notebook_preprocessing

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1 Predicting Dengue Cases

- Student name: ***Aysu Erdemir***
- Student pace: ***Flex***
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- Instructor name: ***Abhineet Kulkarni***

1.1 Overview:

Dengue fever is a mosquito-borne disease that occurs in tropical and sub-tropical parts of the world. In mild cases, symptoms are similar to the flu: fever, rash, and muscle and joint pain. In severe cases, dengue fever can cause severe bleeding, low blood pressure, and even death.

Because it is carried by mosquitoes, the transmission dynamics of dengue are related to climate variables such as temperature and precipitation; however the relationship to climate is known to be complex. The way the disease spreads and causes endemics has significant public health implications worldwide.

- CDC is interested in predicting local epidemics of dengue fever so that they can take necessary precautions and efforts before the next spike. They want to know if we can predict the number of dengue fever cases reported each week in San Juan, Puerto Rico.
- My goal is to build several machine learning models to forecast the upcoming weekly dengue cases as accurately as possible.

1.2 Business and Data Understanding

- The data was obtained from DrivenData. The data set included weekly dengue case counts along with environmental data collected by various U.S. Federal Government agencies—from the Centers for Disease Control and Prevention to the National Oceanic and Atmospheric Administration in the U.S. Department of Commerce.
- The full dataset included cases from year 1990 to 2008. The data from 2008-2013 included only features without case counts.
- In this project I will be focusing on data on `Puerto Rico` only. The relevant variables/features included in the dataset are:

Target Feature: * `total_cases` - Weekly total dengue cases.

Predictive Features:

Date Indicators:

- `week_start_date` - Date given in yyyy-mm-dd format.

NOAA's GHCN daily climate data weather station measurements:

- `station_max_temp_c` - Maximum temperature
- `station_min_temp_c` - Minimum temperature
- `station_avg_temp_c` - Average temperature
- `station_precip_mm` - Total precipitation
- `station_diur_temp_rng_c` - Diurnal temperature range

PERSIANN satellite precipitation measurements (0.25x0.25 degree scale):

- `precipitation_amt_mm` - Total precipitation

NOAA's NCEP Climate Forecast System Reanalysis measurements (0.5x0.5 degree scale):

- `reanalysis_sat_precip_amt_mm` - Total precipitation
- `reanalysis_dew_point_temp_k` - Mean dew point temperature
- `reanalysis_air_temp_k` - Mean air temperature
- `reanalysis_relative_humidity_percent` - Mean relative humidity
- `reanalysis_specific_humidity_g_per_kg` - Mean specific humidity
- `reanalysis_precip_amt_kg_per_m2` - Total precipitation
- `reanalysis_max_air_temp_k` - Maximum air temperature
- `reanalysis_min_air_temp_k` - Minimum air temperature
- `reanalysis_avg_temp_k` - Average air temperature
- `reanalysis_tdtr_k` - Diurnal temperature range

Satellite vegetation -greenness - Normalized difference vegetation index (NDVI) - NOAA's CDR Normalized Difference Vegetation Index (0.5x0.5 degree scale) measurements:

- `ndvi_se` - Pixel southeast of city centroid
- `ndvi_sw` - Pixel southeast of city centroid
- `ndvi_ne` - Pixel southeast of city centroid
- `ndvi_nw` - Pixel southeast of city centroid

For example, when you have negative values, it's highly likely that it's water. On the other hand, if you have an NDVI value close to +1, there's a high possibility that it's dense green leaves. But when NDVI is close to zero, there are likely no green leaves and it could even be an urbanized area.

1.3 Preprocessing:

1.3.1 Null Replacement:

- Null values for the climate features - except the four ndvi fatures - were imputed with **interpolation** since the missing data points are scarse.
- Null values for the four ndvi fatures were imputed using **k-Nearest Neighbors - KNN** since there were bigger chunks of missing values.

1.3.2 Feature Engineering:

- Create `month` and `seasons`: Created new variables representing the month and seasons.
- Create `average_ndvi` and its **categorical** version: Created a new feature representing the average NDVI values using the four different locations. Then created a categorical version of average_ndvi to represent watery, soily, sparce_grassy areas.
- Create **shifts** and **rolled averages** for the main climate variables: Research seems to indicate that past sustained heat, precipitation or humidity impacts dengue cases more profoundly than the climate situation right at the time of cases.
  - **Shifted** the variables by 2 weeks to account for the mosquito to reach adulthood and the incubation period of the virus until someone tests positive.
  - Engineered **rolled - cumulative** means over a period of time ranging from 1 weeks to 20 weeks to see the variable with the highest correlation. The lag with the highest corralation was kept in the final dataset. The final lags ranged from 2 months to 4 months.

Some initial thoughts based on past research:

Precipitation: - Mosquitos thrive wet climates, the wetter the better! - A rise in **accumulated rainfall** was shown to result in an increase in the number and quality of breeding sites. - Elevated relative risk of dengue was observed when the weekly average rainfall was more than 150 mm at **lagged weeks 12 to 20**. - However, **above a certain rainfall level**, suitable mosquito breeding sites can be exposed to flooding, so the population is likely to decrease in such cases.

Humidity: - Humidity generates conditions that are favorable to adult mosquitoes increasing the life of the mosquito.
- Humidity range of **60% - 90%** is the optimum moisture for growth and development of the Aedes aegypti mosquito.

Temperature: - Mosquitoes more likely to transmit dengue virus in hot weather. Mosquitoes function best at 80 degrees F. **Higher temperatures (73-85°F)** results in more rapid viral growth and higher levels of virus. - The relative risk of dengue fever increases when the weekly average temperature is high **at lagged weeks 5 to 18**. - Under **fluctuating temperatures**, the mosquitoes show lower levels of virus in their salivary glands. - **Extreme heat waves** can negatively impact mosquito life as very high temperatures reduce adult lifespan and egg survival, resulting in reduced Aedes population and lower risk of dengue transmission.

NDVI index: - The relationship between dengue epidemic and greenness indexes is not clear or consistent. - Some studies indicate increased density of vegetation to provide suitable habitat for the immature mosquitoes. - Others indicated that low vegetation cover areas with increased dengue incidence rates. This inconsistency may be explained by regional differences.

[1]:
```
# Import required packages
```

```python
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

import missingno
from sklearn.preprocessing import StandardScaler
from sklearn.impute import KNNImputer

import warnings
warnings.filterwarnings("ignore")
# check package versions when necessary:
# pd.__version__
```

2 Data Exploration:

---

[2]:
```python
# load the files
from google.colab import files
uploaded = files.upload()
```

```
<IPython.core.display.HTML object>

Saving dengue_labels_train.csv to dengue_labels_train.csv
Saving dengue_features_train.csv to dengue_features_train.csv
Saving dengue_features_test.csv to dengue_features_test.csv
```

[3]:
```python
# Read the Data
train_features = pd.read_csv("dengue_features_train.csv")
train_labels = pd.read_csv("dengue_labels_train.csv")
test_features = pd.read_csv("dengue_features_test.csv")
```

[4]:
```python
# Checking the columns/rows  for train_features
train_features.head()
```

[4]:
```
   year  weekofyear week_start_date   ndvi_ne   ndvi_nw   ndvi_se   ndvi_sw  \
0  1990          18         4/30/90  0.122600  0.103725  0.198483  0.177617
1  1990          19          5/7/90  0.169900  0.142175  0.162357  0.155486
2  1990          20         5/14/90  0.032250  0.172967  0.157200  0.170843
3  1990          21         5/21/90  0.128633  0.245067  0.227557  0.235886
4  1990          22         5/28/90  0.196200  0.262200  0.251200  0.247340

   precipitation_amt_mm  reanalysis_air_temp_k  reanalysis_avg_temp_k  …  \
0                 12.42             297.572857             297.742857  …
```

```
1                 22.82            298.211429             298.442857  …
2                 34.54            298.781429             298.878571  …
3                 15.36            298.987143             299.228571  …
4                  7.52            299.518571             299.664286  …

   reanalysis_precip_amt_kg_per_m2  reanalysis_relative_humidity_percent  \
0                            32.00                             73.365714
1                            17.94                             77.368571
2                            26.10                             82.052857
3                            13.90                             80.337143
4                            12.20                             80.460000

   reanalysis_sat_precip_amt_mm  reanalysis_specific_humidity_g_per_kg  \
0                         12.42                              14.012857
1                         22.82                              15.372857
2                         34.54                              16.848571
3                         15.36                              16.672857
4                          7.52                              17.210000

   reanalysis_tdtr_k  station_avg_temp_c  station_diur_temp_rng_c  \
0           2.628571           25.442857                 6.900000
1           2.371429           26.714286                 6.371429
2           2.300000           26.714286                 6.485714
3           2.428571           27.471429                 6.771429
4           3.014286           28.942857                 9.371429

   station_max_temp_c  station_min_temp_c  station_precip_mm
0                29.4                20.0               16.0
1                31.7                22.2                8.6
2                32.2                22.8               41.4
3                33.3                23.3                4.0
4                35.0                23.9                5.8

[5 rows x 23 columns]
```

[5]:
```
# Checking the columns/rows  for train_labels
train_labels.head()
```

[5]:
```
   year  weekofyear  total_cases
0  1990          18            4
1  1990          19            5
2  1990          20            4
3  1990          21            3
4  1990          22            6
```

[6]:
```
# Checking the columns/rows  for test_features
test_features.head()
```

[6]:
```
   year  weekofyear week_start_date  ndvi_ne   ndvi_nw   ndvi_se   ndvi_sw  \
0  2008          18         4/29/08  -0.0189 -0.018900  0.102729  0.091200
1  2008          19          5/6/08  -0.0180 -0.012400  0.082043  0.072314
2  2008          20         5/13/08  -0.0015       NaN  0.151083  0.091529
3  2008          21         5/20/08      NaN -0.019867  0.124329  0.125686
4  2008          22         5/27/08   0.0568  0.039833  0.062267  0.075914

   precipitation_amt_mm  reanalysis_air_temp_k  reanalysis_avg_temp_k  …  \
0                 78.60             298.492857             298.550000  …
1                 12.56             298.475714             298.557143  …
2                  3.66             299.455714             299.357143  …
3                  0.00             299.690000             299.728571  …
4                  0.76             299.780000             299.671429  …

   reanalysis_precip_amt_kg_per_m2  reanalysis_relative_humidity_percent  \
0                            25.37                             78.781429
1                            21.83                             78.230000
2                             4.12                             78.270000
3                             2.20                             73.015714
4                             4.36                             74.084286

   reanalysis_sat_precip_amt_mm  reanalysis_specific_humidity_g_per_kg  \
0                         78.60                              15.918571
1                         12.56                              15.791429
2                          3.66                              16.674286
3                          0.00                              15.775714
4                          0.76                              16.137143

   reanalysis_tdtr_k  station_avg_temp_c  station_diur_temp_rng_c  \
0           3.128571           26.528571                 7.057143
1           2.571429           26.071429                 5.557143
2           4.428571           27.928571                 7.785714
3           4.342857           28.057143                 6.271429
4           3.542857           27.614286                 7.085714

   station_max_temp_c  station_min_temp_c  station_precip_mm
0                33.3                21.7               75.2
1                30.0                22.2               34.3
2                32.8                22.8                3.0
3                33.3                24.4                0.3
4                33.3                23.3               84.1

[5 rows x 23 columns]
```

[7]:
```python
# Merge the features dataset with the labels dataset (total cases) to form a␣
↪new dataset called "train".
train = pd.merge(train_features, train_labels, on=[ "year", "weekofyear"])
```

```python
train.head()
```

[7]:
```
   year  weekofyear week_start_date   ndvi_ne   ndvi_nw   ndvi_se   ndvi_sw  \
0  1990          18         4/30/90  0.122600  0.103725  0.198483  0.177617
1  1990          19          5/7/90  0.169900  0.142175  0.162357  0.155486
2  1990          20         5/14/90  0.032250  0.172967  0.157200  0.170843
3  1990          21         5/21/90  0.128633  0.245067  0.227557  0.235886
4  1990          22         5/28/90  0.196200  0.262200  0.251200  0.247340

   precipitation_amt_mm  reanalysis_air_temp_k  reanalysis_avg_temp_k  …  \
0                 12.42             297.572857             297.742857  …
1                 22.82             298.211429             298.442857  …
2                 34.54             298.781429             298.878571  …
3                 15.36             298.987143             299.228571  …
4                  7.52             299.518571             299.664286  …

   reanalysis_relative_humidity_percent  reanalysis_sat_precip_amt_mm  \
0                             73.365714                         12.42
1                             77.368571                         22.82
2                             82.052857                         34.54
3                             80.337143                         15.36
4                             80.460000                          7.52

   reanalysis_specific_humidity_g_per_kg  reanalysis_tdtr_k  \
0                              14.012857           2.628571
1                              15.372857           2.371429
2                              16.848571           2.300000
3                              16.672857           2.428571
4                              17.210000           3.014286

   station_avg_temp_c  station_diur_temp_rng_c  station_max_temp_c  \
0           25.442857                 6.900000                29.4
1           26.714286                 6.371429                31.7
2           26.714286                 6.485714                32.2
3           27.471429                 6.771429                33.3
4           28.942857                 9.371429                35.0

   station_min_temp_c  station_precip_mm  total_cases
0                20.0               16.0            4
1                22.2                8.6            5
2                22.8               41.4            4
3                23.3                4.0            3
4                23.9                5.8            6

[5 rows x 24 columns]
```

- Many of the temperature features coded more than once in celcius and fehrenheit using different data sources.

[8]:
```python
# check row and column numbers for the new dataset
print(train_features.shape)
print(train_labels.shape)
print(train.shape)
```

```
(936, 23)
(936, 3)
(936, 24)
```

[9]:
```python
train.info()
```

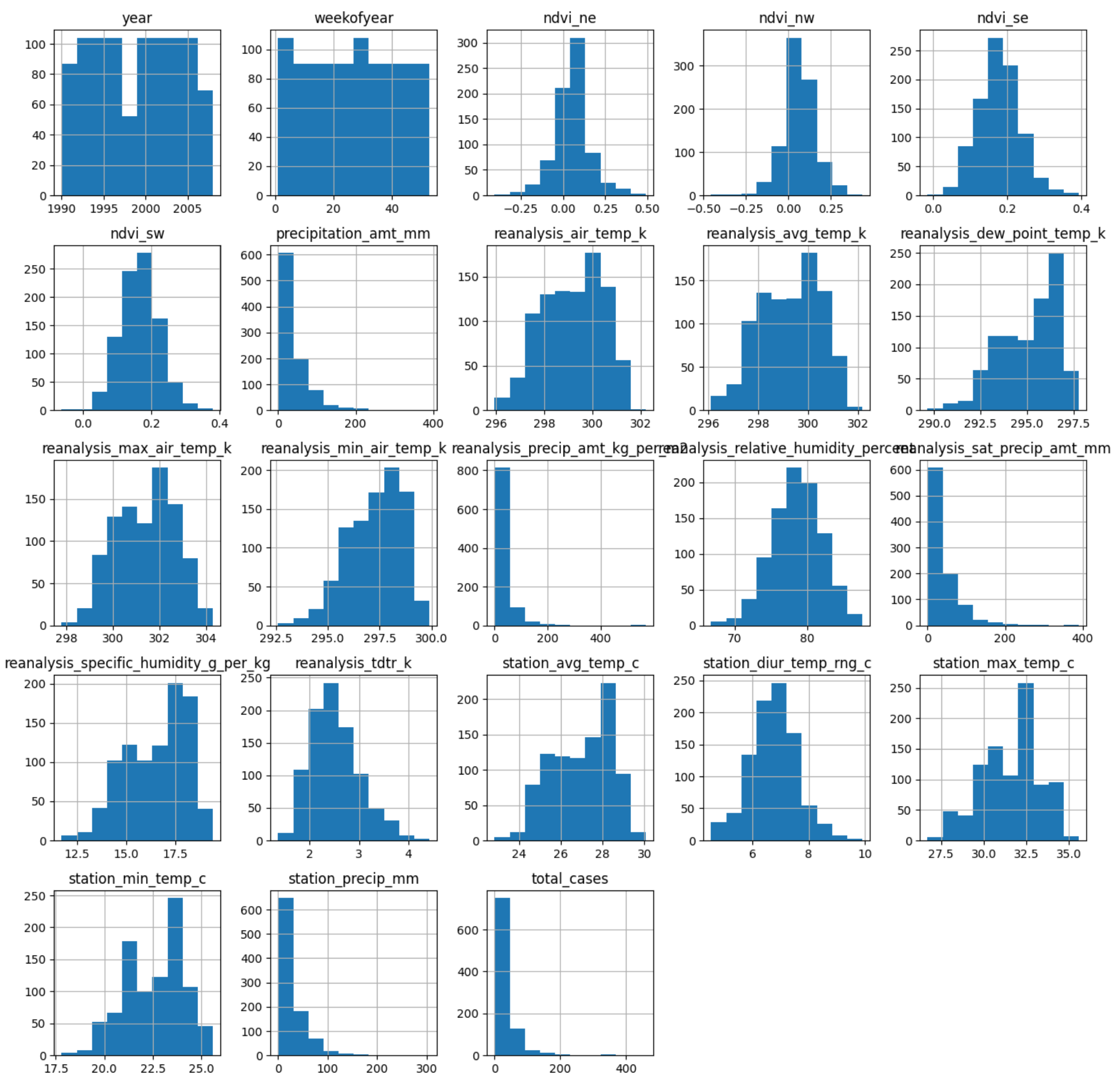
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 936 entries, 0 to 935
Data columns (total 24 columns):
 #   Column                                 Non-Null Count  Dtype
---  ------                                 --------------  -----
 0   year                                   936 non-null    int64
 1   weekofyear                             936 non-null    int64
 2   week_start_date                        936 non-null    object
 3   ndvi_ne                                745 non-null    float64
 4   ndvi_nw                                887 non-null    float64
 5   ndvi_se                                917 non-null    float64
 6   ndvi_sw                                917 non-null    float64
 7   precipitation_amt_mm                   927 non-null    float64
 8   reanalysis_air_temp_k                  930 non-null    float64
 9   reanalysis_avg_temp_k                  930 non-null    float64
 10  reanalysis_dew_point_temp_k            930 non-null    float64
 11  reanalysis_max_air_temp_k              930 non-null    float64
 12  reanalysis_min_air_temp_k              930 non-null    float64
 13  reanalysis_precip_amt_kg_per_m2        930 non-null    float64
 14  reanalysis_relative_humidity_percent   930 non-null    float64
 15  reanalysis_sat_precip_amt_mm           927 non-null    float64
 16  reanalysis_specific_humidity_g_per_kg  930 non-null    float64
 17  reanalysis_tdtr_k                      930 non-null    float64
 18  station_avg_temp_c                     930 non-null    float64
 19  station_diur_temp_rng_c                930 non-null    float64
 20  station_max_temp_c                     930 non-null    float64
 21  station_min_temp_c                     930 non-null    float64
 22  station_precip_mm                      930 non-null    float64
 23  total_cases                            936 non-null    int64
dtypes: float64(20), int64(3), object(1)
memory usage: 182.8+ KB
```

- All variables appear as numerical except for week_start_date which is an object / string.
- There are many null values, especially in ndvi index values.

[10]:
```
train.total_cases.describe()
# Total weekly cases range from 0 to 461
```

[10]:
```
count    936.000000
mean      34.180556
std       51.381372
min        0.000000
25%        9.000000
50%       19.000000
75%       37.000000
max      461.000000
Name: total_cases, dtype: float64
```

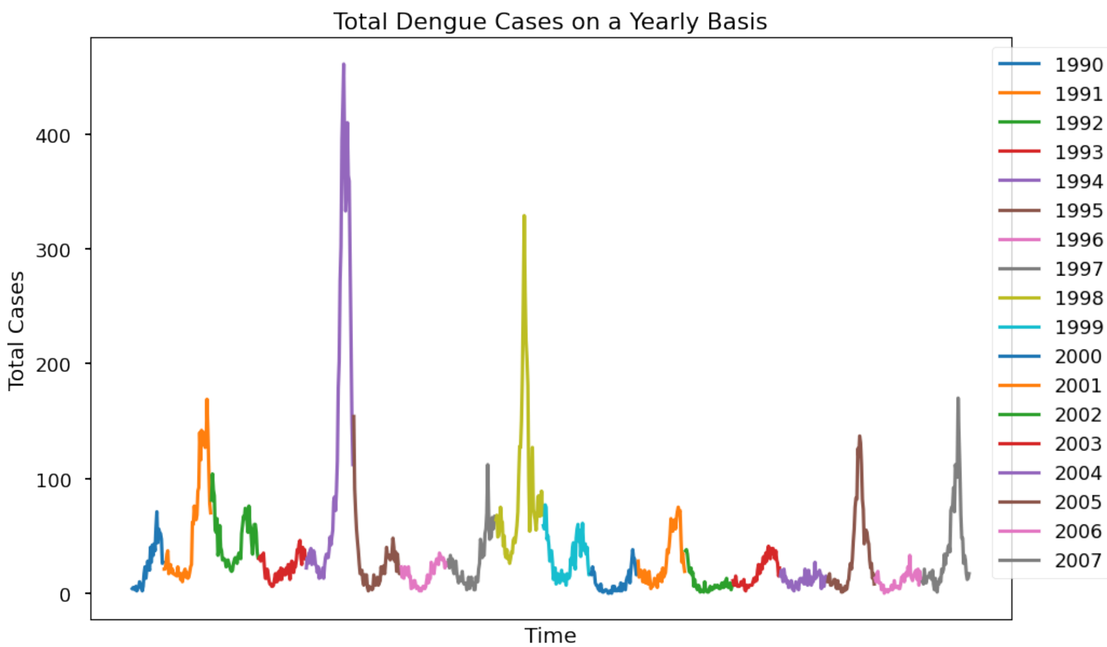
[11]:
```
# Let's see the distribution of the data for each one of the variables.
train.hist(figsize = (16,16));
```



- All feature variables seem to follow more or less a normal distribution except for precipitation fatures.
- Precipitation follows a positive skew, where there are rare but extremely high values.

[12]:
```
# See the distribution of case counts per each successive year:
with plt.style.context('seaborn-talk'):
    fig, ax = plt.subplots(figsize=(11,7))

    years = np.arange(1990,2008,1).astype(int)
    for year in years:
        sns.lineplot(data=train[train.year == year],
                     x="week_start_date", y='total_cases', ax = ax, label =␣
 ↪year)
        ax.get_xaxis().set_ticks([]) # hide week_start_date
        ax.set_xlabel('Time')
        ax.set_ylabel('Total Cases')
        ax.set_title('Total Dengue Cases on a Yearly Basis')
    fig.patch.set_alpha(0) # make the figure background transparent
    plt.legend(bbox_to_anchor=(1.12, 1), loc="upper right");
    fig.savefig('total_cases_years.png', dpi=300)
    files.download("total_cases_years.png")
```

```
<IPython.core.display.Javascript object>

<IPython.core.display.Javascript object>
```



- The data is from 1990 through 2008 with peak outbreaks at certain years.

2.1 Check for null values:

[13]:
```
train.isnull().sum()
# There are many null values
```

[13]:
```
year                                      0
weekofyear                                0
week_start_date                           0
ndvi_ne                                 191
ndvi_nw                                  49
ndvi_se                                  19
ndvi_sw                                  19
precipitation_amt_mm                      9
reanalysis_air_temp_k                     6
reanalysis_avg_temp_k                     6
reanalysis_dew_point_temp_k               6
reanalysis_max_air_temp_k                 6
reanalysis_min_air_temp_k                 6
reanalysis_precip_amt_kg_per_m2           6
reanalysis_relative_humidity_percent      6
reanalysis_sat_precip_amt_mm              9
reanalysis_specific_humidity_g_per_kg     6
reanalysis_tdtr_k                         6
station_avg_temp_c                        6
station_diur_temp_rng_c                   6
station_max_temp_c                        6
station_min_temp_c                        6
station_precip_mm                         6
total_cases                               0
dtype: int64
```

[14]:
```
# Proportion of null values for each variable:
nulls = ((train.isnull().sum()*100) / len(train_features)).
 ↪sort_values(ascending=False)
nulls[nulls > 0]
```

[14]:
```
ndvi_ne                                 20.405983
ndvi_nw                                  5.235043
ndvi_se                                  2.029915
ndvi_sw                                  2.029915
precipitation_amt_mm                     0.961538
reanalysis_sat_precip_amt_mm             0.961538
reanalysis_min_air_temp_k                0.641026
reanalysis_precip_amt_kg_per_m2          0.641026
station_avg_temp_c                       0.641026
```

```
reanalysis_tdtr_k                        0.641026
reanalysis_specific_humidity_g_per_kg    0.641026
reanalysis_relative_humidity_percent     0.641026
reanalysis_dew_point_temp_k              0.641026
station_min_temp_c                       0.641026
reanalysis_max_air_temp_k                0.641026
station_max_temp_c                       0.641026
reanalysis_avg_temp_k                    0.641026
reanalysis_air_temp_k                    0.641026
station_precip_mm                        0.641026
station_diur_temp_rng_c                  0.641026
dtype: float64
```

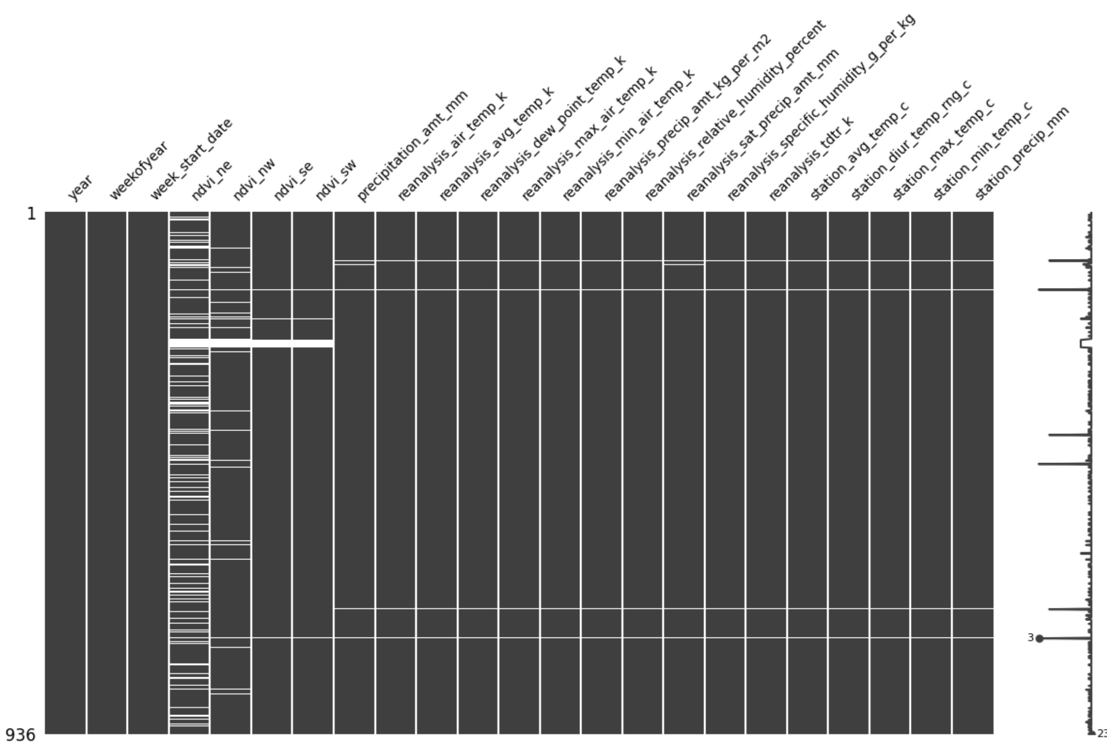
- ndvi variables have the highest proportion of null values.

2.1.1 Display missing values:

- **Missingno** library offers a very nice way to visualize the distribution of Null values.

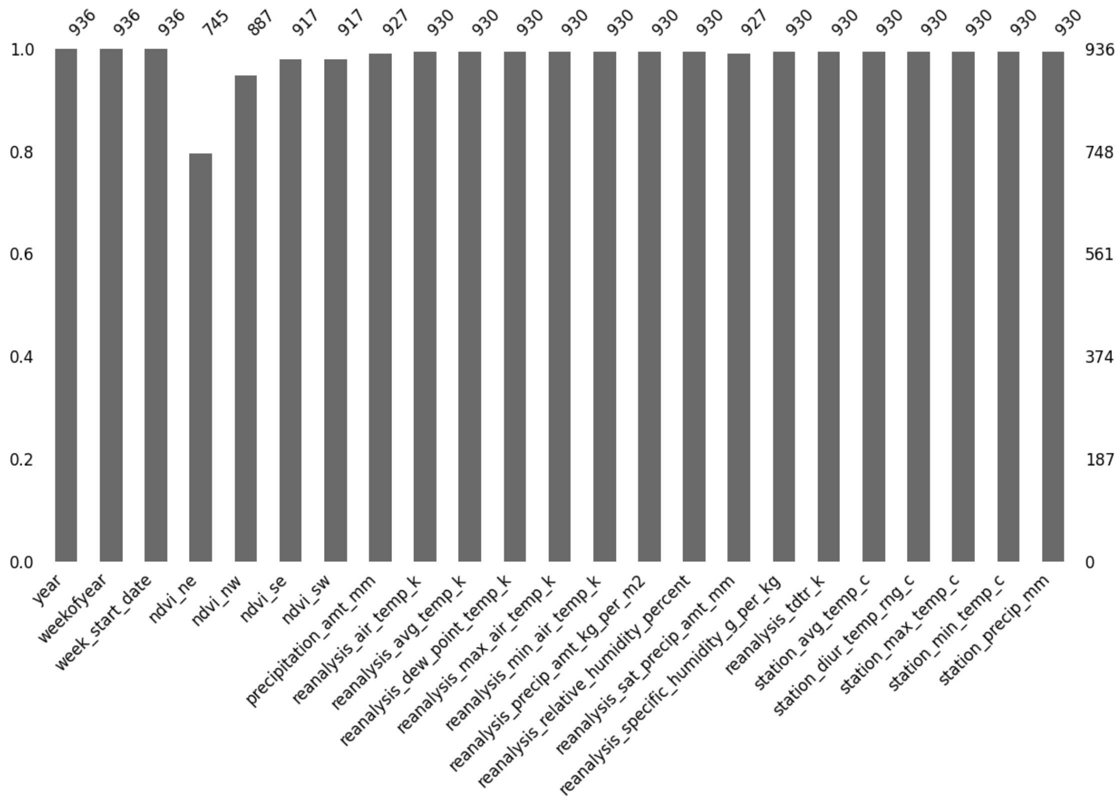
[15]:
```python
# Display null values across all rows/columns to check for specific patterns␣
↪for the absence of data:
missingno.matrix(train_features , figsize=(14, 7), fontsize = 10)
```

[15]: <Axes: >



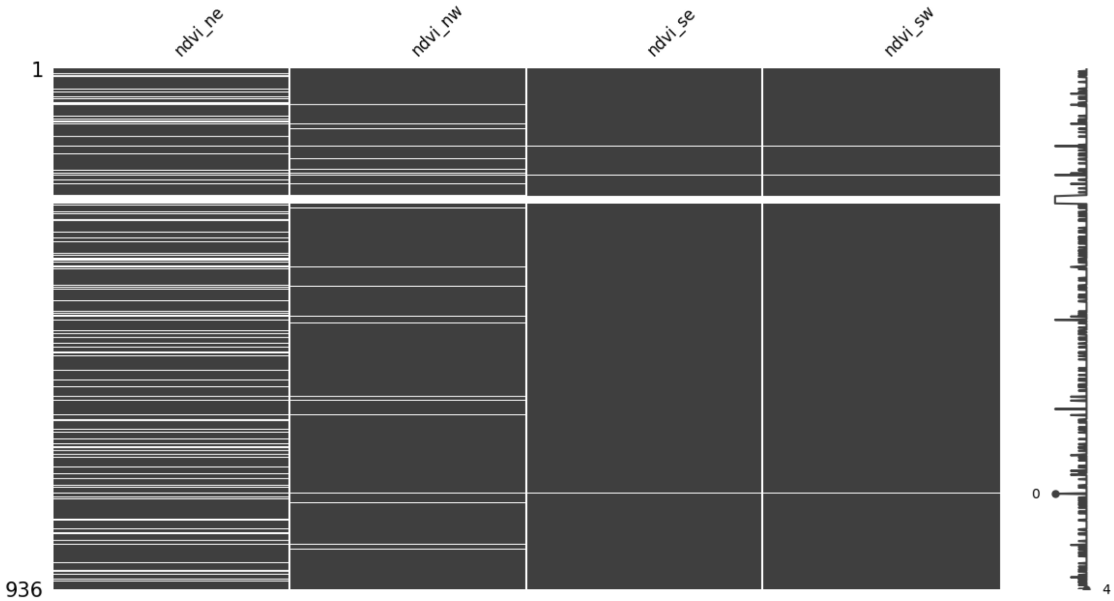
[16]:

```
# let's see the same data with a bar chart
missingno.bar(train_features, figsize = (14,7), fontsize = 12);
```



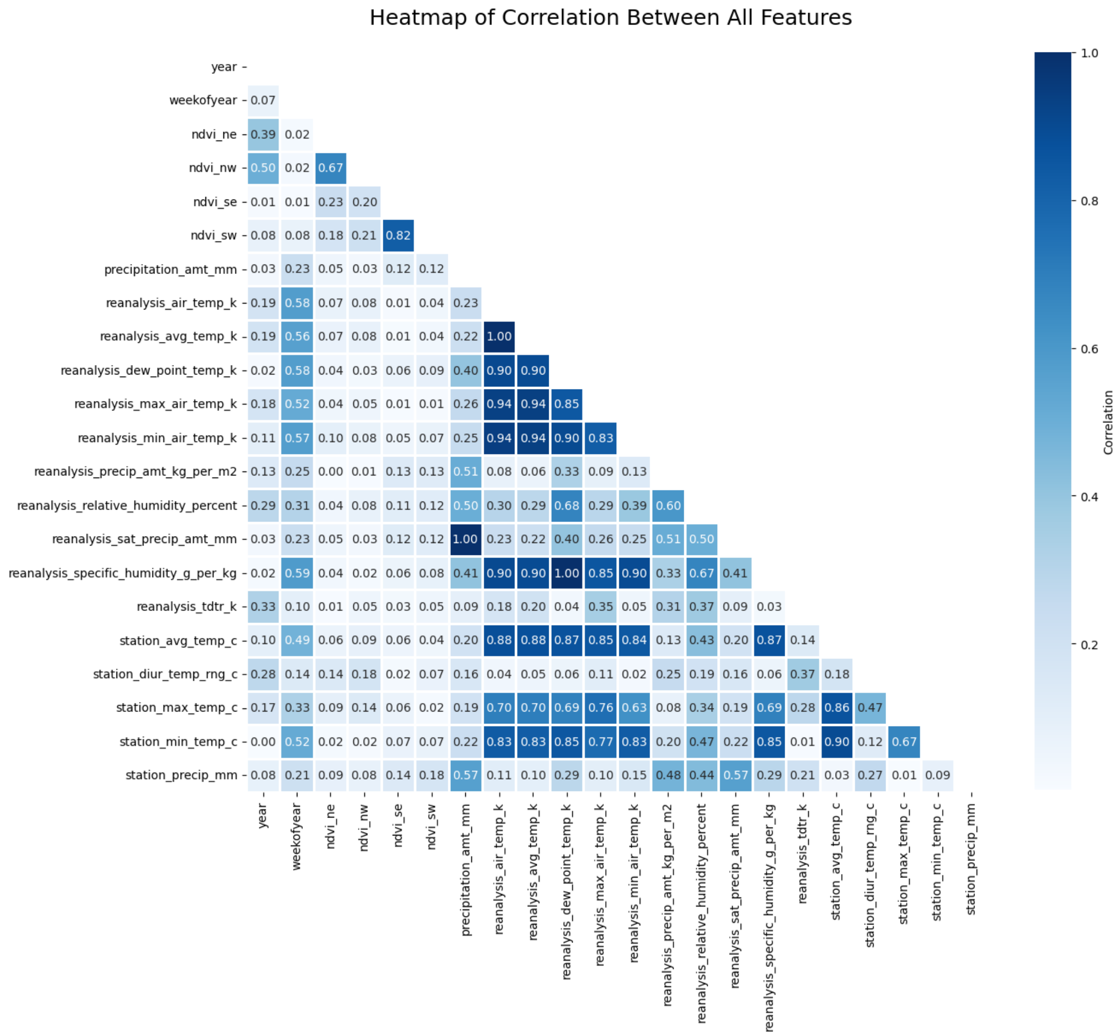
[17]:

```
# Check the null matrix for the four variables with most null values to see if␣
↪there is a pattern
missingno.matrix(train_features[['ndvi_ne', 'ndvi_nw', 'ndvi_se', 'ndvi_sw']], ␣
↪figsize=(14, 7), fontsize = 12);
```



- Null values for most climate measures are scarce but ndvi indexes have null values in bigger chunks.

[18]:
```
# Heat Map showing the correlation between all variables including the target
corr = train_features.corr().abs()
fig, ax = plt.subplots(figsize=(14,14))
matrix = np.triu(corr) # Getting the Lower Triangle of the correlation matrix
cbar_kws={"label": "Correlation", "shrink":0.8}
heatmap = sns.heatmap(data = corr,  linewidths = 1, square= True, 
 ↪cmap='Blues', ax=ax, annot=True, mask=matrix, fmt= ".2f", cbar_kws=cbar_kws)
fig.suptitle('Heatmap of Correlation Between All Features', fontsize=18, y=.84,
 ↪x = .43);
```



- There are very strong correlations among the majority of the variables, mostly due to
  - the same kind of climate variables being recorded from different resources using different scales.
  - the nature of climate features being dependent on each other especially with regard to temperature.

3 Feature Engineering: Null Replacement

3.0.1 Null replacement using interpolation and predictive modeling:

- We will replace the null values of all climate features except ndvi variables using **interpolation** since the missing data points are scarse.
- We will replace the null values of features for ndvi variables using **k-Nearest Neighbors** since there are bigger chunks of missing values.

[19]:
```
# Null replacement with interpolation for the below variables:
train_features_interpolated = train_features

vars_to_interpolate = ['precipitation_amt_mm', 'reanalysis_air_temp_k',
       'reanalysis_avg_temp_k', 'reanalysis_dew_point_temp_k',
       'reanalysis_max_air_temp_k', 'reanalysis_min_air_temp_k',
       'reanalysis_precip_amt_kg_per_m2',
       'reanalysis_relative_humidity_percent', 'reanalysis_sat_precip_amt_mm',
       'reanalysis_specific_humidity_g_per_kg', 'reanalysis_tdtr_k',
       'station_avg_temp_c', 'station_diur_temp_rng_c', 'station_max_temp_c',
       'station_min_temp_c', 'station_precip_mm']

for var in vars_to_interpolate:
    train_features_interpolated[var].interpolate(method ='linear',␣
 ↪limit_direction ='forward', inplace = True)
```

Null replacement using KNN neighbours for the remaining ndvi variables:

- The default distance measure is a Euclidean distance measure that is NaN aware.
- The number of neighbors is set to five by default and can be configured by the "n_neighbors" argument.
- `week_start_date` column was dropped and the data was scaled before imputing using KNN neighbours.
- After imputation, reversed the scaling to bring the values back to original scaling.

[20]:
```
# Drop `week_start_date` since we cannot work with this variable.
train_features_interpolated = train_features_interpolated.
 ↪drop("week_start_date", axis = 1)
```

[21]:
```
# Scale the data first using StandardScaler
scaler = StandardScaler()
train_features_scaled = pd.DataFrame(scaler.
 ↪fit_transform(train_features_interpolated), columns =␣
 ↪train_features_interpolated.columns)
# Define imputer
imputer = KNNImputer(n_neighbors=5)
# The fit imputer is applied to the dataset to create a copy of the dataset␣
 ↪with all missing values for each column replaced with an estimated value.
train_features_imputed= pd.DataFrame(imputer.
 ↪fit_transform(train_features_scaled), columns = train_features_scaled.
 ↪columns)
# inverse the Standard Scaling
train_features_full = pd.DataFrame(scaler.
 ↪inverse_transform(train_features_imputed), columns = train_features_imputed.
 ↪columns)
train_features_full.head()
```

[21]:

```
     year  weekofyear   ndvi_ne   ndvi_nw   ndvi_se   ndvi_sw  \
0  1990.0        18.0  0.122600  0.103725  0.198483  0.177617
1  1990.0        19.0  0.169900  0.142175  0.162357  0.155486
2  1990.0        20.0  0.032250  0.172967  0.157200  0.170843
3  1990.0        21.0  0.128633  0.245067  0.227557  0.235886
4  1990.0        22.0  0.196200  0.262200  0.251200  0.247340

   precipitation_amt_mm  reanalysis_air_temp_k  reanalysis_avg_temp_k  \
0                 12.42             297.572857             297.742857
1                 22.82             298.211429             298.442857
2                 34.54             298.781429             298.878571
3                 15.36             298.987143             299.228571
4                  7.52             299.518571             299.664286

   reanalysis_dew_point_temp_k  …  reanalysis_precip_amt_kg_per_m2  \
0                   292.414286  …                            32.00
1                   293.951429  …                            17.94
2                   295.434286  …                            26.10
3                   295.310000  …                            13.90
4                   295.821429  …                            12.20

   reanalysis_relative_humidity_percent  reanalysis_sat_precip_amt_mm  \
0                             73.365714                         12.42
1                             77.368571                         22.82
2                             82.052857                         34.54
3                             80.337143                         15.36
4                             80.460000                          7.52

   reanalysis_specific_humidity_g_per_kg  reanalysis_tdtr_k  \
0                              14.012857           2.628571
1                              15.372857           2.371429
2                              16.848571           2.300000
3                              16.672857           2.428571
4                              17.210000           3.014286

   station_avg_temp_c  station_diur_temp_rng_c  station_max_temp_c  \
0           25.442857                 6.900000                29.4
1           26.714286                 6.371429                31.7
2           26.714286                 6.485714                32.2
3           27.471429                 6.771429                33.3
4           28.942857                 9.371429                35.0

   station_min_temp_c  station_precip_mm
0                20.0               16.0
1                22.2                8.6
2                22.8               41.4
3                23.3                4.0
```

```
4                 23.9                5.8

[5 rows x 22 columns]
```

[22]:
```
# Making sure no null values remained
train_features_imputed.isna().sum().any() == 0
```

[22]:
```
True
```

[23]:
```
# Display the dataset for ndvi values before and after knn imputation
with plt.style.context('seaborn-talk'):
    fig, (ax1, ax2) = plt.subplots(nrows=2, ncols=1, figsize=(14,10))
    for var in ["ndvi_ne", "ndvi_nw", "ndvi_se", "ndvi_sw"]:
        train_features[150:300][var].plot.line(lw=1.2, ax = ax1)
    ax1.set_title('Vegetation Index over Time - Original Data')
    ax1.set_xlabel('Time')
    ax1.legend(loc='lower right')
    for var in ["ndvi_ne", "ndvi_nw", "ndvi_se", "ndvi_sw"]:
        train_features_full[150:300][var].plot.line(lw=1.2, ax = ax2)
    ax2.set_title('Vegetation Index over Time - Imputed Data')
    ax2.set_xlabel('Time')
    ax2.legend(loc='lower right')
    fig.tight_layout();
    fig.patch.set_alpha(0) # make the figure background transparent
    fig.savefig('KNN_ndvi.png', dpi=300, bbox_inches='tight')
    files.download("KNN_ndvi.png")
```

```
<IPython.core.display.Javascript object>

<IPython.core.display.Javascript object>
```

[24]:
```
# Merge the immputed dataset with the labels
train_full = pd.merge(train_features_full, train_labels, on=[ "year",␣
↪"weekofyear"])
train_full.head()
```

[24]:
```
     year  weekofyear   ndvi_ne   ndvi_nw   ndvi_se   ndvi_sw  \
0  1990.0        18.0  0.122600  0.103725  0.198483  0.177617
1  1990.0        19.0  0.169900  0.142175  0.162357  0.155486
2  1990.0        20.0  0.032250  0.172967  0.157200  0.170843
3  1990.0        21.0  0.128633  0.245067  0.227557  0.235886
4  1990.0        22.0  0.196200  0.262200  0.251200  0.247340

   precipitation_amt_mm  reanalysis_air_temp_k  reanalysis_avg_temp_k  \
0                 12.42             297.572857             297.742857
1                 22.82             298.211429             298.442857
2                 34.54             298.781429             298.878571
3                 15.36             298.987143             299.228571
4                  7.52             299.518571             299.664286

   reanalysis_dew_point_temp_k  …  reanalysis_relative_humidity_percent  \
0                   292.414286  …                             73.365714
1                   293.951429  …                             77.368571
```

```
2                  295.434286  …                            82.052857
3                  295.310000  …                            80.337143
4                  295.821429  …                            80.460000

   reanalysis_sat_precip_amt_mm  reanalysis_specific_humidity_g_per_kg  \
0                         12.42                              14.012857
1                         22.82                              15.372857
2                         34.54                              16.848571
3                         15.36                              16.672857
4                          7.52                              17.210000

   reanalysis_tdtr_k  station_avg_temp_c  station_diur_temp_rng_c  \
0           2.628571           25.442857                 6.900000
1           2.371429           26.714286                 6.371429
2           2.300000           26.714286                 6.485714
3           2.428571           27.471429                 6.771429
4           3.014286           28.942857                 9.371429

   station_max_temp_c  station_min_temp_c  station_precip_mm  total_cases
0                29.4                20.0               16.0            4
1                31.7                22.2                8.6            5
2                32.2                22.8               41.4            4
3                33.3                23.3                4.0            3
4                35.0                23.9                5.8            6

[5 rows x 23 columns]
```

3.0.2 Repeat all imputation steps for the test_features dataset:

[25]:
```
# See how many null values present in the test dataset
test_features.isnull().sum()
```

[25]:
```
year                                      0
weekofyear                                0
week_start_date                           0
ndvi_ne                                  43
ndvi_nw                                  11
ndvi_se                                   1
ndvi_sw                                   1
precipitation_amt_mm                      2
reanalysis_air_temp_k                     2
reanalysis_avg_temp_k                     2
reanalysis_dew_point_temp_k               2
reanalysis_max_air_temp_k                 2
reanalysis_min_air_temp_k                 2
reanalysis_precip_amt_kg_per_m2           2
reanalysis_relative_humidity_percent      2
```

```
reanalysis_sat_precip_amt_mm              2
reanalysis_specific_humidity_g_per_kg     2
reanalysis_tdtr_k                         2
station_avg_temp_c                        2
station_diur_temp_rng_c                   2
station_max_temp_c                        2
station_min_temp_c                        2
station_precip_mm                         2
dtype: int64
```

[26]:
```python
# Interpolation
test_features_interpolated = test_features
for var in vars_to_interpolate:
    test_features_interpolated[var].interpolate(method ='linear',␣
 ↪limit_direction ='forward', inplace = True)

# Drop week_start_date:
test_features_interpolated = test_features_interpolated.drop("week_start_date",␣
 ↪axis = 1)

# Scale, imputer using KNN inputer, inverse scale
test_features_scaled = pd.DataFrame(scaler.
 ↪fit_transform(test_features_interpolated), columns =␣
 ↪test_features_interpolated.columns)
test_features_imputed = pd.DataFrame(imputer.
 ↪fit_transform(test_features_scaled), columns = test_features_scaled.columns)
test_features_full = pd.DataFrame(scaler.
 ↪inverse_transform(test_features_imputed), columns = test_features_imputed.
 ↪columns)

# Making sure no null values remained
test_features_full.isna().sum().any() == 0
```

[26]:
```
True
```

Full Imputed datasets are: * train_full * test_features_full

4 Feature Engineering: Feature Selection / Creation

[27]:
```python
train_featured = train_full.copy()
```

Let's create a new month variable and dummy coded season variables:

[28]:
```python
# Add the `week_start_date` column from the original dataset to the new dataset
train_featured['week_start_date'] = train_features['week_start_date']
```

[29]:
```
# create a new month variable:
train_featured["week_start_date"] = pd.
 ↪to_datetime(train_featured["week_start_date"])
train_featured['month'] = train_featured['week_start_date'].dt.month
```

[30]:
```
# create a new season variable:
seasons = ["winter", "winter", "spring", "spring", "spring",
           "summer", "summer", "summer", "fall", "fall", "fall", "winter"]

month_to_season = dict(zip(range(1,13), seasons))
month_to_season

train_featured['season'] = train_featured['month'].map(month_to_season)
```

[31]:
```
# See the new variables:
train_featured[['week_start_date','month','season']].sample(5)
```

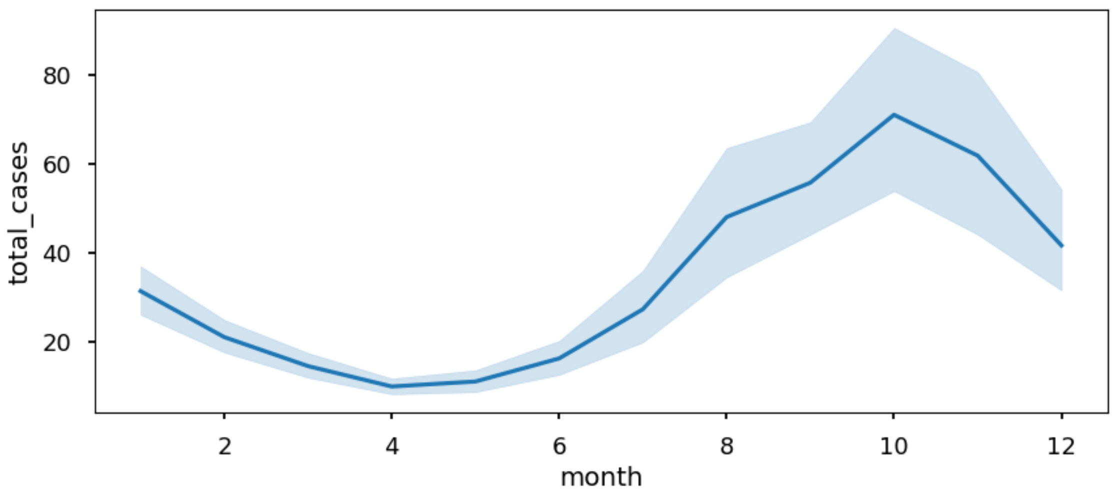
[31]:
```
    week_start_date  month  season
530      2000-07-08      7  summer
9        1990-07-02      7  summer
769      2005-02-12      2  winter
181      1993-10-22     10    fall
874      2007-02-19      2  winter
```

[32]:
```
# Get the season dummy coded
season_features = pd.get_dummies(train_featured['season'])
# combine the dummy coded variables with the original dataset
train_featured = pd.concat([train_featured, season_features], axis = 1)
train_featured.head()
```

[32]:
```
     year  weekofyear   ndvi_ne   ndvi_nw   ndvi_se   ndvi_sw  \
0  1990.0        18.0  0.122600  0.103725  0.198483  0.177617
1  1990.0        19.0  0.169900  0.142175  0.162357  0.155486
2  1990.0        20.0  0.032250  0.172967  0.157200  0.170843
3  1990.0        21.0  0.128633  0.245067  0.227557  0.235886
4  1990.0        22.0  0.196200  0.262200  0.251200  0.247340

   precipitation_amt_mm  reanalysis_air_temp_k  reanalysis_avg_temp_k  \
0                 12.42             297.572857             297.742857
1                 22.82             298.211429             298.442857
2                 34.54             298.781429             298.878571
3                 15.36             298.987143             299.228571
4                  7.52             299.518571             299.664286

   reanalysis_dew_point_temp_k  …  station_min_temp_c  station_precip_mm  \
0                   292.414286  …                20.0               16.0
1                   293.951429  …                22.2                8.6
```

```
2                     295.434286  …                 22.8                 41.4
3                     295.310000  …                 23.3                  4.0
4                     295.821429  …                 23.9                  5.8

   total_cases  week_start_date  month  season  fall  spring  summer  winter
0            4       1990-04-30      4  spring     0       1       0       0
1            5       1990-05-07      5  spring     0       1       0       0
2            4       1990-05-14      5  spring     0       1       0       0
3            3       1990-05-21      5  spring     0       1       0       0
4            6       1990-05-28      5  spring     0       1       0       0

[5 rows x 30 columns]
```

[33]:
```
# Seasonality: See the distribution of case counts on a monthly basis:
with plt.style.context('seaborn-talk'):
    fig, ax = plt.subplots(figsize=(10,4))
    sns.lineplot(data=train_featured, x="month", y='total_cases', ax = ax)
```



- Maximum number of cases are seen in late fall.

5 Feature elimination / selection:

[34]:
```
# Show the mostly correlated pairs starting with strongest correlations:
dataCorr = train_featured.drop('total_cases',axis =1).corr().abs()
dataCorr = dataCorr.mask(np.triu(np.ones(dataCorr.shape)).astype(bool)) #␣
 ↪convert upper triangle of values to NaN to remove repeated values from the␣
 ↪table
dataCorr = dataCorr.stack().reset_index().sort_values(0, ascending=False) #0 is␣
 ↪the column automatically generated by the stacking
```

```
dataCorr = dataCorr[(dataCorr[0]>.8) & (dataCorr[0]<1)] # only show those with␣
↪a correlation higher than .8
dataCorr =  dataCorr.rename(columns = {'level_0': 'var_1', 'level_1': 'var_2',␣
↪0:'corr_coef'})
dataCorr
```

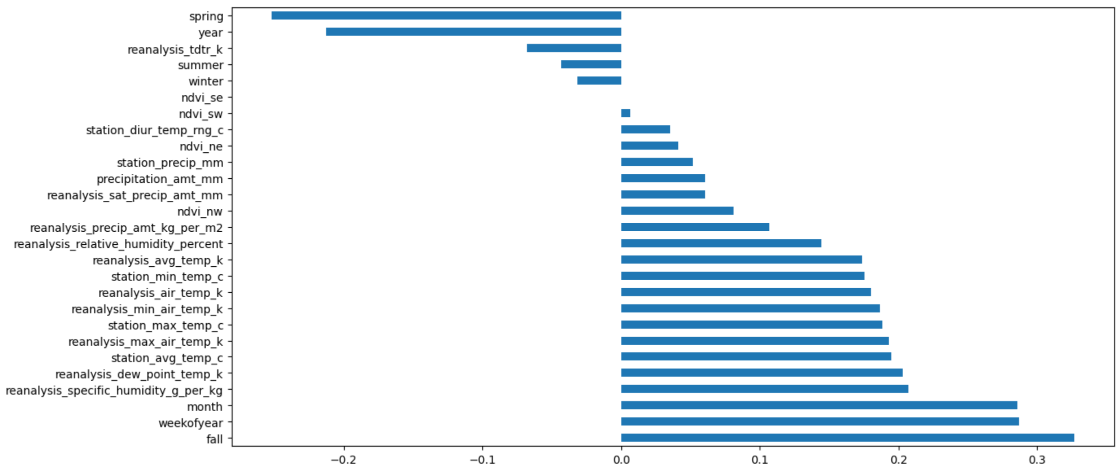
[34]:

```
                                    var_1  \
114  reanalysis_specific_humidity_g_per_kg
35                  reanalysis_avg_temp_k
232                                 month
62              reanalysis_min_air_temp_k
53              reanalysis_max_air_temp_k
63              reanalysis_min_air_temp_k
52              reanalysis_max_air_temp_k
112  reanalysis_specific_humidity_g_per_kg
43            reanalysis_dew_point_temp_k
64              reanalysis_min_air_temp_k
207                    station_min_temp_c
113  reanalysis_specific_humidity_g_per_kg
116  reanalysis_specific_humidity_g_per_kg
44            reanalysis_dew_point_temp_k
143                    station_avg_temp_c
144                    station_avg_temp_c
151                    station_avg_temp_c
145                    station_avg_temp_c
188                    station_max_temp_c
115  reanalysis_specific_humidity_g_per_kg
146                    station_avg_temp_c
199                    station_min_temp_c
205                    station_min_temp_c
54              reanalysis_max_air_temp_k
147                    station_avg_temp_c
197                    station_min_temp_c
201                    station_min_temp_c
65              reanalysis_min_air_temp_k
198                    station_min_temp_c
14                                ndvi_sw

                                    var_2  corr_coef
114           reanalysis_dew_point_temp_k   0.998533
35                  reanalysis_air_temp_k   0.997507
232                            weekofyear   0.955143
62                  reanalysis_air_temp_k   0.942248
53                  reanalysis_avg_temp_k   0.939202
63                  reanalysis_avg_temp_k   0.939127
52                  reanalysis_air_temp_k   0.935339
112                 reanalysis_air_temp_k   0.905004
```

```
43                 reanalysis_air_temp_k   0.903481
64            reanalysis_dew_point_temp_k   0.899008
207                   station_avg_temp_c   0.898506
113                reanalysis_avg_temp_k   0.896420
116             reanalysis_min_air_temp_k   0.896376
44                 reanalysis_avg_temp_k   0.895373
143                reanalysis_air_temp_k   0.880871
144                reanalysis_avg_temp_k   0.879118
151  reanalysis_specific_humidity_g_per_kg   0.869982
145           reanalysis_dew_point_temp_k   0.868837
188                   station_avg_temp_c   0.865240
115             reanalysis_max_air_temp_k   0.853629
146             reanalysis_max_air_temp_k   0.852831
199           reanalysis_dew_point_temp_k   0.850479
205  reanalysis_specific_humidity_g_per_kg   0.849573
54            reanalysis_dew_point_temp_k   0.847654
147             reanalysis_min_air_temp_k   0.841300
197                reanalysis_air_temp_k   0.833158
201             reanalysis_min_air_temp_k   0.829792
65              reanalysis_max_air_temp_k   0.828665
198                reanalysis_avg_temp_k   0.827497
14                               ndvi_se   0.820109
```

- Many of the temperature data are strongly correlated with one another especially because the same feature was coded multiple times from different resources.
- We can not use all these variables in the modeling since the same kind of information would be repeated.
- We need to hand pick some of these variables.

[35]:
```
# Show how strongly the features are correlated with the target variable -␣
↪total cases:
fig, ax = plt.subplots(figsize=(14,7))
train_featured.corr()['total_cases'].drop('total_cases').
↪sort_values(ascending=False).plot.barh(ax=ax);
```



- None of the features seem to have a strong relationship with the target variable - total_cases.
- Total_cases seems to only have weak correlations with other variables.
- We need to engineer some new features hoping they would have stronger relationship with total_cases.

5.0.1 Select the best variables for:

- Average temp
- Min temp
- Max temp
- daily temp range
- humidity
- precipitation
- vegetation

5.0.2 Select the best average temperature variable:

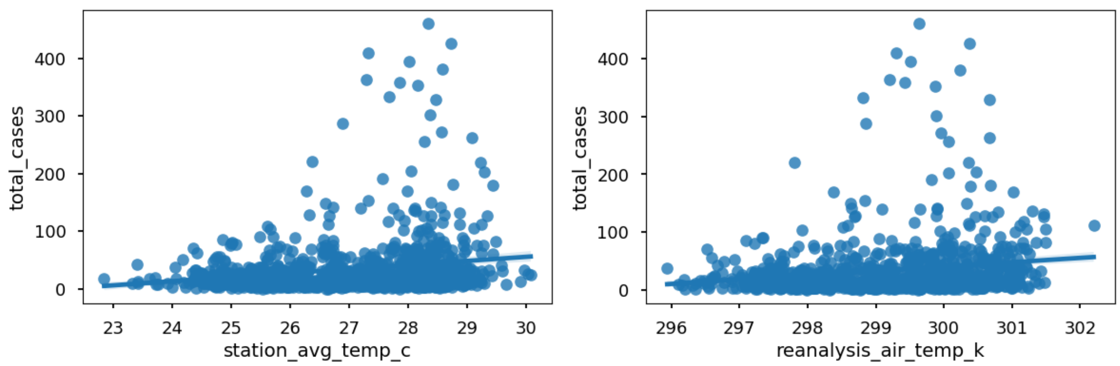
- `station_avg_temp_c` has the strongest correlation.
- Let's keep max and min temperature on the same scale as well.

[36]:
```
# see the correlations among all average temperature variables:
train_featured[['total_cases','station_avg_temp_c','reanalysis_air_temp_k','reanalysis_avg_tem
↪corr()
```

[36]:
```
                     total_cases  station_avg_temp_c  reanalysis_air_temp_k  \
total_cases             1.000000            0.194823               0.180311
station_avg_temp_c      0.194823            1.000000               0.880871
reanalysis_air_temp_k   0.180311            0.880871               1.000000
reanalysis_avg_temp_k   0.173670            0.879118               0.997507

                     reanalysis_avg_temp_k
total_cases                       0.173670
```

```
station_avg_temp_c                   0.879118
reanalysis_air_temp_k                0.997507
reanalysis_avg_temp_k                1.000000
```

[37]:
```
with plt.style.context('seaborn-talk'):
    fig, (ax1, ax2) = plt.subplots(nrows=1, ncols=2,figsize=(14,4))
    sns.regplot(data=train_featured, x="station_avg_temp_c", y='total_cases',␣
 ↪ax = ax1, label = 'station_avg_temp_c')
    sns.regplot(data=train_featured, x="reanalysis_air_temp_k",␣
 ↪y='total_cases', ax = ax2, label = 'reanalysis_air_temp_k')
```



5.0.3 Select the best daily temperature change variable:

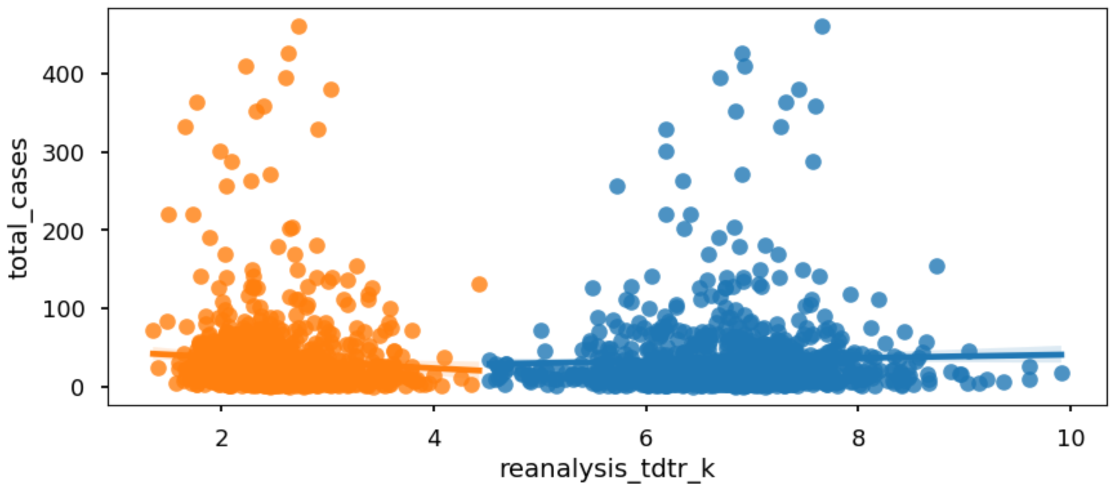
- reanalysis_tdtr_k has the strongest correlation to total cases
- Let's also replace the single outlier with a better value.

[38]:
```
# see the correlations among daily temperature range variables:
train_featured[['total_cases','station_diur_temp_rng_c','reanalysis_tdtr_k']].
 ↪corr()
```

[38]:
```
                        total_cases  station_diur_temp_rng_c  \
total_cases                1.000000                 0.035303
station_diur_temp_rng_c    0.035303                 1.000000
reanalysis_tdtr_k         -0.067623                 0.372414

                        reanalysis_tdtr_k
total_cases                     -0.067623
station_diur_temp_rng_c          0.372414
reanalysis_tdtr_k                1.000000
```

[39]:
```
with plt.style.context('seaborn-talk'):
    fig, ax = plt.subplots(figsize=(10,4))
```

```
    sns.regplot(data=train_featured, x="station_diur_temp_rng_c",␣
↪y='total_cases', ax = ax, label = 'station_diur_temp_rng_c')
    sns.regplot(data=train_featured, x="reanalysis_tdtr_k", y='total_cases', ax␣
↪= ax, label = 'reanalysis_tdtr_k')
```



[40]:
```
# check out the outlier for 'reanalysis_tdtr_k':
train_featured[train_featured['reanalysis_tdtr_k'] ==␣
↪train_featured['reanalysis_tdtr_k'].max()]
```

[40]:
```
       year  weekofyear  ndvi_ne  ndvi_nw   ndvi_se   ndvi_sw  \
799  2005.0        36.0   0.0022  -0.0271  0.205029  0.220233

     precipitation_amt_mm  reanalysis_air_temp_k  reanalysis_avg_temp_k  \
799                  23.3             301.465714             301.514286

     reanalysis_dew_point_temp_k  …  station_min_temp_c  station_precip_mm  \
799                   296.642857  …                24.4                8.9

     total_cases  week_start_date  month  season  fall  spring  summer  winter
799          131       2005-09-10      9    fall     1       0       0       0

[1 rows x 30 columns]
```

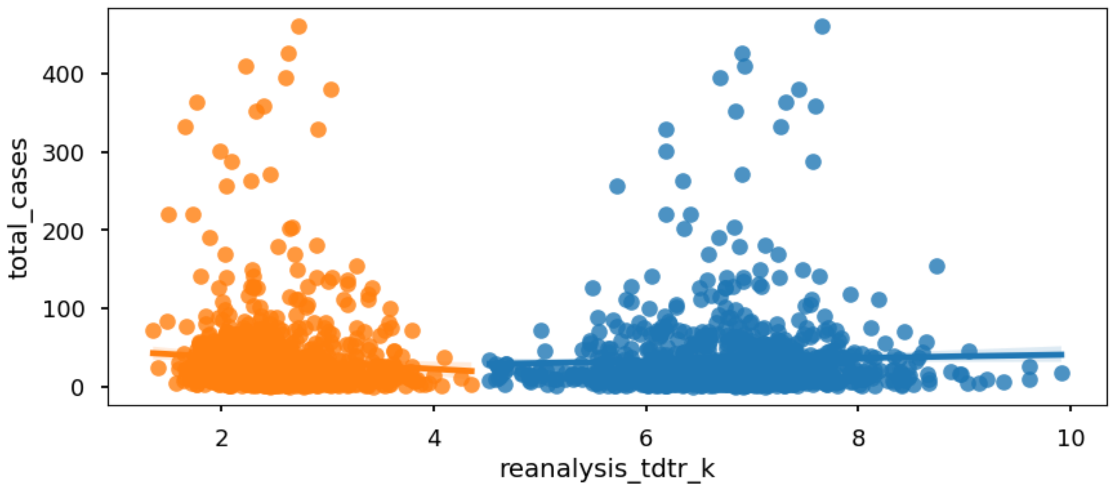
[41]:
```
# replace the outlier with the previous value in the series
train_featured = train_featured.replace(train_featured['reanalysis_tdtr_k'].
↪max(), method='ffill')
train_featured[799:800]
```

[41]:
```
       year  weekofyear  ndvi_ne  ndvi_nw   ndvi_se   ndvi_sw  \
799  2005.0        36.0   0.0022  -0.0271  0.205029  0.220233

     precipitation_amt_mm  reanalysis_air_temp_k  reanalysis_avg_temp_k  \
799                  23.3             301.465714             301.514286

     reanalysis_dew_point_temp_k  …  station_min_temp_c  station_precip_mm  \
799                   296.642857  …                24.4                8.9

     total_cases  week_start_date  month  season  fall  spring  summer  winter
799          131       2005-09-10      9    fall     1       0       0       0

[1 rows x 30 columns]
```

[42]:
```
# check the correlations again:
train_featured[['total_cases','station_diur_temp_rng_c','reanalysis_tdtr_k']].
 ↪corr()
```

[42]:
```
                         total_cases  station_diur_temp_rng_c  \
total_cases                 1.000000                 0.035303
station_diur_temp_rng_c     0.035303                 1.000000
reanalysis_tdtr_k          -0.073160                 0.374047

                         reanalysis_tdtr_k
total_cases                      -0.073160
station_diur_temp_rng_c           0.374047
reanalysis_tdtr_k                 1.000000
```

[43]:
```
with plt.style.context('seaborn-talk'):
    fig, ax = plt.subplots(figsize=(10,4))
    sns.regplot(data=train_featured, x="station_diur_temp_rng_c",␣
 ↪y='total_cases', ax = ax, label = 'station_diur_temp_rng_c')
    sns.regplot(data=train_featured, x="reanalysis_tdtr_k", y='total_cases', ax␣
 ↪= ax, label = 'reanalysis_tdtr_k')
```



5.0.4 Select the best humidity variable:

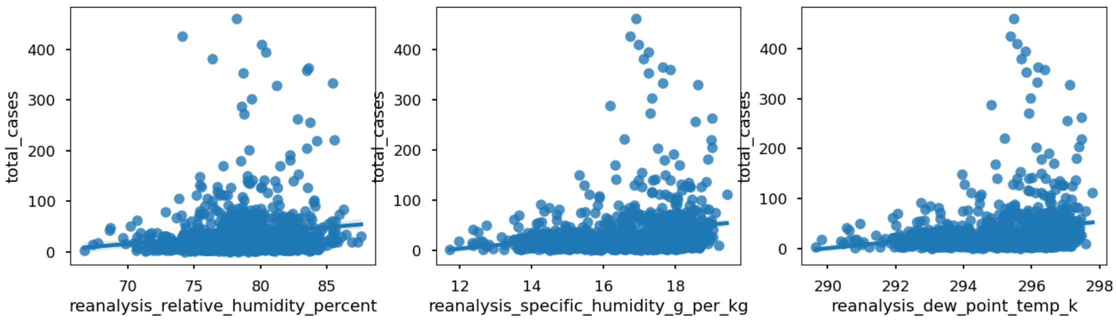
- `reanalysis_specific_humidity_g_per_kg` has the strongest correlation

[44]:
```
train_featured[['total_cases','reanalysis_relative_humidity_percent',␣
↪'reanalysis_specific_humidity_g_per_kg','reanalysis_dew_point_temp_k']].
↪corr()
```

[44]:
```
                                       total_cases  \
total_cases                               1.000000
reanalysis_relative_humidity_percent      0.144404
reanalysis_specific_humidity_g_per_kg     0.206942
reanalysis_dew_point_temp_k               0.202807

                                       reanalysis_relative_humidity_percent  \
total_cases                                                        0.144404
reanalysis_relative_humidity_percent                               1.000000
reanalysis_specific_humidity_g_per_kg                              0.673010
reanalysis_dew_point_temp_k                                        0.678116

                                       reanalysis_specific_humidity_g_per_kg  \
total_cases                                                         0.206942
reanalysis_relative_humidity_percent                                0.673010
reanalysis_specific_humidity_g_per_kg                               1.000000
reanalysis_dew_point_temp_k                                         0.998533

                                       reanalysis_dew_point_temp_k
total_cases                                               0.202807
reanalysis_relative_humidity_percent                      0.678116
```

```
reanalysis_specific_humidity_g_per_kg                        0.998533
reanalysis_dew_point_temp_k                                  1.000000
```

[45]:
```
with plt.style.context('seaborn-talk'):
    fig, (ax1, ax2, ax3) = plt.subplots(ncols = 3, nrows = 1, figsize=(16,4))
    sns.regplot(data=train_featured, x="reanalysis_relative_humidity_percent",␣
 ↪y='total_cases', ax = ax1, label = 'reanalysis_relative_humidity_percent')
    sns.regplot(data=train_featured, x="reanalysis_specific_humidity_g_per_kg",␣
 ↪y='total_cases', ax = ax2, label = 'reanalysis_specific_humidity_g_per_kg')
    sns.regplot(data=train_featured, x="reanalysis_dew_point_temp_k",␣
 ↪y='total_cases', ax = ax3, label = 'reanalysis_dew_point_temp_k')
```



5.0.5 Select the best precipitation variable:

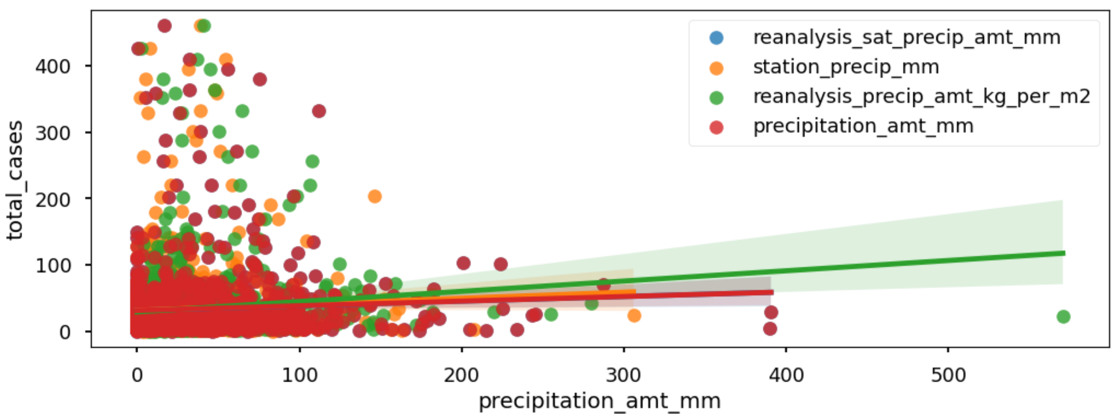
- reanalysis_precip_amt_kg_per_m2 has the strongest correlation

[46]:
```
train_featured[['total_cases','reanalysis_sat_precip_amt_mm','station_precip_mm',
                'reanalysis_precip_amt_kg_per_m2', 'precipitation_amt_mm']].
 ↪corr()
```

[46]:
```
                                 total_cases  reanalysis_sat_precip_amt_mm  \
total_cases                         1.000000                      0.060296
reanalysis_sat_precip_amt_mm        0.060296                      1.000000
station_precip_mm                   0.051883                      0.566660
reanalysis_precip_amt_kg_per_m2     0.106939                      0.508274
precipitation_amt_mm                0.060296                      1.000000

                                 station_precip_mm  \
total_cases                               0.051883
reanalysis_sat_precip_amt_mm              0.566660
station_precip_mm                         1.000000
reanalysis_precip_amt_kg_per_m2           0.477984
precipitation_amt_mm                      0.566660
```

```
                                  reanalysis_precip_amt_kg_per_m2  \
total_cases                                              0.106939
reanalysis_sat_precip_amt_mm                             0.508274
station_precip_mm                                        0.477984
reanalysis_precip_amt_kg_per_m2                          1.000000
precipitation_amt_mm                                     0.508274

                                  precipitation_amt_mm
total_cases                                   0.060296
reanalysis_sat_precip_amt_mm                  1.000000
station_precip_mm                             0.566660
reanalysis_precip_amt_kg_per_m2               0.508274
precipitation_amt_mm                          1.000000
```

[47]:
```
with plt.style.context('seaborn-talk'):
    fig, ax = plt.subplots(figsize=(12,4))
    for var in ["reanalysis_sat_precip_amt_mm","station_precip_mm",␣
↪"reanalysis_precip_amt_kg_per_m2", "precipitation_amt_mm"]:
      sns.regplot(data=train_featured, x=var, y='total_cases', ax = ax, label =␣
↪var)
      plt.legend()
```



5.1 Summary - feature selection:

Let's focus on these variables below since they provide the highest correlations. Let's keep all the temperature variables same scale (celcius) for interpretability except the diurnal which gave better correlation in kelvin.

Using NOAA's NCEP Climate Forecast System Reanalysis measurements (0.5x0.5 degree scale):

Temperature variables: `station_avg_temp_c`,`station_min_temp_c`, `station_max_temp_c`, `reanalysis_tdtr_k` (Diurnal temperature range)

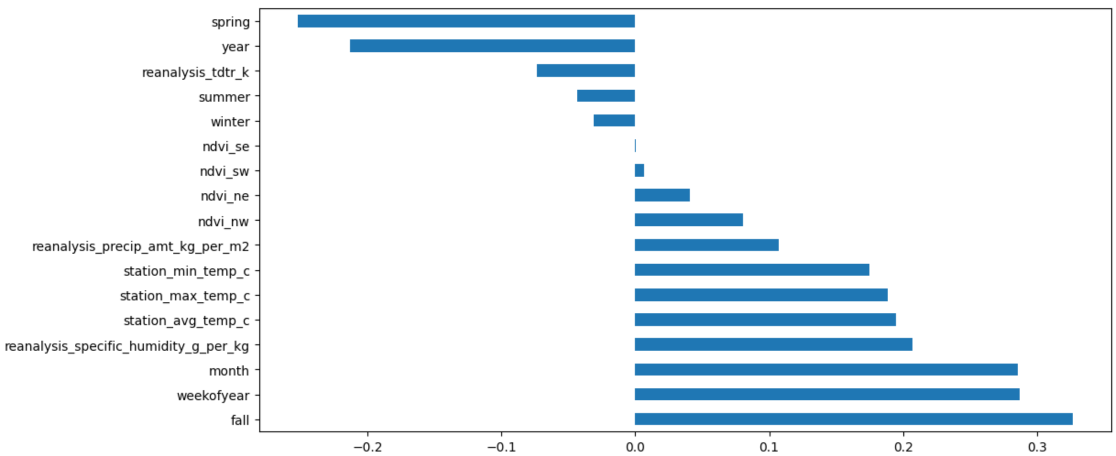
Humidity: `reanalysis_specific_humidity_g_per_kg`

Precipitation: `reanalysis_precip_amt_kg_per_m2` (Total precipitation)

Vegetation: `ndvi_ne`, `ndvi_nw`, `ndvi_se`, `ndvi_sw`

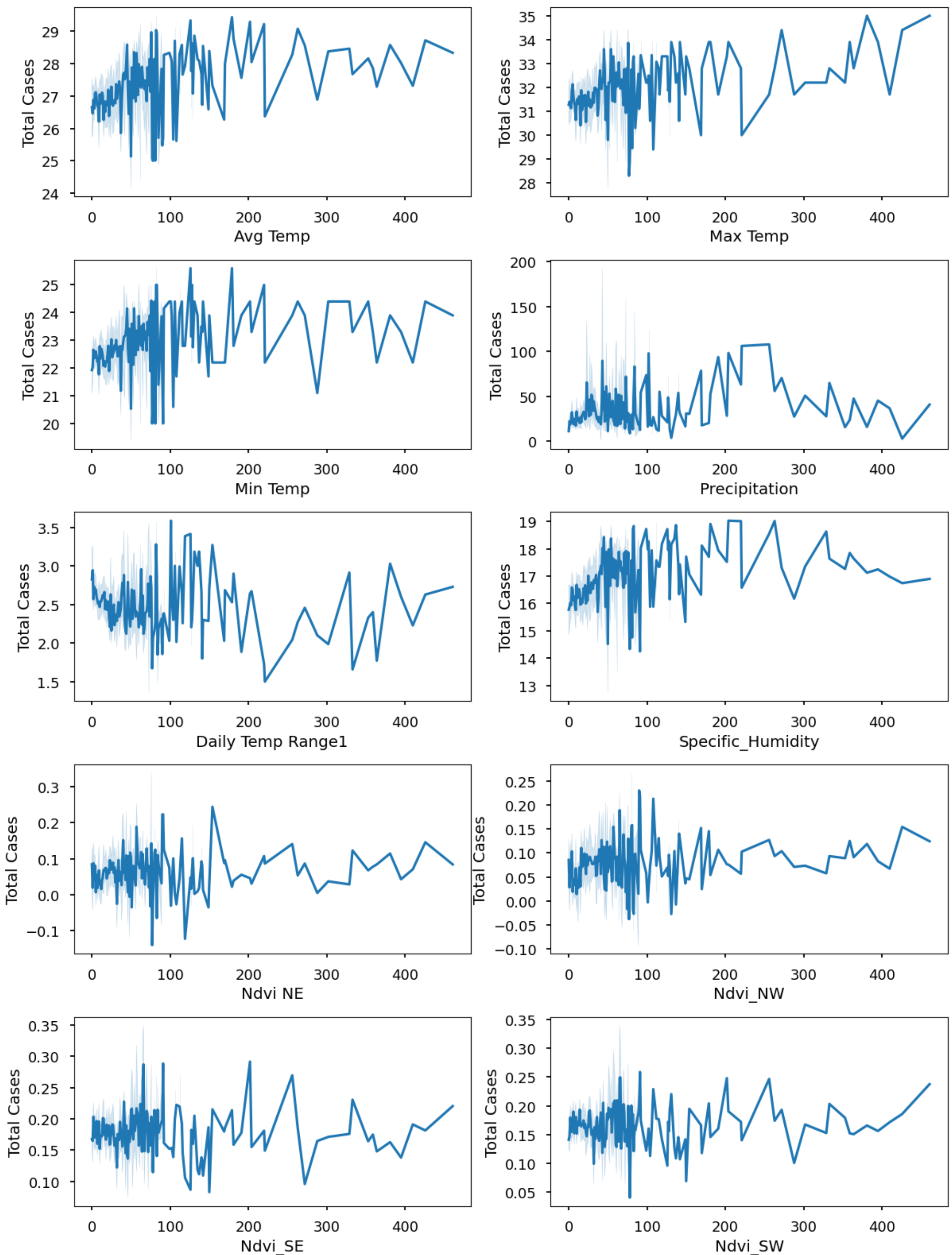
[48]:
```
# Keeping the below variables as primary:
train_featured = train_featured[['total_cases', 'year', 'weekofyear',␣
↪'week_start_date',
                                 'month',  'fall', 'spring', 'summer','winter',
                                 'station_avg_temp_c', 'station_max_temp_c',
                                 'station_min_temp_c', 'reanalysis_tdtr_k',
                                 'reanalysis_specific_humidity_g_per_kg',
                                 'reanalysis_precip_amt_kg_per_m2',
                                 'ndvi_ne', 'ndvi_nw', 'ndvi_se', 'ndvi_sw']]
```

[49]:
```
# See how these hand picked variables correlate with total cases
fig, ax = plt.subplots(figsize=(12,6))
train_featured.corr()['total_cases'].drop('total_cases').
↪sort_values(ascending=False).plot.barh(ax=ax);
```



[50]:
```
# Plot how the total case numbers differ based on each climate feature:
columns = ['station_avg_temp_c', 'station_max_temp_c',
           'station_min_temp_c', 'reanalysis_precip_amt_kg_per_m2',
           'reanalysis_tdtr_k', 'reanalysis_specific_humidity_g_per_kg',
           'ndvi_ne', 'ndvi_nw',
           'ndvi_se', 'ndvi_sw']

labels = ["Avg Temp", "Max Temp",
          "Min Temp", "Precipitation",
          "Daily Temp Range1", "Specific_Humidity",
          "Ndvi NE", "Ndvi_NW",
          "Ndvi_SE", "Ndvi_SW"]
```

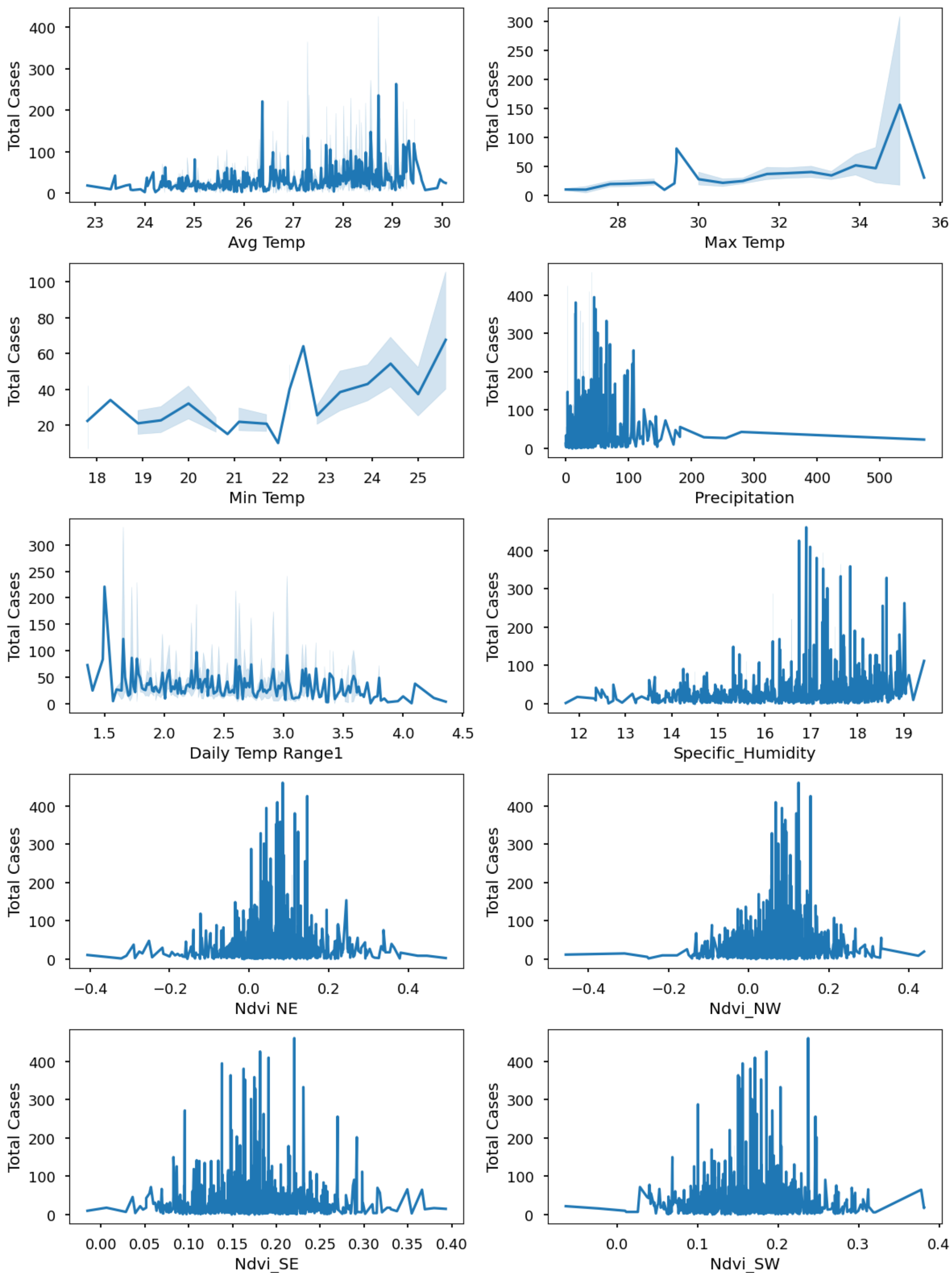
```
nrows =5
ncols =2
with plt.style.context('seaborn-talk'):

    fig, ax_list = plt.subplots(nrows = nrows, ncols = ncols, figsize=(12,16))

    j=0
    for i in range(nrows):
        for u in range(ncols):
            sns.lineplot(data =train_featured, y=columns[j], x="total_cases", ax = ax_list[i,u]) # need to use index for column because otherwise it does not itirate.
            ax_list[i,u].set_xlabel(labels[j])
            ax_list[i,u].set_ylabel("Total Cases")
            j = j+1

    fig.tight_layout();
```



- For all the variables, the relationship seems stronger until case number 100 reaches, possible because there are fewer extra high dengue cases.

[51]:

```
# Plot how the total case numbers differ based on each climate feature, the␣
↪other way around:
columns = ['station_avg_temp_c', 'station_max_temp_c',
           'station_min_temp_c', 'reanalysis_precip_amt_kg_per_m2',
           'reanalysis_tdtr_k', 'reanalysis_specific_humidity_g_per_kg',
           'ndvi_ne', 'ndvi_nw',
           'ndvi_se', 'ndvi_sw']

labels = ["Avg Temp", "Max Temp",
          "Min Temp", "Precipitation",
          "Daily Temp Range1", "Specific_Humidity",
          "Ndvi NE", "Ndvi_NW",
          "Ndvi_SE", "Ndvi_SW"]

nrows =5
ncols =2
with plt.style.context('seaborn-talk'):

    fig, ax_list = plt.subplots(nrows = nrows, ncols = ncols, figsize=(12,16))

    j=0
    for i in range(nrows):
        for u in range(ncols):
            sns.lineplot(data =train_featured, x=columns[j], y="total_cases",␣
↪ax = ax_list[i,u]) # need to use index for column because otherwise it does␣
↪not itirate.
            ax_list[i,u].set_xlabel(labels[j])
            ax_list[i,u].set_ylabel("Total Cases")
            j = j+1

    fig.tight_layout();
```



- Extremely high **average temp**, **maximum temp**, **temp range**, or **precipitation** seem to impact dengue cases negatively.
- There is no clear linear relationship between ndvi variables and total cases as lower and higher

values tend to result in lower total cases, but moderate values tend to result in higher total cases.

5.2 Convert NDVI into Categorical variables:

- NDVI calculation range from -1 to 1. Negative values correspond to areas with water surfaces, manmade structures, rocks, clouds, snow. Bare soil usually falls within 0.1- 0.2 range. Plants will always have positive values between 0.2 and 1. Healthy, dense vegetation canopy should be above 0.5. Sparse vegetation will most likely fall within 0.2 to 0.5.
- Since there is no clear linear relationship between ndvi and total cases, let's create a categorical version of the variables. |
  - Let's first create a new feature representing the average NDVI values from the four different locations.
  - Then let's create a categorical version of the variable to represent **watery, soily, sparce_grassy** areas.

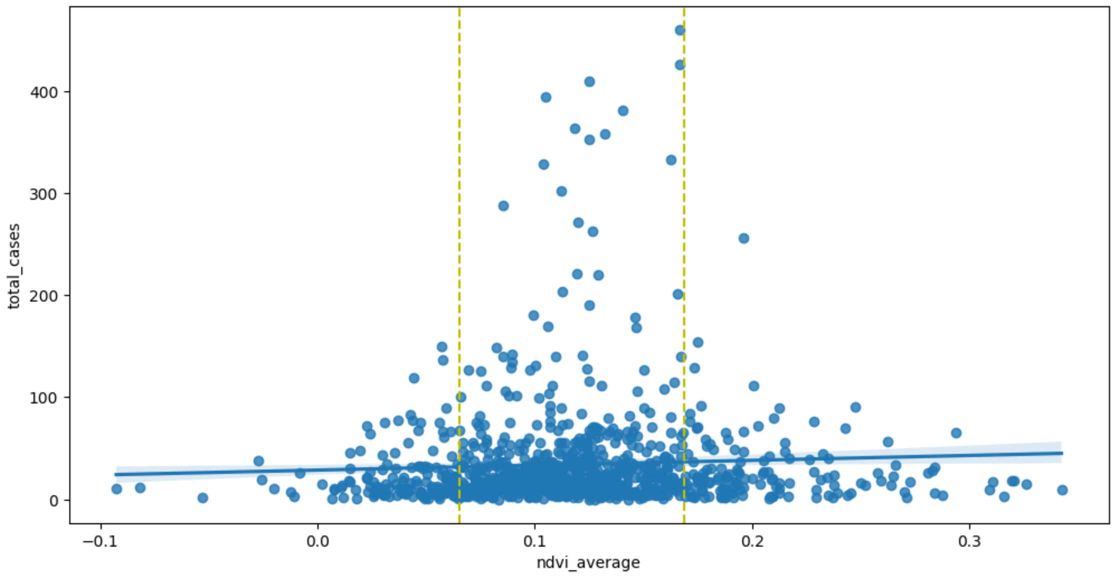
[52]:
```
# Create `ndvi_average` by taking the mean of all 4 coodinates.
train_featured['ndvi_average'] = (train_featured['ndvi_ne']+train_featured['ndvi_nw']+ train_featured['ndvi_se']+train_featured['ndvi_sw'])/4
```

[53]:
```
# Let's check the distibution of ndvi_average:
train_featured[['ndvi_average']].describe()
```

[53]:

	ndvi_average
count	936.000000
mean	0.117157
std	0.056231
min	-0.092565
25%	0.079570
50%	0.112724
75%	0.147122
max	0.342338

[54]:
```
# Let's see the bottom and top 15th percentile for `ndvi_average`:
fig, ax = plt.subplots(figsize=(12,6))
sns.regplot(data = train_featured, x='ndvi_average', y="total_cases", ax = ax)
ax.axvline(x=train_featured['ndvi_average'].quantile(0.15), ymin=0, ymax=1, color='y', linestyle='--')
ax.axvline(x=train_featured['ndvi_average'].quantile(0.85), ymin=0, ymax=1, color='y', linestyle='--');
```

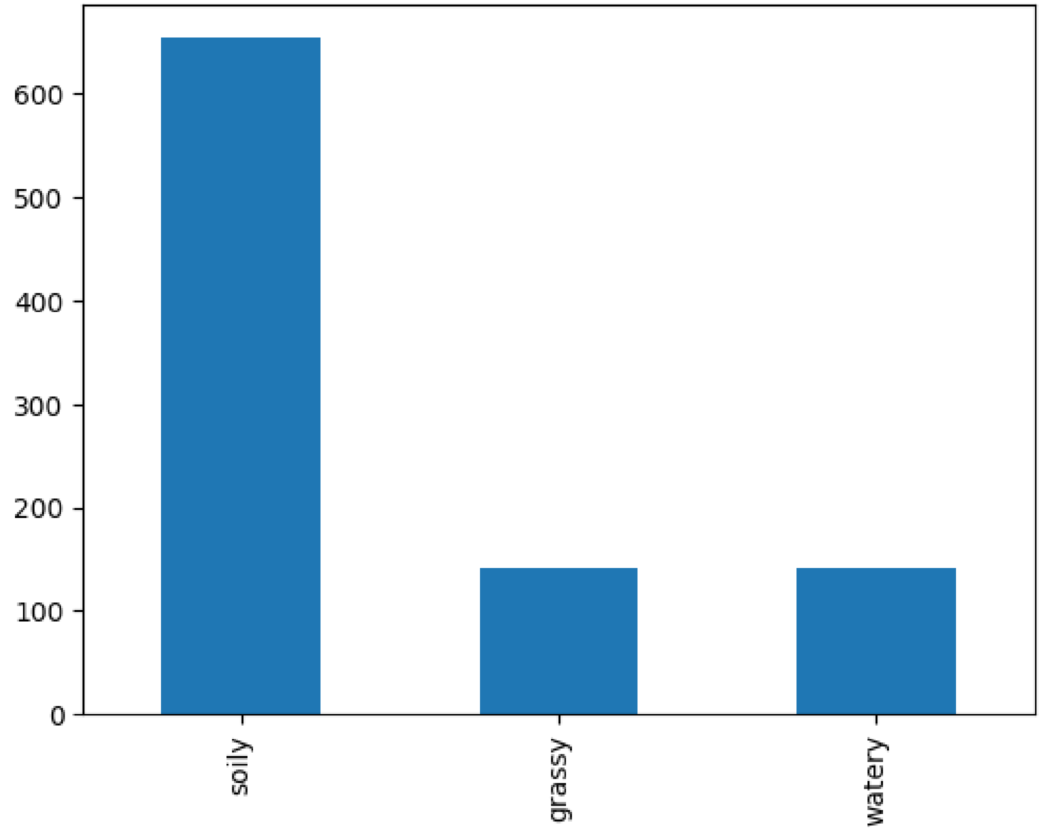


- Total cases seem to be low for low and high ndvi, and high for moderate ndvi

[55]:
```
# Create a function to transform `ndvi_average` into a categorical variable.
# watery (dead plants) --> soily (unhealthy plants) --> grassy (healthy plants)
def get_ndvi_cat(x):
    if x < train_featured['ndvi_average'].quantile(0.15):
        return "watery"
    if x >= train_featured['ndvi_average'].quantile(0.15) and x <=␣
 ↪train_featured['ndvi_average'].quantile(0.85):
        return "soily"
    else:
        return "grassy"
```

[56]:
```
# Apply the transformation
train_featured["ndvi_average_cat"] = train_featured["ndvi_average"].
 ↪apply(get_ndvi_cat)
```

[57]:
```
# See the count values after transformation
train_featured['ndvi_average_cat'].value_counts().plot(kind='bar');
```



[58]:
```
# Get dummy codes for 'ndvi_average_cat` and merge with the dataset:
ndvi_features = pd.get_dummies(train_featured['ndvi_average_cat'])
train_featured = pd.concat([train_featured, ndvi_features], axis = 1)
train_featured.head()
```

[58]:
```
   total_cases    year  weekofyear week_start_date  month  fall  spring  \
0            4  1990.0        18.0      1990-04-30      4     0       1
1            5  1990.0        19.0      1990-05-07      5     0       1
2            4  1990.0        20.0      1990-05-14      5     0       1
3            3  1990.0        21.0      1990-05-21      5     0       1
4            6  1990.0        22.0      1990-05-28      5     0       1

   summer  winter  station_avg_temp_c  …  reanalysis_precip_amt_kg_per_m2  \
0       0       0           25.442857  …                            32.00
1       0       0           26.714286  …                            17.94
2       0       0           26.714286  …                            26.10
3       0       0           27.471429  …                            13.90
4       0       0           28.942857  …                            12.20

    ndvi_ne    ndvi_nw    ndvi_se    ndvi_sw  ndvi_average  ndvi_average_cat  \
```

```
0  0.122600  0.103725  0.198483  0.177617      0.150606             soily
1  0.169900  0.142175  0.162357  0.155486      0.157479             soily
2  0.032250  0.172967  0.157200  0.170843      0.133315             soily
3  0.128633  0.245067  0.227557  0.235886      0.209286            grassy
4  0.196200  0.262200  0.251200  0.247340      0.239235            grassy

   grassy  soily  watery
0       0      1       0
1       0      1       0
2       0      1       0
3       1      0       0
4       1      0       0

[5 rows x 24 columns]
```

[59]:
```
# Let's see if correlations improved after the transformation:
ndvi_data =␣
 ↪train_featured[['total_cases','ndvi_average','grassy'        ,'soily'        ,'watery']]
ndvi_data.corr()['total_cases']
```

[59]:
```
total_cases     1.000000
ndvi_average    0.052466
grassy         -0.043124
soily           0.102880
watery         -0.088839
Name: total_cases, dtype: float64
```

- Converting the numerical average_ndvi values into categorical values seems to improve the correlation to total_cases

5.3 Create new shifted variables with rolled means:

- Research seems to indicate that past **sustained** heat, precipitation or humidity impacts dengue cases more profoundly than the climate situation right at the time of cases.
- I will be creating a series of rolled means for each of the chosen variable.
  - First shift the variables by 2 weeks to account for the growth of mosquito and the incubation period of the virus until testing positive.
  - Then create rolled - cumulative means with lags ranging from 2 week to 20 weeks and find the lagged variable with the highest correlation.

[60]:
```
train_shifted = train_featured.copy()
```

[61]:
```
# The variables to shift and roll:
shifted_varbls =['station_avg_temp_c', 'station_max_temp_c',␣
 ↪'station_min_temp_c', 'reanalysis_tdtr_k',
                 'reanalysis_specific_humidity_g_per_kg',␣
 ↪'reanalysis_precip_amt_kg_per_m2',
```

```
                   'grassy', 'soily','watery']
```

[62]:
```
# shift the variables two weeks ahead so that total cases would correspond with␣
 ↪climate variables from two weeks ago:
for var in shifted_varbls:
    train_shifted[f"{var}_shift"] = train_shifted[var].shift(2)
# drop the two rows with NA
train_shifted.dropna(axis=0, inplace=True)
# reset the index
train_shifted = train_shifted.reset_index(drop=True)
```

[63]:
```
# Making sure it shifted corretly
train_shifted[['year', 'weekofyear','week_start_date', 'station_avg_temp_c',␣
 ↪'station_avg_temp_c_shift',  'grassy', 'grassy_shift']].head()
```

[63]:
```
     year  weekofyear week_start_date  station_avg_temp_c  \
0  1990.0        20.0      1990-05-14           26.714286
1  1990.0        21.0      1990-05-21           27.471429
2  1990.0        22.0      1990-05-28           28.942857
3  1990.0        23.0      1990-06-04           28.114286
4  1990.0        24.0      1990-06-11           27.414286

   station_avg_temp_c_shift  grassy  grassy_shift
0                 25.442857       0           0.0
1                 26.714286       1           0.0
2                 26.714286       1           0.0
3                 27.471429       1           1.0
4                 28.942857       0           1.0
```

[64]:
```
# create another copy to get the rolled means
train_rolled = train_shifted.copy()
```

[65]:
```
# We will check the correlations between these variables and its shifted␣
 ↪versions
varbls_to_see_lags = ['total_cases',
                             'reanalysis_precip_amt_kg_per_m2',
                             'reanalysis_specific_humidity_g_per_kg',
                             'reanalysis_tdtr_k',
                             'station_avg_temp_c',
                             'station_max_temp_c',
                             'station_min_temp_c',
                             'grassy', 'soily','watery',
                             'reanalysis_precip_amt_kg_per_m2_shift',
                             'reanalysis_specific_humidity_g_per_kg_shift',
                             'reanalysis_tdtr_k_shift',
                             'station_avg_temp_c_shift',
                             'station_max_temp_c_shift',
```

```
                                   'station_min_temp_c_shift',
                                   'grassy_shift', 'soily_shift','watery_shift']
```

[66]:
```
train_rolled = train_rolled[varbls_to_see_lags]
```

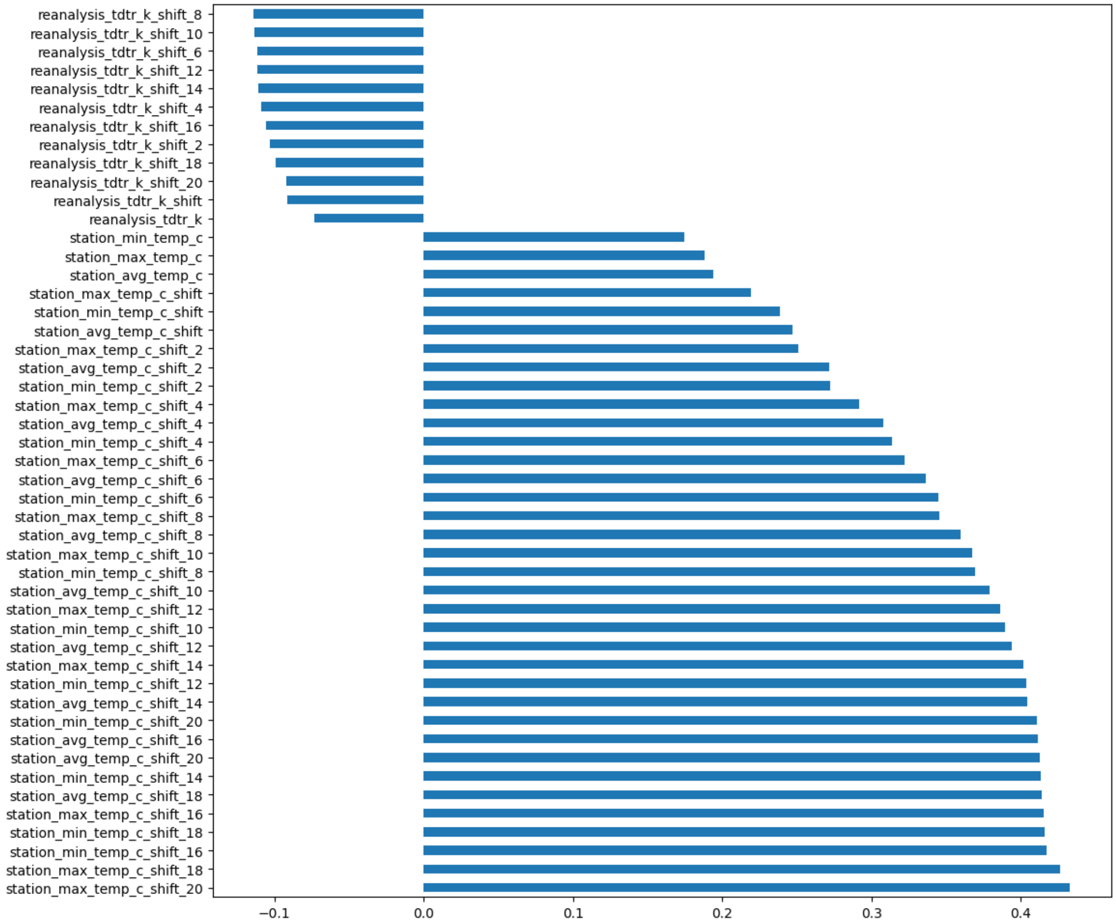
[67]:
```
rolled_varbls = ['reanalysis_precip_amt_kg_per_m2_shift',
                 'reanalysis_specific_humidity_g_per_kg_shift',
                 'reanalysis_tdtr_k_shift',
                 'station_avg_temp_c_shift',
                 'station_max_temp_c_shift',
                 'station_min_temp_c_shift',
                 'grassy_shift', 'soily_shift','watery_shift']
```

[68]:
```
# Create cumulative means of lags of 2 through 20 weeks (about 3-4 months):
# Use a min period of 10 for a lag of 20 so we do not lose all the first 20␣
 ↪weeks of data.
window = np.linspace(2,20,10).astype(int)
min_periods = np.linspace(1,10,10).astype(int)

for var in rolled_varbls:
    for num,min in zip(window,min_periods):
        train_rolled[f"{var}_{num}"] = train_rolled[var].rolling(window = num,␣
 ↪min_periods = min).mean()
```

[69]:
```
# Create 4 seperate datasets for temp, humid, prec, ndvi variables with shifted␣
 ↪and rolled versions:
temp_cols = [col for col in train_rolled.columns if 'temp' in col or 'tdtr' in␣
 ↪col]
hum_cols = [col for col in train_rolled.columns if 'hum' in col]
prec_cols = [col for col in train_rolled.columns if 'prec' in col]
ndvi_cols = [col for col in train_rolled.columns if 'grassy' in col or 'soily'␣
 ↪in col or 'watery' in col]
```

[70]:
```
# Add total_cases
temp = train_rolled[temp_cols]
temp['total_cases'] = train_rolled['total_cases']

hum = train_rolled[hum_cols]
hum['total_cases'] = train_rolled['total_cases']

prec = train_rolled[prec_cols]
prec['total_cases'] = train_rolled['total_cases']

ndvi = train_rolled[ndvi_cols]
ndvi['total_cases'] = train_rolled['total_cases']
```

```
[71]: # see the correlations between all temperature variables along with their
       ↪lagged versions and total case counts
      fig, ax = plt.subplots(figsize=(12,12))
      temp.corr()['total_cases'].drop('total_cases').sort_values(ascending=False).
       ↪plot.barh(ax=ax);
```

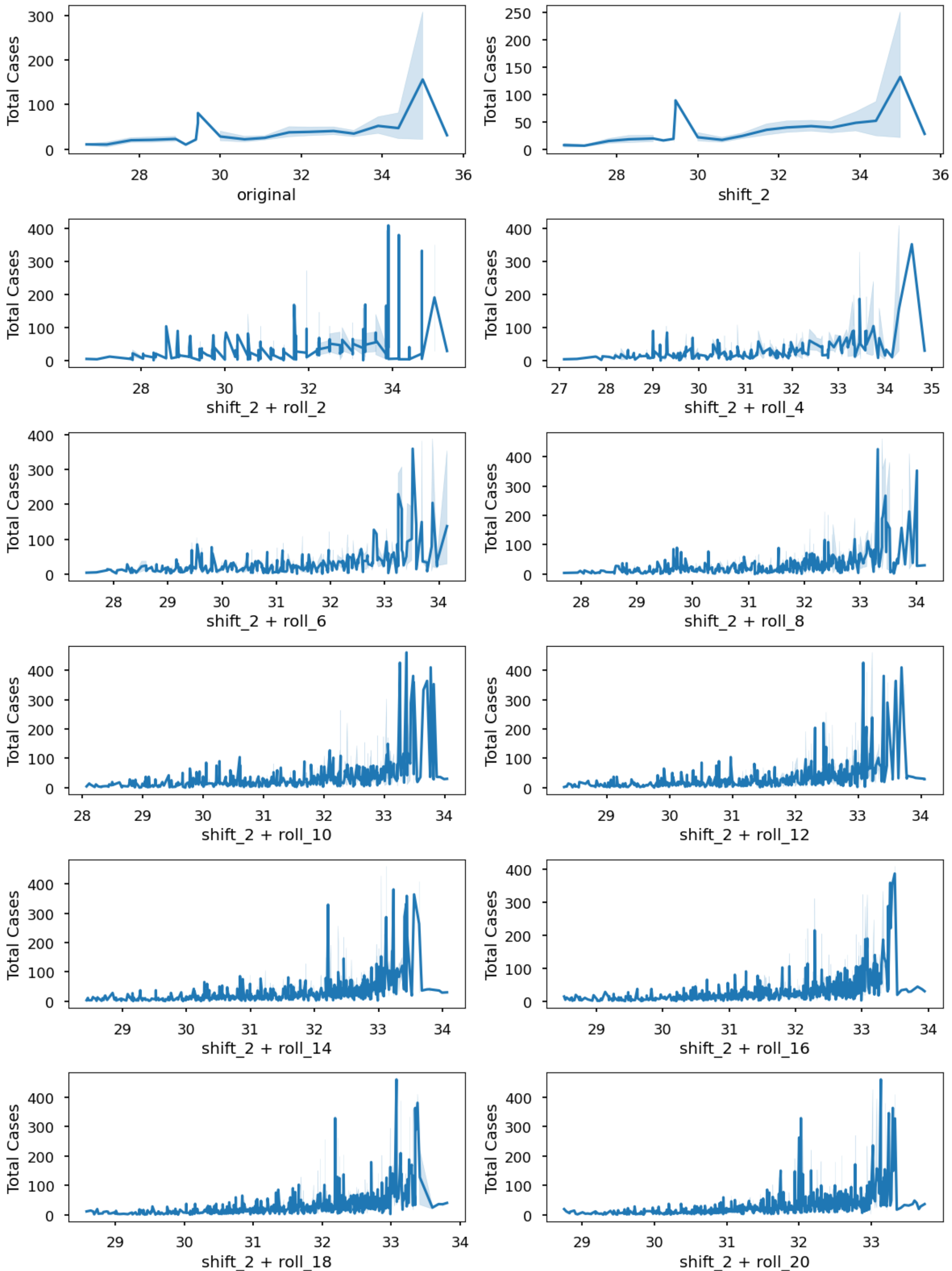


- reanalysis_tdtr_k_shift (daily temp range) gives the best correlation with a lag of 8
- Max, min and average temperature seem to give the best correalation with a lag of abour 18.

```
[72]: # create a function to see how original, shifted and lagged versions of a
       ↪variable is related to total cases.
      def lag_graph(df, var):

          columns = [f"{var}", f"{var}_shift",
                     f"{var}_shift_2", f"{var}_shift_4",
                     f"{var}_shift_6", f"{var}_shift_8",
                     f"{var}_shift_10", f"{var}_shift_12",
                     f"{var}_shift_14", f"{var}_shift_16",
```

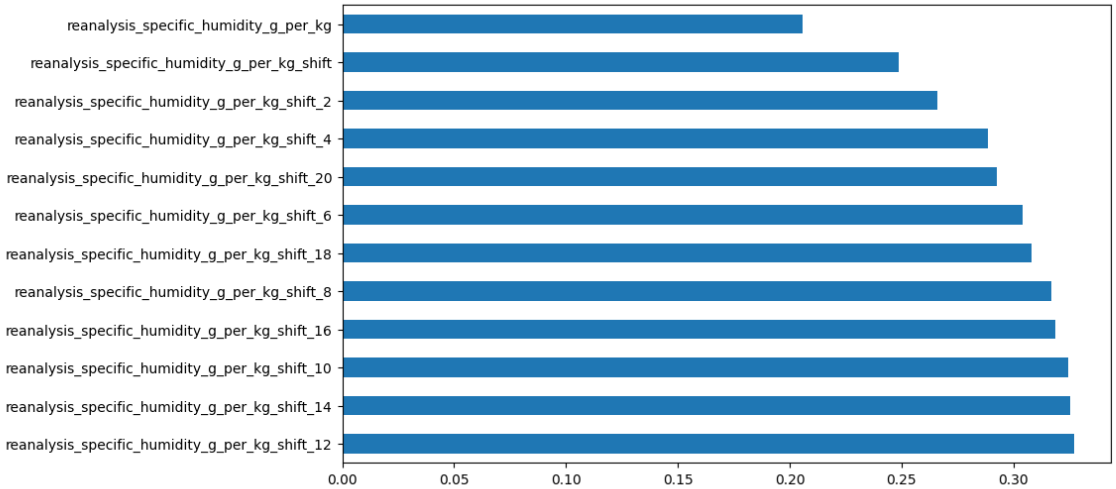
```
                f"{var}_shift_18", f"{var}_shift_20"]

    labels = ["original", "shift_2", "shift_2 + roll_2", "shift_2 + roll_4",␣
↪"shift_2 + roll_6",
              "shift_2 + roll_8","shift_2 + roll_10", "shift_2 + roll_12",␣
↪"shift_2 + roll_14",
              "shift_2 + roll_16", "shift_2 + roll_18", "shift_2 + roll_20"]

    ncols = 2
    nrows = 6
    with plt.style.context('seaborn-talk'):


        fig, ax_list = plt.subplots(nrows = nrows, ncols = ncols,␣
↪figsize=(12,16))

        j=0
        for i in range(nrows):
            for u in range(ncols):
                sns.lineplot(data = df, x=columns[j], y="total_cases", ax =␣
↪ax_list[i,u]) # need to use index for column because otherwise it does not␣
↪itirate.
                ax_list[i,u].set_xlabel(labels[j])
                ax_list[i,u].set_ylabel("Total Cases")
                j = j+1

        fig.tight_layout();
```

[73]:
```
lag_graph(train_rolled, "station_max_temp_c")
```



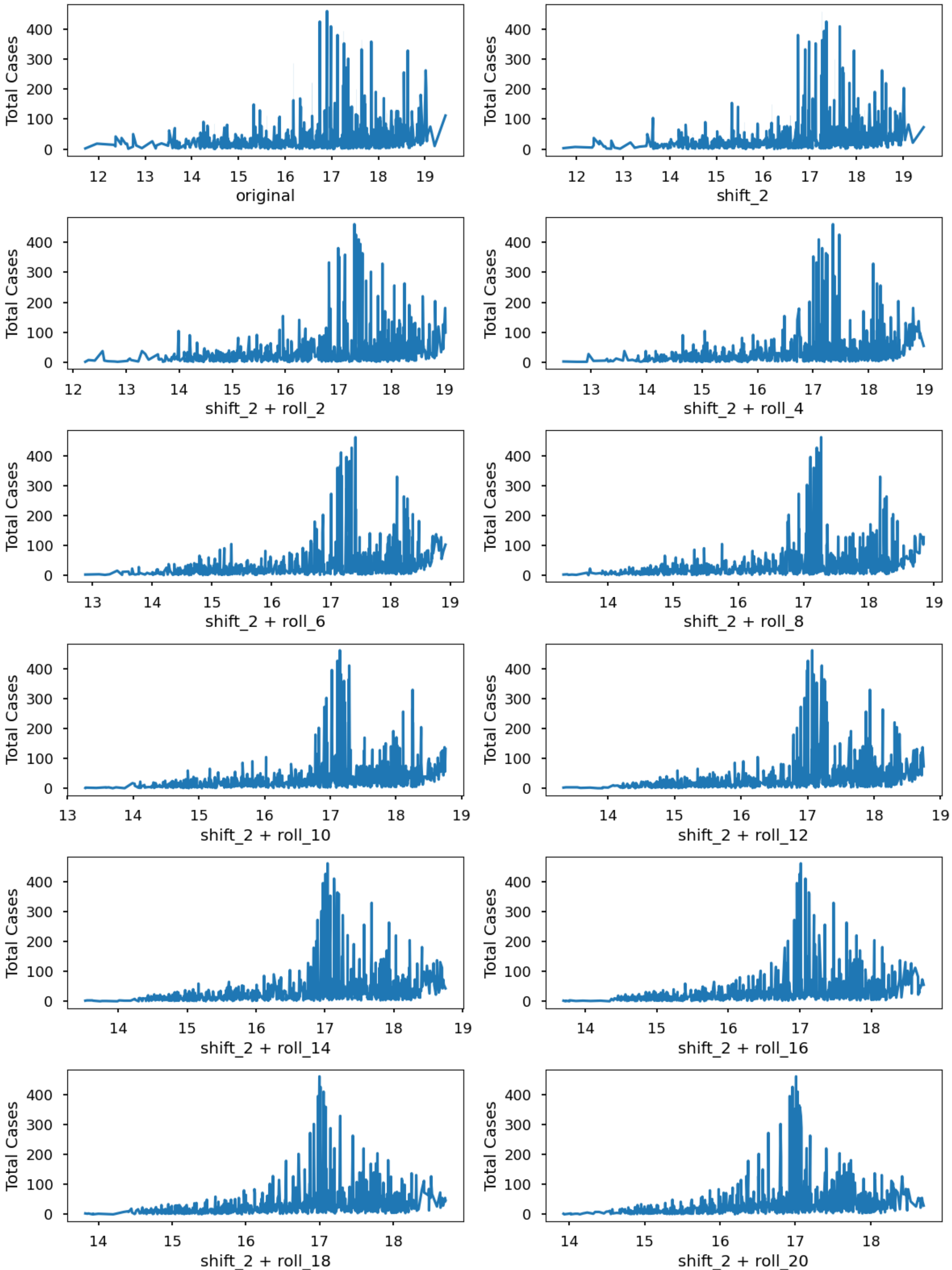
- The relationship between maximum temperature and total cases seem to get stronger with increased lags.

[74]:
```
# see the correlations between the humidity variable along with its lagged␣
↪versions and total case counts
fig, ax = plt.subplots(figsize=(10,6))
hum.corr()['total_cases'].drop('total_cases').sort_values(ascending=False).plot.
↪barh(ax=ax);
```



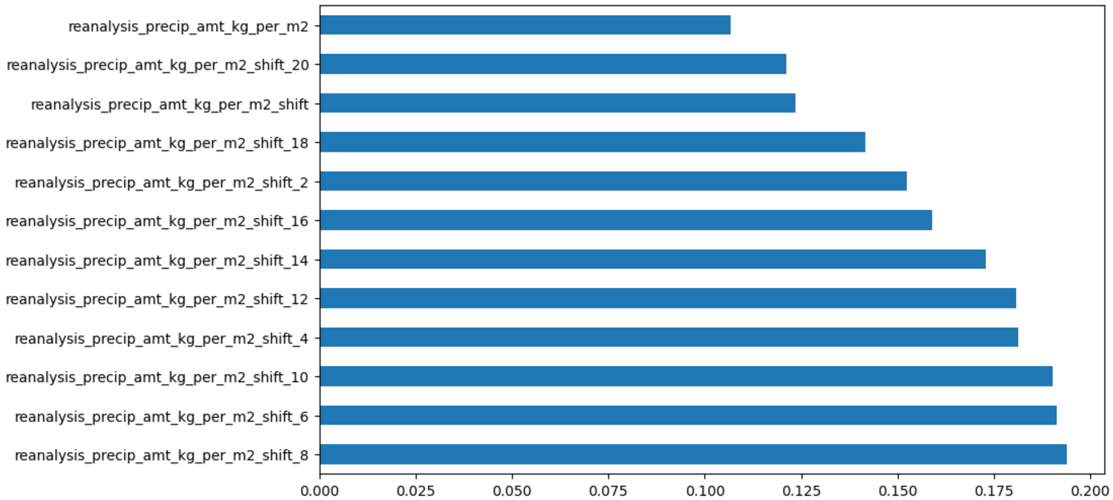
- Humidity gives the best correlation with a lag of 12.

[75]:
```
lag_graph(train_rolled, "reanalysis_specific_humidity_g_per_kg")
```



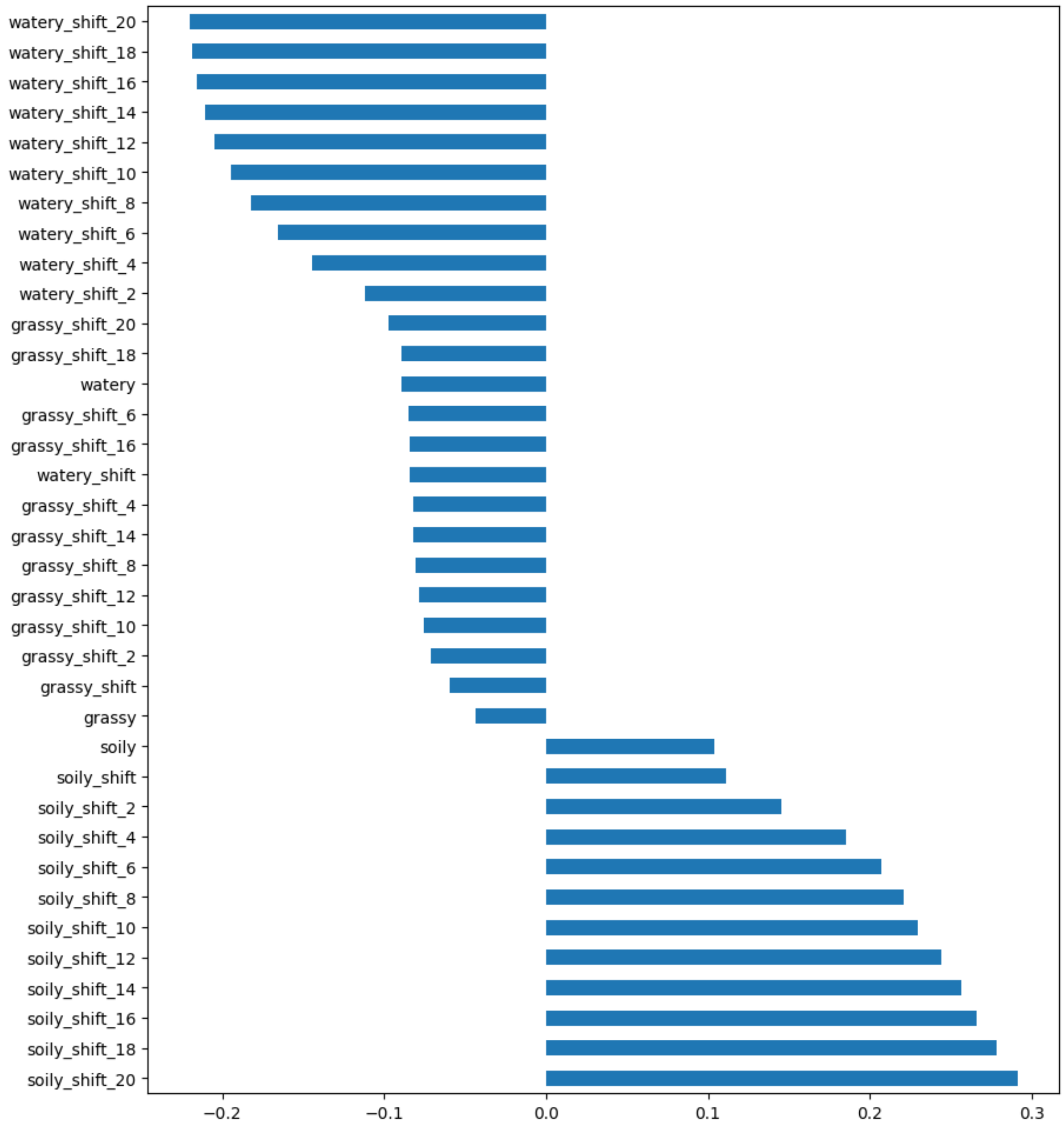
[76]:
```
# see the correlations between the precipitation variable along with its lagged
↪versions and total case counts
```

```
fig, ax = plt.subplots(figsize=(10,6))
prec.corr()['total_cases'].drop('total_cases').sort_values(ascending=False).
 ↪plot.barh(ax=ax);
```



- Precipitation gives the best correlation with a lag of 8.

[77]:
```
# see the correlations between the vegetation variables along with their lagged␣
 ↪versions and total case counts
fig, ax = plt.subplots(figsize=(10,12))
ndvi.corr()['total_cases'].drop('total_cases').sort_values(ascending=False).
 ↪plot.barh(ax=ax);
```



- All vegetation variables gives the best correlations with the maximum lag of 20.
- Since there seems to be an apparent tendency to more strongly correlate with total cases as the lag numbers increase, we could have tried lags more than 20 weeks as well. But since we do not want to pass the 4-5 month period and we kept the max lag to 18 weeks for other variables, we will stop at 20 for ndvi as well.

6 Based on above graphs I will be using these variables which provided the highest correlations to total cases:

- `station_max_temp_c_shift_18`,
- `station_min_temp_c_shift_18`,

- station_avg_temp_c_shift_18,
- reanalysis_tdtr_k_shift_8,
- reanalysis_specific_humidity_g_per_kg_shift_12,
- reanalysis_precip_amt_kg_per_m2_shift_8,
- grassy_shift_20,
- soily_shift_20,
- watery_shift_20

[78]:
```
rolled_varbls_to_use = ['station_max_temp_c_shift_18',
                        'station_min_temp_c_shift_18',
                        'station_avg_temp_c_shift_18',
                        'reanalysis_tdtr_k_shift_8',
                        'reanalysis_specific_humidity_g_per_kg_shift_12',
                        'reanalysis_precip_amt_kg_per_m2_shift_8',
                        'grassy_shift_20',
                        'soily_shift_20','watery_shift_20']
```

[79]:
```
# Add the rolled variables to the dataset
train_final = train_shifted.join(train_rolled[rolled_varbls_to_use])
train_final.head(10)
```

[79]:
```
   total_cases    year  weekofyear week_start_date  month  fall  spring  \
0            4  1990.0        20.0      1990-05-14      5     0       1
1            3  1990.0        21.0      1990-05-21      5     0       1
2            6  1990.0        22.0      1990-05-28      5     0       1
3            2  1990.0        23.0      1990-06-04      6     0       0
4            4  1990.0        24.0      1990-06-11      6     0       0
5            5  1990.0        25.0      1990-06-18      6     0       0
6           10  1990.0        26.0      1990-06-25      6     0       0
7            6  1990.0        27.0      1990-07-02      7     0       0
8            8  1990.0        28.0      1990-07-09      7     0       0
9            2  1990.0        29.0      1990-07-16      7     0       0

   summer  winter  station_avg_temp_c  …  watery_shift  \
0       0       0           26.714286  …           0.0
1       0       0           27.471429  …           0.0
2       0       0           28.942857  …           0.0
3       1       0           28.114286  …           0.0
4       1       0           27.414286  …           0.0
5       1       0           28.371429  …           0.0
6       1       0           28.328571  …           0.0
7       1       0           28.328571  …           0.0
8       1       0           27.557143  …           0.0
9       1       0           28.128571  …           0.0

   station_max_temp_c_shift_18  station_min_temp_c_shift_18  \
0                          NaN                          NaN
```

```
1                     NaN                      NaN
2                     NaN                      NaN
3                     NaN                      NaN
4                     NaN                      NaN
5                     NaN                      NaN
6                     NaN                      NaN
7                     NaN                      NaN
8               32.888889                22.777778
9               32.990000                22.940000

   station_avg_temp_c_shift_18  reanalysis_tdtr_k_shift_8  \
0                          NaN                        NaN
1                          NaN                        NaN
2                          NaN                        NaN
3                          NaN                   2.432143
4                          NaN                   2.548571
5                          NaN                   2.473810
6                          NaN                   2.412245
7                          NaN                   2.307143
8                    27.501587                   2.214286
9                    27.584286                   2.169643

   reanalysis_specific_humidity_g_per_kg_shift_12  \
0                                             NaN
1                                             NaN
2                                             NaN
3                                             NaN
4                                             NaN
5                                       16.221667
6                                       16.366327
7                                       16.567679
8                                       16.703492
9                                       16.840286

   reanalysis_precip_amt_kg_per_m2_shift_8  grassy_shift_20  soily_shift_20  \
0                                      NaN              NaN             NaN
1                                      NaN              NaN             NaN
2                                      NaN              NaN             NaN
3                                22.485000              NaN             NaN
4                                20.428000              NaN             NaN
5                                21.438333              NaN             NaN
6                                23.890000              NaN             NaN
7                                24.653750              NaN             NaN
8                                25.342500              NaN             NaN
9                                26.650000              0.3             0.7

   watery_shift_20
```

```
0               NaN
1               NaN
2               NaN
3               NaN
4               NaN
5               NaN
6               NaN
7               NaN
8               NaN
9               0.0

[10 rows x 42 columns]
```

[80]:
```
# We are losing the first 9 rows
train_final = train_final.dropna().reset_index(drop=True)
```

[81]:
```
train_final.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 925 entries, 0 to 924
Data columns (total 42 columns):
 #   Column                                 Non-Null Count  Dtype
---  ------                                 --------------  -----
 0   total_cases                            925 non-null    int64
 1   year                                   925 non-null    float64
 2   weekofyear                             925 non-null    float64
 3   week_start_date                        925 non-null
datetime64[ns]
 4   month                                  925 non-null    int64
 5   fall                                   925 non-null    uint8
 6   spring                                 925 non-null    uint8
 7   summer                                 925 non-null    uint8
 8   winter                                 925 non-null    uint8
 9   station_avg_temp_c                     925 non-null    float64
 10  station_max_temp_c                     925 non-null    float64
 11  station_min_temp_c                     925 non-null    float64
 12  reanalysis_tdtr_k                      925 non-null    float64
 13  reanalysis_specific_humidity_g_per_kg  925 non-null    float64
 14  reanalysis_precip_amt_kg_per_m2        925 non-null    float64
 15  ndvi_ne                                925 non-null    float64
 16  ndvi_nw                                925 non-null    float64
 17  ndvi_se                                925 non-null    float64
 18  ndvi_sw                                925 non-null    float64
 19  ndvi_average                           925 non-null    float64
 20  ndvi_average_cat                       925 non-null    object
 21  grassy                                 925 non-null    uint8
 22  soily                                  925 non-null    uint8
```

```
 23  watery                                          925 non-null    uint8
 24  station_avg_temp_c_shift                        925 non-null    float64
 25  station_max_temp_c_shift                        925 non-null    float64
 26  station_min_temp_c_shift                        925 non-null    float64
 27  reanalysis_tdtr_k_shift                         925 non-null    float64
 28  reanalysis_specific_humidity_g_per_kg_shift     925 non-null    float64
 29  reanalysis_precip_amt_kg_per_m2_shift           925 non-null    float64
 30  grassy_shift                                    925 non-null    float64
 31  soily_shift                                     925 non-null    float64
 32  watery_shift                                    925 non-null    float64
 33  station_max_temp_c_shift_18                     925 non-null    float64
 34  station_min_temp_c_shift_18                     925 non-null    float64
 35  station_avg_temp_c_shift_18                     925 non-null    float64
 36  reanalysis_tdtr_k_shift_8                       925 non-null    float64
 37  reanalysis_specific_humidity_g_per_kg_shift_12  925 non-null    float64
 38  reanalysis_precip_amt_kg_per_m2_shift_8         925 non-null    float64
 39  grassy_shift_20                                 925 non-null    float64
 40  soily_shift_20                                  925 non-null    float64
 41  watery_shift_20                                 925 non-null    float64
dtypes: datetime64[ns](1), float64(31), int64(2), object(1), uint8(7)
memory usage: 259.4+ KB
```

[82]:
```
# length of the original dataset
len(train_features)
```

[82]:
```
936
```

We ended up with 925 data points in the final dataset, only 11 weeks less then the original dataset.

6.1 Repeat all steps for the final test set:

- First add the last 21 (19 +2 for shifting) rows of the train_full to test_full to not to lose the first part of the dataset while transforming

[83]:
```
# Add week_start_date to both datasets
test_features_full['week_start_date'] = test_features['week_start_date']
train_features_full['week_start_date'] = train_features['week_start_date']
```

[84]:
```
# Create a long dataset with the tail rows from train added:
test_features_long = pd.concat([train_features_full.tail(21),␣
↪test_features_full],ignore_index=True)
test_features_long
```

[84]:
```
       year  weekofyear  ndvi_ne   ndvi_nw   ndvi_se   ndvi_sw  \
0    2007.0        49.0 -0.03976 -0.042350  0.095600  0.089000
1    2007.0        50.0 -0.13305 -0.045550  0.151440  0.143171
2    2007.0        51.0  0.02945 -0.039000  0.173417  0.150171
3    2007.0        52.0  0.01480  0.016300  0.207267  0.144578
```

```
4    2008.0         1.0  0.00060 -0.309600  0.239814  0.195557
..      …          …       …        …         …         …
276  2013.0        13.0 -0.08740 -0.016183  0.156343  0.105186
277  2013.0        14.0 -0.20325 -0.077833  0.204171  0.178914
278  2013.0        15.0 -0.11760 -0.008200  0.192700  0.170429
279  2013.0        16.0  0.08275  0.031200  0.135014  0.074857
280  2013.0        17.0 -0.08730 -0.048667  0.129814  0.117671

     precipitation_amt_mm  reanalysis_air_temp_k  reanalysis_avg_temp_k  \
0                   17.85             299.020000             299.021429
1                   31.30             298.900000             298.971429
2                   62.11             298.668571             298.757143
3                    0.00             298.602857             298.750000
4                    0.00             298.038571             298.121429
..                    …                      …                      …
276                 30.34             298.670000             298.885714
277                  6.55             298.035714             298.157143
278                  0.00             299.057143             299.328571
279                  0.00             298.912857             299.064286
280                 45.47             298.067143             298.042857

     reanalysis_dew_point_temp_k  …  reanalysis_relative_humidity_percent  \
0                     294.288571  …                             75.368571
1                     294.774286  …                             78.015714
2                     294.977143  …                             80.178571
3                     293.928571  …                             75.448571
4                     293.514286  …                             76.148571
..                           …  …                                    …
276                   294.675714  …                             78.780000
277                   294.628571  …                             81.650000
278                   294.948571  …                             78.285714
279                   294.678571  …                             77.674286
280                   294.132857  …                             79.045714

     reanalysis_sat_precip_amt_mm  reanalysis_specific_humidity_g_per_kg  \
0                           17.85                              15.675714
1                           31.30                              16.130000
2                           62.11                              16.344286
3                            0.00                              15.318571
4                            0.00                              14.911429
..                            …                                    …
276                         30.34                              15.985714
277                          6.55                              15.881429
278                          0.00                              16.212857
279                          0.00                              15.965714
280                         45.47                              15.451429
```

```
     reanalysis_tdtr_k  station_avg_temp_c  station_diur_temp_rng_c  \
0             2.100000           25.842857                 5.400000   
1             2.485714           25.771429                 5.085714   
2             2.371429           25.071429                 4.914286   
3             2.985714           25.085714                 6.242857   
4             1.842857           25.400000                 5.300000   
..                 …                   …                        …   
276           3.314286           27.542857                 7.942857   
277           2.828571           26.642857                 6.642857   
278           3.171429           27.914286                 8.114286   
279           3.042857           27.728571                 6.942857   
280           2.342857           26.442857                 6.742857   

     station_max_temp_c  station_min_temp_c  station_precip_mm  \
0                  29.4                22.8               34.5   
1                  28.9                22.2               30.2   
2                  28.9                21.7              108.2   
3                  28.3                21.1               16.8   
4                  29.4                22.2               55.5   
..                  …                  …                 …     
276                33.9                22.8                3.5   
277                33.3                22.8               17.6   
278                32.8                23.3                9.4   
279                31.7                23.9               22.9   
280                31.1                21.7               47.5   

     week_start_date  
0             12/3/07  
1            12/10/07  
2            12/17/07  
3            12/24/07  
4              1/1/08  
..               …  
276           3/26/13  
277            4/2/13  
278            4/9/13  
279           4/16/13  
280           4/23/13  

[281 rows x 23 columns]
```

[85]:

```python
# create a new month variable:
test_featured = test_features_long.copy()
test_featured["week_start_date"] = pd.
 ↪to_datetime(test_featured["week_start_date"])
test_featured['month'] = test_featured['week_start_date'].dt.month
```

```
# create a new season variable:
test_featured['season'] = test_featured['month'].map(month_to_season)
season_features = pd.get_dummies(test_featured['season'])
test_featured = pd.concat([test_featured, season_features], axis = 1)

test_featured = test_featured[['year', 'weekofyear', 'week_start_date',
                               'month',  'fall', 'spring', 'summer','winter',
                               'station_avg_temp_c', 'station_max_temp_c',
                               'station_min_temp_c', 'reanalysis_tdtr_k',
                               'reanalysis_specific_humidity_g_per_kg',
                               'reanalysis_precip_amt_kg_per_m2',
                               'ndvi_ne', 'ndvi_nw', 'ndvi_se', 'ndvi_sw']]

# create a new ndvi_average variable:
test_featured['ndvi_average'] = ␣
 ↪(test_featured['ndvi_ne']+test_featured['ndvi_nw']+
                                         ␣
 ↪test_featured['ndvi_se']+test_featured['ndvi_sw'])/4
# convert ndvi_average to categorical:
test_featured["ndvi_average_cat"] = test_featured["ndvi_average"].
 ↪apply(get_ndvi_cat)

# Get them dummy coded
ndvi_features = pd.get_dummies(test_featured['ndvi_average_cat'])
test_featured = pd.concat([test_featured, ndvi_features], axis = 1)

# shift by 2 weeks
test_shifted = test_featured.copy()

for var in shifted_varbls:
    test_shifted[f"{var}_shift"] = test_shifted[var].shift(2)

test_shifted.dropna(axis=0, inplace=True)
# test_shifted = test_shifted.reset_index(drop=True)

# get rolled means
test_rolled = test_shifted.copy()
varbls_to_see_lags = ['reanalysis_precip_amt_kg_per_m2',
                      'reanalysis_specific_humidity_g_per_kg',
                      'reanalysis_tdtr_k',
                      'station_avg_temp_c',
                      'station_max_temp_c',
                      'station_min_temp_c',
                      'grassy', 'soily','watery',
                      'reanalysis_precip_amt_kg_per_m2_shift',
                      'reanalysis_specific_humidity_g_per_kg_shift',
                      'reanalysis_tdtr_k_shift',
```

```
                                'station_avg_temp_c_shift',
                                'station_max_temp_c_shift',
                                'station_min_temp_c_shift',
                                'grassy_shift', 'soily_shift','watery_shift']

test_rolled = test_rolled[varbls_to_see_lags]

for var in rolled_varbls:
    for num in window:
        test_rolled[f"{var}_{num}"] = test_rolled[var].rolling(num).mean()

rolled_varbls_to_use = ['station_avg_temp_c_shift',
                        'station_max_temp_c_shift',
                        'station_min_temp_c_shift',
                        'reanalysis_precip_amt_kg_per_m2_shift',
                        'reanalysis_specific_humidity_g_per_kg_shift',
                        'reanalysis_tdtr_k_shift',
                        'grassy_shift', 'soily_shift','watery_shift',
                        'station_max_temp_c_shift_18',
                        'station_min_temp_c_shift_18',
                        'station_avg_temp_c_shift_18',
                        'reanalysis_tdtr_k_shift_8',
                        'reanalysis_specific_humidity_g_per_kg_shift_12',
                        'reanalysis_precip_amt_kg_per_m2_shift_8',
                        'grassy_shift_20',
                        'soily_shift_20','watery_shift_20']

# Create the final dataset by joining the rolled variables
test_final = test_featured.join(test_rolled[rolled_varbls_to_use])
test_final = test_final.dropna().reset_index(drop=True)
test_final
```

[85]:

```
       year  weekofyear week_start_date  month  fall  spring  summer  winter  \
0    2008.0        18.0      2008-04-29      4     0       1       0       0
1    2008.0        19.0      2008-05-06      5     0       1       0       0
2    2008.0        20.0      2008-05-13      5     0       1       0       0
3    2008.0        21.0      2008-05-20      5     0       1       0       0
4    2008.0        22.0      2008-05-27      5     0       1       0       0
..      …           …             …      …    …      …       …       …
255  2013.0        13.0      2013-03-26      3     0       1       0       0
256  2013.0        14.0      2013-04-02      4     0       1       0       0
257  2013.0        15.0      2013-04-09      4     0       1       0       0
258  2013.0        16.0      2013-04-16      4     0       1       0       0
259  2013.0        17.0      2013-04-23      4     0       1       0       0

     station_avg_temp_c  station_max_temp_c  …  watery_shift  \
0             26.528571                33.3  …           0.0
```

```
1            26.071429                30.0  …           1.0
2            27.928571                32.8  …           1.0
3            28.057143                33.3  …           1.0
4            27.614286                33.3  …           0.0
..                 …                    …  …           …
255          27.542857                33.9  …           0.0
256          26.642857                33.3  …           1.0
257          27.914286                32.8  …           1.0
258          27.728571                31.7  …           1.0
259          26.442857                31.1  …           1.0

     station_max_temp_c_shift_18  station_min_temp_c_shift_18  \
0                      28.816667                    21.300000
1                      28.972222                    21.388889
2                      29.250000                    21.422222
3                      29.283333                    21.422222
4                      29.533333                    21.516667
..                           …                            …
255                    30.766667                    22.377778
256                    30.550000                    22.194444
257                    30.611111                    22.105556
258                    30.733333                    22.016667
259                    30.827778                    21.983333

     station_avg_temp_c_shift_18  reanalysis_tdtr_k_shift_8  \
0                      24.997619                   2.678571
1                      25.107143                   2.887500
2                      25.187302                   2.951786
3                      25.224603                   3.012500
4                      25.388889                   3.082143
..                           …                          …
255                    26.509524                   2.723214
256                    26.352381                   2.775000
257                    26.298413                   2.891071
258                    26.227778                   2.910714
259                    26.244444                   2.971429

     reanalysis_specific_humidity_g_per_kg_shift_12  \
0                                         14.065833
1                                         14.171071
2                                         14.395476
3                                         14.514167
4                                         14.692143
..                                              …
255                                       14.662024
256                                       14.439048
257                                       14.439524
```

```
258                                     14.490000
259                                     14.648452

     reanalysis_precip_amt_kg_per_m2_shift_8  grassy_shift_20  soily_shift_20  \
0                                    9.28500              0.0            0.50
1                                    8.74875              0.0            0.50
2                                   11.10750              0.0            0.50
3                                   12.66375              0.0            0.45
4                                   13.06625              0.0            0.45
..                                       …              …             …
255                                  7.32500              0.0            0.60
256                                  6.88750              0.0            0.55
257                                  6.24375              0.0            0.55
258                                 12.39375              0.0            0.50
259                                 11.53125              0.0            0.45

    watery_shift_20
0              0.50
1              0.50
2              0.50
3              0.55
4              0.55
..              …
255            0.40
256            0.45
257            0.45
258            0.50
259            0.55

[260 rows x 41 columns]
```

[86]:
```python
# Making sure test_final has the same length with older version
len(test_features_full) ==  len(test_final)
```

[86]: True

[87]:
```python
# Making sure test_final follows train_final correctly in terms of date
print(train_final['week_start_date'])
print('----------------')
print(test_final['week_start_date'])
```

```
0      1990-07-16
1      1990-07-23
2      1990-07-30
3      1990-08-06
4      1990-08-13
          …
```

```
920   2008-03-25
921   2008-04-01
922   2008-04-08
923   2008-04-15
924   2008-04-22
Name: week_start_date, Length: 925, dtype: datetime64[ns]
----------------
0     2008-04-29
1     2008-05-06
2     2008-05-13
3     2008-05-20
4     2008-05-27
         …
255   2013-03-26
256   2013-04-02
257   2013-04-09
258   2013-04-16
259   2013-04-23
Name: week_start_date, Length: 260, dtype: datetime64[ns]
```

[88]:
```
train_final.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 925 entries, 0 to 924
Data columns (total 42 columns):
 #   Column                                Non-Null Count  Dtype
---  ------                                --------------  -----
 0   total_cases                           925 non-null    int64
 1   year                                  925 non-null    float64
 2   weekofyear                            925 non-null    float64
 3   week_start_date                       925 non-null
datetime64[ns]
 4   month                                 925 non-null    int64
 5   fall                                  925 non-null    uint8
 6   spring                                925 non-null    uint8
 7   summer                                925 non-null    uint8
 8   winter                                925 non-null    uint8
 9   station_avg_temp_c                    925 non-null    float64
 10  station_max_temp_c                    925 non-null    float64
 11  station_min_temp_c                    925 non-null    float64
 12  reanalysis_tdtr_k                     925 non-null    float64
 13  reanalysis_specific_humidity_g_per_kg 925 non-null    float64
 14  reanalysis_precip_amt_kg_per_m2       925 non-null    float64
 15  ndvi_ne                               925 non-null    float64
 16  ndvi_nw                               925 non-null    float64
 17  ndvi_se                               925 non-null    float64
 18  ndvi_sw                               925 non-null    float64
 19  ndvi_average                          925 non-null    float64
```

```
 20  ndvi_average_cat                               925 non-null    object
 21  grassy                                         925 non-null    uint8
 22  soily                                          925 non-null    uint8
 23  watery                                         925 non-null    uint8
 24  station_avg_temp_c_shift                       925 non-null    float64
 25  station_max_temp_c_shift                       925 non-null    float64
 26  station_min_temp_c_shift                       925 non-null    float64
 27  reanalysis_tdtr_k_shift                        925 non-null    float64
 28  reanalysis_specific_humidity_g_per_kg_shift    925 non-null    float64
 29  reanalysis_precip_amt_kg_per_m2_shift          925 non-null    float64
 30  grassy_shift                                   925 non-null    float64
 31  soily_shift                                    925 non-null    float64
 32  watery_shift                                   925 non-null    float64
 33  station_max_temp_c_shift_18                    925 non-null    float64
 34  station_min_temp_c_shift_18                    925 non-null    float64
 35  station_avg_temp_c_shift_18                    925 non-null    float64
 36  reanalysis_tdtr_k_shift_8                      925 non-null    float64
 37  reanalysis_specific_humidity_g_per_kg_shift_12 925 non-null    float64
 38  reanalysis_precip_amt_kg_per_m2_shift_8        925 non-null    float64
 39  grassy_shift_20                                925 non-null    float64
 40  soily_shift_20                                 925 non-null    float64
 41  watery_shift_20                                925 non-null    float64
dtypes: datetime64[ns](1), float64(31), int64(2), object(1), uint8(7)
memory usage: 259.4+ KB
```

[89]:
```
test_final.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 260 entries, 0 to 259
Data columns (total 41 columns):
 #   Column                                         Non-Null Count  Dtype
---  ------                                         --------------  -----
 0   year                                           260 non-null    float64
 1   weekofyear                                     260 non-null    float64
 2   week_start_date                                260 non-null
datetime64[ns]
 3   month                                          260 non-null    int64
 4   fall                                           260 non-null    uint8
 5   spring                                         260 non-null    uint8
 6   summer                                         260 non-null    uint8
 7   winter                                         260 non-null    uint8
 8   station_avg_temp_c                             260 non-null    float64
 9   station_max_temp_c                             260 non-null    float64
 10  station_min_temp_c                             260 non-null    float64
 11  reanalysis_tdtr_k                              260 non-null    float64
 12  reanalysis_specific_humidity_g_per_kg          260 non-null    float64
 13  reanalysis_precip_amt_kg_per_m2                260 non-null    float64
 14  ndvi_ne                                        260 non-null    float64
```

```
 15  ndvi_nw                                        260 non-null    float64
 16  ndvi_se                                        260 non-null    float64
 17  ndvi_sw                                        260 non-null    float64
 18  ndvi_average                                   260 non-null    float64
 19  ndvi_average_cat                               260 non-null    object
 20  grassy                                         260 non-null    uint8
 21  soily                                          260 non-null    uint8
 22  watery                                         260 non-null    uint8
 23  station_avg_temp_c_shift                       260 non-null    float64
 24  station_max_temp_c_shift                       260 non-null    float64
 25  station_min_temp_c_shift                       260 non-null    float64
 26  reanalysis_precip_amt_kg_per_m2_shift          260 non-null    float64
 27  reanalysis_specific_humidity_g_per_kg_shift    260 non-null    float64
 28  reanalysis_tdtr_k_shift                        260 non-null    float64
 29  grassy_shift                                   260 non-null    float64
 30  soily_shift                                    260 non-null    float64
 31  watery_shift                                   260 non-null    float64
 32  station_max_temp_c_shift_18                    260 non-null    float64
 33  station_min_temp_c_shift_18                    260 non-null    float64
 34  station_avg_temp_c_shift_18                    260 non-null    float64
 35  reanalysis_tdtr_k_shift_8                      260 non-null    float64
 36  reanalysis_specific_humidity_g_per_kg_shift_12 260 non-null    float64
 37  reanalysis_precip_amt_kg_per_m2_shift_8        260 non-null    float64
 38  grassy_shift_20                                260 non-null    float64
 39  soily_shift_20                                 260 non-null    float64
 40  watery_shift_20                                260 non-null    float64
dtypes: datetime64[ns](1), float64(31), int64(1), object(1), uint8(7)
memory usage: 71.0+ KB
```

Final datasets include:

- 925 datapoints in train
- 260 datapoints in test
- no null values
- newly engineered categorical variables
- newly engineered rolled averages
- all variables are numerical except week_start_date which is datetime.

[90]:
```
# Export the final datasets as csv to be used for modeling
train_final.to_csv("train_final.csv")
test_final.to_csv("test_final.csv")
```

6.1.1 Export as PDF:

[91]:
```
# Packages required for using nbconvert PDF
# ! apt-get install texlive texlive-xetex texlive-latex-extra pandoc
# ! pip install pypandoc
# ! pip install nbconvert
```

[92]:

```
# First you need to download a copy of the ipynb notebook and upload it back to␣
↪the drive, it is placed under /content/
# ! jupyter nbconvert --to pdf /content/notebook_preprocessing.ipynb
```