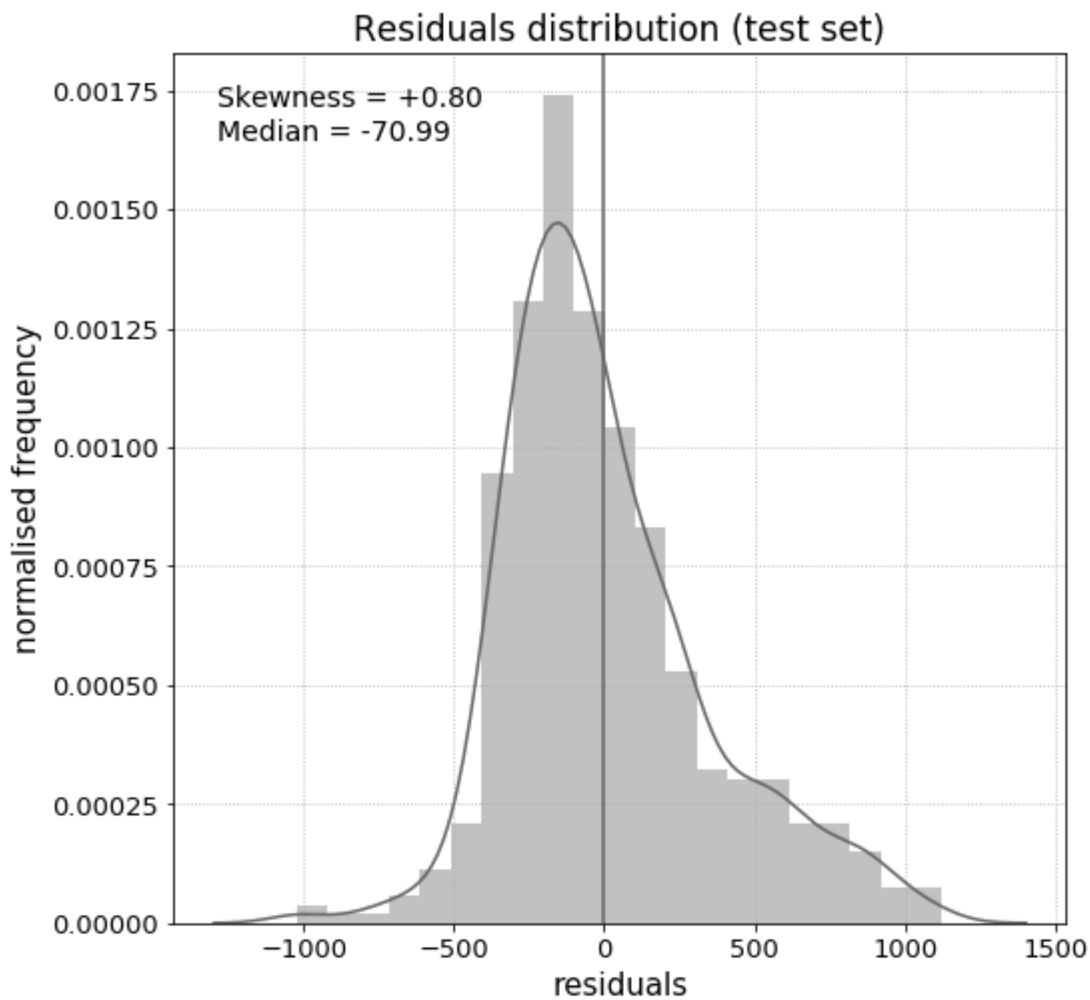
In [140…

```
MAE(verif.loc['2017':,'y'].values, verif.loc['2017':,'yhat'].values)
```

Out[140]: 263.2457637079962

In [141…

```
f, ax = plt.subplots(figsize=(8,8))
sns.distplot((verif.loc['2017':,'yhat'] - verif.loc['2017':,'y']), ax=ax, color='0.4
ax.grid(ls=':')
ax.set_xlabel('residuals', fontsize=15)
ax.set_ylabel("normalised frequency", fontsize=15)
ax.grid(ls=':')

[l.set_fontsize(13) for l in ax.xaxis.get_ticklabels()]
[l.set_fontsize(13) for l in ax.yaxis.get_ticklabels()];

ax.text(0.05, 0.9, "Skewness = {:+4.2f}\nMedian = {:+4.2f}".\
        format(skew(verif.loc['2017':,'yhat'] - verif.loc['2017':,'y']), (verif.loc[
        fontsize=14, transform=ax.transAxes)

ax.axvline(0, color='0.4')

ax.set_title('Residuals distribution (test set)', fontsize=17)

for ext in ['png','jpeg','pdf']:
    f.savefig(f'../figures/paper/residuals_distribution_test_set_no_climate.{ext}',
```



incorporating the effects of weather conditions

Now we add daytime (i.e. 6 AM to 9 PM) averaged temperature, rainfall, sunshine fraction and windspeed as **extra regressors** in the fbprophet model

temperature

In [142…
```
temp = pd.read_csv('../data/weather/hourly/commute/temp_day.csv', index_col=0, parse
```

In [143…
```
temp = temp.loc[:,['Tmin(C)']]
```

In [144…
```
temp.columns = ['temp']
```

In [145…
```
temp.head()
```

Out[145]:

	temp
2012-01-01	19.807143
2012-01-02	18.000000
2012-01-03	19.335714
2012-01-04	19.307143
2012-01-05	19.978571

rainfall

In [146…
```
rain = pd.read_csv('../data/weather/hourly/commute/rain_day.csv', index_col=0, parse
```

In [147…
```
rain = rain.loc[:,['Amount(mm)']]
```

In [148…
```
rain.columns = ['rain']
```

In [149…
```
rain.head()
```

Out[149]:

	rain
2012-01-01	0.000000
2012-01-02	0.000000
2012-01-03	0.028571
2012-01-04	0.185714
2012-01-05	0.014286

sunshine fraction

In [150…
```
sun = pd.read_csv('../data/weather/hourly/commute/sun_day.csv', index_col=0, parse_d
```

In [151…
```
sun.columns = ['sun']
```

In [152…
```
sun.head()
```

Out[152]:

	sun
2012-01-01	0.078571
2012-01-02	0.128571
2012-01-03	0.321429
2012-01-04	0.128571
2012-01-05	0.378571

wind

In [153…
```
wind = pd.read_csv('../data/weather/hourly/commute/wind_day.csv', index_col=0, parse
```

In [154…
```
wind = wind.loc[:,['Speed(m/s)']]
```

In [155…
```
wind.columns = ['wind']
```

In [156…
```
wind.head()
```

Out[156]:

	wind
2011-01-01	8.464286
2011-01-02	3.857143
2011-01-03	3.871429
2011-01-04	2.392857
2011-01-05	6.621429

restrict to the available period

In [157…
```
temp = temp.loc['2013':'2018-06-01',:]
```

In [158…
```
rain = rain.loc['2013':'2018-06-01',:]
```

In [159…
```
sun = sun.loc['2013':'2018-06-01',:]
```

In [160…
```
wind = wind.loc['2013':'2018-06-01',:]
```

interpolate so that there are no missing values

In [161…
```
temp = temp.interpolate(method='linear')
```

In [162…
```
rain = rain.interpolate(method='linear')
```

In [163…
```
sun = sun.interpolate(method='linear')
```

In [164…
```
wind = wind.interpolate(method='linear')
```

adds the climate regressors to the data

In [165…
```
data_with_regressors = utils.add_regressor(data, temp, varname='temp')
```

In [166…
```
data_with_regressors = utils.add_regressor(data_with_regressors, rain, varname='rain
```

In [167…
```
data_with_regressors = utils.add_regressor(data_with_regressors, sun, varname='sun')
```

In [168…
```
data_with_regressors = utils.add_regressor(data_with_regressors, wind, varname='wind
```

In [169…
```
data_with_regressors.head()
```

Out[169]:

datetime	y	temp	rain	sun	wind
2013-01-01	1163.0	20.000000	0.000000	0.950000	6.100000
2013-01-02	1112.0	20.342857	0.000000	0.535714	4.428571
2013-01-03	527.0	16.278571	0.228571	0.014286	4.728571
2013-01-04	1045.0	17.635714	0.000000	0.742857	8.978571
2013-01-05	1422.0	19.592857	0.000000	0.964286	6.185714

In [170…
```
data_with_regressors.tail()
```

Out[170]:

datetime	y	temp	rain	sun	wind
2018-05-28	1107.0	8.750000	0.0	0.271429	3.200000
2018-05-29	1464.0	7.764286	0.0	0.671429	2.571429
2018-05-30	1298.0	7.614286	0.0	0.621429	2.378571
2018-05-31	1239.0	8.192857	0.0	0.678571	2.057143
2018-06-01	1196.0	9.085714	0.0	0.635714	2.178571

prepare the data and subsets (train and test set)

In [171…
```
data_train, data_test = utils.prepare_data(data_with_regressors, 2017)
```

we first instantiates a new fbprophet model, using the exact same prior scales and parameters as before

In [172…
```
m = Prophet(mcmc_samples=300, holidays=holidays_df, holidays_prior_scale=0.25, chang
            yearly_seasonality=10, \
            weekly_seasonality=True, \
            daily_seasonality=False)
```

Then we add the **extra-regressors** to the model using the `add_regressor` method

In [173…
```
m.add_regressor('temp', prior_scale=0.5, mode='multiplicative')
m.add_regressor('rain', prior_scale=0.5, mode='multiplicative')
m.add_regressor('sun', prior_scale=0.5, mode='multiplicative')
m.add_regressor('wind', prior_scale=0.5, mode='multiplicative')
```

Out[173]:
```
<fbprophet.forecaster.Prophet at 0x1a27218fd0>
```

fit the new model

In [174…
```
m.fit(data_train)
```

```
/Users/nicolasf/anaconda3/envs/PANGEO/lib/python3.6/site-packages/pystan/misc.py:45
6: DeprecationWarning: inspect.getargspec() is deprecated, use inspect.signature()
or inspect.getfullargspec()
  if "chain_id" in inspect.getargspec(init).args:
```

Out[174]:
```
<fbprophet.forecaster.Prophet at 0x1a27218fd0>
```

make the future DataFrame

In [175…
```
future = m.make_future_dataframe(periods=len(data_test), freq='1D')
```

add the extra-regressors observed over the `future` DataFrame period

In [176…
```
futures = utils.add_regressor_to_future(future, [temp, rain, sun, wind])
```

the `future` DataFrame now includes the temperature, rainfall, sunshine fraction and wind speed as external (extra) regressors

In [177…
```
futures.head()
```

Out[177]:

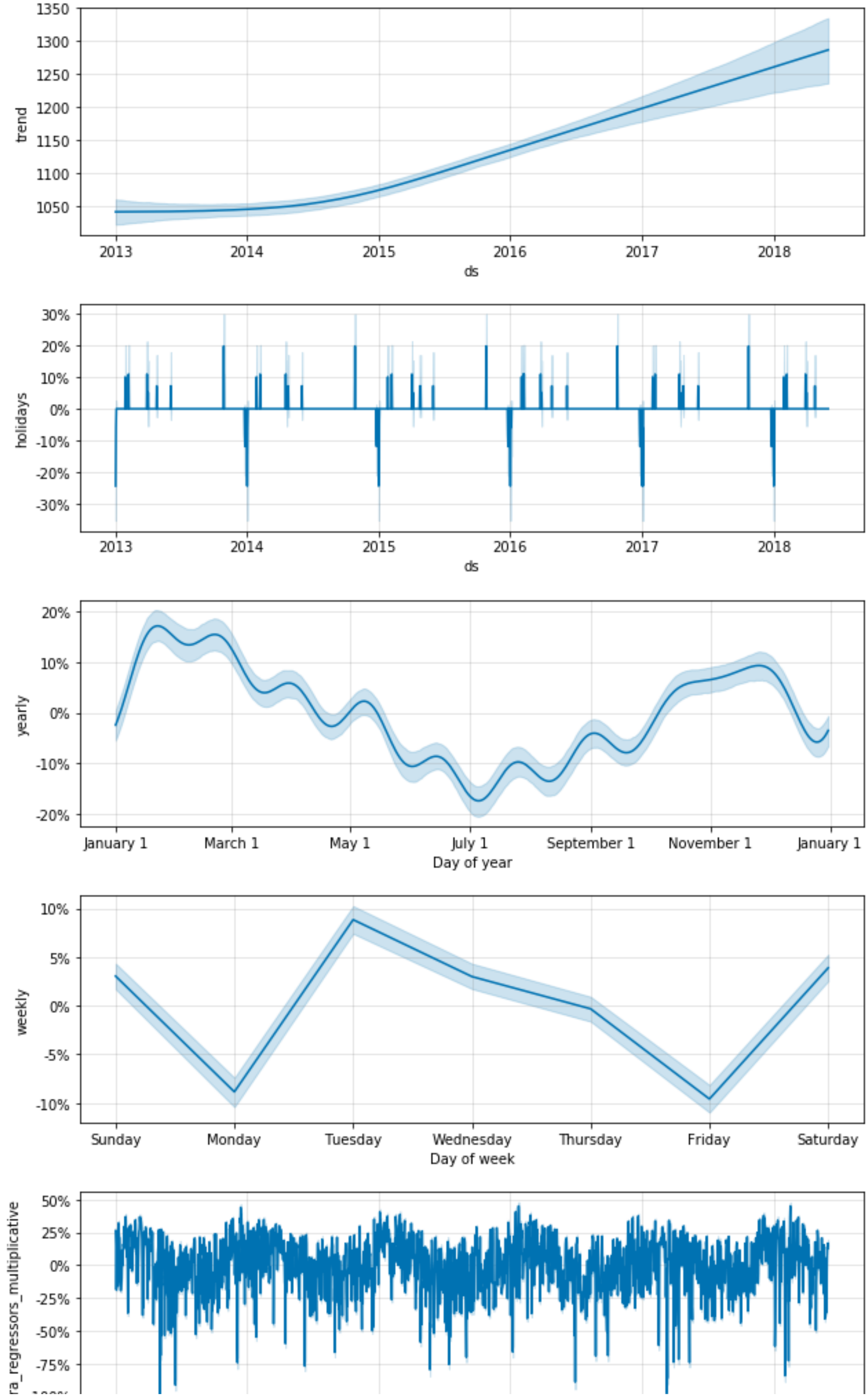
	ds	temp	rain	sun	wind
0	2013-01-01	20.000000	0.000000	0.950000	6.100000
1	2013-01-02	20.342857	0.000000	0.535714	4.428571
2	2013-01-03	16.278571	0.228571	0.014286	4.728571
3	2013-01-04	17.635714	0.000000	0.742857	8.978571
4	2013-01-05	19.592857	0.000000	0.964286	6.185714

forecast using the extra-regressors as predictors

In [178…
```
forecast = m.predict(futures)
```

In [179…

```
f = m.plot_components(forecast)
```


trend
ds
holidays
ds
yearly
Day of year
January 1
March 1
May 1
July 1
September 1
November 1
January 1
weekly
Day of week
Sunday
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
ra_regressors_multiplicative

make the `verif` pandas.DataFrame

In [180…

```
verif = utils.make_verif(forecast, data_train, data_test)
```

In [181…

```
verif.head()
```

Out[181]:

ds	ds	trend	yhat_lower	yhat_upper	trend_lower	trend_upper	Anzac Day
2013-01-01	2013-01-01	1041.968490	867.327085	1383.488956	1022.757210	1060.854410	0.0
2013-01-02	2013-01-02	1041.970362	907.425700	1399.215953	1022.827449	1060.787991	0.0
2013-01-03	2013-01-03	1041.972234	607.108535	1079.706467	1022.900050	1060.716429	0.0
2013-01-04	2013-01-04	1041.974106	745.316585	1195.949890	1022.947680	1060.643675	0.0
2013-01-05	2013-01-05	1041.975978	1132.463703	1619.396101	1022.937273	1060.570922	0.0

5 rows × 71 columns

clips the forecasts so that no value is negative (can't have a negative number of cyclists !)

In [182…

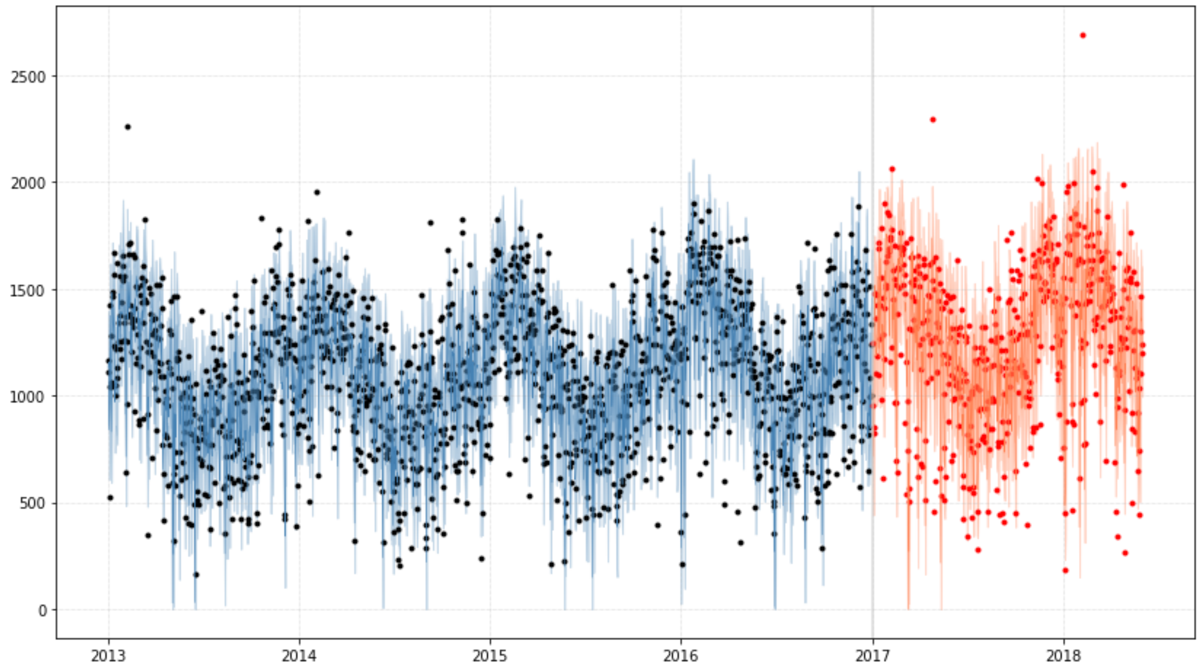
```
verif.loc[:,'yhat'] = verif.yhat.clip_lower(0)
```

In [183…

```
verif.loc[:,'yhat_lower'] = verif.yhat_lower.clip_lower(0)
```

In [184…

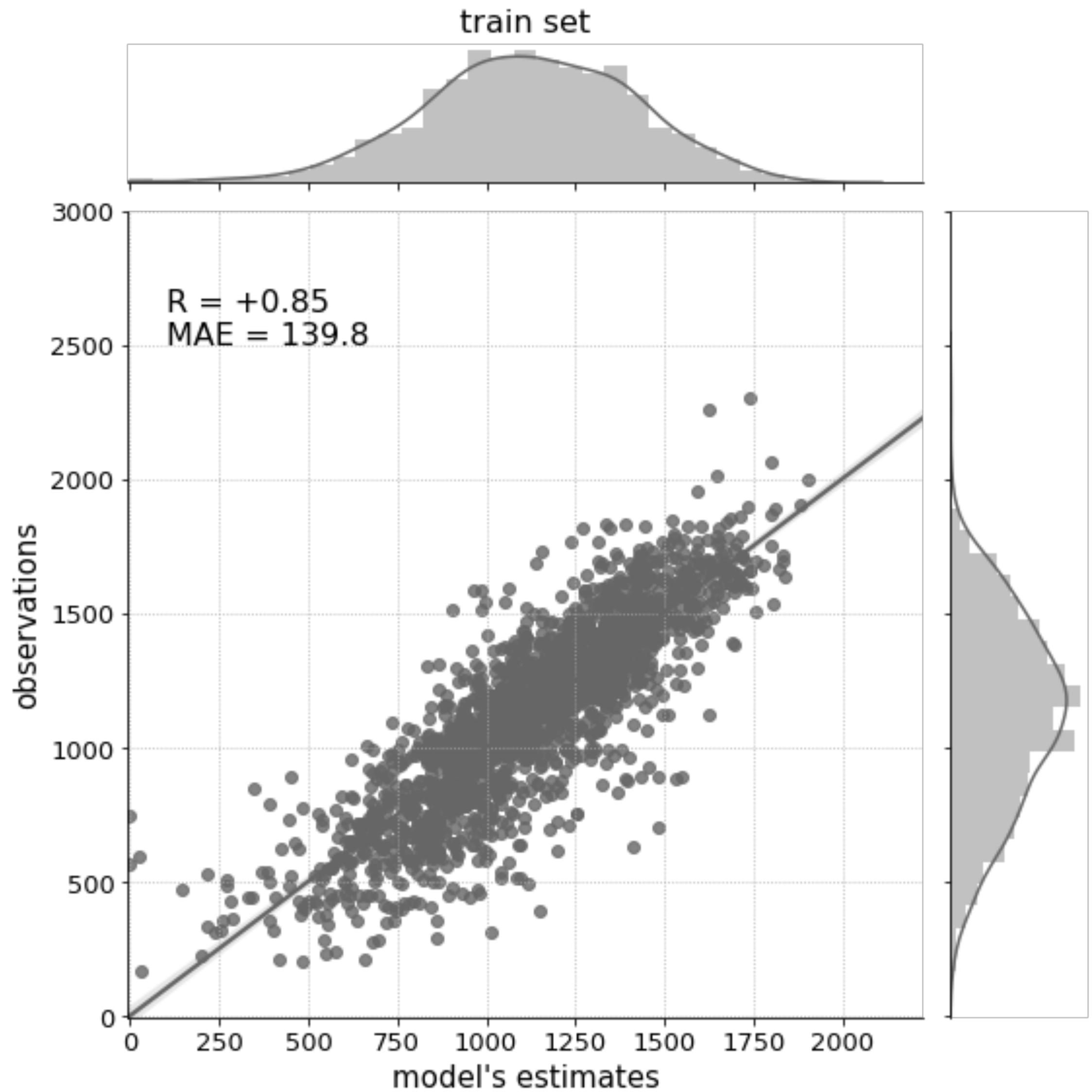
```
f =  utils.plot_verif(verif)
```



scatter plot, marginal distribution and correlation between observations and modelled / predicted values

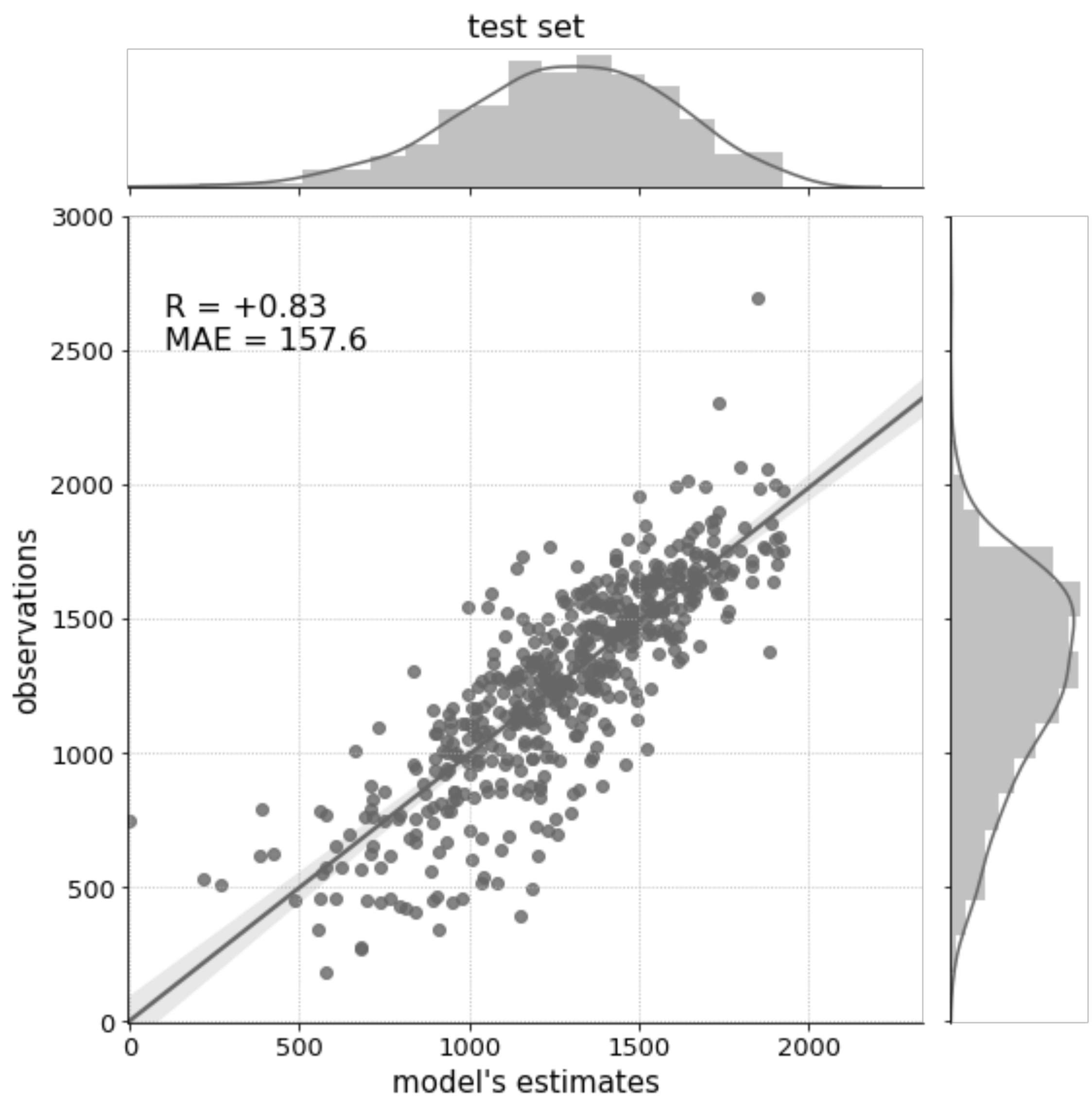
In [185…

```
utils.plot_joint_plot(verif.loc[:'2017',:], title='train set', fname='train_set_join
```



In [186…

```
utils.plot_joint_plot(verif.loc['2017':,:], title='test set', fname='test_set_joint_
```



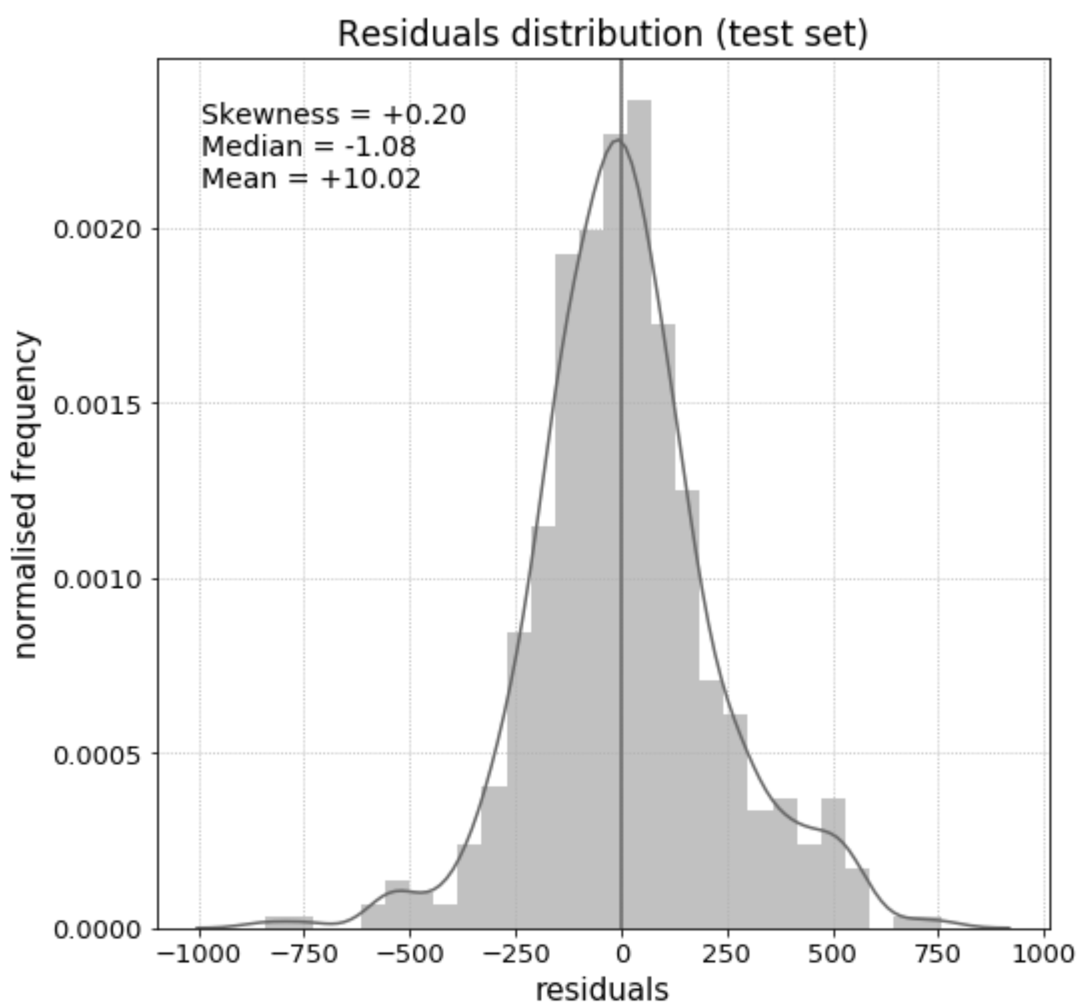
residuals distributions (test set)

In [187…

```
residuals = verif.loc['2017':,'yhat'] - verif.loc['2017':,'y']
```

In [188…

```
f, ax = plt.subplots(figsize=(8,8))
sns.distplot(residuals, ax=ax, color='0.4')
ax.grid(ls=':')
ax.set_xlabel('residuals', fontsize=15)
ax.set_ylabel("normalised frequency", fontsize=15)
ax.grid(ls=':')

[l.set_fontsize(13) for l in ax.xaxis.get_ticklabels()]
[l.set_fontsize(13) for l in ax.yaxis.get_ticklabels()];

ax.axvline(0, color='0.4')

ax.set_title('Residuals distribution (test set)', fontsize=17)

ax.text(0.05, 0.85, "Skewness = {:+4.2f}\nMedian = {:+4.2f}\nMean = {:+4.2f}".\
        format(skew(residuals), residuals.median(), residuals.mean()), \
        fontsize=14, transform=ax.transAxes)

for ext in ['png','jpeg','pdf']:
    f.savefig(f'../figures/paper/residuals_distribution_test_set_climate.{ext}', dpi
```



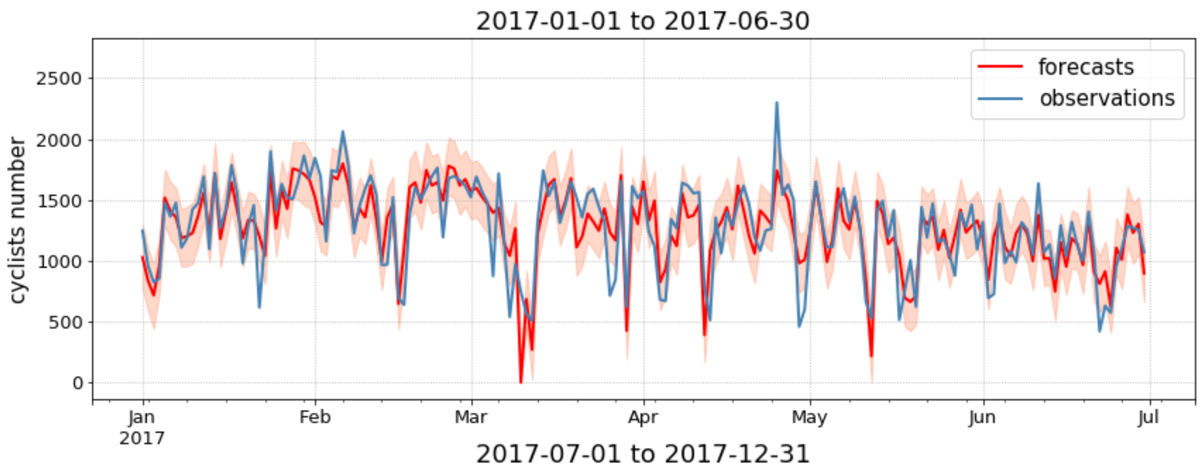
plots the forecasts (`yhat` , red line) and the observed values (`y` , blue line) in 6 months blocks

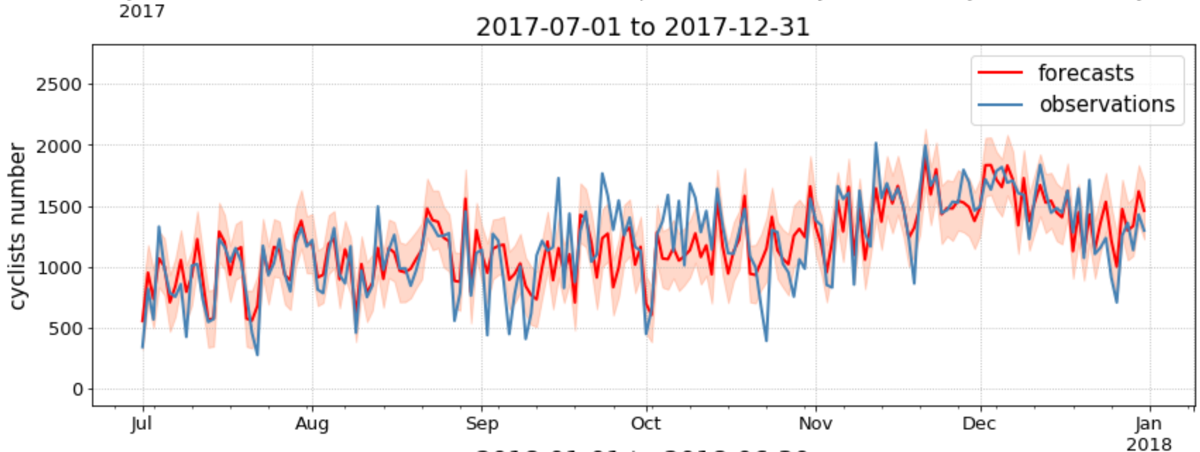
In [189…

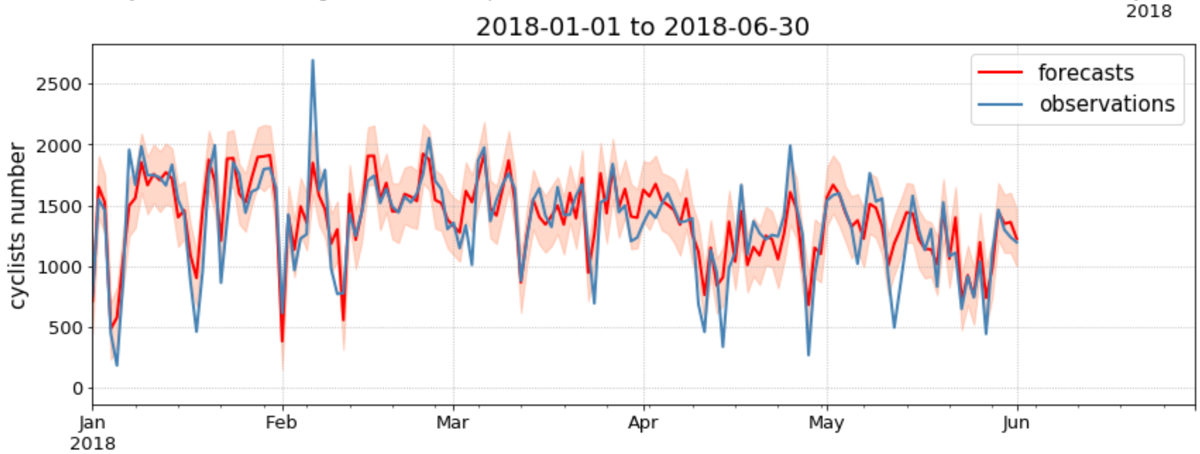
```
def make_plot_block(verif, start_date, end_date, ax=None):

    df = verif.loc[start_date:end_date,:]

    df.loc[:,'yhat'].plot(lw=2, ax=ax, color='r', ls='-', label='forecasts')

    ax.fill_between(df.index, df.loc[:,'yhat_lower'], df.loc[:,'yhat_upper'], color=

    df.loc[:,'y'].plot(lw=2, ax=ax, color='steelblue', ls='-', label='observations')

    ax.grid(ls=':')
    ax.legend(fontsize=15)
    [l.set_fontsize(13) for l in ax.xaxis.get_ticklabels()]
    [l.set_fontsize(13) for l in ax.yaxis.get_ticklabels()]
    ax.set_ylabel('cyclists number', fontsize=15)
    ax.set_xlabel('', fontsize=15)

    ax.set_title(f'{start_date} to {end_date}', fontsize=18)
```

In [190…

```
f, axes = plt.subplots(nrows=3, figsize=(14,16), sharey=True)

ax = axes[0]

make_plot_block(verif, '2017-01-01', '2017-06-30', ax=ax)

ax = axes[1]

make_plot_block(verif, '2017-07-01', '2017-12-31', ax=ax)

ax = axes[2]

make_plot_block(verif, '2018-01-01', '2018-06-30', ax=ax)

ax.set_xlim(['2018-01-01','2018-06-30'])

for ext in ['png','jpeg','pdf']:
    f.savefig('../figures/paper/forecasts_obs_2017-08.{}'.format(ext), dpi=200)
```







running correlations (over 90 days) between observed and modelled / predicted values

In [191…

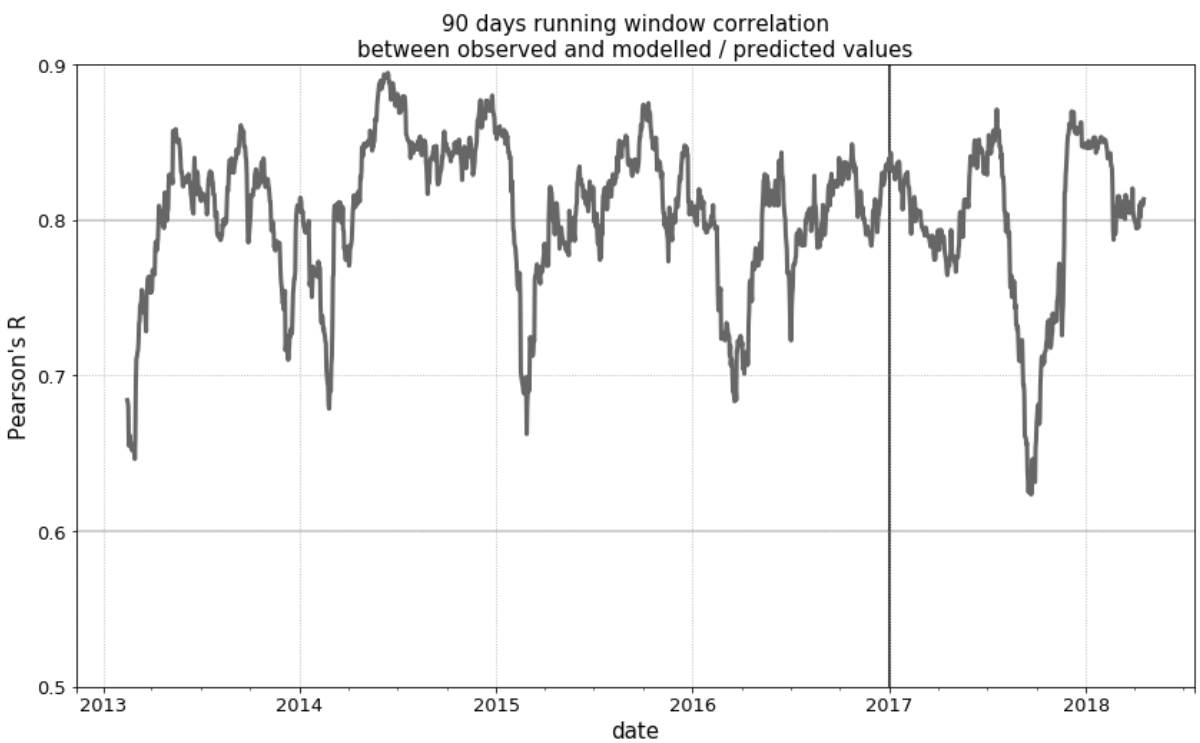
```
corr = verif.loc[:,['y','yhat']].rolling(window=90, center=True).corr().iloc[0::2,1]
```

In [192…

```
corr.index = corr.index.droplevel(1)
```

In [193…

```
f, ax = plt.subplots(figsize=(14, 8))

corr.plot(ax=ax, lw=3, color='0.4')

ax.axhline(0.8, color='0.8', zorder=-1)
ax.axhline(0.6, color='0.8', zorder=-1)
ax.axvline('2017', color='k', zorder=-1)
ax.grid(ls=':')
ax.set_ylim([0.5, 0.9])
ax.set_xlabel('date', fontsize=15)
ax.set_ylabel("Pearson's R", fontsize=15)
ax.grid(ls=':')
[l.set_fontsize(13) for l in ax.xaxis.get_ticklabels()]
[l.set_fontsize(13) for l in ax.yaxis.get_ticklabels()]

ax.set_yticks(np.arange(0.5, 1., 0.1));

ax.set_title('90 days running window correlation\nbetween observed and modelled / pr

for ext in ['png','jpeg','pdf']:
    f.savefig(f'../figures/paper/moving_corr.{ext}', dpi=200)
```



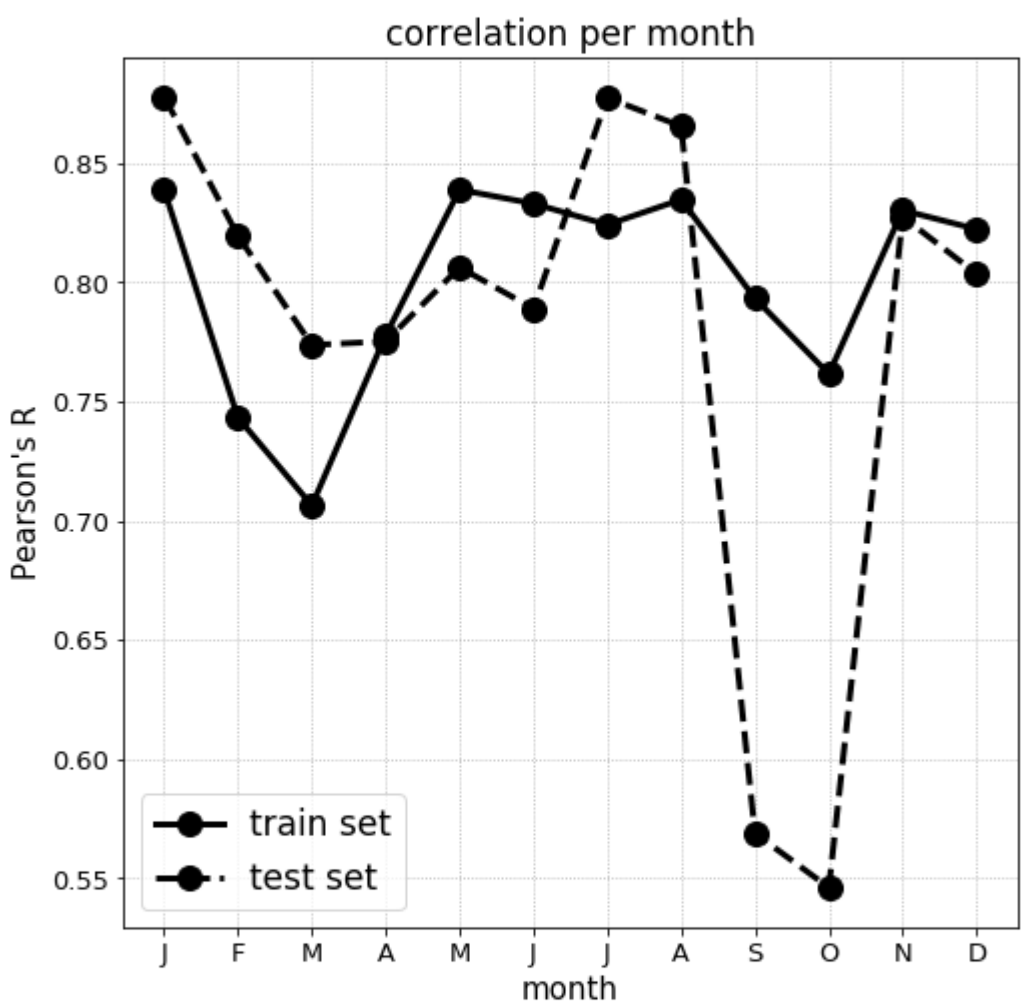
correlation grouped by month, is there seasonality in the performance of the model ?

In [194…

```
corr_season_test = verif.loc['2017':,['y','yhat']].groupby(verif.loc['2017':,:].inde
corr_season_train = verif.loc[:'2017',['y','yhat']].groupby(verif.loc[:'2017',:].ind
corr_season = verif.loc[:,['y','yhat']].groupby(verif.loc[:,:].index.month).corr()
```

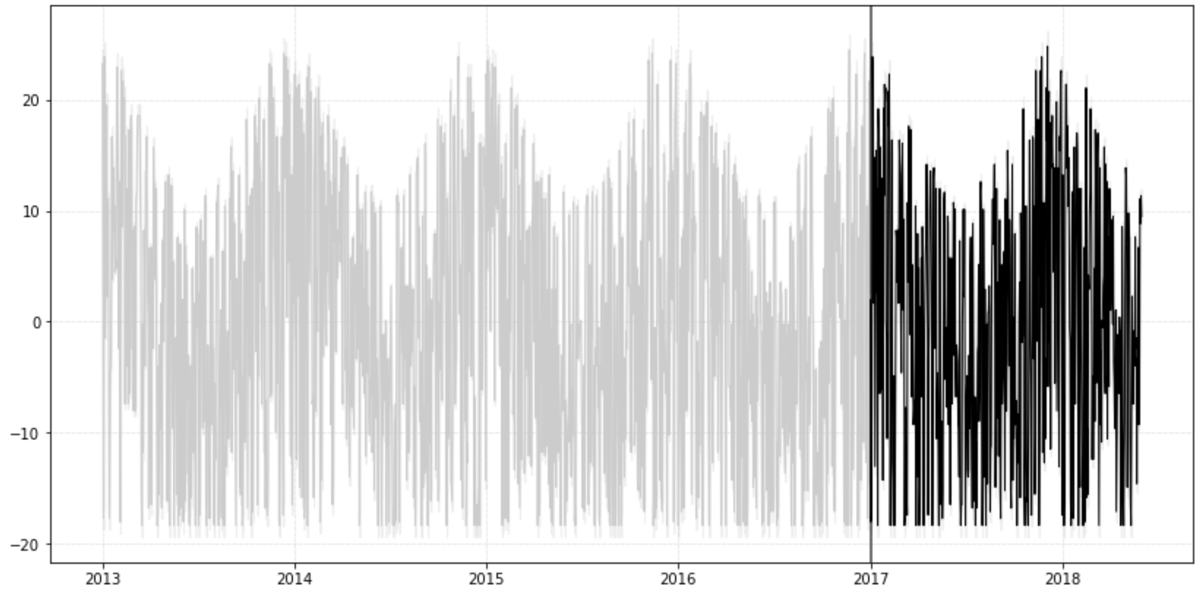
In [195…

```
f, ax = plt.subplots(figsize=(8,8))
corr_season_train.xs('y', axis=0, level=1)['yhat'].plot(ax=ax, lw=3, marker='o', mar
corr_season_test.xs('y', axis=0, level=1)['yhat'].plot(ax=ax, lw=3, marker='o', mark
# corr_season.xs('y', axis=0, level=1)['yhat'].plot(ax=ax, lw=3, marker='o', markers

ax.legend(fontsize=17, loc=3)

ax.set_xticks(range(1, 13))
ax.set_xticklabels(list('JFMAMJJASOND'))
ax.set_xlabel('month', fontsize=15)
ax.set_ylabel("Pearson's R", fontsize=15)
ax.grid(ls=':')
[l.set_fontsize(13) for l in ax.xaxis.get_ticklabels()]
[l.set_fontsize(13) for l in ax.yaxis.get_ticklabels()]

ax.set_title('correlation per month', fontsize=17)

for ext in ['png','jpeg','pdf']:
    f.savefig(f'../figures/paper/correlation_obs_pred_per_month.{ext}', dpi=200)
```

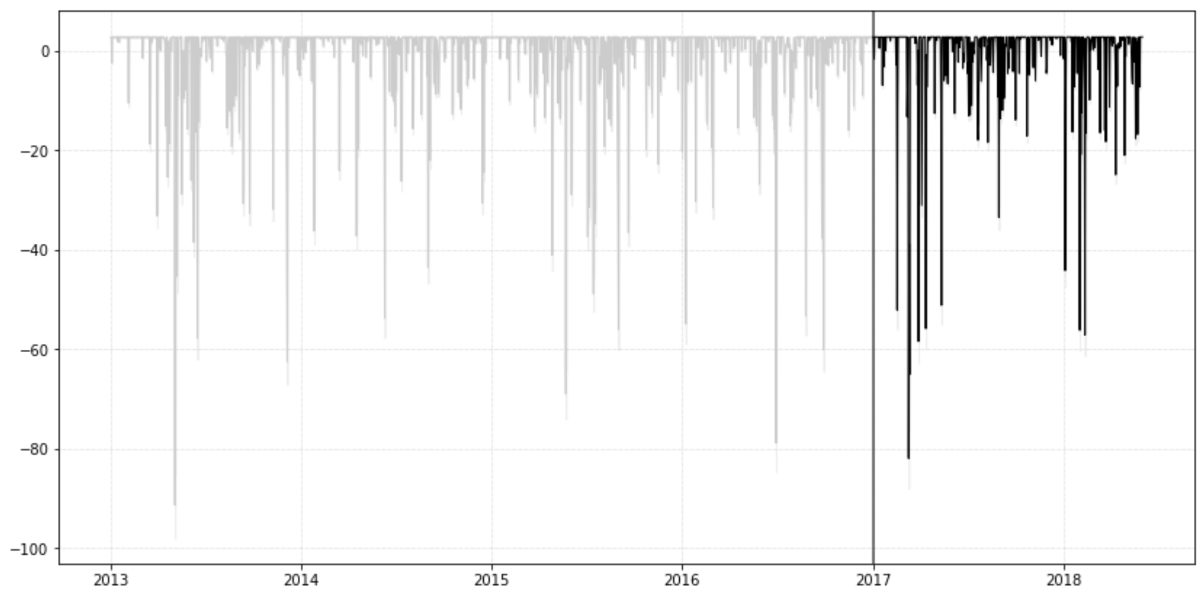


plot the contribution of the different climate variables to the response variable (in percentage of the trend component, as we chose a multiplicative model)

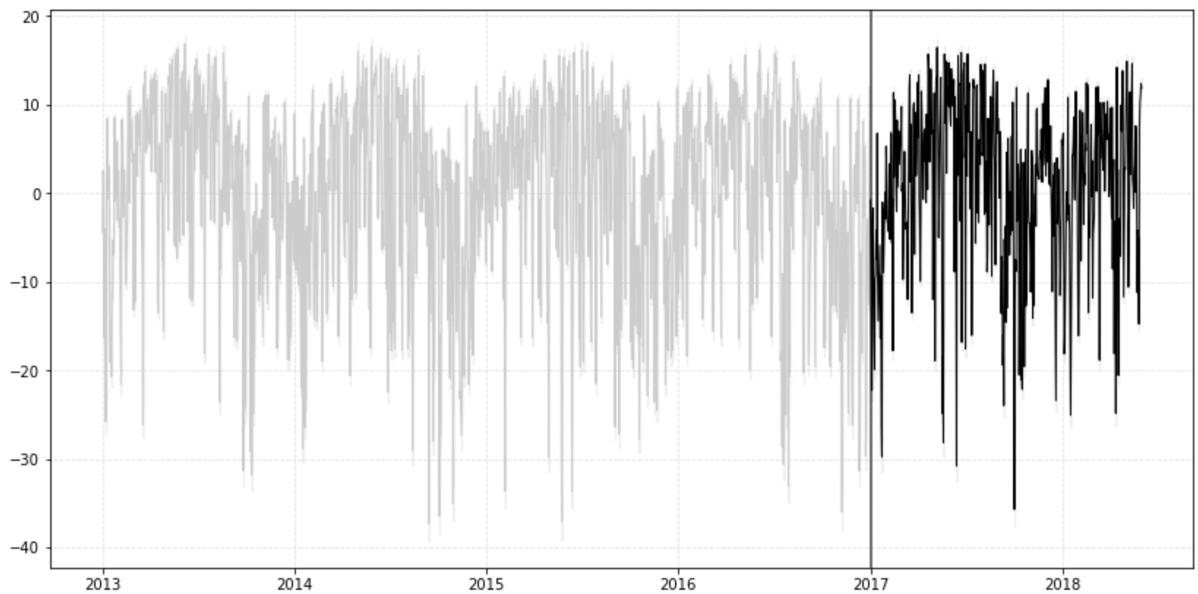
In [196…
```
f  = utils.plot_verif_component(verif, component = 'sun')
```



In [197…
```
f  = utils.plot_verif_component(verif, component = 'rain')
```



In [198…
```
f  = utils.plot_verif_component(verif, component = 'wind')
```



plots the combined contribution of the climate extra-regressors

In [199…

```
f = utils.plot_verif_component(verif, component = 'extra_regressors_multiplicative')
```