LSTM Deep Learning Model – Soil Moisture Prediction

```
# ====================================
# LSTM for Soil Moisture Prediction
# Fully Clean & Error-Safe Version
# ====================================

# ---------- Suppress TensorFlow log noise ----------
import os
os.environ["TF_CPP_MIN_LOG_LEVEL"] = "3"

# ---------- Imports ----------
import pandas as pd
import numpy as np
import glob
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout, Input
from tensorflow.keras.callbacks import EarlyStopping

# ---------- Load Dataset ----------
dataset_path = "/kaggle/input/datasets/sathyanarayanrao89/soil-moisture-data-from-field-scale-sensor-network"
hourly_files = glob.glob(dataset_path + "/Hourly/*.txt")

if len(hourly_files) == 0:
    raise ValueError("No hourly files found. Check dataset path.")

def load_and_combine(files):
    dfs = []
    for f in files:
        try:
            df = pd.read_csv(f, sep='\t', engine='python')
            dfs.append(df)
        except Exception as e:
            print(f"Skipping {f} due to error: {e}")
    if len(dfs) == 0:
        raise ValueError("No files could be loaded.")
    return pd.concat(dfs, ignore_index=True)

hourly_df = load_and_combine(hourly_files)

# ---------- Basic Cleaning ----------
hourly_df.replace([np.inf, -np.inf], np.nan, inplace=True)
hourly_df.ffill(inplace=True)
hourly_df.bfill(inplace=True)

# ---------- Safe Datetime Conversion ----------
for col in hourly_df.columns:
    if 'time' in col.lower() or 'date' in col.lower():
        hourly_df[col] = pd.to_datetime(hourly_df[col], errors='coerce')

# ---------- Feature Selection ----------
target_col = 'VW_30cm'

if target_col not in hourly_df.columns:
    raise ValueError(f"{target_col} not found in dataset.")

hourly_df.dropna(subset=[target_col], inplace=True)

feature_cols = [
    c for c in hourly_df.columns
    if c not in ['Date', 'Time', 'Location', target_col]
    and np.issubdtype(hourly_df[c].dtype, np.number)
]

if len(feature_cols) == 0:
    raise ValueError("No numeric feature columns found.")

X = hourly_df[feature_cols].values
y = hourly_df[target_col].values.reshape(-1, 1)
```

```
# ---------- Scaling ----------
scaler_X = MinMaxScaler()
scaler_y = MinMaxScaler()

X_scaled = scaler_X.fit_transform(X)
y_scaled = scaler_y.fit_transform(y)

# ---------- Create Sequences ----------
TIME_STEPS = 24

def create_sequences(X, y, steps):
    X_seq, y_seq = [], []
    for i in range(len(X) - steps):
        X_seq.append(X[i:i+steps])
        y_seq.append(y[i+steps])
    return np.array(X_seq), np.array(y_seq)

X_seq, y_seq = create_sequences(X_scaled, y_scaled, TIME_STEPS)

if len(X_seq) == 0:
    raise ValueError("Not enough data to create sequences.")

# ---------- Remove NaNs if any ----------
mask = ~np.isnan(y_seq).flatten()
X_seq = X_seq[mask]
y_seq = y_seq[mask]

# ---------- Optional Stratified Split ----------
try:
    y_bins = pd.qcut(y_seq.flatten(), q=5, labels=False, duplicates='drop')
    X_train, X_test, y_train, y_test = train_test_split(
        X_seq, y_seq, test_size=0.2, random_state=42, stratify=y_bins
    )
except:
    X_train, X_test, y_train, y_test = train_test_split(
        X_seq, y_seq, test_size=0.2, random_state=42
    )

# ---------- Build LSTM Model ----------
model = Sequential([
    Input(shape=(X_train.shape[1], X_train.shape[2])),
    LSTM(64, return_sequences=True),
    Dropout(0.2),
    LSTM(32),
    Dropout(0.2),
    Dense(1)
])

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

# ---------- Early Stopping ----------
early_stop = EarlyStopping(
    monitor='val_loss',
    patience=3,
    restore_best_weights=True
)

# ---------- Train ----------
history = model.fit(
    X_train, y_train,
    validation_data=(X_test, y_test),
    epochs=15,
    batch_size=32,
    callbacks=[early_stop],
    verbose=1
)

# ---------- Predict ----------
y_pred_scaled = model.predict(X_test)
y_pred = scaler_y.inverse_transform(y_pred_scaled)
y_true = scaler_y.inverse_transform(y_test)

# ---------- Sample Output ----------
print("\nSample Predictions:\n")
for i in range(min(5, len(y_pred))):
    print(f"Predicted: {y_pred[i][0]:.4f} | Actual: {y_true[i][0]:.4f}")
```

```
WARNING: All log messages before absl::InitializeLog() is called are written to STDERR
E0000 00:00:1771079014.046642     111 cuda_dnn.cc:8579] Unable to register cuDNN factory: Attempting to register factory for plu
E0000 00:00:1771079014.053498     111 cuda_blas.cc:1407] Unable to register cuBLAS factory: Attempting to register factory for p
W0000 00:00:1771079014.070583     111 computation_placer.cc:177] computation placer already registered. Please check linkage and
W0000 00:00:1771079014.070608     111 computation_placer.cc:177] computation placer already registered. Please check linkage and
W0000 00:00:1771079014.070611     111 computation_placer.cc:177] computation placer already registered. Please check linkage and
W0000 00:00:1771079014.070613     111 computation_placer.cc:177] computation placer already registered. Please check linkage and
/tmp/ipykernel_111/815850690.py:50: UserWarning: Could not infer format, so each element will be parsed individually, falling ba
  hourly_df[col] = pd.to_datetime(hourly_df[col], errors='coerce')
I0000 00:00:1771079064.172992     111 gpu_device.cc:2019] Created device /job:localhost/replica:0/task:0/device:GPU:0 with 13757
I0000 00:00:1771079064.175701     111 gpu_device.cc:2019] Created device /job:localhost/replica:0/task:0/device:GPU:1 with 13757
Epoch 1/15
I0000 00:00:1771079074.290705     169 cuda_dnn.cc:529] Loaded cuDNN version 91002
84341/84341 ━━━━━━━━━━━━━━━━━━━━ 563s 7ms/step - loss: 0.0018 - val_loss: 5.4526e-04
Epoch 2/15
84341/84341 ━━━━━━━━━━━━━━━━━━━━ 551s 7ms/step - loss: 5.9456e-04 - val_loss: 3.6852e-04
Epoch 3/15
84341/84341 ━━━━━━━━━━━━━━━━━━━━ 552s 7ms/step - loss: 4.1624e-04 - val_loss: 2.5462e-04
Epoch 4/15
84341/84341 ━━━━━━━━━━━━━━━━━━━━ 554s 7ms/step - loss: 3.5125e-04 - val_loss: 2.2535e-04
Epoch 5/15
84341/84341 ━━━━━━━━━━━━━━━━━━━━ 554s 7ms/step - loss: 3.1763e-04 - val_loss: 1.9566e-04
Epoch 6/15
84341/84341 ━━━━━━━━━━━━━━━━━━━━ 554s 7ms/step - loss: 2.9861e-04 - val_loss: 1.8333e-04
Epoch 7/15
84341/84341 ━━━━━━━━━━━━━━━━━━━━ 554s 7ms/step - loss: 2.7187e-04 - val_loss: 1.8462e-04
Epoch 8/15
84341/84341 ━━━━━━━━━━━━━━━━━━━━ 553s 7ms/step - loss: 2.5878e-04 - val_loss: 1.8666e-04
Epoch 9/15
84341/84341 ━━━━━━━━━━━━━━━━━━━━ 553s 7ms/step - loss: 2.4544e-04 - val_loss: 1.6585e-04
Epoch 10/15
84341/84341 ━━━━━━━━━━━━━━━━━━━━ 554s 7ms/step - loss: 2.3698e-04 - val_loss: 1.6092e-04
Epoch 11/15
84341/84341 ━━━━━━━━━━━━━━━━━━━━ 554s 7ms/step - loss: 2.2830e-04 - val_loss: 1.4338e-04
Epoch 12/15
84341/84341 ━━━━━━━━━━━━━━━━━━━━ 555s 7ms/step - loss: 2.2691e-04 - val_loss: 1.2808e-04
Epoch 13/15
84341/84341 ━━━━━━━━━━━━━━━━━━━━ 555s 7ms/step - loss: 2.2256e-04 - val_loss: 1.4995e-04
Epoch 14/15
84341/84341 ━━━━━━━━━━━━━━━━━━━━ 553s 7ms/step - loss: 2.1305e-04 - val_loss: 1.3580e-04
Epoch 15/15
84341/84341 ━━━━━━━━━━━━━━━━━━━━ 555s 7ms/step - loss: 2.1252e-04 - val_loss: 1.4636e-04
21086/21086 ━━━━━━━━━━━━━━━━━━━━ 40s 2ms/step

Sample Predictions:

Predicted: 0.3090 | Actual: 0.3180
Predicted: 0.1693 | Actual: 0.1680
Predicted: 0.2267 | Actual: 0.2290
Predicted: 0.2589 | Actual: 0.2560
Predicted: 0.1507 | Actual: 0.1480
```

Data Description:

```
# --------------------------------
# Hourly Dataset Inspection
# --------------------------------

print("============ Hourly Dataset Info ============")
display(hourly_df.info())   # data types and missing values

print("Missing values per column:")
display(hourly_df.isnull().sum())

print("\n============ Hourly Dataset Statistics ============")
display(hourly_df.describe())  # check ranges for scaling

# Target columns
target_cols = ['VW_30cm', 'VW_60cm', 'VW_90cm', 'VW_120cm', 'VW_150cm']

print("\nTarget Column Ranges (Hourly):")
display(hourly_df[target_cols].describe())

# --------------------------------
# Feature-target correlation (numeric only)
# --------------------------------

# Select numeric columns
```

```
numeric_cols = hourly_df.select_dtypes(include='number').columns
# Filter target columns that are numeric
target_numeric = [c for c in target_cols if c in numeric_cols]

print("\nFeature-Target Correlation (Hourly, numeric only):")
display(hourly_df[numeric_cols].corr()[target_numeric])

# ------------------------------
# Daily Dataset Safe Check
# ------------------------------

try:
    print("\n============ Daily Dataset Info ============")
    display(daily_df.info())
    print("Missing values per column:")
    display(daily_df.isnull().sum())

    print("\n============ Daily Dataset Statistics ============")
    display(daily_df.describe())
except NameError:
    print("\nDaily dataset not defined. Skipping daily dataset inspection.")
```

Data Cleaning Using Deep Learning:

```
# =====================================
# Final Soil Moisture Cleaning + Daily Aggregation Pipeline
# =====================================

import pandas as pd

def clean_soil_data(df, display_info=True):
    """
    Clean soil moisture dataset:
    - Standardize column names
    - Remove empty/duplicate rows
    - Convert date/time columns to datetime
    - Convert numeric columns
    - Fill missing values
    - Sort by datetime
    """
    # 1. Clean column names
    df.columns = (
        df.columns
        .str.strip()
        .str.lower()
        .str.replace(" ", "_")
        .str.replace(r"[^\w]", "", regex=True)
    )

    # 2. Remove empty rows
    df.dropna(how="all", inplace=True)
```

```
    # 3. Remove duplicate rows
    df.drop_duplicates(inplace=True)

    # 4. Convert time/date columns to datetime
    for col in df.columns:
        if "time" in col or "date" in col:
            df[col] = pd.to_datetime(df[col], errors="coerce")

    # 5. Convert numeric columns
    for col in df.columns:
        if df[col].dtype == "object" and not any(x in col for x in ["date", "time"]):
            df[col] = pd.to_numeric(df[col], errors="coerce")

    # 6. Fill missing values
    df.ffill(inplace=True)
    df.bfill(inplace=True)

    # 7. Sort by datetime if available
    time_cols = [c for c in df.columns if "time" in c or "date" in c]
    if time_cols:
        df.sort_values(by=time_cols[0], inplace=True)

    df.reset_index(drop=True, inplace=True)

    # 8. Display basic info
    if display_info:
        print("Dataset shape:", df.shape)
        display(df.head())
        display(df.describe())
        print("Missing values per column:")
        display(df.isnull().sum())

    return df

# --------------------------------
# 1. Clean hourly dataset
# --------------------------------
hourly_df = clean_soil_data(hourly_df)

# --------------------------------
# 2. Create daily dataset from hourly
# --------------------------------
daily_df = (
    hourly_df
    .groupby('date')  # aggregate by date
    .agg({
        'vw_30cm': 'mean',
        'vw_60cm': 'mean',
        'vw_90cm': 'mean',
        'vw_120cm': 'mean',
        'vw_150cm': 'mean',
        't_30cm': 'mean',
        't_60cm': 'mean',
        't_90cm': 'mean',
        't_120cm': 'mean',
        't_150cm': 'mean',
        'location': 'first'  # take first available location
    })
    .reset_index()
)

# 3. Clean daily dataset safely
daily_df = clean_soil_data(daily_df)

# --------------------------------
# 4. Check target column ranges
# --------------------------------
target_cols_hourly = [c for c in hourly_df.columns if "vw" in c]
print("\nTarget column ranges (hourly):")
display(hourly_df[target_cols_hourly].describe())

target_cols_daily = [c for c in daily_df.columns if "vw" in c]
print("\nTarget column ranges (daily):")
display(daily_df[target_cols_daily].describe())
```

	VW_30cm	VW_60cm	VW_90cm	VW_120cm	VW_150cm
VW_30cm	1.000000	0.633828	0.447626	0.296804	0.271748

VW_60cm	0.622828	1.000000	0.589014	0.413713	0.441001
VW_90cm	0.447626	0.589014	1.000000	0.567232	0.434157
VW_120cm	0.296894	0.413713	0.567232	1.000000	0.601593
VW_150cm	0.271748	0.441001	0.434157	0.601593	1.000000
T_30cm	-0.458444	-0.198398	-0.114729	-0.071585	-0.012161
T_60cm	-0.477233	-0.329577	-0.203701	-0.089300	-0.051118
T_90cm	-0.500717	-0.347875	-0.275006	-0.084795	-0.062489
T_120cm	-0.490649	-0.311372	-0.200535	-0.171390	-0.118136
T_150cm	-0.505099	-0.368610	-0.280439	-0.162056	-0.193205

```
============ Daily Dataset Info ============

Daily dataset not defined. Skipping daily dataset inspection.
```

```
Dataset shape: (3372768, 13)
```

	location	date	time	vw_30cm	vw_60cm	vw_90cm	vw_120cm	vw_150cm	t_30cm	t_60cm	t_90cm	t_120cm	t_150cm
0	NaN	2007-04-20	2026-02-14 00:00:00	0.394	0.420	0.232	0.151	0.185	16.0	9.9	8.5	8.0	7.8
1	NaN	2007-04-20	2026-02-14 20:00:00	0.191	0.221	0.217	0.223	0.132	13.1	15.5	12.2	11.8	8.0
2	NaN	2007-04-20	2026-02-14 21:00:00	0.191	0.221	0.217	0.223	0.132	13.1	15.5	12.2	11.8	8.0
3	NaN	2007-04-20	2026-02-14 22:00:00	0.191	0.221	0.217	0.223	0.132	13.1	15.5	12.2	11.8	8.0
4	NaN	2007-04-20	2026-02-14 23:00:00	0.191	0.221	0.217	0.223	0.132	13.1	15.5	12.2	11.8	8.0

	location	date	time	vw_30cm	vw_60cm	vw_90cm	vw_120cm	vw_150cm	t_30cm	
count	0.0	3372768	3372768	3.372768e+06	3.372768e+06	3.372768e+06	3.372768e+06	3.372768e+06	3.372768e+06	3
mean	NaN	2011-11-17 12:00:00	2026-02-14 11:29:59.999997952	2.552551e-01	2.910813e-01	3.136591e-01	3.355885e-01	3.469931e-01	1.176521e+01	1
min	NaN	2007-04-20 00:00:00	2026-02-14 00:00:00	7.700000e-02	4.000000e-03	6.100000e-02	9.300000e-02	7.400000e-02	-9.100000e+00	-7
25%	NaN	2009-08-03 00:00:00	2026-02-14 05:45:00	2.050000e-01	2.180000e-01	2.360000e-01	2.580000e-01	2.760000e-01	5.600000e+00	6
50%	NaN	2011-11-17 12:00:00	2026-02-14 11:30:00	2.370000e-01	2.830000e-01	3.110000e-01	3.400000e-01	3.460000e-01	1.310000e+01	1
75%	NaN	2014-03-03 00:00:00	2026-02-14 17:15:00	3.050000e-01	3.530000e-01	3.970000e-01	4.060000e-01	4.150000e-01	1.740000e+01	1
max	NaN	2016-06-16 00:00:00	2026-02-14 23:00:00	1.010000e+00	6.520000e-01	6.090000e-01	6.310000e-01	6.140000e-01	2.900000e+01	2
std	NaN	NaN	NaN	7.486343e-02	9.471589e-02	9.486317e-02	9.388905e-02	9.505713e-02	6.505893e+00	5

```
Missing values per column:
location    3372768
date              0
time              0
vw_30cm           0
vw_60cm           0
vw_90cm           0
vw_120cm          0
vw_150cm          0
t_30cm            0
t_60cm            0
t_90cm            0
t_120cm           0
t_150cm           0
dtype: int64
Dataset shape: (3346, 12)
```

	date	vw_30cm	vw_60cm	vw_90cm	vw_120cm	vw_150cm	t_30cm	t_60cm	t_90cm	t_120cm	t_150cm	location
0	2007-04-20	0.235770	0.292321	0.325345	0.346498	0.351891	12.867560	12.531151	12.013988	11.191071	10.821726	NaN
1	2007-04-21	0.239368	0.296035	0.327103	0.349431	0.353853	12.782837	12.426885	11.985913	11.106944	10.778571	NaN
2	2007-04-22	0.239236	0.295967	0.327097	0.349429	0.353855	12.794246	12.431052	11.988095	11.107143	10.778770	NaN

Data Pre-Processing:

```
# ======================================
# Soil Moisture Dataset Pre-Processing (DL-Ready)
# ======================================

import numpy as np
import pandas as pd
from sklearn.preprocessing import StandardScaler

def preprocess_soil_data(df):
    """
    Preprocess soil moisture dataset for deep learning.

    Steps:
    1. Extract time features (year, month, day, hour) if datetime column exists
```

```
    2. Select numeric columns
    3. Handle remaining NaNs (fill with median)
    4. Clip outliers using Interquartile Range (IQR)
    5. Remove constant columns (zero variance)
    6. Scale numeric features using StandardScaler

    Returns:
    - df: processed dataframe
    - numeric_cols: list of numeric columns used
    - scaler: fitted StandardScaler
    """
    df = df.copy()

    # 1. Identify datetime column
    time_cols = [c for c in df.columns if "time" in c.lower() or "date" in c.lower()]
    time_col = time_cols[0] if time_cols else None

    # 2. Extract time-based features
    if time_col:
        df["year"]  = df[time_col].dt.year
        df["month"] = df[time_col].dt.month
        df["day"]   = df[time_col].dt.day
        df["hour"]  = df[time_col].dt.hour

    # 3. Select numeric columns
    numeric_cols = df.select_dtypes(include=["int64", "float64"]).columns.tolist()

    # 4. Handle NaNs by filling with column median
    df[numeric_cols] = df[numeric_cols].fillna(df[numeric_cols].median())

    # 5. Clip outliers using IQR
    for col in numeric_cols:
        Q1 = df[col].quantile(0.25)
        Q3 = df[col].quantile(0.75)
        IQR = Q3 - Q1
        lower = Q1 - 1.5 * IQR
        upper = Q3 + 1.5 * IQR
        df[col] = np.clip(df[col], lower, upper)

    # 6. Remove constant columns (zero variance)
    constant_cols = [col for col in numeric_cols if df[col].nunique() <= 1]
    numeric_cols = [col for col in numeric_cols if col not in constant_cols]

    # 7. Scale numeric features
    scaler = StandardScaler()
    df[numeric_cols] = scaler.fit_transform(df[numeric_cols])

    return df, numeric_cols, scaler

# ----------------------------
# Apply preprocessing
# ----------------------------
hourly_processed, hourly_numeric, hourly_scaler = preprocess_soil_data(hourly_df)
daily_processed, daily_numeric, daily_scaler = preprocess_soil_data(daily_df)

# ----------------------------
# Check results
# ----------------------------
print("Hourly processed shape:", hourly_processed.shape)
print("Daily processed shape:", daily_processed.shape)

display(hourly_processed.head())
display(daily_processed.head())
```

```
Hourly processed shape: (3372768, 17)
Daily processed shape: (3346, 16)
```

	location	date	time	vw_30cm	vw_60cm	vw_90cm	vw_120cm	vw_150cm	t_30cm	t_60cm	t_90cm	t_120cm	t_150cm
0	NaN	2007-04-20	2026-02-14 00:00:00	1.926774	1.366398	-0.860809	-1.966516	-1.704166	0.650917	-0.242034	-0.503143	-0.662508	-0.746527
1	NaN	2007-04-20	2026-02-14 20:00:00	-0.878292	-0.741459	-1.018932	-1.199426	-2.261726	0.205167	0.807887	0.304837	0.306235	-0.689633
2	NaN	2007-04-20	2026-02-14 21:00:00	-0.878292	-0.741459	-1.018932	-1.199426	-2.261726	0.205167	0.807887	0.304837	0.306235	-0.689633
3	NaN	2007-04-20	2026-02-14 22:00:00	-0.878292	-0.741459	-1.018932	-1.199426	-2.261726	0.205167	0.807887	0.304837	0.306235	-0.689633
4	NaN	2007-04-20	2026-02-14 23:00:00	-0.878292	-0.741459	-1.018932	-1.199426	-2.261726	0.205167	0.807887	0.304837	0.306235	-0.689633

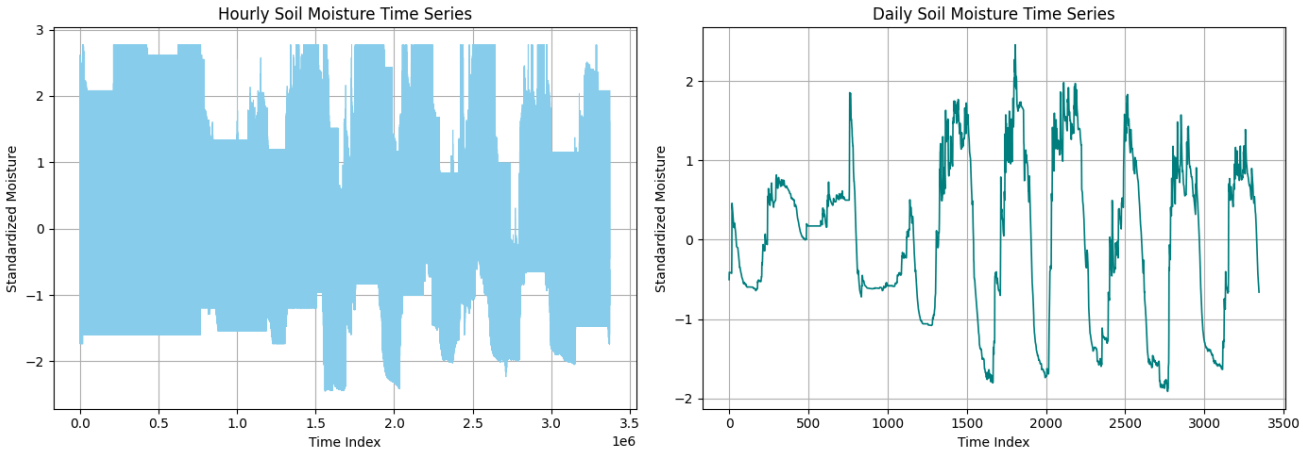
	date	vw_30cm	vw_60cm	vw_90cm	vw_120cm	vw_150cm	t_30cm	t_60cm	t_90cm	t_120cm	t_150cm	location	year	month
0	2007-04-20	-0.502782	0.026599	0.272227	0.292149	0.159540	0.213302	0.315028	0.338054	0.196952	0.162608	NaN	2007	4
1	2007-04-21	-0.409936	0.106245	0.313177	0.370681	0.223461	0.196909	0.290519	0.330210	0.168979	0.144894	NaN	2007	4
2	2007-04-22	-0.410756	0.104798	0.313039	0.370654	0.223525	0.199116	0.291499	0.330820	0.169045	0.144976	NaN	2007	4
3	2007-04-23	-0.411088	0.103905	0.313270	0.370681	0.223590	0.201420	0.292618	0.331346	0.169078	0.145872	NaN	2007	4
4	2007-04-24	-0.412394	0.102926	0.313177	0.370920	0.223525	0.204107	0.294087	0.332095	0.169836	0.145872	NaN	2007	4

Deep Learning EDA:

```
# ======================================
# Time-Series EDA for Deep Learning: Hourly vs Daily
# ======================================

import matplotlib.pyplot as plt

# ---------- Function to pick a numeric sensor column ----------
def pick_sensor(df, numeric_cols):
    """
    Pick the first numeric sensor column (excluding time features)
    from preprocessed numeric columns.
    """
    for col in numeric_cols:
        if col not in ["year", "month", "day", "hour"]:
            return col
    raise ValueError("No numeric sensor column found")

# ---------- Pick representative sensors ----------
hourly_sensor = pick_sensor(hourly_processed, hourly_numeric)
daily_sensor  = pick_sensor(daily_processed, daily_numeric)

print("Hourly sensor used:", hourly_sensor)
print("Daily sensor used :", daily_sensor)

# ---------- Side-by-side time series plot ----------
plt.figure(figsize=(14, 5))

# Hourly data
plt.subplot(1, 2, 1)
plt.plot(hourly_processed[hourly_sensor], linewidth=0.6, color='skyblue')
plt.title("Hourly Soil Moisture Time Series")
plt.xlabel("Time Index")
plt.ylabel("Standardized Moisture")
plt.grid(True)
```

```
# Daily data
plt.subplot(1, 2, 2)
plt.plot(daily_processed[daily_sensor], linewidth=1.2, color='teal')
plt.title("Daily Soil Moisture Time Series")
plt.xlabel("Time Index")
plt.ylabel("Standardized Moisture")
plt.grid(True)

plt.tight_layout()
plt.show()

# ---------- Optional: summary statistics ----------
print("\nHourly sensor statistics:")
display(hourly_processed[hourly_sensor].describe())

print("\nDaily sensor statistics:")
display(daily_processed[daily_sensor].describe())
```

```
Hourly sensor used: vw_30cm
Daily sensor used : vw_30cm
```



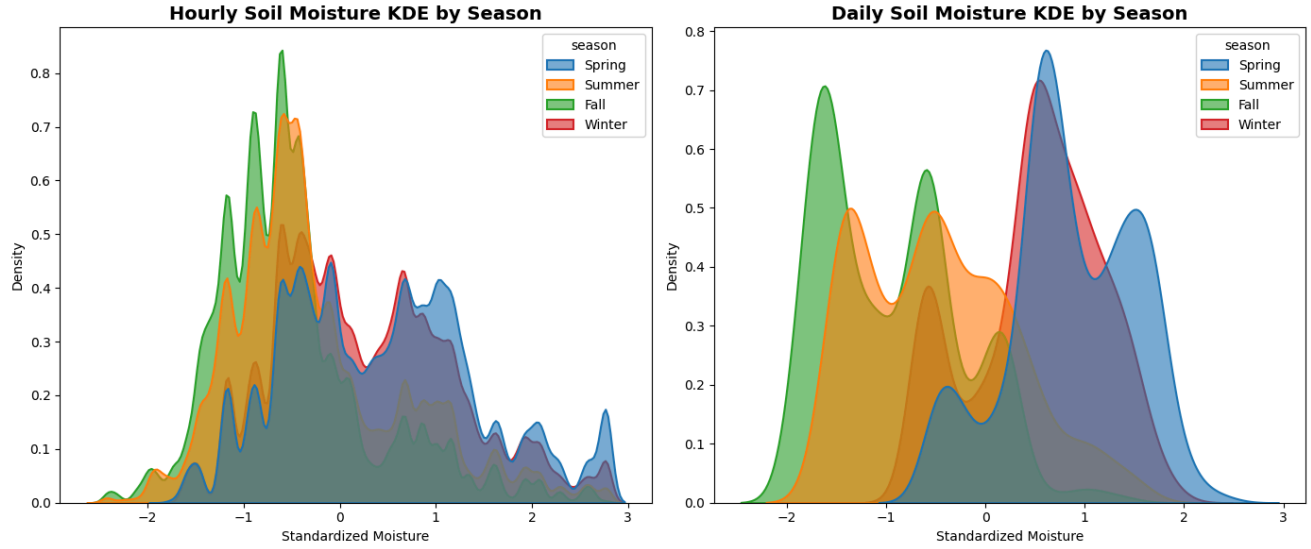

```
Hourly sensor statistics:
count    3.372768e+06
mean     1.063937e-15
std      1.000000e+00
min     -2.453550e+00
25%     -6.848388e-01
50%     -2.426610e-01
75%      6.969668e-01
max      2.769675e+00
Name: vw_30cm, dtype: float64

Daily sensor statistics:
count    3.346000e+03
mean     2.633213e-16
std      1.000149e+00
min     -1.911765e+00
25%     -6.310037e-01
50%      1.266431e-01
75%      7.476396e-01
max      2.455541e+00
Name: vw_30cm, dtype: float64
```

DL-Friendly KDE Plots: Soil Moisture by Season

```
import matplotlib.pyplot as plt
import seaborn as sns

# ---------- Function to pick a numeric sensor column ----------
def pick_sensor(df, numeric_cols):
    """
    Pick the first numeric sensor column (excluding time features)
    """
    for col in numeric_cols:
```

```
            if col not in ["year", "month", "day", "hour"]:
                return col
        raise ValueError("No numeric sensor column found")

    # Pick representative sensors
    hourly_sensor = pick_sensor(hourly_processed, hourly_numeric)
    daily_sensor  = pick_sensor(daily_processed, daily_numeric)

    print("Hourly sensor used:", hourly_sensor)
    print("Daily sensor used :", daily_sensor)

    # ---------- Map months to seasons ----------
    def month_to_season(month):
        if month in [12, 1, 2]:
            return "Winter"
        elif month in [3, 4, 5]:
            return "Spring"
        elif month in [6, 7, 8]:
            return "Summer"
        else:
            return "Fall"

    hourly_processed["season"] = hourly_processed["month"].apply(month_to_season)
    daily_processed["season"]  = daily_processed["month"].apply(month_to_season)

    # ---------- KDE Plots ----------
    plt.figure(figsize=(14, 6))

    # Hourly KDE
    plt.subplot(1, 2, 1)
    sns.kdeplot(
        data=hourly_processed,
        x=hourly_sensor,
        hue="season",
        fill=True,
        common_norm=False,
        alpha=0.6,
        linewidth=1.5
    )
    plt.title("Hourly Soil Moisture KDE by Season", fontsize=14, fontweight='bold')
    plt.xlabel("Standardized Moisture")
    plt.ylabel("Density")

    # Daily KDE
    plt.subplot(1, 2, 2)
    sns.kdeplot(
        data=daily_processed,
        x=daily_sensor,
        hue="season",
        fill=True,
        common_norm=False,
        alpha=0.6,
        linewidth=1.5
    )
    plt.title("Daily Soil Moisture KDE by Season", fontsize=14, fontweight='bold')
    plt.xlabel("Standardized Moisture")
    plt.ylabel("Density")

    plt.tight_layout()
    plt.show()
```

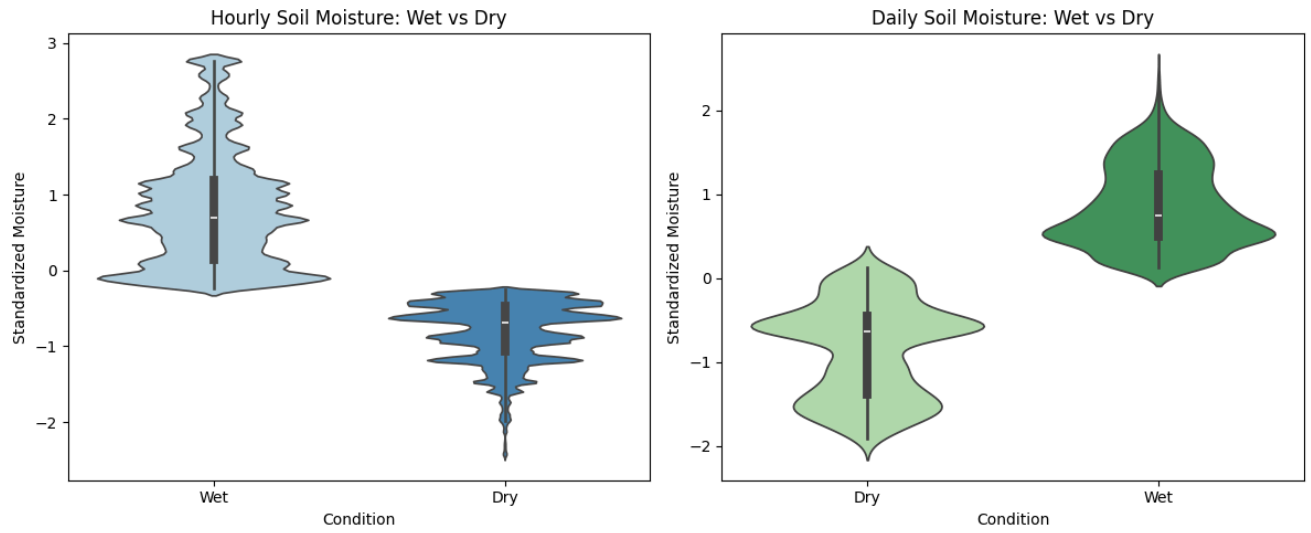
```
Hourly sensor used: vw_30cm
Daily sensor used : vw_30cm
```



Violin Plot: Wet vs Dry Periods

```
import matplotlib.pyplot as plt
import seaborn as sns

# Function to pick a numeric sensor column
def pick_sensor(df, numeric_cols):
    for col in numeric_cols:
        if col not in ["year", "month", "day", "hour"]:
            return col
    raise ValueError("No numeric sensor column found")

# Select representative sensors
hourly_sensor = pick_sensor(hourly_processed, hourly_numeric)
daily_sensor  = pick_sensor(daily_processed, daily_numeric)

# Label wet vs dry
def label_wet_dry(df, sensor):
    median_val = df[sensor].median()
    return df[sensor].apply(lambda x: "Wet" if x >= median_val else "Dry")

hourly_processed["wet_dry"] = label_wet_dry(hourly_processed, hourly_sensor)
daily_processed["wet_dry"]  = label_wet_dry(daily_processed, daily_sensor)

# Plot
plt.figure(figsize=(12, 5))

plt.subplot(1, 2, 1)
sns.violinplot(
    x="wet_dry",
    y=hourly_sensor,
    hue="wet_dry",
    data=hourly_processed,
    palette="Blues",
    dodge=False,
    legend=False
)
plt.title("Hourly Soil Moisture: Wet vs Dry")
plt.xlabel("Condition")
plt.ylabel("Standardized Moisture")

plt.subplot(1, 2, 2)
sns.violinplot(
    x="wet_dry",
    y=daily_sensor,
    hue="wet_dry",
    data=daily_processed,
```

```
    palette="Greens",
    dodge=False,
    legend=False
)
plt.title("Daily Soil Moisture: Wet vs Dry")
plt.xlabel("Condition")
plt.ylabel("Standardized Moisture")

plt.tight_layout()
plt.show()
```

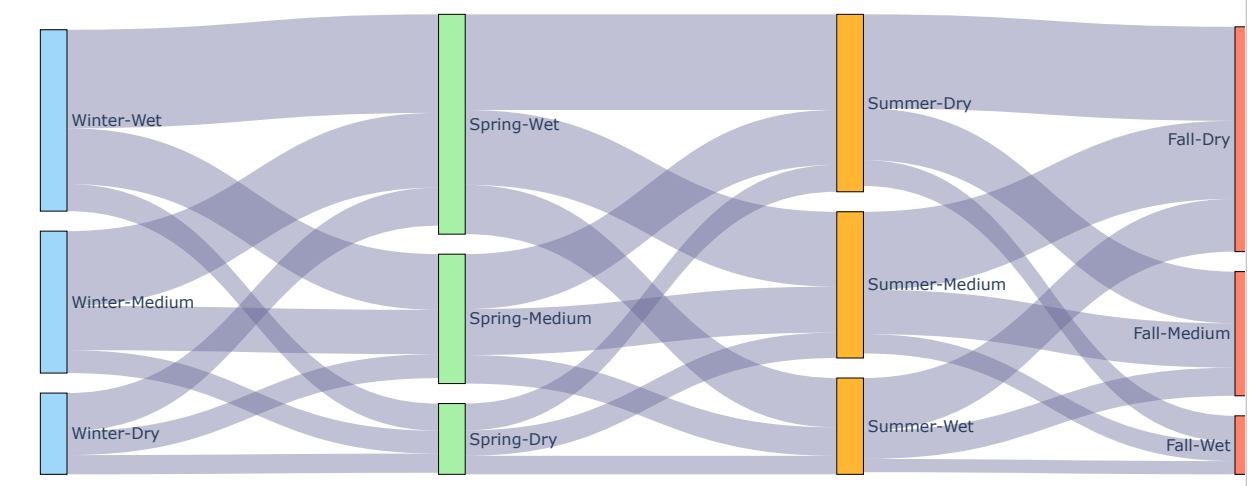


Sankey Diagram: Wet / Medium / Dry Across 4 Seasons

```
# =====================================
# Sankey Diagram: Wet / Medium / Dry Across 4 Seasons (DL-ready)
# =====================================

import pandas as pd
import plotly.graph_objects as go

# -------------------------------
# Helper functions
# -------------------------------

def pick_sensor(df, target_cols=None):
    """
    Pick a sensor (VW depth) automatically.
    By default, pick the first target column if not specified.
    """
    if target_cols is None:
        target_cols = [c for c in df.columns if "vw" in c]
    if not target_cols:
        raise ValueError("No VW target columns found in dataframe.")
    return target_cols[0]  # pick the first VW column

def month_to_season(month):
    """
    Convert month number (1-12) to meteorological season.
    """
    if month in [12, 1, 2]:
        return "Winter"
    elif month in [3, 4, 5]:
        return "Spring"
    elif month in [6, 7, 8]:
        return "Summer"
    elif month in [9, 10, 11]:
        return "Fall"
    else:
        return "Unknown"
```

```
# --------------------------------
# Prepare dataframe
# --------------------------------

df = hourly_df.copy()  # Use cleaned hourly_df

# Ensure month column exists
df["month"] = df["date"].dt.month

# Pick sensor automatically
sensor = pick_sensor(df)

# --------------------------------
# Categorize soil moisture
# --------------------------------
q1 = df[sensor].quantile(0.33)
q2 = df[sensor].quantile(0.66)

def moisture_category(x):
    if x <= q1:
        return "Dry"
    elif x <= q2:
        return "Medium"
    else:
        return "Wet"

df["moisture_cat"] = df[sensor].apply(moisture_category)

# --------------------------------
# Assign seasons
# --------------------------------
df["season"] = df["month"].apply(month_to_season)

# --------------------------------
# Build source → target pairs for Sankey
# --------------------------------
season_order = ["Winter", "Spring", "Summer", "Fall"]
pairs = []

for i in range(len(season_order)-1):
    s1 = season_order[i]
    s2 = season_order[i+1]

    df_s1 = df[df["season"] == s1].reset_index()
    df_s2 = df[df["season"] == s2].reset_index()

    min_len = min(len(df_s1), len(df_s2))
    for c1, c2 in zip(df_s1["moisture_cat"].iloc[:min_len],
                      df_s2["moisture_cat"].iloc[:min_len]):
        pairs.append((f"{s1}-{c1}", f"{s2}-{c2}"))

# Count occurrences
flow_counts = pd.Series(pairs).value_counts()

# --------------------------------
# Define Sankey nodes & links
# --------------------------------
labels = list(set([x[0] for x in flow_counts.index] + [x[1] for x in flow_counts.index]))
label_idx = {l:i for i,l in enumerate(labels)}

source = [label_idx[x[0]] for x in flow_counts.index]
target = [label_idx[x[1]] for x in flow_counts.index]
value  = flow_counts.values

# Node colors by season
season_colors = {
    "Winter": "rgba(135,206,250,0.8)",   # Light Blue
    "Spring": "rgba(144,238,144,0.8)",   # Light Green
    "Summer": "rgba(255,165,0,0.8)",     # Orange
    "Fall":   "rgba(255,99,71,0.8)"      # Tomato Red
}

node_colors = [season_colors.get(label.split("-")[0], "lightgray") for label in labels]

# --------------------------------
# Plot Sankey diagram
# --------------------------------
```

```
fig = go.Figure(data=[go.Sankey(
    node=dict(
        pad=15,
        thickness=20,
        line=dict(color="black", width=0.5),
        label=labels,
        color=node_colors
    ),
    link=dict(
        source=source,
        target=target,
        value=value,
        color="rgba(100,100,150,0.4)"  # Slightly transparent
    )
)])

fig.update_layout(title_text=f"Seasonal Soil Moisture Flow ({sensor}): Dry / Medium / Wet", font_size=12)
fig.show()
```



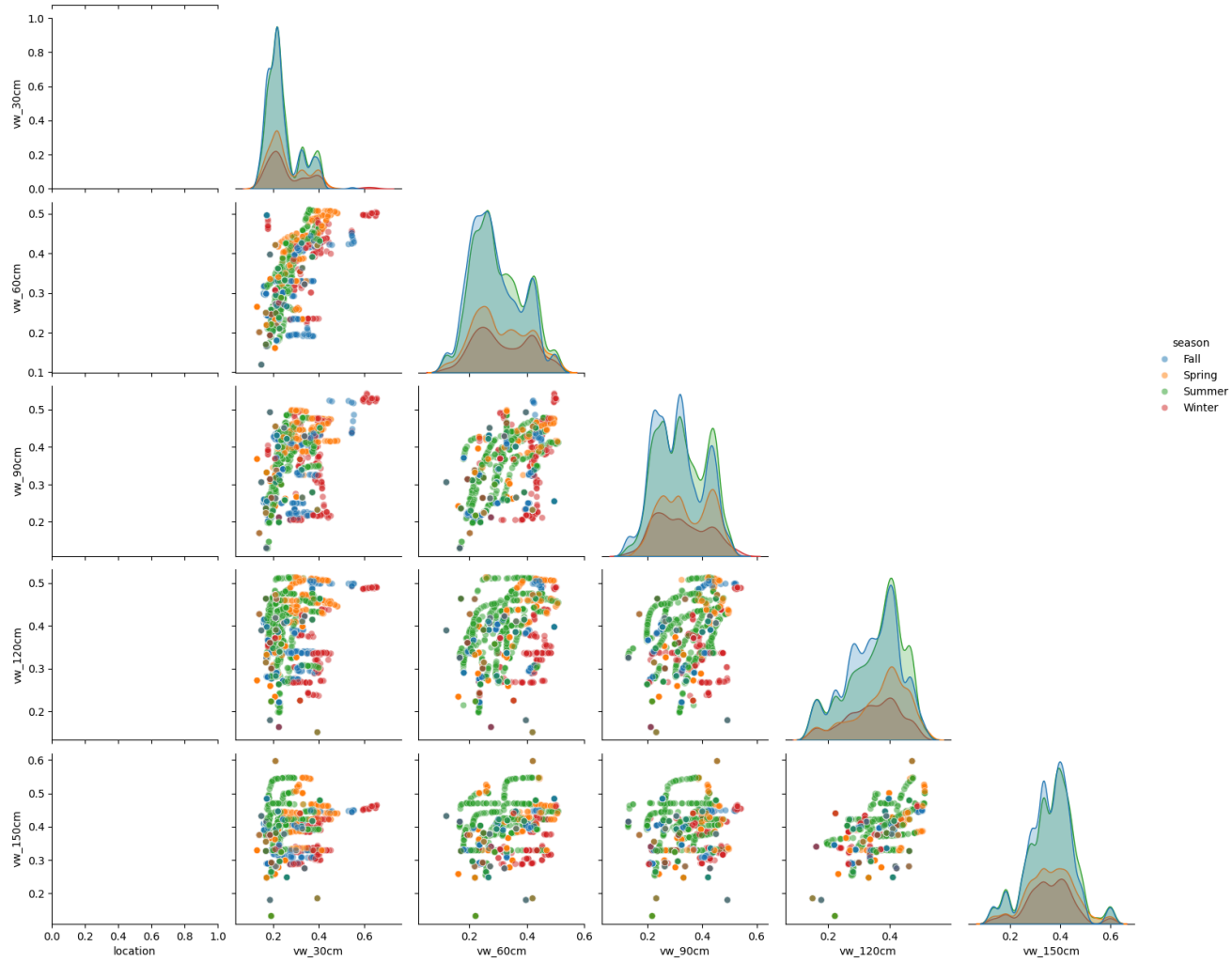
Year-wise Seasonal Pair Plots for Top Sensors (DL-ready)

```
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd

# ------------------------------
# Prepare DataFrame
# ------------------------------
df = hourly_df.copy()  # Use cleaned DL-ready hourly dataset

# Ensure 'month' column exists
if "month" not in df.columns:
    df["month"] = df["date"].dt.month

# Assign seasons
def month_to_season(m):
    if m in [12, 1, 2]:
        return "Winter"
    elif m in [3, 4, 5]:
        return "Spring"
    elif m in [6, 7, 8]:
        return "Summer"
    else:
        return "Fall"
```

```
df["season"] = df["month"].apply(month_to_season)

# Ensure 'year' column exists
if "year" not in df.columns:
    df["year"] = df["date"].dt.year

# --------------------------------
# Detect sensor columns
# --------------------------------
def get_sensor_columns(df):
    """
    Select numeric columns suitable as sensors (exclude date/time columns)
    """
    exclude = ["year", "month", "day", "hour", "minute", "second"]
    return [c for c in df.columns if df[c].dtype in ["int64", "float64"]
            and all(e not in c.lower() for e in exclude)]

sensor_cols = get_sensor_columns(df)

# Limit to top 6 sensors for speed
if len(sensor_cols) > 6:
    sensor_cols = sensor_cols[:6]

print("Sensor columns used for pair plots:", sensor_cols)

# --------------------------------
# Loop through each year and plot
# --------------------------------
years = sorted(df["year"].unique())

for yr in years:
    df_year = df[df["year"] == yr]

    # Sample to reduce plotting time (max 10,000 rows)
    df_sample = df_year.sample(n=min(10000, len(df_year)), random_state=42)

    plt.figure(figsize=(12, 12))
    sns.pairplot(
        df_sample,
        vars=sensor_cols,
        hue="season",
        diag_kind="kde",
        corner=True,
        plot_kws={'alpha': 0.5}
    )
    plt.suptitle(f"Year-wise Seasonal Pair Plot: {yr}", y=1.02, fontsize=16)
    plt.show()
```

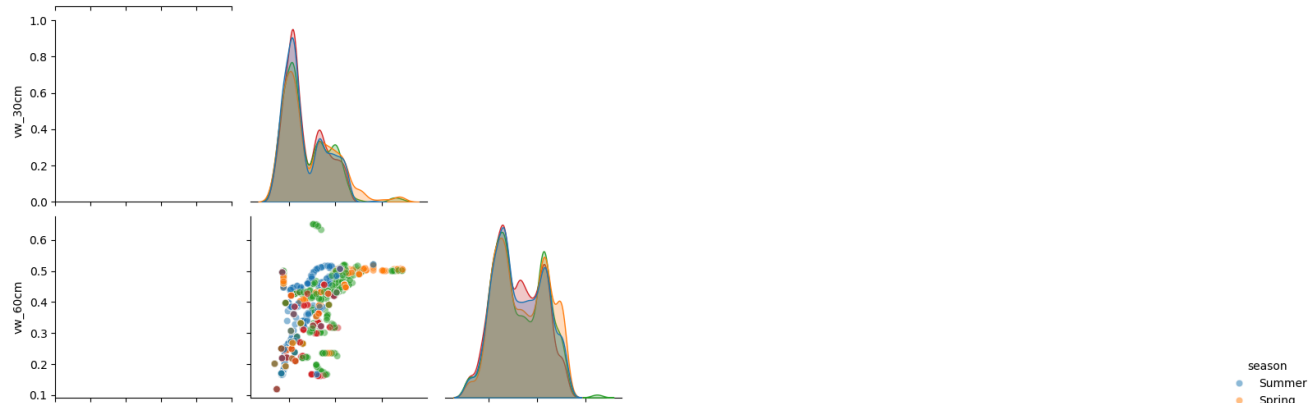
```
Sensor columns used for pair plots: ['location', 'vw_30cm', 'vw_60cm', 'vw_90cm', 'vw_120cm', 'vw_150cm']
<Figure size 1200x1200 with 0 Axes>
```

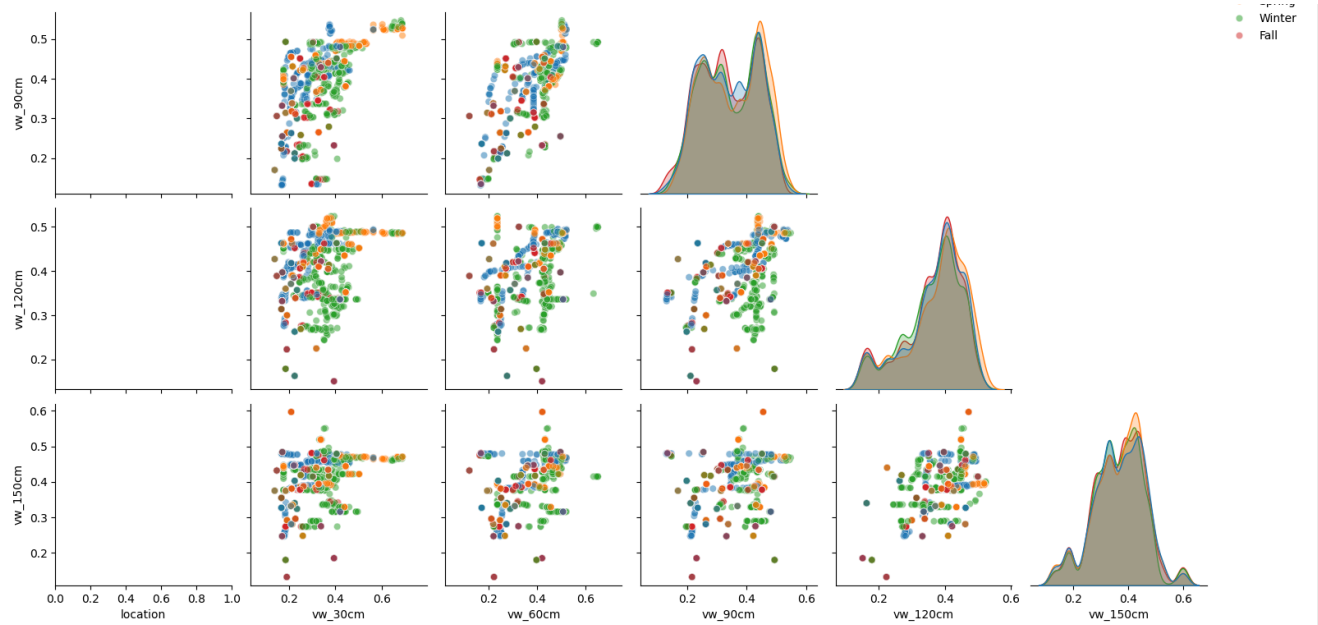
Year-wise Seasonal Pair Plot: 2007




```
<Figure size 1200x1200 with 0 Axes>
```

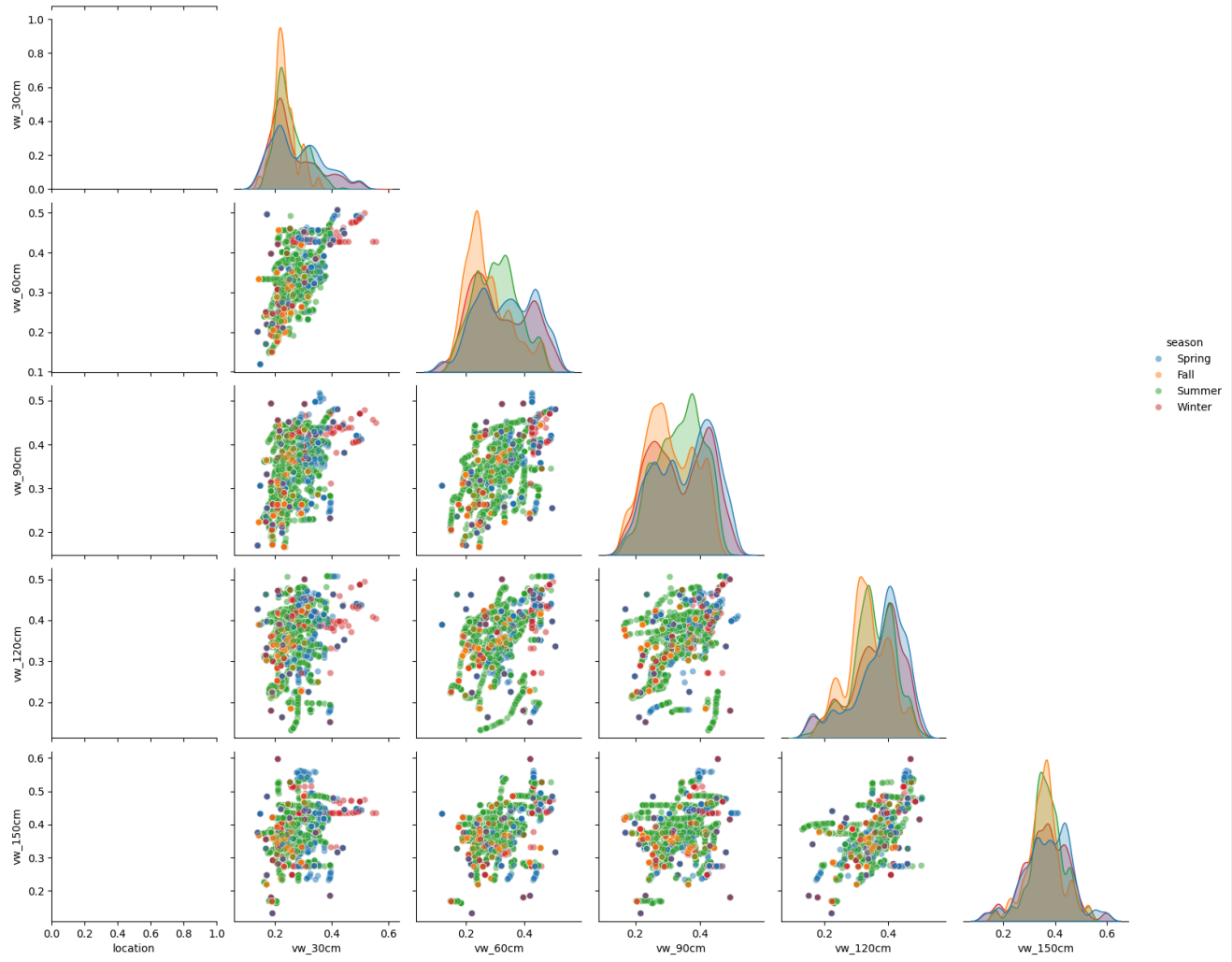
Year-wise Seasonal Pair Plot: 2008





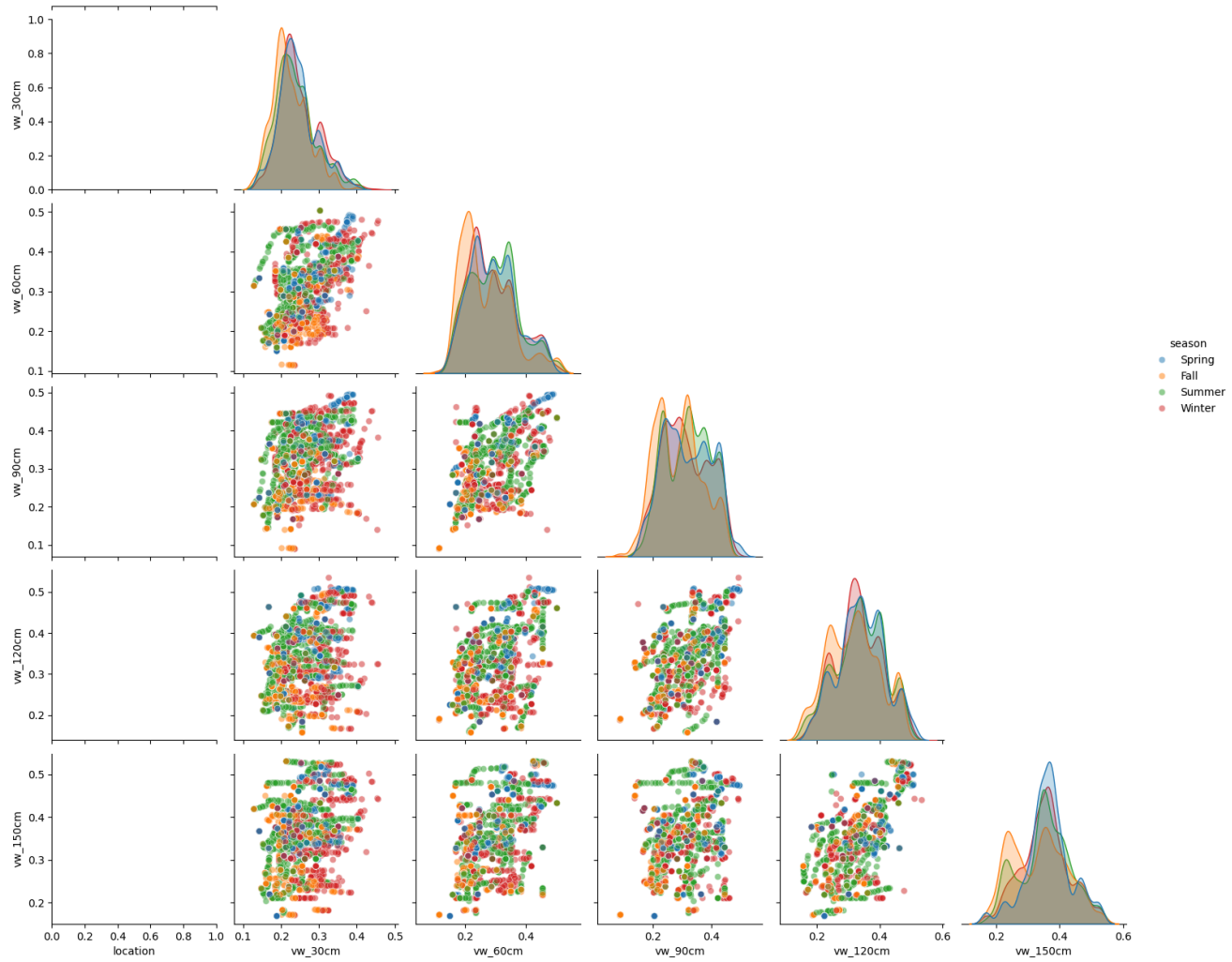
<Figure size 1200x1200 with 0 Axes>

Year-wise Seasonal Pair Plot: 2009



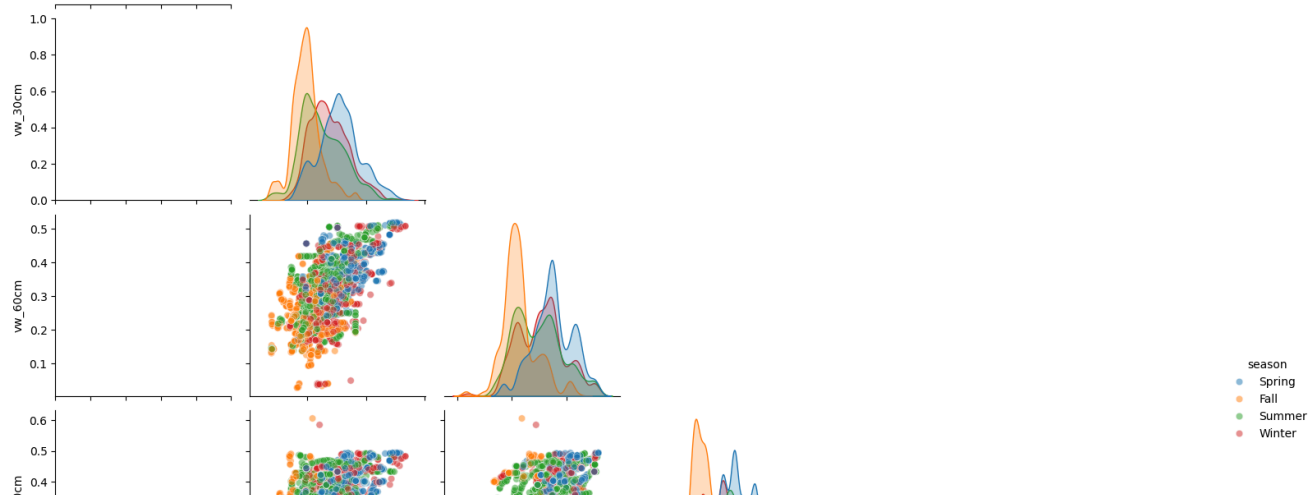
<Figure size 1200x1200 with 0 Axes>

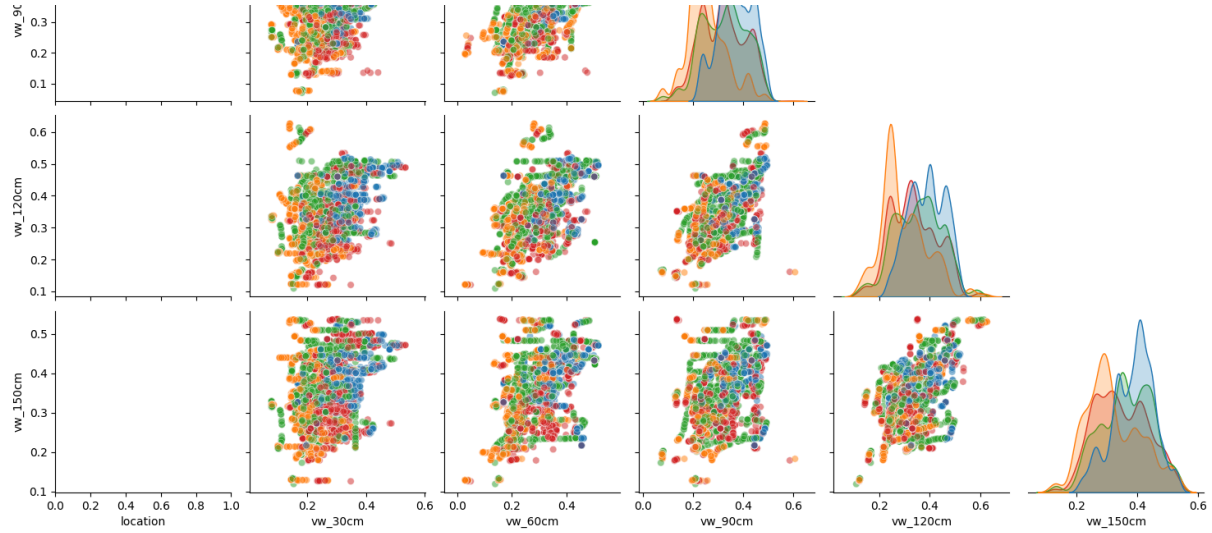
Year-wise Seasonal Pair Plot: 2010




```
<Figure size 1200x1200 with 0 Axes>
```

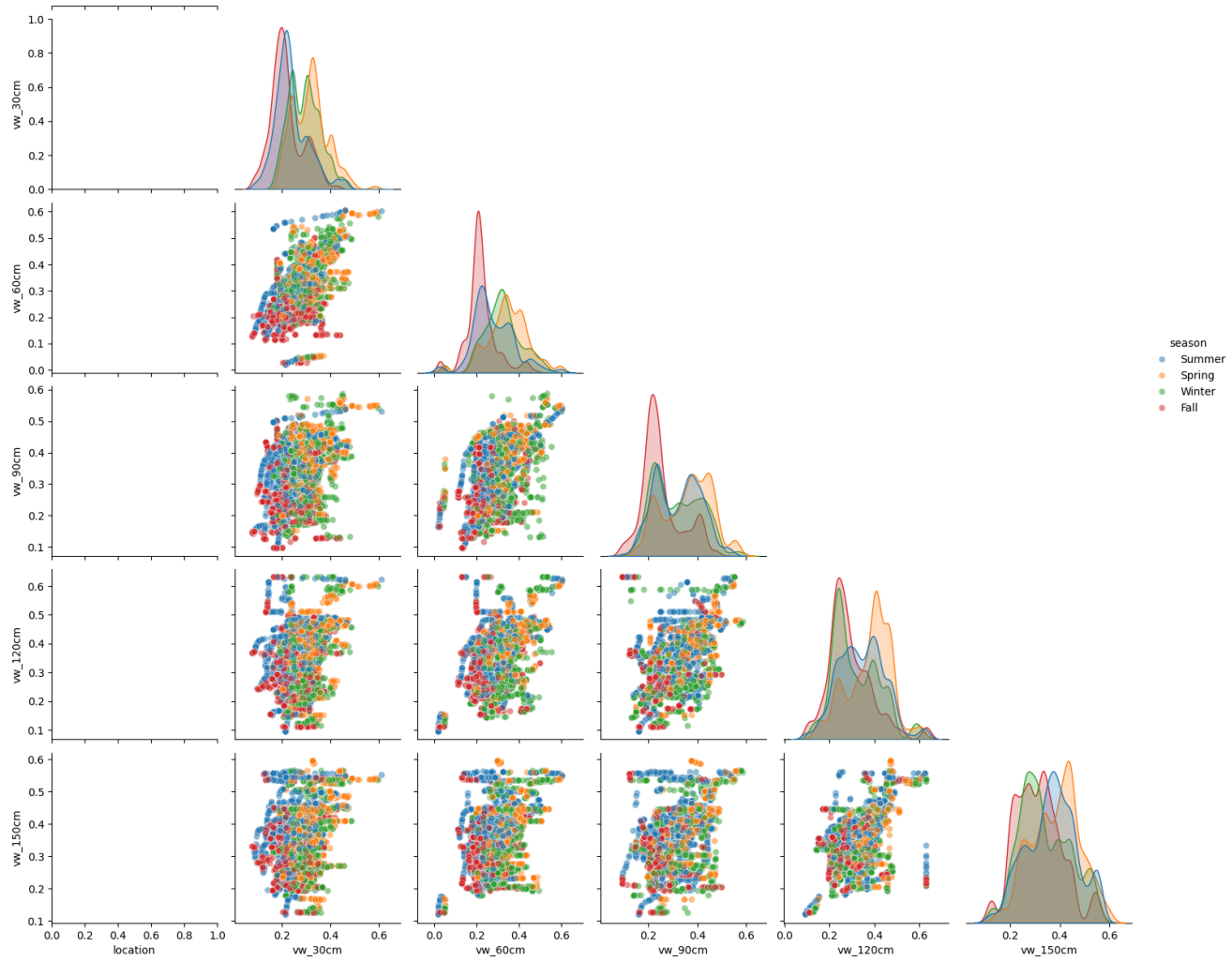
Year-wise Seasonal Pair Plot: 2011





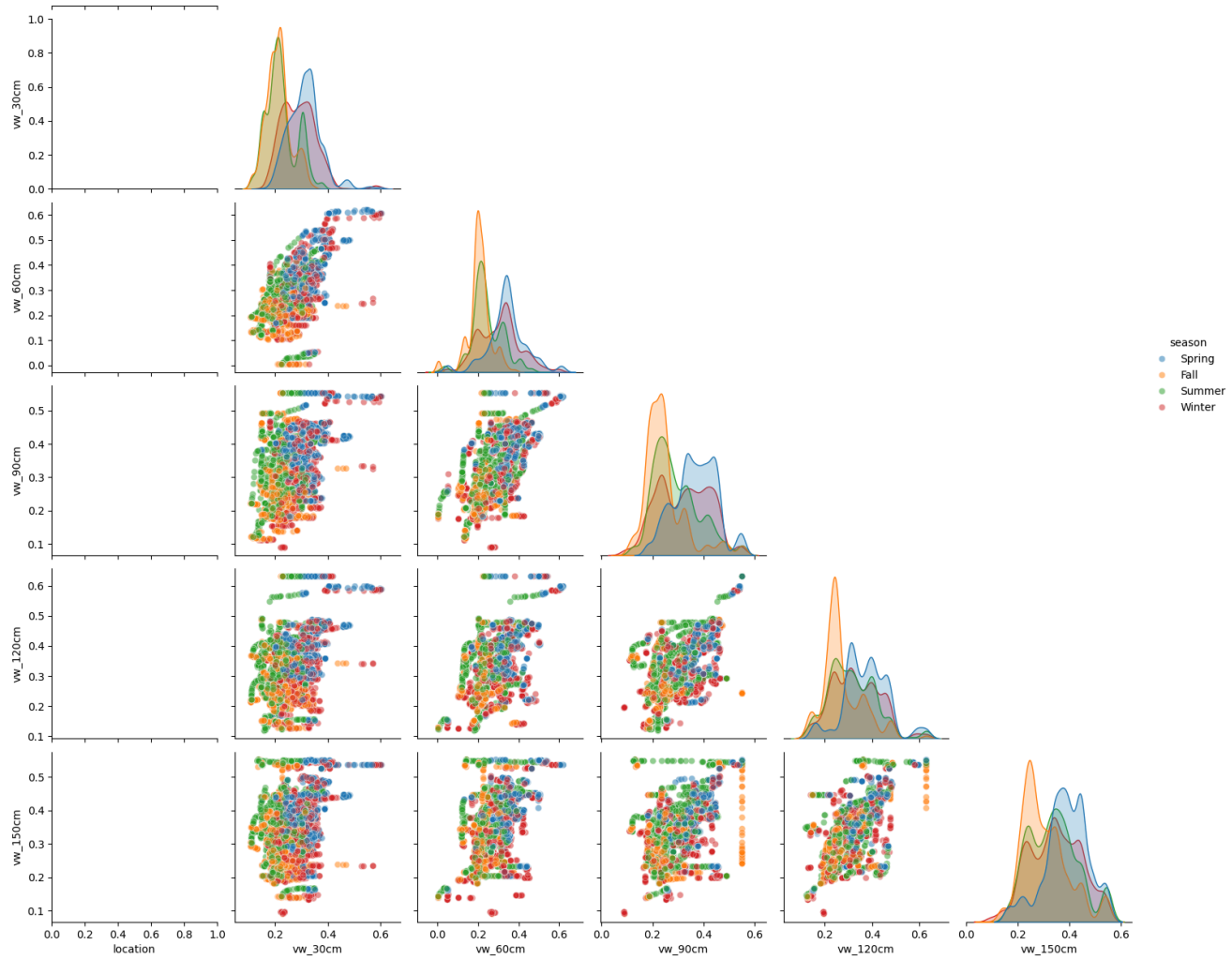

```
<Figure size 1200x1200 with 0 Axes>
```

Year-wise Seasonal Pair Plot: 2012



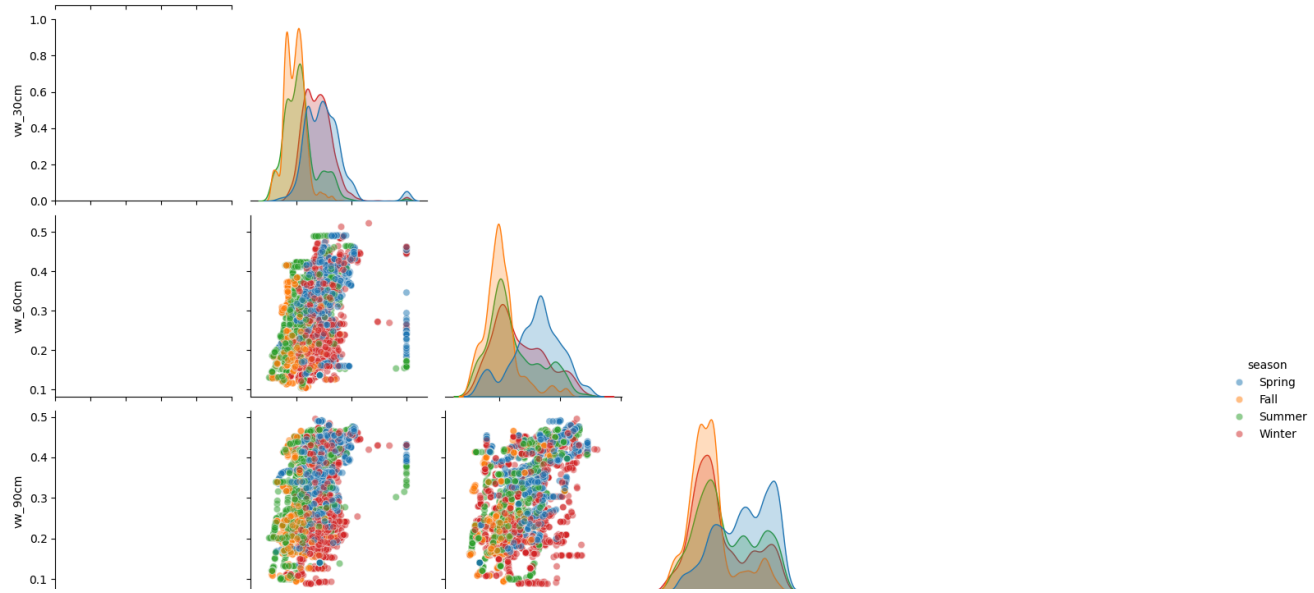

```
<Figure size 1200x1200 with 0 Axes>
```

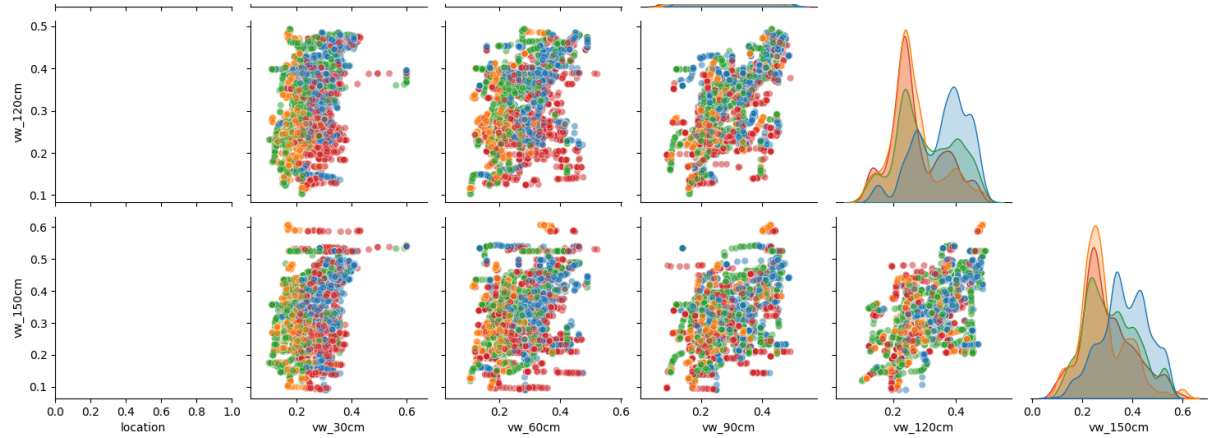
Year-wise Seasonal Pair Plot: 2013




```
<Figure size 1200x1200 with 0 Axes>
```

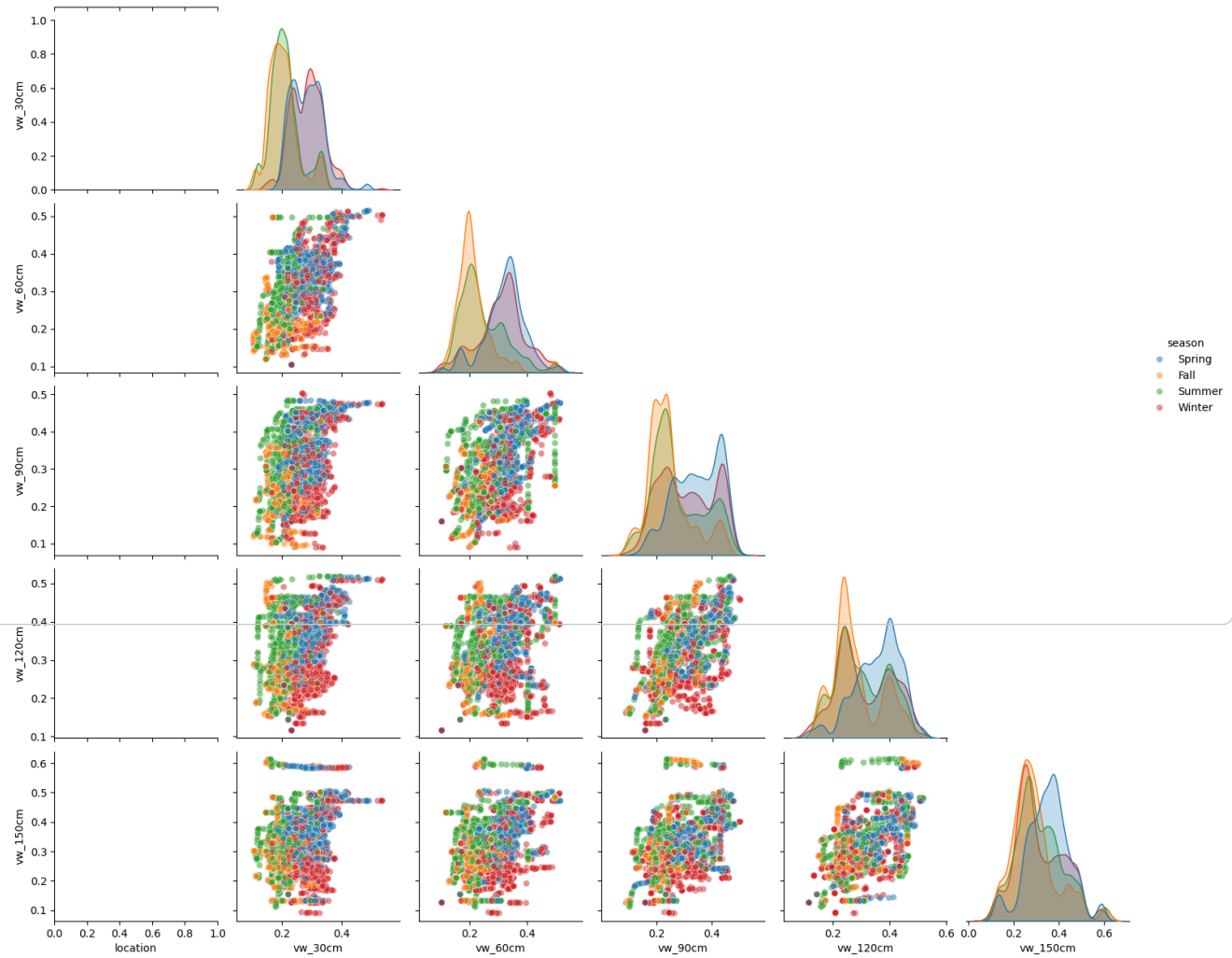
Year-wise Seasonal Pair Plot: 2014






```
<Figure size 1200x1200 with 0 Axes>
```

Year-wise Seasonal Pair Plot: 2015




```
<Figure size 1200x1200 with 0 Axes>
```

Year-wise Seasonal Pair Plot: 2016

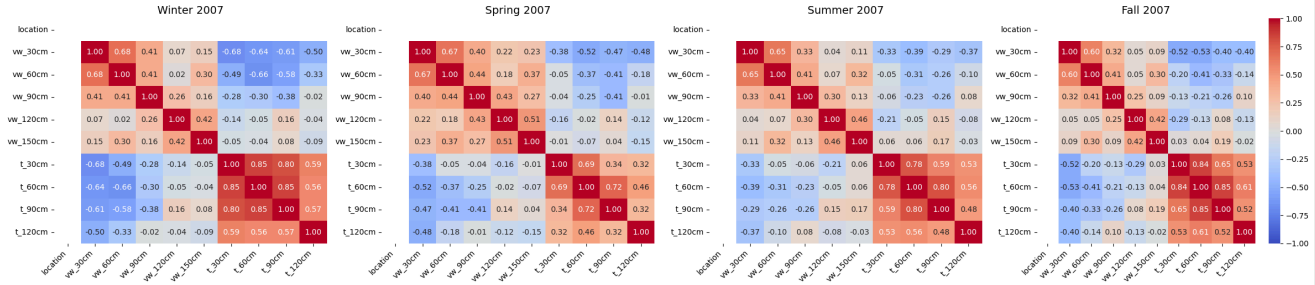
Year-wise Seasonal Sensor Correlation Heatmaps

```
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import numpy as np

# --------------------------------
# Prepare DataFrame
# --------------------------------
df = hourly_df.copy()  # Use cleaned DL-ready hourly dataset

# Ensure 'month' column exists
if "month" not in df.columns:
    df["month"] = df["date"].dt.month

# Ensure 'year' column exists
if "year" not in df.columns:
    df["year"] = df["date"].dt.year

# Assign seasons
def month_to_season(m):
    if m in [12, 1, 2]:
        return "Winter"
    elif m in [3, 4, 5]:
        return "Spring"
    elif m in [6, 7, 8]:
        return "Summer"
    else:
        return "Fall"

if "season" not in df.columns:
    df["season"] = df["month"].apply(month_to_season)

# --------------------------------
# Detect numeric sensor columns
# --------------------------------
def get_sensor_columns(df):
    exclude = ["year", "month", "day", "hour", "minute", "second"]
    return [c for c in df.columns if df[c].dtype in ["int64", "float64"]
            and all(e not in c.lower() for e in exclude)]

sensor_cols = get_sensor_columns(df)

# Limit to top 10 sensors for clarity
if len(sensor_cols) > 10:
    sensor_cols = sensor_cols[:10]

print("Sensor columns used for correlation heatmaps:", sensor_cols)

# --------------------------------
# Plot seasonal correlation heatmaps per year
# --------------------------------
years = sorted(df["year"].unique())
seasons = ["Winter", "Spring", "Summer", "Fall"]

for yr in years:
    plt.figure(figsize=(24, 6))  # Wide figure for clarity
    for i, season in enumerate(seasons, 1):
        df_sub = df[(df["year"] == yr) & (df["season"] == season)]
        if len(df_sub) < 2:
            continue  # Skip if not enough data

        # Compute correlation
        corr = df_sub[sensor_cols].corr()

        plt.subplot(1, 4, i)
        sns.heatmap(
            corr, annot=True, fmt=".2f", cmap="coolwarm",
            cbar=(i == 4), vmin=-1, vmax=1, annot_kws={"size": 10}
        )
        plt.xticks(rotation=45, ha='right', fontsize=10)
        plt.yticks(rotation=0, fontsize=10)
        plt.title(f"{season} {yr}", fontsize=14)
```

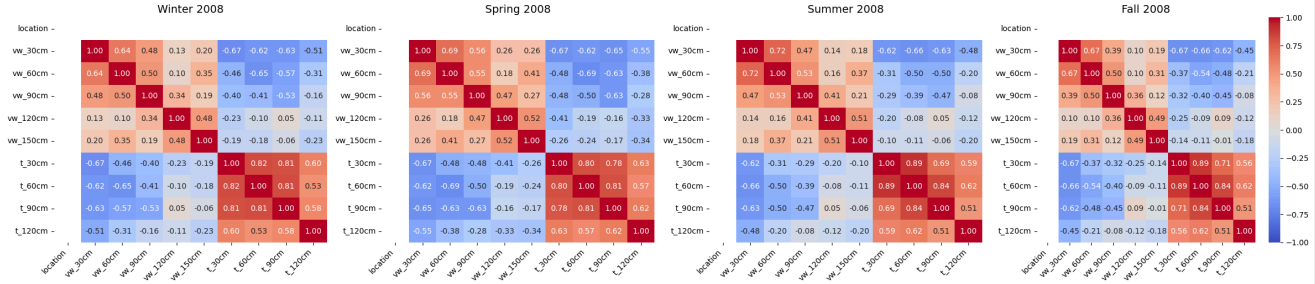
```
    plt.suptitle(f"Sensor Correlation Heatmaps for {yr}", fontsize=18)
    plt.tight_layout(rect=[0, 0, 1, 0.95])
    plt.show()
```

```
Sensor columns used for correlation heatmaps: ['location', 'vw_30cm', 'vw_60cm', 'vw_90cm', 'vw_120cm', 'vw_150cm', 't_30cm', 't
```

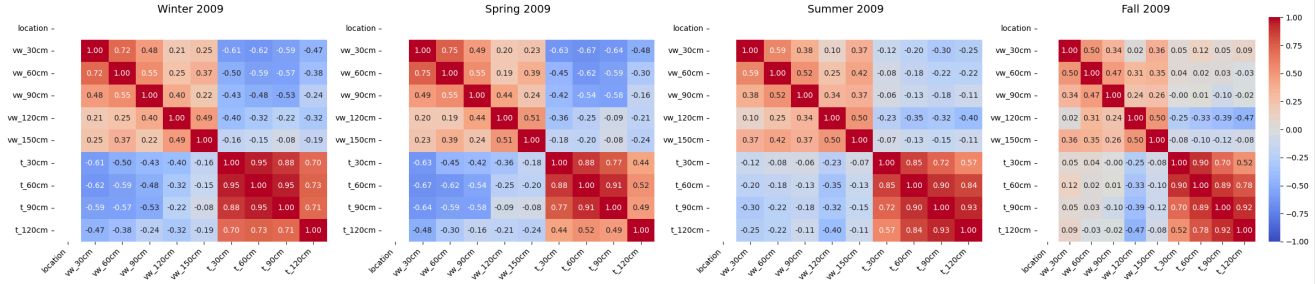
Sensor Correlation Heatmaps for 2007



Sensor Correlation Heatmaps for 2008



Sensor Correlation Heatmaps for 2009



Sensor Correlation Heatmaps for 2010