ET0_NN

May 19, 2025

[21]:
```python
import xarray as xr
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.cm as cm
from datetime import datetime
import pandas as pd
from glob import glob
```

[22]:
```python
# import zipfile

# #** unzip the folder GLEM_daily_dataset.zip **
# with zipfile.ZipFile("GLEM_daily_dataset.zip", "r") as zip_ref:
#     zip_ref.extractall("GLEM_daily_dataset")

# #** unzip the folder MADIA_daily_dataset_v1.3.zip **
# with zipfile.ZipFile("MADIA_daily_dataset_v1.3.zip", "r") as zip_ref:
#     zip_ref.extractall("MADIA_daily_dataset_v1.3")
```

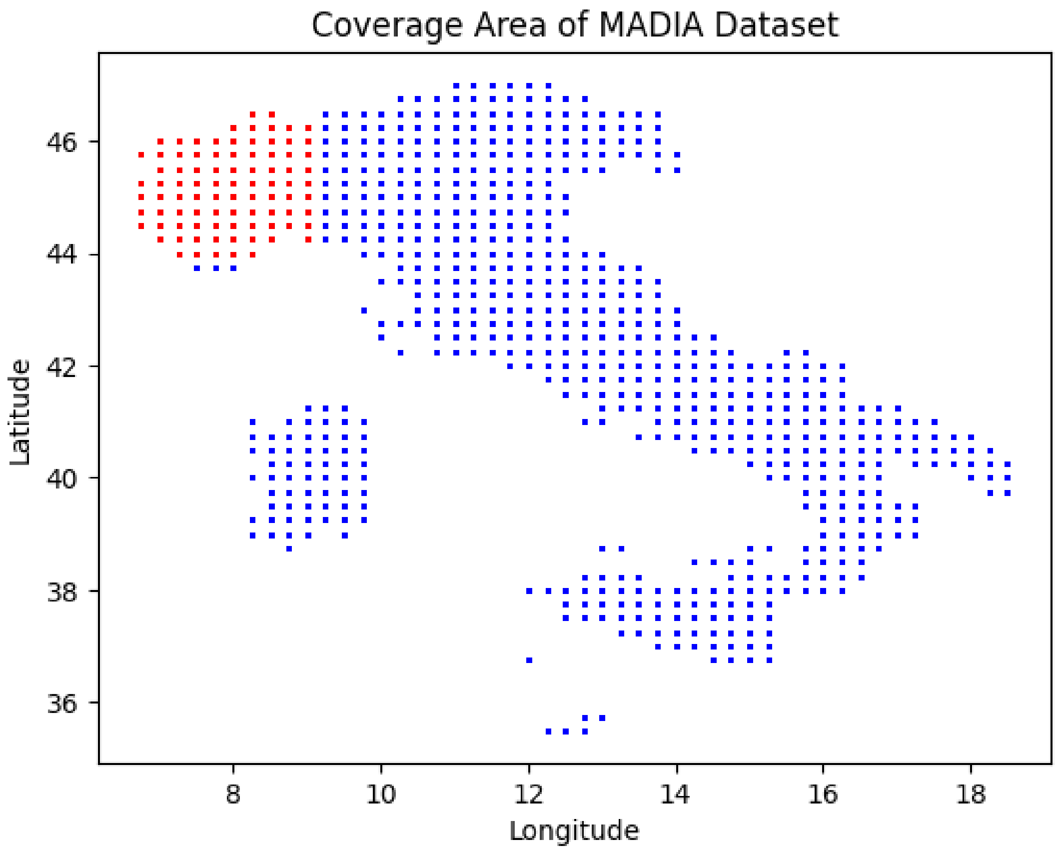
[23]:
```python
#** load the dataframe of climatological variables **

# load data from the csv files
csv_files = sorted(glob("./MADIA_daily_dataset_v1.3/csv_data/*_e5_d.csv"))
csv_files = [file for file in csv_files if 1991 <= int(file.split('/')[-1].
↪split('_')[0]) <= 1992]

dailyClimatological_data = pd.DataFrame()

for file in csv_files:
    df = pd.read_csv(file)

    # keep only the data that are referred to the Piedmont region
    df_piedmont = df[df['latitude'].between(44.0, 46.5) & df['longitude'].
↪between(6.5, 9.0)]

    global_dailyClimatological_data = pd.concat([dailyClimatological_data, df],␣
↪ignore_index=True)
```

```
    dailyClimatological_data = pd.concat([dailyClimatological_data,␣
 ↪df_piedmont], ignore_index=True)

print(dailyClimatological_data.head())

# tasmin    mean of daily minimum near-surface air temperature
# tasmean   mean of daily average near-surface air temperature
# tasmax    mean of daily maximum near-surface air temperature
# rhmin     mean of daily minimum near-surface relative air humidity
# rhmax     mean of daily maximum near-surface relative air humidity
# ws10      mean of daily wind speed
# ssrd      mean of daily surface solar radiation downwards (shortwave␣
 ↪radiation)
# ppn       sum of daily depth of water-equivalent precipitation
# pev       sum of daily crop reference evapotranspiration estimated by FAO␣
 ↪Penman-Monteith method
# zg        geopotential height: average cell height (metres) above the geoid,␣
 ↪which corresponds approximately to the elevation
# dekad     number of dekad from the beginning of the year
# expver    code which identi es temporary data when expver=5
# mask      boolean code to identify cells belonging to the Italian country
```

```
   longitude  latitude        time    tasmin    tasmax   tasmean     rhmin  \
0       7.25      44.0  1991-01-01 -2.247864  5.563782  1.657959  0.592831
1       7.25      44.0  1991-01-02 -3.348724  3.856262  0.253769  0.444172
2       7.25      44.0  1991-01-03 -0.891388  7.161102  3.134857  0.650528
3       7.25      44.0  1991-01-04  0.054962  3.950562  2.002762  0.706066
4       7.25      44.0  1991-01-05 -5.585663  4.696960 -0.444351  0.307958

      rhmax      ws10      ssrd       ppn       pev  expver  mask
0  0.936595  1.581366  7.215224  0.002508  0.417441     1.0   1.0
1  0.850283  1.228787  6.347265  0.000000  0.463205     1.0   1.0
2  0.866600  0.860398  6.891922  0.015718  0.322711     1.0   1.0
3  0.879245  1.040755  5.009695  0.082887  0.377663     1.0   1.0
4  0.872699  1.498034  7.351231  0.000000  0.599895     1.0   1.0
```

[24]:

```
# **show a plot of the coverage area of the MADIA dataset**
# color in red the area of the Piedmont region

plt.scatter(global_dailyClimatological_data['longitude'],␣
 ↪global_dailyClimatological_data['latitude'], s=1, c='blue', alpha=0.5)
plt.scatter(dailyClimatological_data['longitude'],␣
 ↪dailyClimatological_data['latitude'], s=1, c='red', alpha=0.5)
plt.title('Coverage Area of MADIA Dataset')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.show()
```

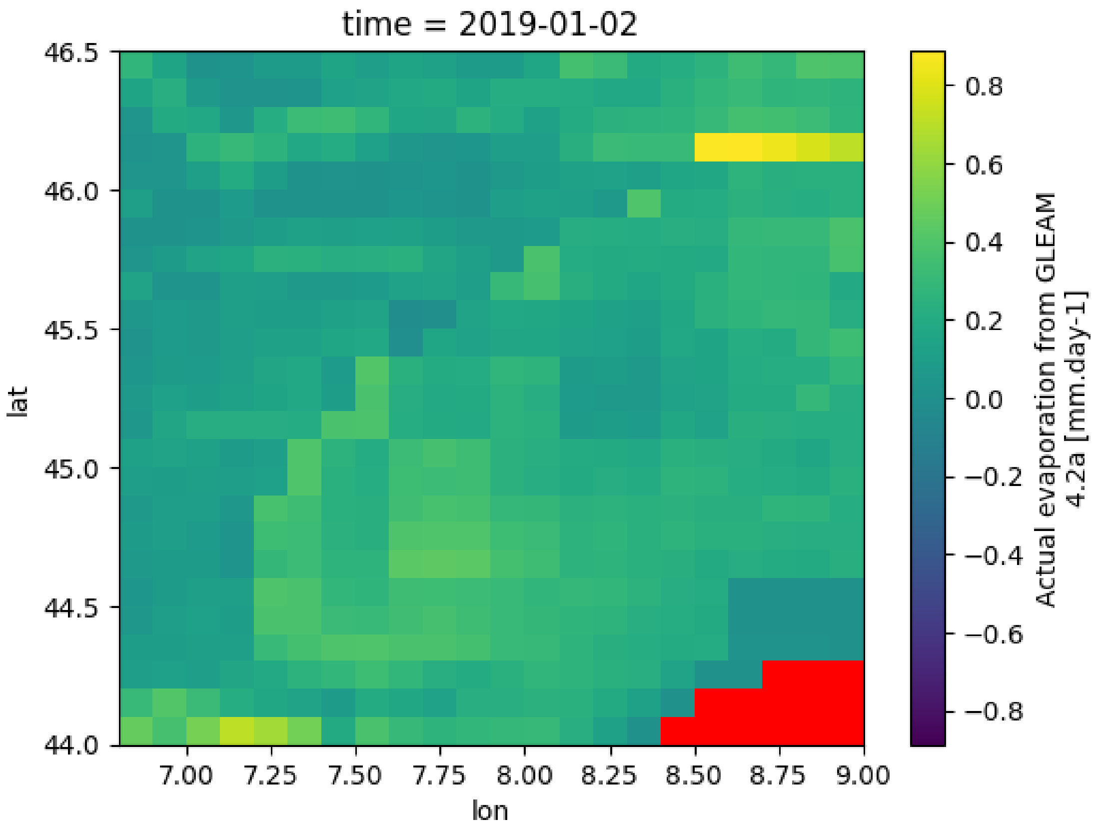


[25]:
```
#** load the dataset of Evapotranspiration from the nc file
nc_files = sorted(glob("./GLEM_daily_dataset/E_*_GLEAM_v4.2a.nc"))

dailyE_data = []

for file in nc_files:
    ds = xr.open_dataset(file)

    # the evapotranspiration data are referenced to the Global territory
    E_lon = ds['lon'].values
    E_lat = ds['lat'].values

    # the climatological data are referenced to the Italian territory
    clim_lon = dailyClimatological_data['longitude'].values
    clim_lat = dailyClimatological_data['latitude'].values

    # select the evapotranspiration data for the Italian territory
    E_lon_idx = np.where((E_lon >= clim_lon.min()) & (E_lon <= clim_lon.max()))
    E_lat_idx = np.where((E_lat >= clim_lat.min()) & (E_lat <= clim_lat.max()))
```

```
    E_lon = E_lon[E_lon_idx]
    E_lat = E_lat[E_lat_idx]

    E_data = ds['E'].sel(lon=E_lon, lat=E_lat)
    dailyE_data.append(E_data)

dailyE_data = xr.concat(dailyE_data, dim='time')
```

[26]:
```
#** show a plot of the Evapotranspiration data **
et = dailyE_data.isel(time=1)

cmap = cm.get_cmap('viridis').copy()    # create a copy of the colormap
cmap.set_bad(color='red')  # highlight NaN values in red

et.plot(cmap=cmap)  # plot the data with the modified colormap

plt.show()

print(f"Daily Evapotranspiration shape (time, latitude, longitude):␣
 ↪{dailyE_data.shape}")

# count the number of pixel that are NaN at any time
nan_pixels = np.isnan(dailyE_data).any(dim='time').sum().item()
print(f"Number of NaN values in the dataset: {nan_pixels}")
```

```
/tmp/ipykernel_38034/3907745109.py:4: MatplotlibDeprecationWarning: The get_cmap
function was deprecated in Matplotlib 3.7 and will be removed in 3.11. Use
``matplotlib.colormaps[name]`` or ``matplotlib.colormaps.get_cmap()`` or
``pyplot.get_cmap()`` instead.
  cmap = cm.get_cmap('viridis').copy()    # create a copy of the colormap
```




```
Daily Evapotranspiration shape (time, latitude, longitude): (1826, 25, 22)
Number of NaN values in the dataset: 14
```

[27]:
```python
#** evaluate the elapsed_days **
dailyClimatological_data['time'] = pd.
 ↪to_datetime(dailyClimatological_data['time'])
dailyClimatological_data['elapsed_days'] = (dailyClimatological_data['time'] -␣
 ↪dailyClimatological_data['time'].min()).dt.days.values
dailyClimatological_data['day_of_year'] = dailyClimatological_data['time'].dt.
 ↪dayofyear.values

print(dailyClimatological_data.head())
print(dailyClimatological_data.tail())
```

```
   longitude  latitude       time    tasmin    tasmax   tasmean     rhmin  \
0       7.25      44.0 1991-01-01 -2.247864  5.563782  1.657959  0.592831
1       7.25      44.0 1991-01-02 -3.348724  3.856262  0.253769  0.444172
2       7.25      44.0 1991-01-03 -0.891388  7.161102  3.134857  0.650528
3       7.25      44.0 1991-01-04  0.054962  3.950562  2.002762  0.706066
4       7.25      44.0 1991-01-05 -5.585663  4.696960 -0.444351  0.307958
```

```
      rhmax      ws10      ssrd       ppn       pev  expver  mask  \
0  0.936595  1.581366  7.215224  0.002508  0.417441     1.0   1.0
1  0.850283  1.228787  6.347265  0.000000  0.463205     1.0   1.0
2  0.866600  0.860398  6.891922  0.015718  0.322711     1.0   1.0
3  0.879245  1.040755  5.009695  0.082887  0.377663     1.0   1.0
4  0.872699  1.498034  7.351231  0.000000  0.599895     1.0   1.0

   elapsed_days  day_of_year
0             0            1
1             1            2
2             2            3
3             3            4
4             4            5
       longitude  latitude       time     tasmin     tasmax    tasmean  \
64323        8.5      46.5 1992-12-27 -12.470581  -9.033173 -10.751877
64324        8.5      46.5 1992-12-28 -18.902466  -9.675293 -14.288879
64325        8.5      46.5 1992-12-29 -18.448822  -6.612701 -12.530762
64326        8.5      46.5 1992-12-30 -16.778015  -9.313232 -13.045624
64327        8.5      46.5 1992-12-31 -16.254120 -11.940277 -14.097198

          rhmin     rhmax      ws10      ssrd       ppn       pev  expver  \
64323  0.470863  0.677514  1.932515  6.230999  0.000000  0.296777     1.0
64324  0.409141  0.930891  0.829336  5.518954  0.123734  0.153633     1.0
64325  0.315114  0.940114  0.500121  6.290980  0.002921  0.105869     1.0
64326  0.431486  0.654308  0.994584  6.747809  0.000000  0.165838     1.0
64327  0.519466  0.683265  1.932434  6.243243  0.000000  0.246382     1.0

       mask  elapsed_days  day_of_year
64323   1.0           726          362
64324   1.0           727          363
64325   1.0           728          364
64326   1.0           729          365
64327   1.0           730          366
```

[28]:
```python
#** associate the Evapotranspiration data to the climatological data **

# build a 2D grid of lat/lon points with the evapotranspiration data
grid_lat = dailyE_data['lat'].values
grid_lon = dailyE_data['lon'].values
grid_lon2d, grid_lat2d = np.meshgrid(grid_lon, grid_lat)

from scipy.spatial import cKDTree

# build a KDTree for fast nearest-neighbor search
grid_points = np.column_stack([grid_lat2d.ravel(), grid_lon2d.ravel()])
tree = cKDTree(grid_points)
```

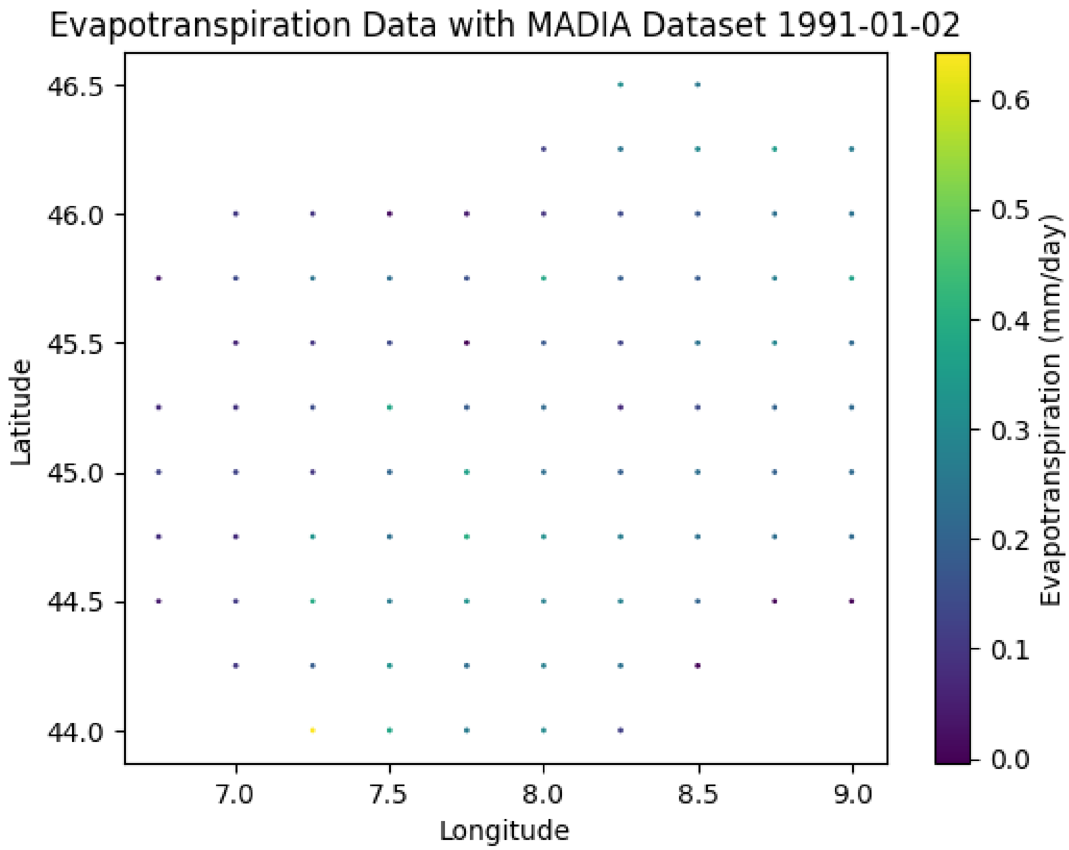
```python
# extract (lat, lon) from the climate data
query_points = dailyClimatological_data[['latitude', 'longitude']].values

# query the nearest grid points once
distances, indices = tree.query(query_points)

# convert flat indices to 2D (lat_idx, lon_idx)
lat_idx, lon_idx = np.unravel_index(indices, grid_lat2d.shape)

# time indices, evaluate the amount of days elapsed since the first day of the␣
↪dataset
time_idx = dailyClimatological_data['elapsed_days']

# get values from xarray using vectorized indexing
E_values = dailyE_data.isel(
    time=xr.DataArray(time_idx, dims='points'),
    lat=xr.DataArray(lat_idx, dims='points'),
    lon=xr.DataArray(lon_idx, dims='points')
).values

# Assign to DataFrame
dailyClimatological_data['E'] = E_values

print(dailyClimatological_data.head())
print(dailyClimatological_data.tail())

print(f"Correction (degrees) - mean: {np.mean(distances):.6f}, min: {np.
↪min(distances):.6f}, max: {np.max(distances):.6f}")
```

```
   longitude  latitude        time    tasmin    tasmax   tasmean     rhmin  \
0       7.25      44.0 1991-01-01 -2.247864  5.563782  1.657959  0.592831
1       7.25      44.0 1991-01-02 -3.348724  3.856262  0.253769  0.444172
2       7.25      44.0 1991-01-03 -0.891388  7.161102  3.134857  0.650528
3       7.25      44.0 1991-01-04  0.054962  3.950562  2.002762  0.706066
4       7.25      44.0 1991-01-05 -5.585663  4.696960 -0.444351  0.307958

      rhmax      ws10      ssrd       ppn       pev  expver  mask  \
0  0.936595  1.581366  7.215224  0.002508  0.417441     1.0   1.0
1  0.850283  1.228787  6.347265  0.000000  0.463205     1.0   1.0
2  0.866600  0.860398  6.891922  0.015718  0.322711     1.0   1.0
3  0.879245  1.040755  5.009695  0.082887  0.377663     1.0   1.0
4  0.872699  1.498034  7.351231  0.000000  0.599895     1.0   1.0

   elapsed_days  day_of_year         E
0             0            1  0.182108
1             1            2  0.642770
2             2            3  0.395599
3             3            4  0.260607
```

```
4              4            5  0.267958
       longitude  latitude       time     tasmin     tasmax    tasmean  \
64323        8.5      46.5 1992-12-27 -12.470581  -9.033173 -10.751877
64324        8.5      46.5 1992-12-28 -18.902466  -9.675293 -14.288879
64325        8.5      46.5 1992-12-29 -18.448822  -6.612701 -12.530762
64326        8.5      46.5 1992-12-30 -16.778015  -9.313232 -13.045624
64327        8.5      46.5 1992-12-31 -16.254120 -11.940277 -14.097198

          rhmin     rhmax      ws10      ssrd       ppn       pev  expver  \
64323  0.470863  0.677514  1.932515  6.230999  0.000000  0.296777     1.0
64324  0.409141  0.930891  0.829336  5.518954  0.123734  0.153633     1.0
64325  0.315114  0.940114  0.500121  6.290980  0.002921  0.105869     1.0
64326  0.431486  0.654308  0.994584  6.747809  0.000000  0.165838     1.0
64327  0.519466  0.683265  1.932434  6.243243  0.000000  0.246382     1.0

       mask  elapsed_days  day_of_year         E
64323   1.0           726          362  0.184309
64324   1.0           727          363  0.164968
64325   1.0           728          364  0.153446
64326   1.0           729          365  0.052505
64327   1.0           730          366  0.080704
Correction (degrees) - mean: 0.048863, min: 0.000000, max: 0.111803
```

[29]:

```python
#** show a plot of the Evapotranspiration data with the MADIA dataset **
et = dailyClimatological_data[dailyClimatological_data['elapsed_days'] == 1]
plt.scatter(et['longitude'], et['latitude'], s=1, c=et['E'], cmap='viridis')
plt.colorbar(label='Evapotranspiration (mm/day)')
plt.title(f'Evapotranspiration Data with MADIA Dataset {et["time"].dt.
 ↪strftime("%Y-%m-%d").values[0]}')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.show()
```



[30]:
```
#** drop the rows with NaN values in the Evapotranspiration column **
print(f"Number of rows before dropping NaN values:␣
 ↪{len(dailyClimatological_data)}")
dailyClimatological_data = dailyClimatological_data.dropna(subset=['E'])
print(f"Number of rows after dropping NaN values:␣
 ↪{len(dailyClimatological_data)}")
```

```
Number of rows before dropping NaN values: 64328
Number of rows after dropping NaN values: 63597
```

[31]:
```
#** print the fields of the dataframe **
print(dailyClimatological_data.columns)
```

```
Index(['longitude', 'latitude', 'time', 'tasmin', 'tasmax', 'tasmean', 'rhmin',
       'rhmax', 'ws10', 'ssrd', 'ppn', 'pev', 'expver', 'mask', 'elapsed_days',
       'day_of_year', 'E'],
      dtype='object')
```

[32]:
```
#** apply normalization to the features **
from sklearn.preprocessing import MinMaxScaler
```

```
# normilize the features
features = ['day_of_year', 'tasmin', 'tasmean', 'tasmax', 'rhmin', 'rhmax',␣
 ↪'ws10', 'ssrd', 'ppn']
featureScaler = MinMaxScaler()
dailyClimatological_data[features] = featureScaler.
 ↪fit_transform(dailyClimatological_data[features])

# normilize the target
target = 'E'
targetScaler = MinMaxScaler()
dailyClimatological_data[target] = targetScaler.
 ↪fit_transform(dailyClimatological_data[[target]])

print(dailyClimatological_data.head())
```

```
   longitude  latitude       time    tasmin    tasmax   tasmean     rhmin  \
0       7.25      44.0 1991-01-01  0.498115  0.456594  0.482039  0.572352
1       7.25      44.0 1991-01-02  0.478368  0.427120  0.456898  0.415352
2       7.25      44.0 1991-01-03  0.522447  0.484165  0.508482  0.633286
3       7.25      44.0 1991-01-04  0.539423  0.428748  0.488213  0.691939
4       7.25      44.0 1991-01-05  0.438243  0.441632  0.444398  0.271497

      rhmax      ws10      ssrd       ppn       pev  expver  mask  \
0  0.921581  0.110296  0.215258  0.000016  0.417441     1.0   1.0
1  0.815228  0.083021  0.187665  0.000000  0.463205     1.0   1.0
2  0.835333  0.054523  0.204980  0.000103  0.322711     1.0   1.0
3  0.850914  0.068475  0.145143  0.000542  0.377663     1.0   1.0
4  0.842849  0.103849  0.219582  0.000000  0.599895     1.0   1.0

   elapsed_days  day_of_year         E
0             0     0.000000  0.043149
1             1     0.002740  0.129007
2             2     0.005479  0.082939
3             3     0.008219  0.057780
4             4     0.010959  0.059150
```

[33]:

```
#** select random samples from the dataset **

# select half of the unique points in the dataset
n_samples = int(len(np.unique(dailyClimatological_data[['longitude',␣
 ↪'latitude']])) / 2)
unique_locations = dailyClimatological_data[['longitude', 'latitude']].
 ↪drop_duplicates()

# sample n_samples unique locations
sampled_locations = unique_locations.sample(n=n_samples, random_state=42)
```

```
X_sequences = []
y_sequences = []

sequence_length = 30

for _, loc in sampled_locations.iterrows():
    loc_data = dailyClimatological_data[
        (dailyClimatological_data['longitude'] == loc['longitude']) &
        (dailyClimatological_data['latitude'] == loc['latitude'])
    ].sort_values(by='elapsed_days')

    features = loc_data[['day_of_year', 'tasmin', 'tasmean', 'tasmax', 'rhmin',␣
↪'rhmax', 'ws10', 'ssrd', 'ppn']].values
    target = loc_data['E'].values

    for i in range(len(loc_data) - sequence_length):
        X_seq = features[i:i+sequence_length]
        y_val = target[i+sequence_length]
        X_sequences.append(X_seq)
        y_sequences.append(y_val)

X = np.array(X_sequences)
y = np.array(y_sequences)
```

[34]:
```
#** build a dataset of shape (n_samples, n_features) **
print(f"Feature matrix shape: {X.shape}")
print(f"Target vector shape: {y.shape}")
print(X[0][:5])
print(y[0])
```

```
Feature matrix shape: (7010, 30, 9)
Target vector shape: (7010,)
[[0.00000000e+00 4.38976240e-01 3.99871814e-01 3.55073876e-01
  5.35220679e-01 7.48862641e-01 1.42518520e-01 1.63447702e-01
  8.37924573e-04]
 [2.73972603e-03 4.17313888e-01 3.83812761e-01 3.44955291e-01
  7.27424028e-01 8.13240839e-01 1.00821348e-01 1.12154049e-01
  1.78187119e-02]
 [5.47945205e-03 5.16741074e-01 4.58097594e-01 3.92508795e-01
  6.15040616e-01 7.92476006e-01 8.95762143e-02 1.83570642e-01
  3.49052478e-04]
 [8.21917808e-03 4.91267613e-01 4.32834112e-01 3.68310369e-01
  7.07170808e-01 8.61935295e-01 5.41307808e-02 7.00210763e-02
  6.68076217e-02]
 [1.09589041e-02 4.16682175e-01 3.86619905e-01 3.50975662e-01
  4.53395045e-01 7.61748197e-01 1.21429120e-01 2.06945495e-01
  1.30285477e-03]]
0.073883764
```

[35]:
```
#** mix the sequences of data **
from sklearn.utils import shuffle

X, y = shuffle(X, y, random_state=42)

print(f"Feature matrix shape after shuffle: {X.shape}")
print(f"Target vector shape after shuffle: {y.shape}")
print(X[0][:5])
print(y[0])
```

```
Feature matrix shape after shuffle: (7010, 30, 9)
Target vector shape after shuffle: (7010,)
[[4.82191781e-01 7.71422031e-01 7.72612256e-01 7.53855887e-01
  6.26858856e-01 9.45970729e-01 5.39435865e-02 6.86132495e-01
  1.93920879e-02]
 [4.84931507e-01 8.20493509e-01 7.85300837e-01 7.31100814e-01
  6.60546730e-01 9.29692332e-01 6.25939608e-02 6.06041176e-01
  1.56564096e-02]
 [4.87671233e-01 8.18239795e-01 8.02212541e-01 7.65877162e-01
  6.06979151e-01 9.25078191e-01 7.53179759e-02 6.73476952e-01
  1.46061137e-02]
 [4.90410959e-01 8.23034066e-01 7.94176058e-01 7.45768523e-01
  5.09607258e-01 8.48999420e-01 1.03396006e-01 6.17521752e-01
  6.67408848e-03]
 [4.93150685e-01 8.22499234e-01 8.04748127e-01 7.66667300e-01
  4.26891136e-01 8.12519107e-01 8.69677043e-02 7.14832113e-01
  2.50630043e-04]]
0.62130296
```

[36]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)

print(f"Training set shape: {X_train.shape}, {y_train.shape}")
print(f"Testing set shape: {X_test.shape}, {y_test.shape}")
```

```
Training set shape: (5608, 30, 9), (5608,)
Testing set shape: (1402, 30, 9), (1402,)
```

[37]:
```
import tensorflow as tf
print(tf.config.list_physical_devices('GPU'))

# the model learns to predict the next day ET value based on the previous 30␣
 ↪days of data

model = tf.keras.Sequential()
```

```python
model.add(tf.keras.layers.Input(shape=(sequence_length, 9)))  # input shape
 ↪(sequence_length, n_features)
model.add(tf.keras.layers.LSTM(128, return_sequences=True))   #
 ↪return_sequences=True, each of the LSTM cells returns its sequence of 128
 ↪outputs. So the output shape is (batch_size, sequence_length, 128)
model.add(tf.keras.layers.Dropout(0.2))
model.add(tf.keras.layers.BatchNormalization()) # normalization is applied to
 ↪the output of the LSTM layer

model.add(tf.keras.layers.LSTM(64, return_sequences=False)) #
 ↪return_sequences=False, the last LSTM cell returns its last output. So the
 ↪output shape is (batch_size, 64)
model.add(tf.keras.layers.Dropout(0.2))
model.add(tf.keras.layers.BatchNormalization()) # normalization is applied to
 ↪the output of the LSTM layer

model.add(tf.keras.layers.Dense(64, activation='relu'))
model.add(tf.keras.layers.Dropout(0.2))

model.add(tf.keras.layers.Dense(1))  # predict a single ET value

model.compile(optimizer='adam', loss='mse')
model.summary()
```

```
[PhysicalDevice(name='/physical_device:GPU:0', device_type='GPU')]
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
lstm_2 (LSTM)	(None, 30, 128)	70,656
dropout_3 (Dropout)	(None, 30, 128)	0
batch_normalization_2 (BatchNormalization)	(None, 30, 128)	512
lstm_3 (LSTM)	(None, 64)	49,408
dropout_4 (Dropout)	(None, 64)	0
batch_normalization_3 (BatchNormalization)	(None, 64)	256
dense_2 (Dense)	(None, 64)	4,160

```
dropout_5 (Dropout)              (None, 64)                    0

dense_3 (Dense)                  (None, 1)                    65


Total params: 125,057 (488.50 KB)

Trainable params: 124,673 (487.00 KB)

Non-trainable params: 384 (1.50 KB)
```

[38]:
```
# i am feeding the NN with 32 sequences at a time (batch size). Each of these␣
↪sequences is made by 30 days of data, each data is made by 8 features
# I have 7010 * 0.8 due to train and test set split, these sequences are␣
↪divided in batches of 32 and with a validation split of 0.2, means that the␣
↪number of iterations needed to complete each epoch is 7010 * 0.8 * 0.8 / 32␣
↪= 140.2
history = model.fit(X_train, y_train, epochs=50, batch_size=32,␣
↪validation_split=0.2)
```

```
Epoch 1/50
141/141              5s 17ms/step -
loss: 0.4748 - val_loss: 0.0398
Epoch 2/50
141/141              2s 17ms/step -
loss: 0.0931 - val_loss: 0.0283
Epoch 3/50
141/141              2s 16ms/step -
loss: 0.0507 - val_loss: 0.0134
Epoch 4/50
141/141              2s 17ms/step -
loss: 0.0374 - val_loss: 0.0102
Epoch 5/50
141/141              2s 14ms/step -
loss: 0.0278 - val_loss: 0.0123
Epoch 6/50
141/141              2s 17ms/step -
loss: 0.0229 - val_loss: 0.0106
Epoch 7/50
141/141              2s 17ms/step -
loss: 0.0203 - val_loss: 0.0098
Epoch 8/50
141/141              2s 15ms/step -
loss: 0.0176 - val_loss: 0.0093
Epoch 9/50
```

```
141/141              2s 15ms/step -
loss: 0.0155 - val_loss: 0.0089
Epoch 10/50
141/141              2s 16ms/step -
loss: 0.0139 - val_loss: 0.0133
Epoch 11/50
141/141              2s 15ms/step -
loss: 0.0147 - val_loss: 0.0095
Epoch 12/50
141/141              2s 15ms/step -
loss: 0.0127 - val_loss: 0.0104
Epoch 13/50
141/141              2s 16ms/step -
loss: 0.0127 - val_loss: 0.0111
Epoch 14/50
141/141              2s 15ms/step -
loss: 0.0112 - val_loss: 0.0088
Epoch 15/50
141/141              2s 15ms/step -
loss: 0.0122 - val_loss: 0.0083
Epoch 16/50
141/141              2s 14ms/step -
loss: 0.0112 - val_loss: 0.0079
Epoch 17/50
141/141              2s 15ms/step -
loss: 0.0103 - val_loss: 0.0083
Epoch 18/50
141/141              3s 19ms/step -
loss: 0.0106 - val_loss: 0.0088
Epoch 19/50
141/141              2s 16ms/step -
loss: 0.0105 - val_loss: 0.0080
Epoch 20/50
141/141              2s 17ms/step -
loss: 0.0096 - val_loss: 0.0075
Epoch 21/50
141/141              2s 16ms/step -
loss: 0.0106 - val_loss: 0.0117
Epoch 22/50
141/141              2s 16ms/step -
loss: 0.0100 - val_loss: 0.0091
Epoch 23/50
141/141              2s 17ms/step -
loss: 0.0096 - val_loss: 0.0096
Epoch 24/50
141/141              2s 16ms/step -
loss: 0.0095 - val_loss: 0.0084
Epoch 25/50
```

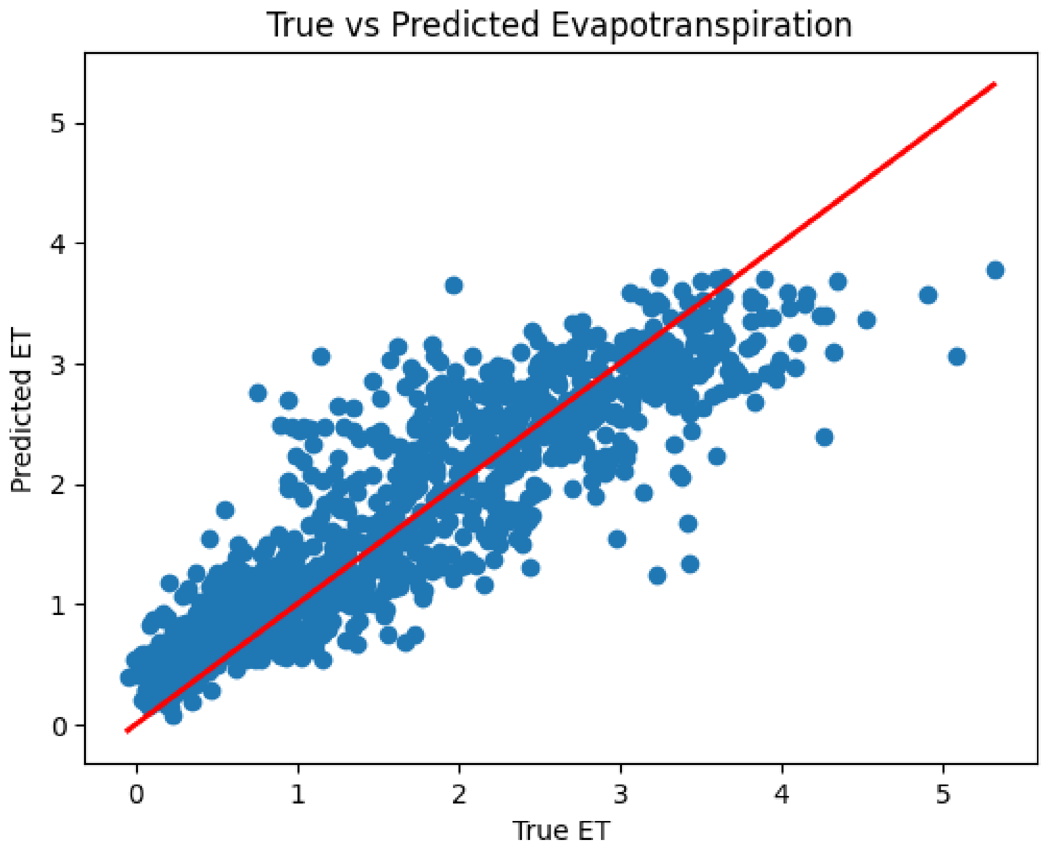
```
141/141             2s 16ms/step -
loss: 0.0093 - val_loss: 0.0071
Epoch 26/50
141/141             2s 16ms/step -
loss: 0.0088 - val_loss: 0.0121
Epoch 27/50
141/141             2s 17ms/step -
loss: 0.0091 - val_loss: 0.0073
Epoch 28/50
141/141             2s 17ms/step -
loss: 0.0096 - val_loss: 0.0071
Epoch 29/50
141/141             3s 19ms/step -
loss: 0.0088 - val_loss: 0.0080
Epoch 30/50
141/141             3s 22ms/step -
loss: 0.0093 - val_loss: 0.0069
Epoch 31/50
141/141             3s 21ms/step -
loss: 0.0091 - val_loss: 0.0071
Epoch 32/50
141/141             3s 24ms/step -
loss: 0.0085 - val_loss: 0.0138
Epoch 33/50
141/141             3s 19ms/step -
loss: 0.0089 - val_loss: 0.0090
Epoch 34/50
141/141             3s 19ms/step -
loss: 0.0086 - val_loss: 0.0069
Epoch 35/50
141/141             3s 22ms/step -
loss: 0.0089 - val_loss: 0.0073
Epoch 36/50
141/141             2s 17ms/step -
loss: 0.0091 - val_loss: 0.0107
Epoch 37/50
141/141             2s 17ms/step -
loss: 0.0082 - val_loss: 0.0123
Epoch 38/50
141/141             3s 18ms/step -
loss: 0.0085 - val_loss: 0.0112
Epoch 39/50
141/141             2s 17ms/step -
loss: 0.0086 - val_loss: 0.0090
Epoch 40/50
141/141             3s 20ms/step -
loss: 0.0088 - val_loss: 0.0082
Epoch 41/50
```

```
141/141              6s 39ms/step -
loss: 0.0085 - val_loss: 0.0080
Epoch 42/50
141/141              3s 23ms/step -
loss: 0.0091 - val_loss: 0.0105
Epoch 43/50
141/141              3s 21ms/step -
loss: 0.0090 - val_loss: 0.0087
Epoch 44/50
141/141              2s 17ms/step -
loss: 0.0090 - val_loss: 0.0085
Epoch 45/50
141/141              3s 17ms/step -
loss: 0.0081 - val_loss: 0.0068
Epoch 46/50
141/141              3s 18ms/step -
loss: 0.0086 - val_loss: 0.0064
Epoch 47/50
141/141              3s 19ms/step -
loss: 0.0085 - val_loss: 0.0076
Epoch 48/50
141/141              3s 21ms/step -
loss: 0.0088 - val_loss: 0.0067
Epoch 49/50
141/141              2s 17ms/step -
loss: 0.0081 - val_loss: 0.0159
Epoch 50/50
141/141              3s 24ms/step -
loss: 0.0082 - val_loss: 0.0074
```

[39]:
```
#** test the model on the test set **
y_pred = model.predict(X_test)

# invert the normalization of the predicted values
y_pred_rescaled = targetScaler.inverse_transform(y_pred)
y_test_rescaled = targetScaler.inverse_transform(y_test.reshape(-1, 1))
```

```
44/44              1s 12ms/step
```

[40]:
```
#**  see a plot of the accuracy of the predictions **
plt.scatter(y_test_rescaled, y_pred_rescaled)
plt.plot([min(y_test_rescaled), max(y_test_rescaled)], [min(y_test_rescaled),␣
 ↪max(y_test_rescaled)], color='red', lw=2)  # Identity line
plt.xlabel('True ET')
plt.ylabel('Predicted ET')
plt.title('True vs Predicted Evapotranspiration')
plt.show()
```


True vs Predicted Evapotranspiration
Predicted ET
True ET
0
1
2
3
4
5