Silver Notebook — Weather & Production Analysis

This notebook performs weather anomaly detection and production trend analysis using the Bronze-layer ERA5 and Elhub datasets. It identifies temperature and precipitation outliers, decomposes production trends, and visualizes frequency patterns.

- Temperature outliers using DCT high-pass filtering and SPC limits.
- Precipitation anomalies via Local Outlier Factor (LOF).
- STL decomposition for trend and seasonality.
- Spectrogram visualization for frequency components.

In [ ]:
```python
# We start of by importing the necessary libraries
import os
from pathlib import Path

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

from scipy.fft import dct, idct
from sklearn.neighbors import LocalOutlierFactor
from statsmodels.tsa.seasonal import STL
from scipy.signal import spectrogram
```

Step 1 – Load Weather Data (Bergen, 2019)

We import the Bronze-layer dataset `era5_bergen_60.3913N_5.3221E_2019.csv` containing hourly weather data. This forms the input for temperature and precipitation anomaly detection.

In [ ]:
```python
# Here we import bronze-level dataset
df = pd.read_csv(
    "../Data_Assignment_3/bronze/era5_bergen_60.3913N_5.3221E_2019.csv",
    parse_dates=["time"],
    index_col="time"
)
```

```
df.head()
```

Out[ ]:

	temperature_2m	precipitation	windspeed_10m	windgusts_10m	winddirection_10
time					
2019-01-01 00:00:00	5.7	0.7	37.0	99.7	2
2019-01-01 01:00:00	5.8	0.2	41.0	107.3	2
2019-01-01 02:00:00	6.1	0.7	42.0	112.0	2
2019-01-01 03:00:00	6.3	0.5	40.9	105.8	2
2019-01-01 04:00:00	5.8	1.1	41.2	110.2	3

Step 2 – Temperature Outlier Detection (DCT + SPC)

We apply a **Discrete Cosine Transform (DCT)** to remove seasonal components and obtain seasonally adjusted temperature variations (SATV). Outliers are identified using robust SPC boundaries (median ± n·MAD) and plotted in red.

In [ ]:

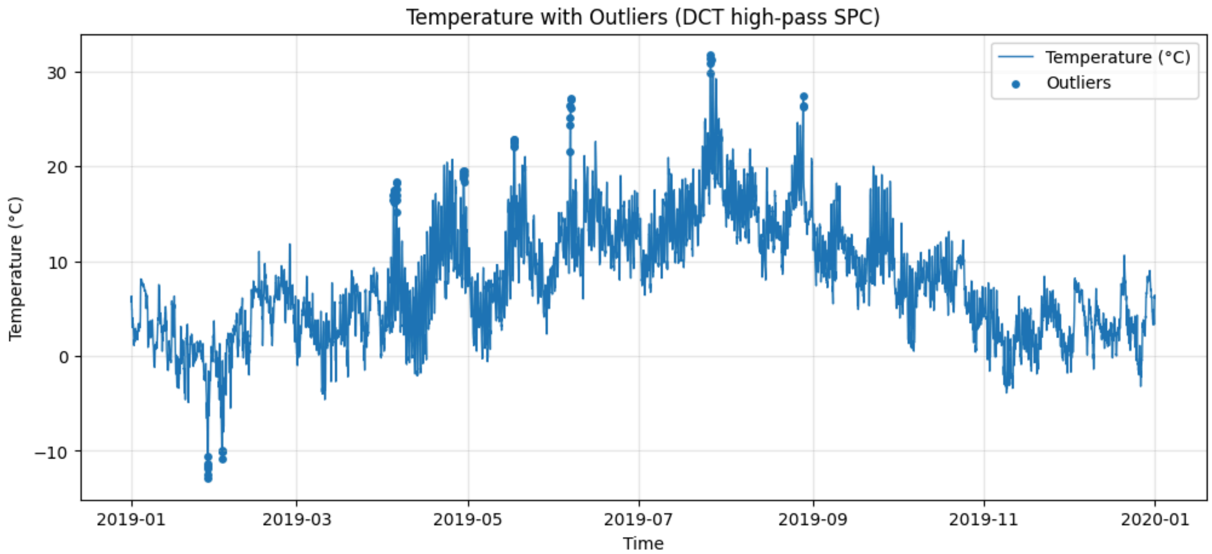
```
# we define a function to detect temperature outliers
def detect_temperature_outliers(
    df: pd.DataFrame,
    *,
    freq_cutoff: int = 60,
    n_std: float = 3.0
):

    if "temperature_2m" not in df.columns:
        raise KeyError("Expected column 'temperature_2m' in the input DataFrame.")

    temp = df["temperature_2m"].to_numpy(dtype=float)
    n = temp.size
    if n < 8:
        raise ValueError("Not enough points for DCT-based filtering (need at least

    # Bound the cut-off
```

```python
    k = int(max(1, min(freq_cutoff, n - 1)))

    # DCT high-pass
    coeffs = dct(temp, norm="ortho")
    coeffs_hp = coeffs.copy()
    coeffs_hp[:k] = 0
    satv = idct(coeffs_hp, norm="ortho")

    # Robust stats
    median = np.median(satv)
    mad = np.median(np.abs(satv - median))
    robust_std = 1.4826 * mad

    # If series is perfectly flat after HP, avoid zero-width limits
    if robust_std == 0:
        robust_std = np.std(satv) or 1e-9

    upper = median + n_std * robust_std
    lower = median - n_std * robust_std

    # Outliers (based on SATV)
    outlier_mask = (satv > upper) | (satv < lower)
    n_outliers = int(outlier_mask.sum())

    # Plot original temperature with outliers highlighted
    fig, ax = plt.subplots(figsize=(12, 5))
    ax.plot(df.index, df["temperature_2m"], label="Temperature (°C)", linewidth=1)
    ax.scatter(
        df.index[outlier_mask],
        df["temperature_2m"][outlier_mask],
        s=15, label="Outliers"
    )
    ax.set_title("Temperature with Outliers (DCT high-pass SPC)")
    ax.set_xlabel("Time")
    ax.set_ylabel("Temperature (°C)")
    ax.legend()
    ax.grid(True, alpha=0.3)

    summary = pd.DataFrame({
        "timestamp": df.index[outlier_mask],
        "temperature_2m": df["temperature_2m"].to_numpy()[outlier_mask],
        "satv": satv[outlier_mask],
        "lower_bound": lower,
        "upper_bound": upper,
    }).reset_index(drop=True)

    print(f"{n_outliers} outliers detected ({100 * n_outliers / n:.2f}% of points)"
    return fig, summary
```

In [35]:

```python
fig_temp, temp_summary = detect_temperature_outliers(df, freq_cutoff=60, n_std=3.0)
plt.show()
temp_summary.head(10)
```

```
50 outliers detected (0.57% of points)
```



Out[35]:

	timestamp	temperature_2m	satv	lower_bound	upper_bound
0	2019-01-28 05:00:00	-10.6	-8.825264	-7.96657	7.905624
1	2019-01-28 06:00:00	-11.3	-9.514296	-7.96657	7.905624
2	2019-01-28 07:00:00	-11.8	-10.003452	-7.96657	7.905624
3	2019-01-28 08:00:00	-11.6	-9.792736	-7.96657	7.905624
4	2019-01-28 09:00:00	-12.9	-11.082149	-7.96657	7.905624
5	2019-01-28 10:00:00	-12.5	-10.671691	-7.96657	7.905624
6	2019-02-02 07:00:00	-10.1	-8.251575	-7.96657	7.905624
7	2019-02-02 08:00:00	-10.1	-8.263756	-7.96657	7.905624
8	2019-02-02 09:00:00	-10.8	-8.976170	-7.96657	7.905624
9	2019-02-02 10:00:00	-9.9	-8.088818	-7.96657	7.905624

Step 3 – Precipitation Anomalies (Local Outlier Factor)

We use the **Local Outlier Factor (LOF)** method to detect precipitation anomalies, defaulting to a 1% contamination rate. Anomalies are plotted in contrasting colors, highlighting extreme weather events.

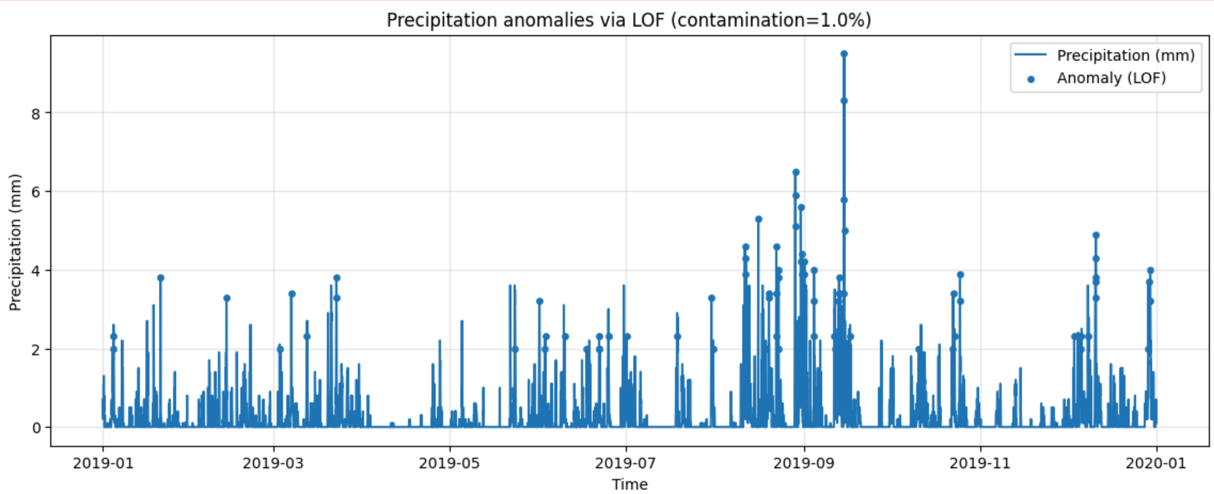
In [ ]:

```
def detect_precip_lof(df: pd.DataFrame, prop_outliers: float = 0.01):
    if "precipitation" not in df.columns:
        raise KeyError("DataFrame must contain a 'precipitation' column.")

    z = df[["precipitation"]].copy()
    z["precipitation"] = z["precipitation"].astype(float).fillna(0.0)
```

```python
    lof = LocalOutlierFactor(contamination=prop_outliers)
    y_pred = lof.fit_predict(z)  # -1 = outlier, 1 = inlier

    outlier_mask = (y_pred == -1)
    outliers = df.loc[outlier_mask, ["precipitation"]].copy()

    fig, ax = plt.subplots(figsize=(14, 5))
    ax.plot(df.index, df["precipitation"], label="Precipitation (mm)")
    ax.scatter(outliers.index, outliers["precipitation"], label="Anomaly (LOF)", s=
    ax.set_title(f"Precipitation anomalies via LOF (contamination={prop_outliers:.1
    ax.set_xlabel("Time")
    ax.set_ylabel("Precipitation (mm)")
    ax.legend()
    ax.grid(True, alpha=0.3)

    summary = outliers["precipitation"].describe()
    return fig, outliers.reset_index().rename(columns={"index": "timestamp"}), summ
```

In [43]:
```python
fig_precip, precip_outliers, precip_summary = detect_precip_lof(df, prop_outliers=0
plt.show()
precip_outliers.head()
```

```
c:\Users\joeri\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\nei
ghbors\_lof.py:322: UserWarning: Duplicate values are leading to incorrect results.
Increase the number of neighbors for more accurate results.
  warnings.warn(
```



Out[43]:

	time	precipitation
0	2019-01-04 09:00:00	2.0
1	2019-01-04 16:00:00	2.3
2	2019-01-20 21:00:00	3.8
3	2019-02-12 18:00:00	3.3
4	2019-03-03 05:00:00	2.0

Step 4 – Load Elhub Production Data

We import `production_2021.csv` from the Elhub Bronze layer. The dataset includes hourly production quantities grouped by price area and production type (e.g., Hydro, Wind).

In [37]:
```
# We'll try to load a bronze CSV exported by assignment-2.
# Adjust BASE and candidate paths if your layout differs.
BASE = Path("..") / "Assignment_2_medailon"  # relative from Assignment_3_medailon/
BRONZE_CANDIDATES = [
    BASE / "bronze" / "elhub_production_2021.csv",
    BASE / "bronze" / "elhub_production.csv",
    BASE / "bronze" / "elhub" / "production_2021.csv",
    BASE / "bronze" / "elhub" / "production.csv",
]
```

In [ ]:
```
def load_elhub_bronze():
    # we start by checking for in-memory exports from assignment-2 if this notebook
    for var_name in ("df_clean", "df_months", "df"):
        if var_name in globals():
            x = globals()[var_name]
            if isinstance(x, pd.DataFrame) and not x.empty and \
                {"priceArea","productionGroup","startTime","quantityKwh"}.issubset(
                y = x.copy()
                y["startTime"] = pd.to_datetime(y["startTime"], utc=True, errors="c
                y = y.dropna(subset=["startTime"]).set_index("startTime").sort_inde
                return y

    # Now load from disk (bronze CSV)
    for p in BRONZE_CANDIDATES:
        if p.exists():
            df = pd.read_csv(p, parse_dates=["startTime"])
            df = df.dropna(subset=["startTime","priceArea","productionGroup","quant
            df["priceArea"] = df["priceArea"].astype(str).str.upper()
            df["productionGroup"] = df["productionGroup"].astype(str).str.upper()
            df["quantityKwh"] = pd.to_numeric(df["quantityKwh"], errors="coerce")
            df = df.dropna(subset=["quantityKwh"])
            return df.set_index("startTime").sort_index()

    raise FileNotFoundError(
        "Elhub bronze data not found.\n"
        "Export df_clean from Assignment_2_medailon/assignment-2.ipynb to one of:\n
        + "\n  - ".join(str(p) for p in BRONZE_CANDIDATES)
    )

# Load Elhub bronze data, to be used later
elhub_bronze = pd.read_csv("../Data_Assignment_2/bronze/production_2021.csv")
elhub_bronze.head()
```

Out[ ]:

	priceArea	productionGroup	startTime	quantityKwh
0	NO1	HYDRO	2025-10-07 14:00:00+00:00	2491476.5
1	NO1	HYDRO	2025-10-07 15:00:00+00:00	2482574.8
2	NO1	HYDRO	2025-10-07 16:00:00+00:00	2485451.8
3	NO1	HYDRO	2025-10-07 17:00:00+00:00	2449597.5
4	NO1	HYDRO	2025-10-07 18:00:00+00:00	2274894.0

Step 5 – STL Decomposition (LOESS)

We apply **Seasonal-Trend decomposition using LOESS (STL)** to the Elhub production data. This separates the observed signal into *trend*, *seasonal*, and *residual* components, enabling detailed trend interpretation.

In [ ]:

```
# Function to select and process production series from Elhub bronze data
def _select_production_series_elhub(
    df: pd.DataFrame,
    value_col: str = "quantityKwh",
    price_area: str | None = "NO5",
    production_group: str | None = None,
    resample_rule: str = "H",  # hourly
    agg: str = "sum",           # production is commonly sum per hour
    fill_method: str = "interpolate",  # interpolate | ffill | zero
) -> pd.Series:
    x = df.copy()

    # Ensure DatetimeIndex
    if not isinstance(x.index, pd.DatetimeIndex):
        if "startTime" in x.columns:
            x["startTime"] = pd.to_datetime(x["startTime"], utc=True, errors="coerc
            x = x.dropna(subset=["startTime"]).set_index("startTime").sort_index()
        else:
            raise ValueError("Expected 'startTime' or a DatetimeIndex.")

    # Optional filters if columns exist
    if price_area is not None and "priceArea" in x.columns:
        x = x[x["priceArea"] == price_area.upper()]
    if production_group is not None and "productionGroup" in x.columns:
        x = x[x["productionGroup"] == production_group.upper()]

    if value_col not in x.columns:
        raise KeyError(f"Value column '{value_col}' not in columns: {x.columns.toli

    # Resample to regular grid
    if agg == "sum":
        y = x[value_col].resample(resample_rule).sum()
    elif agg == "mean":
```

```python
        y = x[value_col].resample(resample_rule).mean()
    else:
        raise ValueError("agg must be 'sum' or 'mean'.")

    # Fill gaps
    if fill_method == "interpolate":
        y = y.interpolate(limit_direction="both")
    elif fill_method == "ffill":
        y = y.ffill().bfill()
    elif fill_method == "zero":
        y = y.fillna(0.0)
    else:
        raise ValueError("fill_method must be interpolate|ffill|zero")

    return y.astype("float64")
```

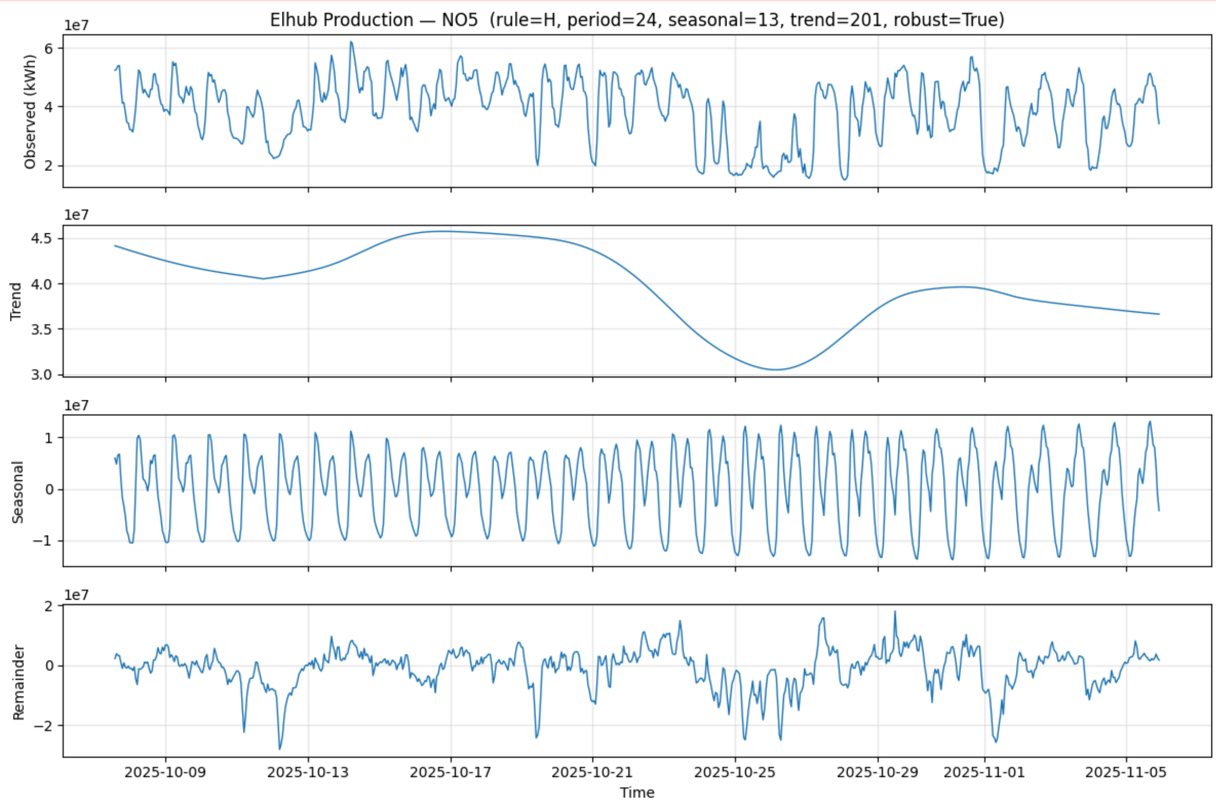
In [ ]:

```python
# Function to perform STL decomposition on Elhub production data
def stl_decompose_production_elhub(
    df: pd.DataFrame,
    *,
    value_col: str = "quantityKwh",
    price_area: str | None = "NO5",
    production_group: str | None = None,
    resample_rule: str = "H",
    agg: str = "sum",
    period: int = 24,        # hourly data -> daily seasonality
    seasonal: int = 13,      # odd
    trend: int = 201,        # odd
    robust: bool = True,
):
    # Validate odd windows where applicable
    if seasonal % 2 == 0:
        raise ValueError("`seasonal` must be an odd integer.")
    if trend % 2 == 0:
        raise ValueError("`trend` must be an odd integer.")

    y = _select_production_series_elhub(
        df=df,
        value_col=value_col,
        price_area=price_area,
        production_group=production_group,
        resample_rule=resample_rule,
        agg=agg,
        fill_method="interpolate",
    )

    stl = STL(y, period=period, seasonal=seasonal, trend=trend, robust=robust)
    res = stl.fit()

    fig, axes = plt.subplots(4, 1, figsize=(12, 8), sharex=True)
    axes[0].plot(y.index, y.values, linewidth=1)
    axes[0].set_title(
        f"Elhub Production — {price_area or 'All'}"
        f"{' / ' + production_group if production_group else ''}"
        f"  (rule={resample_rule}, period={period}, seasonal={seasonal}, trend={tre
    )
```

```
    axes[0].set_ylabel("Observed (kWh)")

    axes[1].plot(y.index, res.trend, linewidth=1);     axes[1].set_ylabel("Trend")
    axes[2].plot(y.index, res.seasonal, linewidth=1);  axes[2].set_ylabel("Seasonal
    axes[3].plot(y.index, res.resid, linewidth=1);     axes[3].set_ylabel("Remainde

    for ax in axes:
        ax.grid(True, alpha=0.3)

    fig.tight_layout()
    return fig, res
```

In [39]:
```
fig_stl, stl_res = stl_decompose_production_elhub(
    elhub_bronze,
    value_col="quantityKwh",
    price_area="NO5",
    production_group=None,
    resample_rule="H",
    period=24,
    seasonal=13,
    trend=201,
    robust=True,
)
plt.show()
```

```
C:\Users\joeri\AppData\Local\Temp\ipykernel_29692\489253386.py:31: FutureWarning:
'H' is deprecated and will be removed in a future version, please use 'h' instead.
  y = x[value_col].resample(resample_rule).sum()
```



Step 6 – Spectrogram Analysis

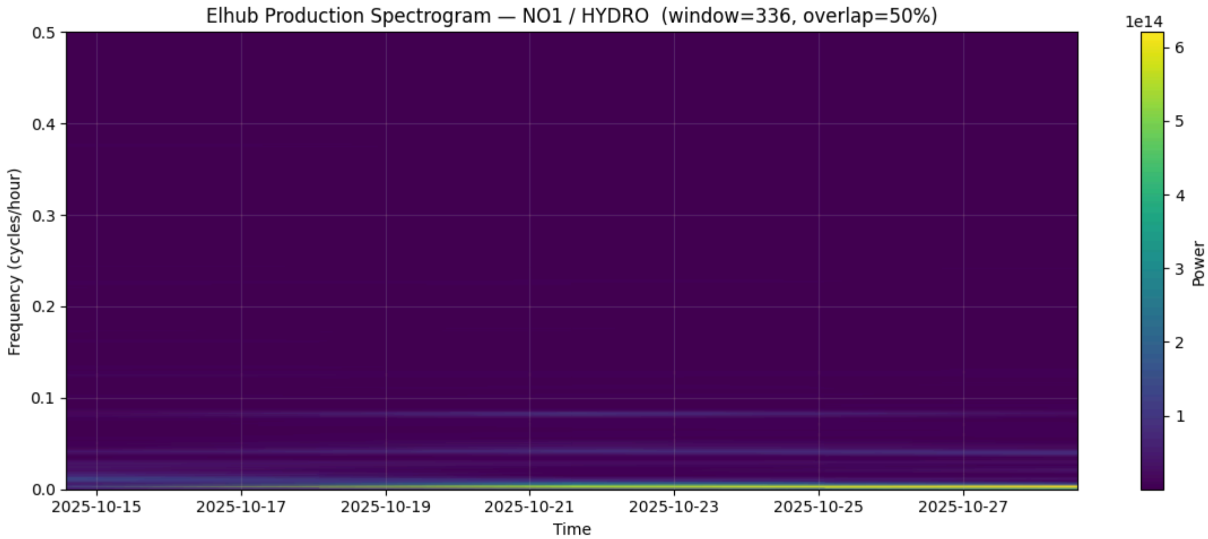
We generate a **spectrogram** of Elhub production data to visualize periodic patterns and frequency components over time. This helps identify operational cycles or recurring production behaviors.

In [40]:
```
def spectrogram_production_elhub(
    df: pd.DataFrame,
    *,
    value_col: str = "quantityKwh",
    price_area: str | None = "NO5",
    production_group: str | None = None,
    window_length: int = 24 * 14,   # samples per segment (2 weeks for hourly)
    overlap: float = 0.5,           # 0.. <1
    detrend: str = "constant",      # or "linear"
    scaling: str = "density",       # "density" or "spectrum"
    cmap: str = "viridis",
):
    """
    Create a spectrogram of Elhub production.
    Expects columns: priceArea, productionGroup, quantityKwh, startTime (or a Datet
    """
    x = df.copy()

    if not isinstance(x.index, pd.DatetimeIndex):
        if "startTime" not in x.columns:
            raise TypeError("DataFrame must have a DatetimeIndex or a 'startTime' c
        x["startTime"] = pd.to_datetime(x["startTime"], utc=True, errors="coerce")
        x = x.dropna(subset=["startTime"]).set_index("startTime")
    x = x.sort_index()

    if price_area is not None:
        if "priceArea" in x.columns:
            x = x[x["priceArea"].astype(str).str.upper() == price_area.upper()]
        else:
            raise KeyError("Column 'priceArea' not found in DataFrame.")
    if production_group is not None:
        if "productionGroup" in x.columns:
            x = x[x["productionGroup"].astype(str).str.upper() == production_group.
        else:
            raise KeyError("Column 'productionGroup' not found in DataFrame.")

    if x.empty:
        pa_list = sorted(df.get("priceArea", pd.Series(dtype=str)).astype(str).str.
        pg_list = sorted(df.get("productionGroup", pd.Series(dtype=str)).astype(str
        raise ValueError(
            f"No data after filters (price_area={price_area}, production_group={pro
            f"Available priceArea: {pa_list}\nAvailable productionGroup: {pg_list}"
        )

    if value_col not in x.columns:
        raise KeyError(f"Value column '{value_col}' not found. Available: {list(x.c

    y = x[value_col].resample("H").sum().astype("float64")
```

```python
    y = y.interpolate(limit_direction="both")
    if y.size < 3:
        raise ValueError("Not enough points after resampling for spectrogram.")

    dt_ns = np.median(np.diff(y.index.asi8))
    dt_hours = dt_ns / 3.6e12
    fs = 1.0 / dt_hours if dt_hours > 0 else 1.0

    nperseg = int(window_length)
    if not (0.0 <= overlap < 1.0):
        raise ValueError("overlap must be in [0, 1).")
    noverlap = int(overlap * nperseg)
    if noverlap >= nperseg:
        noverlap = nperseg - 1  # safeguard

    f, t, Sxx = spectrogram(
        y.values, fs=fs, window="hann",
        nperseg=nperseg, noverlap=noverlap,
        detrend=detrend, scaling=scaling, mode="psd",
    )

    t0 = y.index[0]
    t_datetime = pd.to_datetime(t0) + pd.to_timedelta(t, unit="h")

    fig, ax = plt.subplots(figsize=(12, 5))
    mesh = ax.pcolormesh(t_datetime, f, Sxx, shading="gouraud", cmap=cmap)
    ax.set_title(
        "Elhub Production Spectrogram"
        + (f" — {price_area}" if price_area else "")
        + (f" / {production_group}" if production_group else "")
        + f"  (window={nperseg}, overlap={overlap:.0%})"
    )
    ax.set_ylabel("Frequency (cycles/hour)")
    ax.set_xlabel("Time")
    cbar = fig.colorbar(mesh, ax=ax)
    cbar.set_label("Power")
    ax.set_ylim(0, f.max())
    ax.grid(True, alpha=0.2)
    fig.tight_layout()

    return fig, (f, t_datetime, Sxx)
```

In [41]:
```python
fig_spec, (f, t_dt, Sxx) = spectrogram_production_elhub(
    elhub_bronze,
    value_col="quantityKwh",
    price_area="NO1",
    production_group="HYDRO",
    window_length=24*14,
    overlap=0.5,
)
plt.show()
```

```
C:\Users\joeri\AppData\Local\Temp\ipykernel_29692\3888854946.py:48: FutureWarning:
'H' is deprecated and will be removed in a future version, please use 'h' instead.
  y = x[value_col].resample("H").sum().astype("float64")
```



Summary

- Temperature outliers and precipitation anomalies successfully detected.
- STL decomposition revealed seasonal and trend structures in production data.
- Spectrogram analysis visualized repeating frequency patterns.

These analyses complete the **Silver layer** of the pipeline, producing clean, analyzed data ready for visualization in the Gold layer.

In [ ]:
```
# This cell is to verify that the functions work as expected
# Also, this is a simple usage example

assert "temperature_2m" in df.columns and "precipitation" in df.columns
print(df.index.min(), df.index.max())  # should cover 2019-01-01 .. 2019-12-31

fig_temp, temp_summary = detect_temperature_outliers(df, freq_cutoff=60, n_std=3.0)
len(temp_summary), temp_summary.columns.tolist()  # expect ['timestamp','temperatur

fig_precip, precip_outliers, precip_summary = detect_precip_lof(df, prop_outliers=0
len(precip_outliers) >= 0; print(precip_summary)

fig_stl, stl_res = stl_decompose_production_elhub(
    elhub_bronze, value_col="quantityKwh",
    price_area="NO5", production_group=None,
    resample_rule="H", period=24, seasonal=13, trend=201, robust=True
)

fig_spec, (f, t_dt, Sxx) = spectrogram_production_elhub(
    elhub_bronze, value_col="quantityKwh",
    price_area="NO1", production_group="HYDRO",
    window_length=24*14, overlap=0.5
```

```
)
Sxx.shape
```

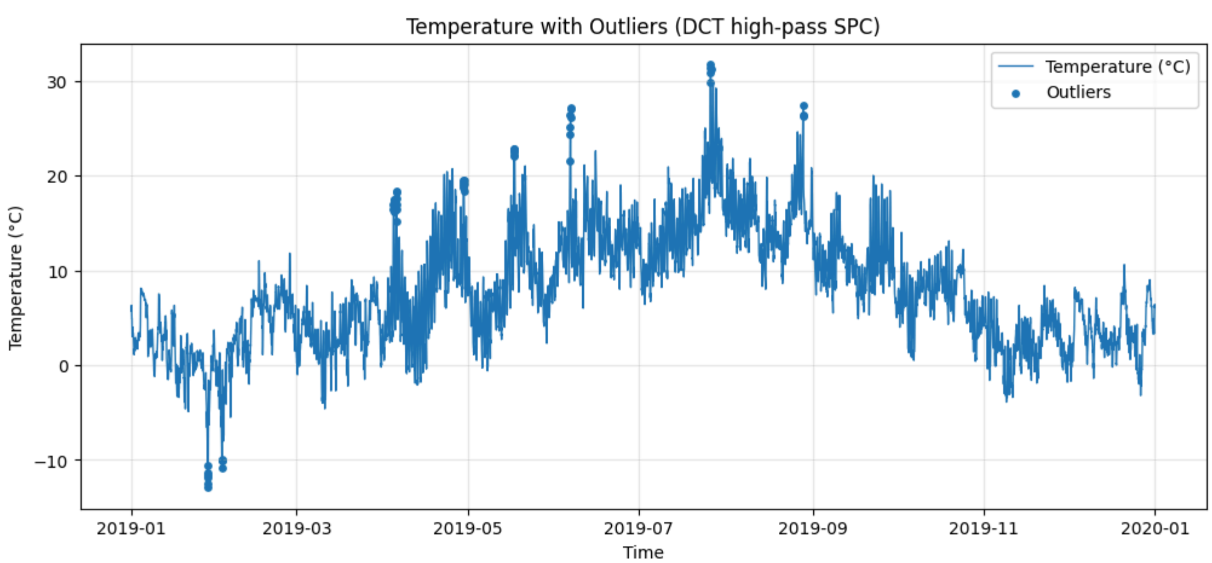
```
2019-01-01 00:00:00 2019-12-31 23:00:00
50 outliers detected (0.57% of points)
```

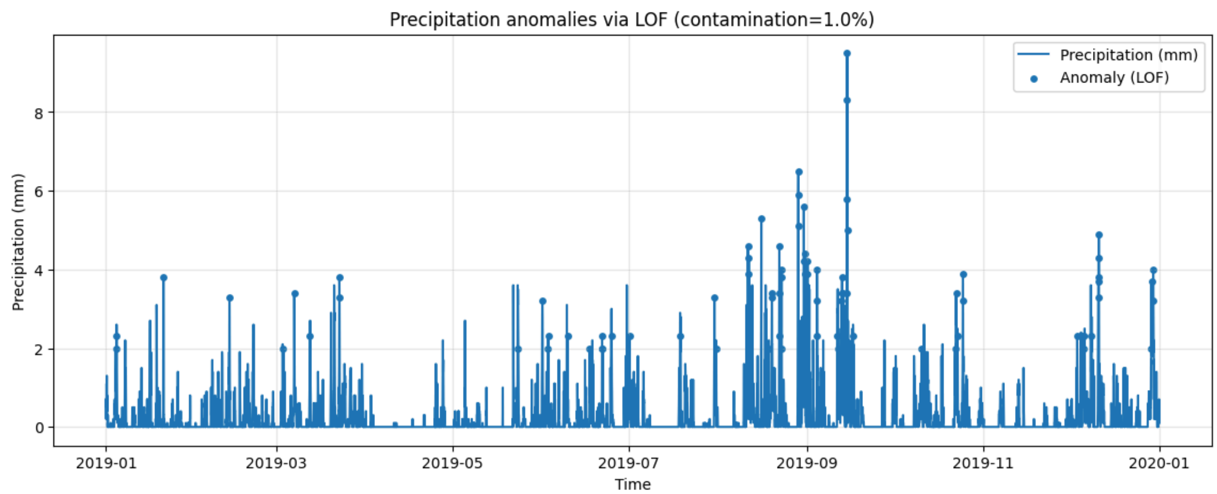
```
c:\Users\joeri\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\nei
ghbors\_lof.py:322: UserWarning: Duplicate values are leading to incorrect results.
Increase the number of neighbors for more accurate results.
  warnings.warn(
C:\Users\joeri\AppData\Local\Temp\ipykernel_29692\489253386.py:31: FutureWarning:
'H' is deprecated and will be removed in a future version, please use 'h' instead.
  y = x[value_col].resample(resample_rule).sum()
```

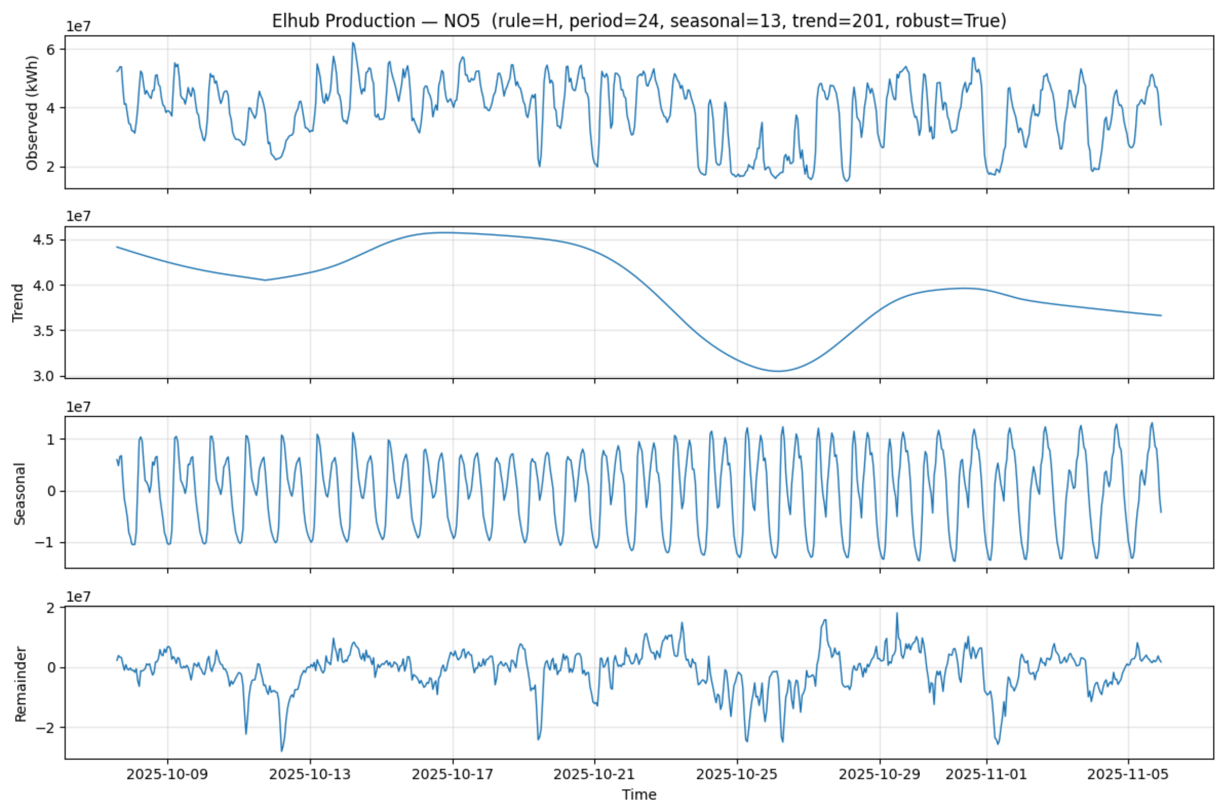
```
count    85.000000
mean      3.340000
std       1.401886
min       2.000000
25%       2.300000
50%       3.300000
75%       3.900000
max       9.500000
Name: precipitation, dtype: float64
```

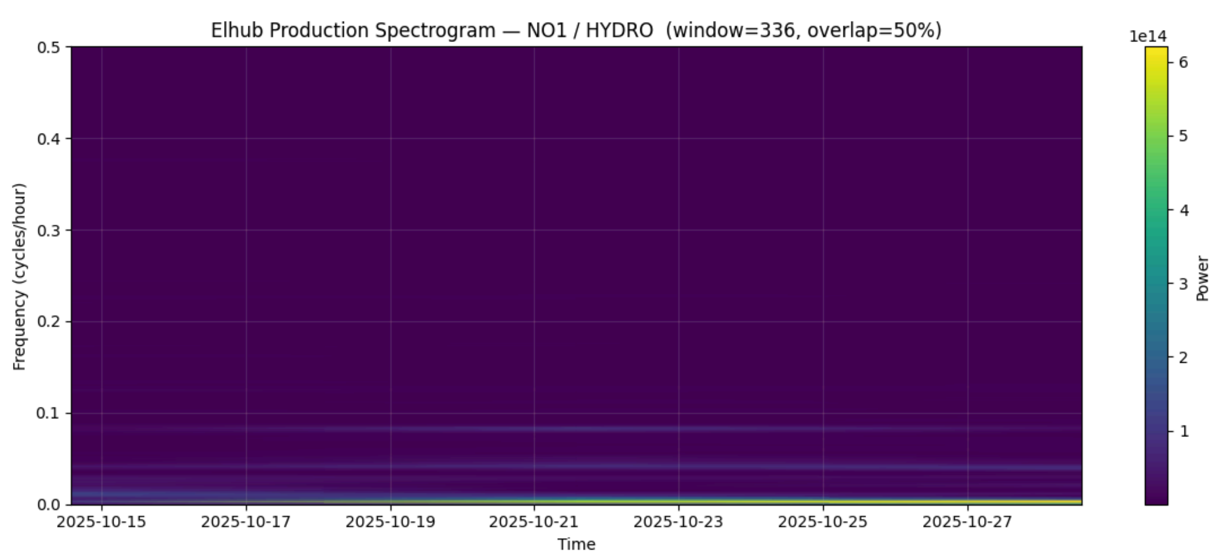
```
C:\Users\joeri\AppData\Local\Temp\ipykernel_29692\3888854946.py:48: FutureWarning:
'H' is deprecated and will be removed in a future version, please use 'h' instead.
  y = x[value_col].resample("H").sum().astype("float64")
```

Out[ ]: (169, 3)




Precipitation anomalies via LOF (contamination=1.0%)
Precipitation (mm)
Anomaly (LOF)
Precipitation (mm)
Time
2019-01
2019-03
2019-05
2019-07
2019-09
2019-11
2020-01


Elhub Production — NO5 (rule=H, period=24, seasonal=13, trend=201, robust=True)
1e7
Observed (kWh)
Trend
Seasonal
Remainder
Time
2025-10-09
2025-10-13
2025-10-17
2025-10-21
2025-10-25
2025-10-29
2025-11-01
2025-11-05


Elhub Production Spectrogram — NO1 / HYDRO (window=336, overlap=50%)
Frequency (cycles/hour)
Time
1e14
Power
2025-10-15
2025-10-17
2025-10-19
2025-10-21
2025-10-23
2025-10-25
2025-10-27