Data Exploration

October 30, 2025

1 Data Exploration

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This notebook explores the newly constructed dataset (`master.csv`) to get more insights into the data and the relationship between features.

[ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

from pathlib import Path
from scipy import stats
from scipy.stats import spearmanr, pearsonr, shapiro
from sklearn.impute import SimpleImputer
from sklearn.feature_selection import mutual_info_regression
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score, mean_squared_error
from statsmodels.tsa.stattools import acf, pacf, grangercausalitytests
import statsmodels.api as sm

pd.set_option("display.max_columns", 200)
```

[82]:
```
CSV = Path(r'/Users/jbalkovec/Desktop/MDR/Temporal/Pipeline/data/master/
↪final_master.csv')
df = pd.read_csv(CSV)
```

1.1 Data Health and Typing

1.1.1 Missing Values

[83]:
```
numeric_cols = df.select_dtypes(include=[np.number]).columns.tolist()
non_numeric_cols = [c for c in df.columns if c not in numeric_cols]

missing_pct = df.isna().mean().sort_values(ascending=False)
print(missing_pct.head(20))
```

```
SM_label                1.000000
soil_temp_50cm          0.504705
soil_temp_20cm          0.504411
soil_temp_100cm         0.503774
soil_moisture_100cm     0.412067
soil_moisture_50cm      0.412067
soil_moisture_20cm      0.412067
soil_temp_10cm          0.257181
soil_temp_5cm           0.256887
SM_prev                 0.245221
soil_moisture_10cm      0.245074
soil_moisture_5cm       0.245074
rh_max                  0.243457
rh_min                  0.243457
rh_mean                 0.236300
air_temp_avg            0.014410
air_temp_max            0.012597
air_temp_min            0.012009
precipitation           0.007793
sur_temp_min            0.007254
dtype: float64
```

1.1.2 Coverage

[84]:
```
coverage = df.groupby("station_id")["date"].agg(["min", "max", "nunique"]).
 ↪sort_values("min")
display(coverage.head(10))
```

	min	max	nunique
station_id			
4223	2007-01-01	2025-10-23	6871
4237	2007-01-01	2025-10-23	6871
4136	2007-07-31	2025-10-23	6660

1.1.3 Dupes

[85]:
```
dupes = df.duplicated(subset=["station_id", "date"]).sum()
print("Duplicate station_id+date rows:", dupes)
```

```
Duplicate station_id+date rows: 0
```

1.2 Summary Statistics

[86]:
```
summary = df[numeric_cols].describe(percentiles=[.01,.05,.25,.5,.75,.95,.99]).T
summary["missing_pct"] = df[numeric_cols].isna().mean()
summary["n_unique"]    = df[numeric_cols].nunique()
summary
```

```
[86]:                     count        mean        std         min  \
station_id            20402.0  4199.314773  44.451429  4136.000000
crx_vn                20402.0     2.238869   0.787300    -9.000000
longitude             20402.0  -120.965163  2.580151  -123.810000
latitude              20402.0    47.827505   0.509056    47.420000
air_temp_max          20145.0    14.934435   9.143370   -16.600000
air_temp_min          20157.0     3.500064   6.142418   -32.600000
air_temp_mean         20401.0     9.240069   7.071791   -25.745134
air_temp_avg          20108.0     8.960339   6.960261   -22.600000
precipitation         20243.0     5.913002  14.727061     0.000000
solar_radiation       20401.0    11.560944   9.297579   -20.481429
sur_temp_max          20254.0    22.352923  15.011428   -14.500000
sur_temp_min          20254.0     2.221764   6.821601   -37.200000
sur_temp_avg          20401.0    10.110846   8.676265   -26.000000
rh_max                15435.0    93.114001   6.983558    29.600000
rh_min                15435.0    55.193424  24.126065     4.000000
rh_mean               15581.0    78.199175  16.172867    21.400000
soil_moisture_5cm     15402.0     0.205727   0.109677    -0.215476
soil_moisture_10cm    15402.0     0.193313   0.127687    -1.084310
soil_moisture_20cm    11995.0     0.167664   0.125750    -0.595357
soil_moisture_50cm    11995.0     0.314161   0.469134    -0.341286
soil_moisture_100cm   11995.0     0.151735   0.088690    -0.040143
soil_temp_5cm         15161.0    10.645617   7.278076    -6.400000
soil_temp_10cm        15155.0    10.466513   6.906450    -4.700000
soil_temp_20cm        10111.0     9.976689   6.885590    -2.300000
soil_temp_50cm        10105.0     9.924265   6.445534    -1.000000
soil_temp_100cm       10124.0     9.891328   6.333417    -0.500000
LST                   20402.0   287.044649  10.411257   263.120717
NDVI                  20402.0     0.632356   0.182936     0.040046
Rain_sat              20402.0     0.174667   0.173268     0.000057
DOY                   20402.0   182.429272 104.977055     1.000000
Rain_3d               20402.0    17.600299  33.621158     0.000000
SM_prev               15399.0     0.205722   0.109686    -0.215476
SM_label                  0.0          NaN        NaN          NaN

                               1%           5%          25%          50%  \
station_id            4136.000000  4136.000000  4136.000000  4223.000000
crx_vn                   1.301000     1.302000     2.402000     2.422000
longitude             -123.810000  -123.810000  -123.810000  -121.450000
latitude                47.420000    47.420000    47.420000    47.510000
air_temp_max            -3.500000     1.400000     7.800000    13.900000
air_temp_min           -14.400000    -6.900000    -0.300000     3.800000
air_temp_mean           -8.100000    -1.900000     4.200000     9.100000
air_temp_avg            -7.500000    -1.765000     3.800000     8.700000
precipitation            0.000000     0.000000     0.000000     0.000000
solar_radiation          0.070000     0.640000     3.470000     9.470000
sur_temp_max            -2.900000     0.400000    10.200000    20.800000
```

sur_temp_min	-16.247000	-8.800000	-1.900000	2.400000
sur_temp_avg	-8.600000	-2.700000	3.600000	9.600000
rh_max	64.800000	79.500000	91.400000	95.500000
rh_min	11.500000	17.300000	35.600000	53.800000
rh_mean	35.900000	45.200000	68.500000	81.400000
soil_moisture_5cm	0.016000	0.027000	0.118000	0.218000
soil_moisture_10cm	-0.041317	0.040000	0.102000	0.179000
soil_moisture_20cm	-0.203329	-0.062426	0.068000	0.200214
soil_moisture_50cm	0.007000	0.021000	0.074000	0.193000
soil_moisture_100cm	-0.025103	0.027000	0.059000	0.169000
soil_temp_5cm	-0.500000	0.000000	4.300000	10.300000
soil_temp_10cm	-0.300000	0.400000	4.300000	10.200000
soil_temp_20cm	-0.100000	0.600000	3.500000	9.700000
soil_temp_50cm	0.300000	1.000000	3.800000	9.800000
soil_temp_100cm	0.600000	1.200000	3.800000	9.800000
LST	267.104231	271.600885	278.163592	287.287636
NDVI	0.095186	0.318498	0.484122	0.655129
Rain_sat	0.006154	0.013472	0.047857	0.103872
DOY	4.000000	19.000000	92.000000	183.000000
Rain_3d	0.000000	0.000000	0.000000	3.300000
SM_prev	0.016000	0.027000	0.118000	0.218000
SM_label	NaN	NaN	NaN	NaN

	75%	95%	99%	max \
station_id	4237.000000	4237.000000	4237.000000	4237.000000
crx_vn	2.622000	2.623000	2.623000	2.623000
longitude	-117.530000	-117.530000	-117.530000	-117.530000
latitude	48.540000	48.540000	48.540000	48.540000
air_temp_max	22.000000	30.500000	34.700000	42.400000
air_temp_min	8.100000	12.500000	14.644000	19.100000
air_temp_mean	14.900000	20.200000	23.000000	30.300000
air_temp_avg	14.500000	19.900000	23.000000	30.200000
precipitation	4.600000	32.700000	69.474000	235.400000
solar_radiation	18.610000	27.430000	32.310000	114.319656
sur_temp_max	33.300000	49.135000	58.600000	88.000000
sur_temp_min	7.100000	12.100000	15.100000	73.900000
sur_temp_avg	16.800000	23.800000	28.500000	77.000000
rh_max	97.000000	99.200000	100.000000	100.000000
rh_min	76.000000	93.300000	96.200000	100.000000
rh_mean	92.200000	96.800000	98.800000	128.113082
soil_moisture_5cm	0.290000	0.356000	0.438999	1.112151
soil_moisture_10cm	0.307000	0.360000	0.402000	0.984601
soil_moisture_20cm	0.261000	0.324000	0.349000	0.616028
soil_moisture_50cm	0.260000	1.605768	2.224887	2.379667
soil_moisture_100cm	0.234000	0.259000	0.282000	0.421357
soil_temp_5cm	16.900000	22.000000	25.500000	30.000000
soil_temp_10cm	16.600000	21.000000	23.700000	26.700000

soil_temp_20cm	16.100000	20.800000	23.100000	25.000000
soil_temp_50cm	15.700000	19.600000	22.200000	24.000000
soil_temp_100cm	15.600000	19.700000	22.000000	23.500000
LST	294.881098	305.659376	309.226752	313.908222
NDVI	0.800980	0.860101	0.878411	0.890417
Rain_sat	0.274082	0.525570	0.762871	0.940472
DOY	273.000000	347.000000	362.000000	366.000000
Rain_3d	19.200000	83.700000	164.000000	398.400000
SM_prev	0.290000	0.356000	0.439001	1.112151
SM_label	NaN	NaN	NaN	NaN

	missing_pct	n_unique
station_id	0.000000	3
crx_vn	0.000000	13
longitude	0.000000	3
latitude	0.000000	3
air_temp_max	0.012597	508
air_temp_min	0.012009	417
air_temp_mean	0.000049	697
air_temp_avg	0.014410	435
precipitation	0.007793	799
solar_radiation	0.000049	3573
sur_temp_max	0.007254	784
sur_temp_min	0.007254	514
sur_temp_avg	0.000049	703
rh_max	0.243457	451
rh_min	0.243457	916
rh_mean	0.236300	852
soil_moisture_5cm	0.245074	1790
soil_moisture_10cm	0.245074	1210
soil_moisture_20cm	0.412067	2462
soil_moisture_50cm	0.412067	2617
soil_moisture_100cm	0.412067	2168
soil_temp_5cm	0.256887	328
soil_temp_10cm	0.257181	295
soil_temp_20cm	0.504411	270
soil_temp_50cm	0.504705	250
soil_temp_100cm	0.503774	241
LST	0.000000	672
NDVI	0.000000	672
Rain_sat	0.000000	672
DOY	0.000000	366
Rain_3d	0.000000	7271
SM_prev	0.245221	1787
SM_label	1.000000	0

1.2.1 Station Level

[87]:
```
station_stats = df.
 ↪groupby("station_id")[["air_temp_mean","precipitation","NDVI","LST",
                                                      ␣
 ↪"soil_moisture_10cm","soil_temp_10cm"]].
 ↪agg(["mean","std","min","max","median"])
station_stats.head(10)
```

[87]:
```
           air_temp_mean                                   precipitation  \
                    mean       std        min   max median          mean
station_id
4136            7.375954  8.346016 -25.745134  28.2    7.2      1.264803
4223           10.025086  6.578159 -13.100000  28.4    9.6      5.699590
4237           10.261650  5.717956  -5.500000  30.3    9.9     10.683904

                                           NDVI                      \
                 std  min    max median      mean       std       min
station_id
4136        3.272197  0.0   38.0    0.0  0.433758  0.118023  0.040046
4223       11.360698  0.0  135.4    0.3  0.744890  0.130592  0.291836
4237       21.532642  0.0  235.4    0.5  0.712321  0.107359  0.318498

                                    LST                                    \
                 max    median         mean        std         min         max
station_id
4136        0.624729  0.451759   289.381878  13.765826  263.120717  313.908222
4223        0.890417  0.782172   285.935077   8.619238  265.883202  299.915973
4237        0.856568  0.718435   285.888766   7.486844  271.057854  298.428487

                      soil_moisture_10cm                                 \
                median              mean       std       min       max
station_id
4136        290.248893          0.186285  0.158631 -1.084310  0.984601
4223        286.679144          0.256972  0.115783 -0.305643  0.624596
4237        286.169535          0.136701  0.055205  0.013000  0.342808

                soil_temp_10cm
           median         mean       std  min   max median
station_id
4136        0.204     9.883998  8.042649 -4.7  26.7    8.7
4223        0.299    10.089284  6.418051 -0.2  22.6   10.1
4237        0.149    11.431102  5.980328 -0.5  24.4   11.2
```

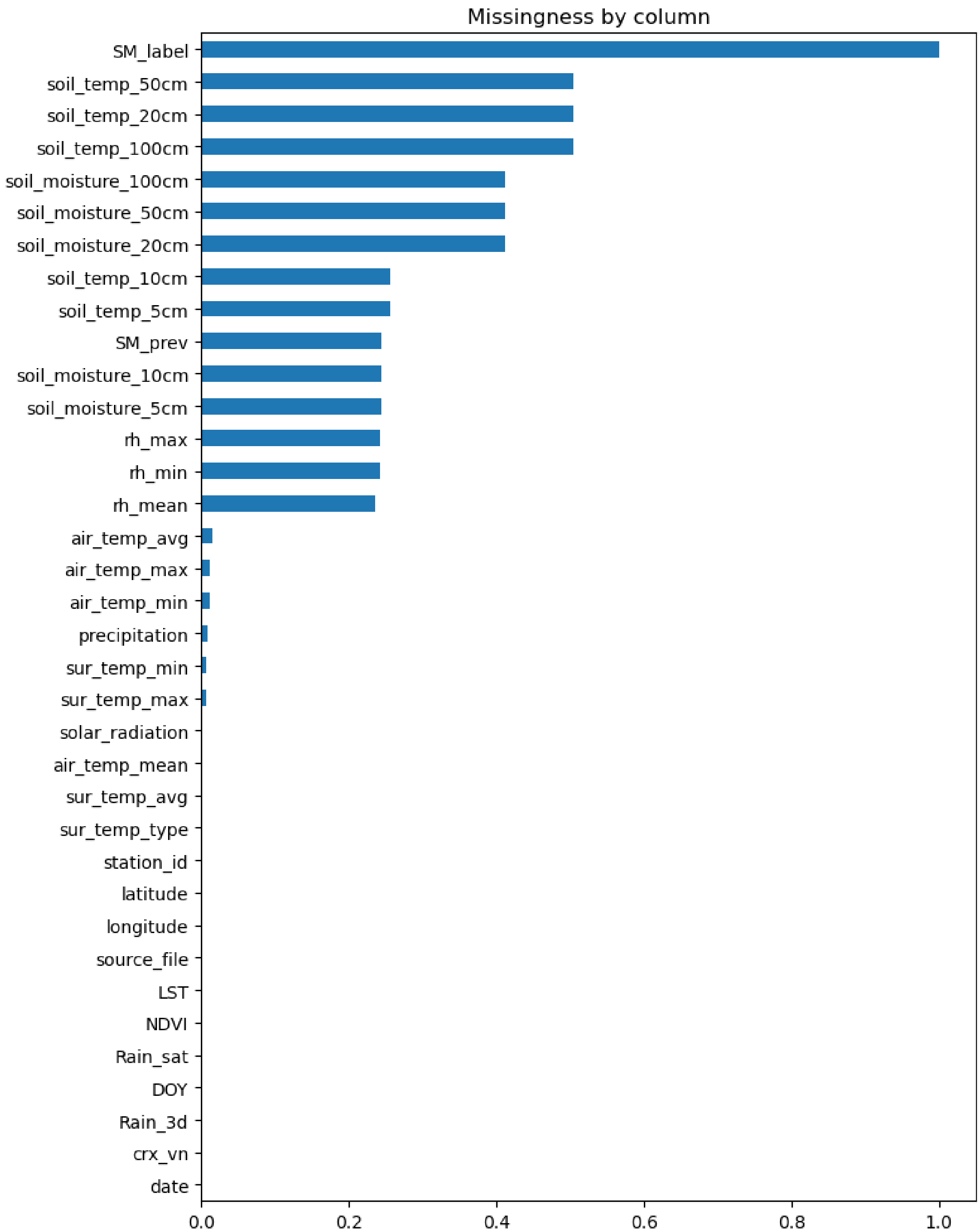
ID	Location
4136	Spokane
4223	Darrington

ID	Location
4237	Quinalt

1.3 Missingness structure

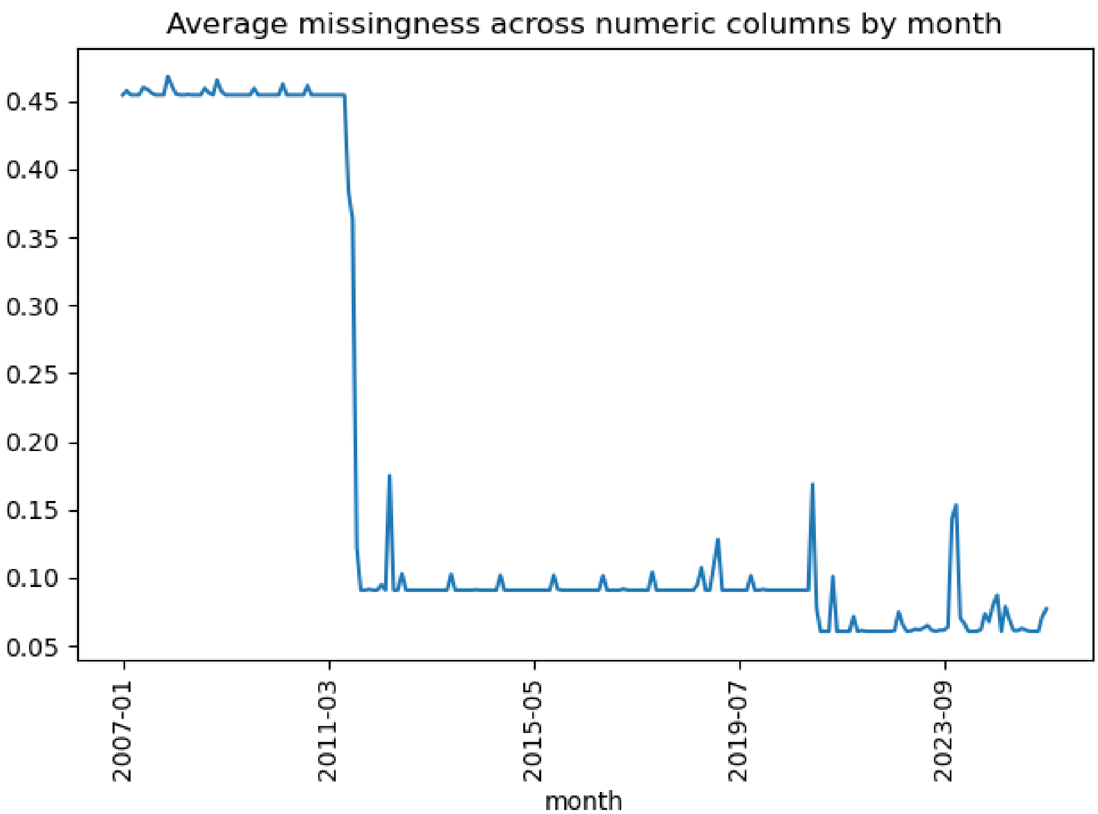
1.3.1 Column

[88]:
```
ax = missing_pct.plot(kind="barh", figsize=(8,10), title="Missingness by␣
↪column")
plt.gca().invert_yaxis()
plt.tight_layout()
plt.show()
```


Missingness by column
SM_label
soil_temp_50cm
soil_temp_20cm
soil_temp_100cm
soil_moisture_100cm
soil_moisture_50cm
soil_moisture_20cm
soil_temp_10cm
soil_temp_5cm
SM_prev
soil_moisture_10cm
soil_moisture_5cm
rh_max
rh_min
rh_mean
air_temp_avg
air_temp_max
air_temp_min
precipitation
sur_temp_min
sur_temp_max
solar_radiation
air_temp_mean
sur_temp_avg
sur_temp_type
station_id
latitude
longitude
source_file
LST
NDVI
Rain_sat
DOY
Rain_3d
crx_vn
date
0.0
0.2
0.4
0.6
0.8
1.0

1.3.2 Month

[89]:
```
df["date"] = pd.to_datetime(df["date"], errors="coerce")
df["month"] = df["date"].dt.to_period("M").astype(str)
miss_by_month = df.groupby("month")[numeric_cols].apply(lambda x: x.isna().
  ↪mean().mean())
miss_by_month.plot(title="Average missingness across numeric columns by month",␣
  ↪rot=90)
plt.tight_layout(); plt.show()
```



1.3.3 Station

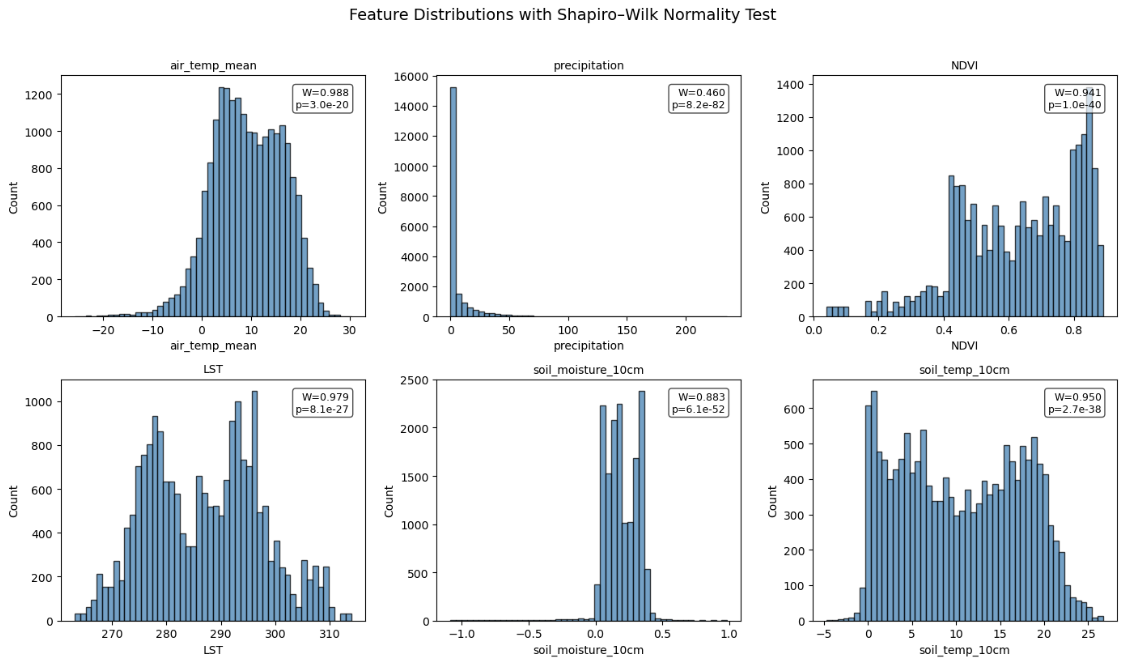
[90]:
```
miss_by_station = df.groupby("station_id")[numeric_cols].apply(lambda x: x.
  ↪isna().mean().mean()).sort_values(ascending=False)
miss_by_station.head(20)
```

[90]:
```
station_id
4237    0.254561
4223    0.139978
4136    0.129812
dtype: float64
```

[93]:
```python
num_df = df[numeric_cols].copy()
num_df = df[numeric_cols].drop(columns=["SM_label"])

imp = SimpleImputer(strategy="median")
num_imputed = pd.DataFrame(imp.fit_transform(num_df), columns=num_df.columns,
↪index=num_df.index)
```

1.4 Distributions and outliers

[ ]:
```python
to_plot = ["air_temp_mean", "precipitation", "NDVI", "LST",
↪"soil_moisture_10cm", "soil_temp_10cm"]

n = len(to_plot)
fig, axes = plt.subplots(2, 3, figsize=(14, 8))
axes = axes.flatten()

for i, col in enumerate(to_plot):
    if col in df.columns:
        s = df[col].dropna()

        axes[i].hist(s, bins=50, color="steelblue", alpha=0.75,
↪edgecolor="black")
        axes[i].set_title(col, fontsize=10)
        axes[i].set_xlabel(col)
        axes[i].set_ylabel("Count")

        sample = s.sample(min(5000, len(s)), random_state=42)
        W, p = shapiro(sample)

        axes[i].text(
            0.95, 0.95,
            f"W={W:.3f}\np={p:.1e}",
            transform=axes[i].transAxes,
            ha="right", va="top",
            fontsize=9,
            bbox=dict(boxstyle="round,pad=0.3", facecolor="white", alpha=0.7)
        )

for j in range(i + 1, len(axes)):
    fig.delaxes(axes[j])

plt.suptitle("Feature Distributions with Shapiro-Wilk Normality Test",
↪fontsize=14, y=1.02)
plt.tight_layout()
plt.show()
```




```
[95]: z = np.abs(stats.zscore(num_imputed[to_plot], nan_policy='omit'))
outlier_mask = (z > 4).any(axis=1)
print("Rows with extreme outliers (|z|>4):", outlier_mask.sum())
```

```
Rows with extreme outliers (|z|>4): 338
```

1.5 Relationships among variables

1.5.1 Pairwise Correlations

```
[96]: spearman_corr = df[numeric_cols].corr(method="spearman")
pearson_corr  = df[numeric_cols].corr(method="pearson")

pairs = [("LST","soil_temp_10cm"),
         ("NDVI","soil_moisture_10cm"),
         ("air_temp_mean","LST"),
         ("precipitation","Rain_sat"),
         ("DOY","NDVI")]

# FMT BETTER
for x,y in pairs:
    if x in df and y in df:
        s = spearmanr(df[x], df[y], nan_policy="omit")
        p = pearsonr(df[[x,y]].dropna()[x], df[[x,y]].dropna()[y])
```

```
        print(f"Spearman rho={s.correlation:.3f},  Pearson r={p.statistic:.3f}␣
↪| {x} vs {y}")
```

```
Spearman rho=0.905,  Pearson r=0.902 | LST vs soil_temp_10cm
Spearman rho=-0.169,  Pearson r=-0.076 | NDVI vs soil_moisture_10cm
Spearman rho=0.836,  Pearson r=0.813 | air_temp_mean vs LST
Spearman rho=0.466,  Pearson r=0.424 | precipitation vs Rain_sat
Spearman rho=0.082,  Pearson r=0.094 | DOY vs NDVI
```

1.5.2 Partial correlation

[97]:
```
def partial_corr(x, y, z):
    df_temp = pd.concat([x, y, z], axis=1).dropna()
    df_temp = df_temp.replace([np.inf, -np.inf], np.nan).dropna()

    x_clean = df_temp.iloc[:, 0]
    y_clean = df_temp.iloc[:, 1]
    z_clean = df_temp.iloc[:, 2]

    X = sm.add_constant(z_clean)

    x_resid = sm.OLS(x_clean, X).fit().resid
    y_resid = sm.OLS(y_clean, X).fit().resid

    return np.corrcoef(x_resid, y_resid)[0, 1]

if set(["LST","soil_temp_10cm","air_temp_mean"]).issubset(df.columns):
    r_pc = partial_corr(df["LST"], df["soil_temp_10cm"], df["air_temp_mean"])
    print("Partial corr(LST, soil_temp_10cm | air_temp_mean) =", round(r_pc,3))
```

```
Partial corr(LST, soil_temp_10cm | air_temp_mean) = 0.667
```

1.5.3 Mutual Information with Target Moisture

[98]:
```
target = "soil_moisture_5cm"
candidates = [c for c in numeric_cols if c not in ["SM_label","SM_prev"] and c !
↪= target]
tmp = df[[target]+candidates].dropna()
X = tmp[candidates].values
y = tmp[target].values
mi = mutual_info_regression(X, y, random_state=42)
mi_series = pd.Series(mi, index=candidates).sort_values(ascending=False)
print(mi_series.head(15))
```

```
soil_moisture_10cm     1.377020
soil_moisture_20cm     1.196677
soil_moisture_50cm     1.071256
soil_moisture_100cm    1.034546
LST                    0.975481
```

```
NDVI                    0.869984
Rain_sat                0.822915
DOY                     0.712436
soil_temp_100cm         0.669966
soil_temp_50cm          0.653823
soil_temp_20cm          0.621326
soil_temp_10cm          0.588288
soil_temp_5cm           0.541468
air_temp_max            0.401960
sur_temp_avg            0.399798
dtype: float64
```

1.5.4 Multicollinearity check (VIF)

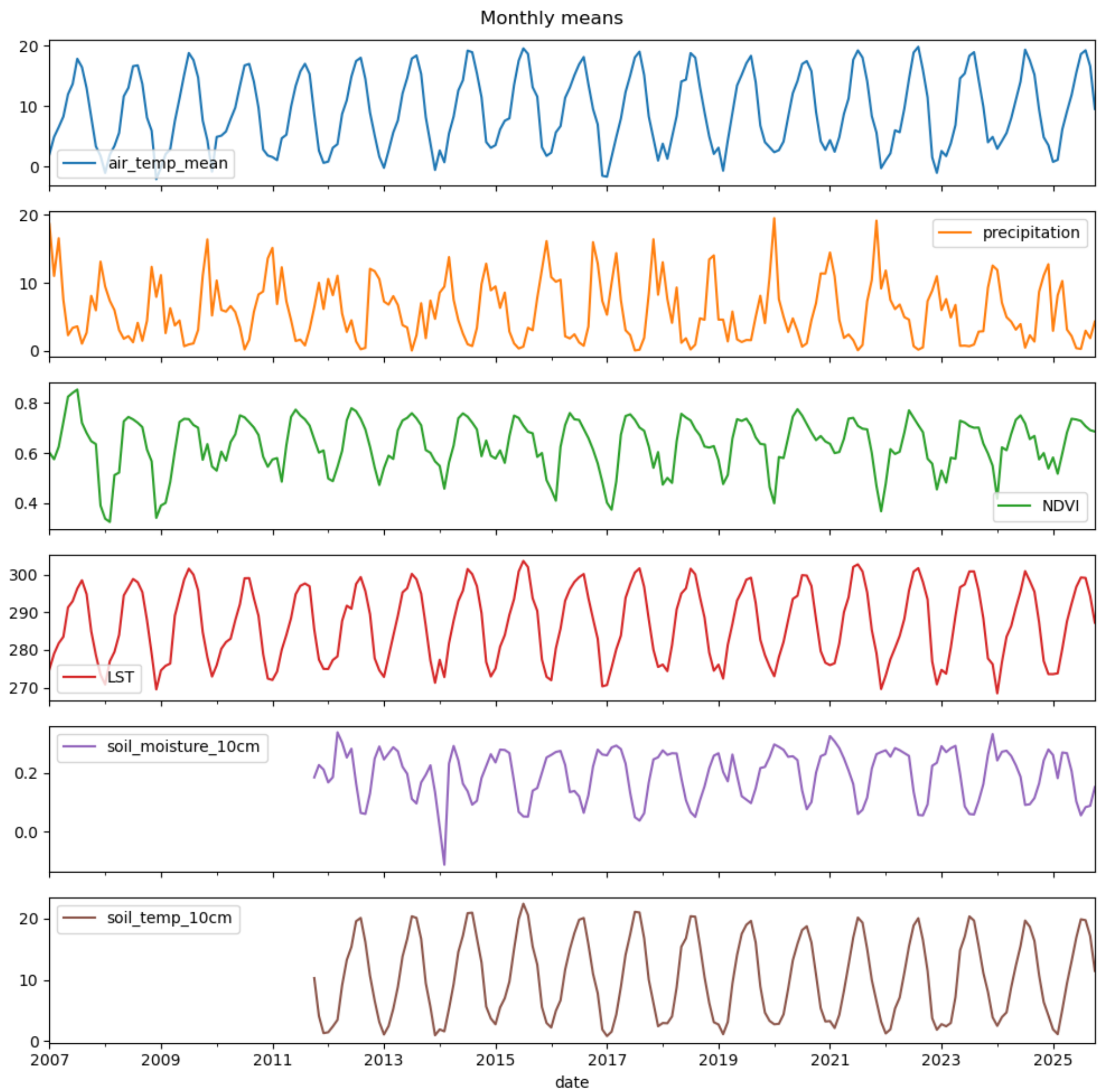
[100]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor

vif_cols = [c for c in candidates if df[c].notna().mean() > 0.95 and c not in␣
↪["station_id", "longitude", "latitude"]]  # keep columns with enough data
X_vif = df[vif_cols].dropna()
X_vif = sm.add_constant(X_vif)
vif = pd.Series([variance_inflation_factor(X_vif.values, i)
                 for i in range(1, X_vif.shape[1])], index=vif_cols)
vif.sort_values(ascending=False).head(15)
```

[100]:
```
air_temp_mean      40089.431329
air_temp_max       16892.554034
air_temp_min        7635.823314
air_temp_avg         133.792083
sur_temp_avg          80.830218
sur_temp_min          34.521055
sur_temp_max          33.600195
LST                    6.274421
solar_radiation        3.427530
Rain_3d                2.703573
precipitation          2.364963
NDVI                   2.294379
Rain_sat               2.070332
DOY                    1.128381
crx_vn                 1.088601
dtype: float64
```

1.6 Temporal Analysis and Seasonality

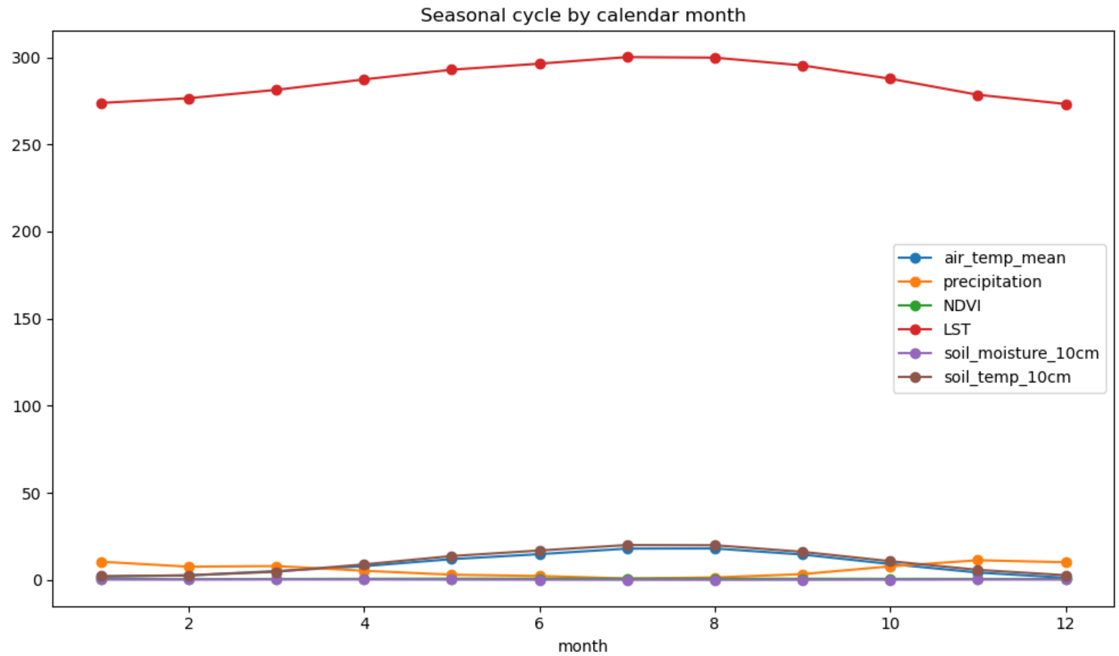
1.6.1 Daily, Weekly, Monthly Trends

[101]:
```
agg_cols =␣
↪["air_temp_mean","precipitation","NDVI","LST","soil_moisture_10cm","soil_temp_10cm"]

daily = df.set_index("date").groupby(pd.Grouper(freq="D"))[agg_cols].mean()
weekly = df.set_index("date").groupby(pd.Grouper(freq="W"))[agg_cols].mean()
monthly = df.set_index("date").groupby(pd.Grouper(freq="M"))[agg_cols].mean()

monthly.plot(subplots=True, figsize=(10,10), title="Monthly means"); plt.
↪tight_layout(); plt.show()
```



1.6.2 Seasonal Cycle

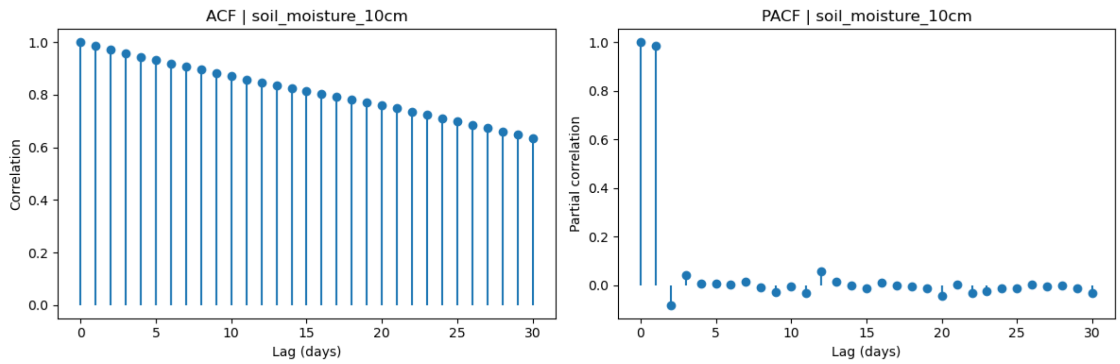
[102]:
```
df["month"] = df["date"].dt.month
seasonal = df.groupby("month")[agg_cols].mean()
seasonal.plot(marker="o", figsize=(10,6), title="Seasonal cycle by calendar␣
↪month"); plt.tight_layout(); plt.show()
```

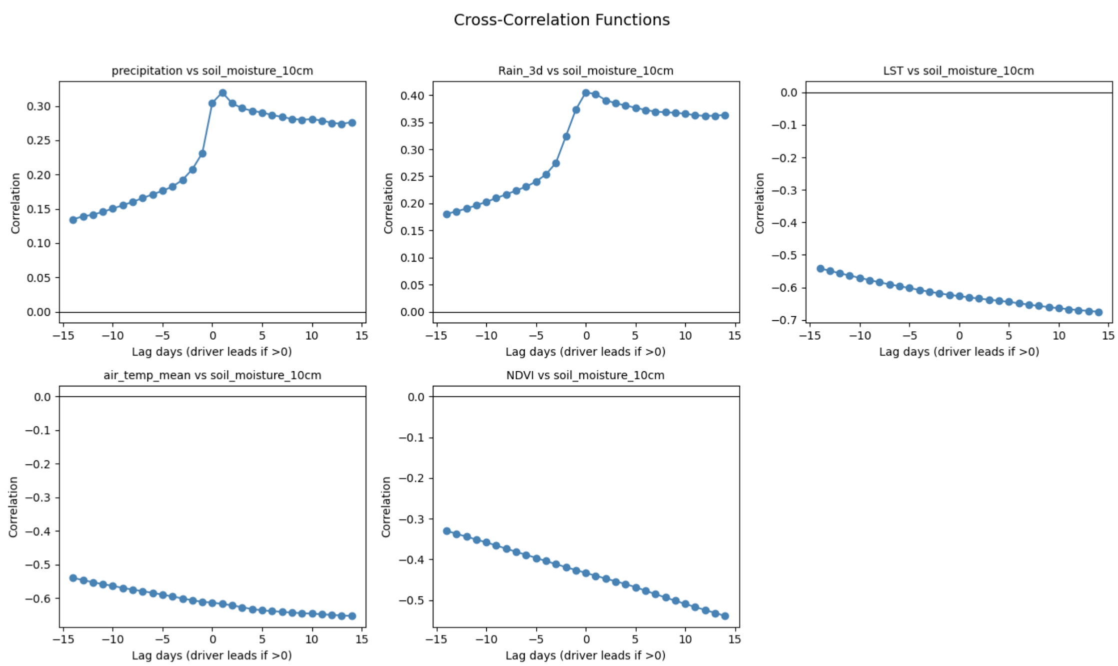


1.7 Cross-correlation and Lag Analysis

[104]:
```
ts = df.set_index("date").sort_index()
series = ts.groupby(pd.Grouper(freq="D"))[
    ["soil_moisture_10cm", "precipitation", "Rain_3d", "NDVI", "LST",␣
↪"air_temp_mean"]
].mean()

sm_series = series["soil_moisture_10cm"].dropna()
lag_acf = acf(sm_series, nlags=30, missing="drop")
lag_pacf = pacf(sm_series, nlags=30, method="ywm")

fig, axes = plt.subplots(1, 2, figsize=(12, 4))
axes[0].stem(range(len(lag_acf)), lag_acf, basefmt=" ")
axes[0].set_title("ACF | soil_moisture_10cm")
axes[0].set_xlabel("Lag (days)")
axes[0].set_ylabel("Correlation")
```

```
axes[1].stem(range(len(lag_pacf)), lag_pacf, basefmt=" ")
axes[1].set_title("PACF | soil_moisture_10cm")
axes[1].set_xlabel("Lag (days)")
axes[1].set_ylabel("Partial correlation")

plt.tight_layout()
plt.show()

def xcorr(x, y, max_lag=14):
    x, y = x.dropna(), y.dropna()
    idx = x.index.intersection(y.index)
    x, y = x.loc[idx], y.loc[idx]
    res = {}
    for lag in range(-max_lag, max_lag + 1):
        if lag < 0:
            r = np.corrcoef(x[-lag:], y[:len(y)+lag])[0, 1]
        elif lag > 0:
            r = np.corrcoef(x[:-lag], y[lag:])[0, 1]
        else:
            r = np.corrcoef(x, y)[0, 1]
        res[lag] = r
    return pd.Series(res)

drivers = ["precipitation", "Rain_3d", "LST", "air_temp_mean", "NDVI"]
n = len(drivers)
fig, axes = plt.subplots(2, 3, figsize=(14, 8))
axes = axes.flatten()

for i, driver in enumerate(drivers):
    if driver in series:
        xr = xcorr(series[driver], series["soil_moisture_10cm"], max_lag=14)
        axes[i].plot(xr.index, xr.values, marker="o", color="steelblue")
        axes[i].axhline(0, color="black", linewidth=0.8)
        axes[i].set_title(f"{driver} vs soil_moisture_10cm", fontsize=10)
        axes[i].set_xlabel("Lag days (driver leads if >0)")
        axes[i].set_ylabel("Correlation")

for j in range(i + 1, len(axes)):
    fig.delaxes(axes[j])

plt.suptitle("Cross-Correlation Functions", fontsize=14, y=1.02)
plt.tight_layout()
plt.show()
```





1.8 Stationary and Stohastic Properties

[105]:
```python
# to mute the warning for obvious stationarity...
import warnings
from statsmodels.tsa.stattools import adfuller, kpss
from statsmodels.tools.sm_exceptions import InterpolationWarning

def adf_kpss_report(s, name):
    s = s.dropna()
    print(f"=== {name} ===")
```

```python
    adf_stat, adf_p, *_ = adfuller(s, autolag="AIC")
    print(f"ADF p-value: {adf_p:.4g}  (p<0.05 suggests stationarity)")

    with warnings.catch_warnings():
        warnings.simplefilter("ignore", category=InterpolationWarning)
        kpss_stat, kpss_p, *_ = kpss(s, nlags="auto")

    print(f"KPSS p-value: {kpss_p:.4g} (p<0.05 suggests non-stationarity)")
    print()

for col in ["soil_moisture_10cm","precipitation","NDVI","LST","air_temp_mean"]:
    if col in series:
        adf_kpss_report(series[col], col)
```

```
=== soil_moisture_10cm ===
ADF p-value: 1.257e-07  (p<0.05 suggests stationarity)
KPSS p-value: 0.1 (p<0.05 suggests non-stationarity)

=== precipitation ===
ADF p-value: 2.852e-13  (p<0.05 suggests stationarity)
KPSS p-value: 0.1 (p<0.05 suggests non-stationarity)

=== NDVI ===
ADF p-value: 2.07e-09  (p<0.05 suggests stationarity)
KPSS p-value: 0.1 (p<0.05 suggests non-stationarity)

=== LST ===
ADF p-value: 8.753e-15  (p<0.05 suggests stationarity)
KPSS p-value: 0.1 (p<0.05 suggests non-stationarity)

=== air_temp_mean ===
ADF p-value: 7.395e-07  (p<0.05 suggests stationarity)
KPSS p-value: 0.1 (p<0.05 suggests non-stationarity)
```

[106]:

```python
sm_diff = series["soil_moisture_10cm"].diff()
adf_kpss_report(sm_diff, "soil_moisture_10cm diff1")
```

```
=== soil_moisture_10cm diff1 ===
ADF p-value: 0  (p<0.05 suggests stationarity)
KPSS p-value: 0.1 (p<0.05 suggests non-stationarity)

ADF p-value: 0  (p<0.05 suggests stationarity)
KPSS p-value: 0.1 (p<0.05 suggests non-stationarity)
```

[107]:
```python
def granger_summary(data, x, y, maxlag=5):
    gtest = grangercausalitytests(data[[x, y]], maxlag=maxlag)
    res = []
    for lag, val in gtest.items():
        pval = val[0]['ssr_ftest'][1]
        res.append((lag, pval))
    return pd.DataFrame(res, columns=["lag", "p_value"]).set_index("lag")

gdf = series[["soil_moisture_10cm","precipitation"]].dropna()
g_summary = granger_summary(gdf, "soil_moisture_10cm", "precipitation",␣
 ↪maxlag=5)
print(g_summary)
```

```
Granger Causality
number of lags (no zero) 1
ssr based F test:         F=82.8747 , p=0.0000  , df_denom=5131, df_num=1
ssr based chi2 test:   chi2=82.9231 , p=0.0000  , df=1
likelihood ratio test: chi2=82.2606 , p=0.0000  , df=1
parameter F test:         F=82.8747 , p=0.0000  , df_denom=5131, df_num=1

Granger Causality
number of lags (no zero) 2
ssr based F test:         F=70.4712 , p=0.0000  , df_denom=5128, df_num=2
ssr based chi2 test:   chi2=141.0799, p=0.0000  , df=2
likelihood ratio test: chi2=139.1759, p=0.0000  , df=2
parameter F test:         F=70.4712 , p=0.0000  , df_denom=5128, df_num=2

Granger Causality
number of lags (no zero) 3
ssr based F test:         F=45.0052 , p=0.0000  , df_denom=5125, df_num=3
ssr based chi2 test:   chi2=135.2000, p=0.0000  , df=3
likelihood ratio test: chi2=133.4498, p=0.0000  , df=3
parameter F test:         F=45.0052 , p=0.0000  , df_denom=5125, df_num=3

Granger Causality
number of lags (no zero) 4
ssr based F test:         F=33.9172 , p=0.0000  , df_denom=5122, df_num=4
ssr based chi2 test:   chi2=135.9073, p=0.0000  , df=4
likelihood ratio test: chi2=134.1385, p=0.0000  , df=4
parameter F test:         F=33.9172 , p=0.0000  , df_denom=5122, df_num=4

Granger Causality
number of lags (no zero) 5
ssr based F test:         F=27.5220 , p=0.0000  , df_denom=5119, df_num=5
ssr based chi2 test:   chi2=137.9055, p=0.0000  , df=5
likelihood ratio test: chi2=136.0844, p=0.0000  , df=5
parameter F test:         F=27.5220 , p=0.0000  , df_denom=5119, df_num=5
```

```
          p_value
lag
1    1.227102e-19
2    6.423502e-31
3    1.061708e-28
4    5.622131e-28
5    1.374883e-27
```

1.9 Feature Engineering Suggestions

[108]:
```python
# lags
for col, lags in [("soil_moisture_10cm",[1,2,3,7]),
                  ("precipitation",[1,2,3]),
                  ("LST",[1,2,3]),
                  ("NDVI",[1,7,14])]:
    if col in df:
        for L in lags:
            df[f"{col}_lag{L}"] = df.groupby("station_id")[col].shift(L)

# rolling aggregates
roll_cfg = [("precipitation","sum",[3,7,14]),
            ("air_temp_mean","mean",[3,7]),
            ("LST","mean",[3,7]),
            ("soil_moisture_10cm","mean",[3,7])]

for col, func, ws in roll_cfg:
    if col in df:
        for w in ws:
            if func == "sum":
                df[f"{col}_roll{w}_sum"] = df.groupby("station_id")[col].
 ↪rolling(w).sum().reset_index(level=0, drop=True)
            else:
                df[f"{col}_roll{w}_mean"] = df.groupby("station_id")[col].
 ↪rolling(w).mean().reset_index(level=0, drop=True)

# thermal indices
if set(["air_temp_max","air_temp_min"]).issubset(df.columns):
    df["diurnal_range"] = df["air_temp_max"] - df["air_temp_min"]

# vegetation dynamics
if "NDVI" in df.columns:
    df["NDVI_diff1"] = df.groupby("station_id")["NDVI"].diff(1)
```

1.10 Predictive Sanity Check

[109]:

```
target = "soil_moisture_5cm"
drop_cols = ["date", "source_file", "SM_label", "station_id"]

# keep only numeric non-object columns
Xcols = [c for c in df.columns if c not in drop_cols + [target] and df[c].dtype␣
↪!= object]

tmp = df[[target] + Xcols].dropna()
X = tmp[Xcols]
y = tmp[target]

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

rf = RandomForestRegressor(n_estimators=300, random_state=42, n_jobs=-1)
rf.fit(X_train, y_train)
pred = rf.predict(X_test)

print("R2:", r2_score(y_test, pred))
print("RMSE:", mean_squared_error(y_test, pred) ** 0.5)
print("n_features:", len(rf.feature_importances_), "==", len(Xcols))

fi = pd.Series(rf.feature_importances_, index=Xcols).
↪sort_values(ascending=False)
print(fi.head(20))
```

```
R2: 0.9732363636565442
RMSE: 0.019558826359290397
n_features: 55 == 55
SM_prev                         0.971461
precipitation                   0.003460
soil_moisture_10cm              0.002471
soil_moisture_10cm_roll7_mean   0.002115
soil_moisture_10cm_roll3_mean   0.002107
soil_moisture_10cm_lag2         0.002005
soil_moisture_10cm_lag3         0.001502
soil_moisture_10cm_lag1         0.001480
precipitation_lag1              0.001236
soil_moisture_20cm              0.001061
soil_moisture_10cm_lag7         0.001053
precipitation_roll3_sum         0.000872
Rain_3d                         0.000788
Rain_sat                        0.000489
precipitation_lag2              0.000449
precipitation_roll14_sum        0.000422
soil_temp_5cm                   0.000417
```

```
rh_min                            0.000409
DOY                               0.000373
soil_temp_100cm                   0.000355
dtype: float64
```

Since that looks a little too good to be true, here's a quick "sanity" check to confirm that

[110]:
```
Xcols_noprev = [c for c in Xcols if c != "SM_prev"]
rf.fit(X_train[Xcols_noprev], y_train)
pred_noprev = rf.predict(X_test[Xcols_noprev])
print("R2 (no SM_prev):", r2_score(y_test, pred_noprev))
print("RMSE (no SM_prev):", mean_squared_error(y_test, pred_noprev) ** 0.5)
```

```
R2 (no SM_prev): 0.9781621550186491
RMSE (no SM_prev): 0.017667500830155898
```

Alright yeah, that's crazy good…

[111]:
```
print([c for c in X.columns if 'lag' in c or 'roll' in c])
```

```
['soil_moisture_10cm_lag1', 'soil_moisture_10cm_lag2',
'soil_moisture_10cm_lag3', 'soil_moisture_10cm_lag7', 'precipitation_lag1',
'precipitation_lag2', 'precipitation_lag3', 'LST_lag1', 'LST_lag2', 'LST_lag3',
'NDVI_lag1', 'NDVI_lag7', 'NDVI_lag14', 'precipitation_roll3_sum',
'precipitation_roll7_sum', 'precipitation_roll14_sum',
'air_temp_mean_roll3_mean', 'air_temp_mean_roll7_mean', 'LST_roll3_mean',
'LST_roll7_mean', 'soil_moisture_10cm_roll3_mean',
'soil_moisture_10cm_roll7_mean']
```

Ok…that list looks good

[112]:
```
sample = df[df["station_id"] == df["station_id"].unique()[0]].
 ↪sort_values("date")

bad = (sample["LST_lag1"] == sample["LST"].shift(-1)).sum()
print("Leaky LST_lag1 rows:", bad)
```

```
Leaky LST_lag1 rows: 6221
```

This explains it…about 6221 rows in the dataset use future values when constructing lag features…in other words they're peaking ahead of time