Trends and Extreme Climate Changes in the Podkarpackie Voivodeship (2002–2025) and Their Impact on Lettuce, Carrot, Tomato, and Sugar Beet

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Abstract

Background: Understanding regional climate variability requires analyzing the interdependencies between global warming and local atmospheric conditions. In the Podkarpackie Voivodeship, it is crucial to examine the dynamics of temperature, precipitation, and their impact on vegetable crops.

Methods: This study used **ERA5** reanalysis data from 2002–2025 for the location 49.79°N, 21.69°E. Exploratory data analysis (EDA) and statistical tests were performed, focusing on the distribution of temperature and precipitation. Plant growth and development data for four crop species (lettuce, carrot, tomato, and sugar beet) were obtained from scientific literature.

Results: Temperature and solar radiation remained relatively stable, whereas precipitation showed higher concentration over short periods, with limited rainfall during high-temperature episodes. The temperature-to-precipitation ratio indicates deteriorating water availability during heat periods. An increasing trend in average daily precipitation intensity was also observed.

Conclusions: Exploratory data analysis (EDA) suggests that machine learning techniques could be applied to predict future conditions in the study area. Potential targets for such models include indicators of water stress or biomass development of individual vegetable species.

Introduction

Global climate change poses a serious challenge for agriculture worldwide, affecting water availability, plant development, and crop productivity. The increase in average temperatures, variability of precipitation, and more frequent occurrence of extreme weather events, such as droughts or intense rainfall, increases the risk for local agricultural systems. This study presents an analysis of climate data for the Podkarpackie Voivodeship in the years 2002–2025, based on ERA5 reanalysis. By combining physical climate data with exploratory data analysis, the study aims to understand the dynamics of the local climate and its potential impacts on agriculture in this region.

Data and Methodology

Raw ERA5 Variables

The study used ERA5 reanalysis data provided by the European Centre for Medium-Range Weather Forecasts (ECMWF) via the Copernicus Climate Data Store. The dataset includes hourly data for the years 2002–2025, which were then aggregated to daily values.

Data were retrieved for the location corresponding to the meteorological sensor: **49.79°N, 21.69°E**.

Key raw variables included:

- **Skin Temperature** (`skt`) – the temperature of the ground surface/topsoil layer, expressed in degrees Celsius.
- **Average Precipitation Rate** (`avg_tprate`) – precipitation intensity indicator ($\mathrm{kg\,m^{-2}\,s^{-1}}$).
- **Downward Shortwave Radiation at Surface** (`sw_radiation_down_W_per_m2`) – total solar radiation in watts per square meter, necessary to estimate the amount of light energy available to plants.

Derived Variables and Calculation Methodology

From the raw variables, more suitable variables for analyzing the impact of climatic conditions on agriculture were derived:

- **Precipitation in mm per hour** (`tprate_mm_per_h`) – converted from the average precipitation rate (`avg_tprate`) using the relationship:

  $$\text{precipitation [mm/h]} = \text{avg\_tprate [kg/m}^2\text{/s]} \times 3600 \text{ s/h}$$

  which gives the amount of water in millimeters falling in one hour.
- **PPFD** ($\mu\mathrm{mol\,m^{-2}\,s^{-1}}$) – photosynthetically active photon flux density, calculated from downward shortwave radiation at the surface (`sw_radiation_down_W_per_m2`) according to the standard conversion:

  $$\text{PPFD} = \text{SW\_down [W/m}^2\text{]} \times 4.57$$

  where the coefficient 4.57 converts energy units to photosynthetically active photon flux, suitable for assessing light available for photosynthesis.

Plant Growth Data

Based on data from the study *Optimizing Microclimatic Conditions for Lettuce, Tomatoes, Carrots, and Beets: Impacts on Growth, Physiology, and Biochemistry Across Greenhouse Types and Climatic Zones* Oana Alina Nitu, n.d., a simplified scheme of optimal climatic conditions was created for each plant species: lettuce (Lactuca sativa L.), carrot (Daucus carota L.), tomato (Solanum lycopersicum L.), and sugar beet (Beta vulgaris L.).

The scheme includes the following factors:

- **Temperature** – temperature ranges

- **Light Intensity (PPFD)** – threshold values of photosynthetically active radiation during the day in [μmol$\cdot$m$^{-2}\cdot$s^{-1}],
- **Photoperiod** – number of hours of daily illumination.

Each row has a simplified rating on a 0–3 scale:

- 0 – unsuitable conditions,
- 1 – plant stress,
- 2 – acceptable conditions,
- 3 – optimal conditions for growth.

Lettuce (Lactuca sativa L.)

Table 1: Temperature ranges for lettuce (Lactuca sativa L.) in a temperate climate

Temperature Range [°C]	Rating
<15	0
15–20	3
20–22	2
22–24	1
>25	0

Table 2: Optimal light intensity (PPFD) and photoperiod for lettuce (Lactuca sativa L.)

PPFD Range [μmol $\cdot$ m^{-2} $\cdot$ s^{-1}]	Photoperiod [h]	Rating
<150	0–16	0
150–200	16	2
200	16	3
200–400	16–18	2
400–600	18	1
>600	18–24	0

Carrot (Daucus carota L.)

Table 3: Temperature ranges for carrot (Daucus carota L.) in a temperate climate

Temperature Range [°C]	Rating
<15	0
15–18	1
18–20	2
20–25	3
25–28	2
28–30	1
>30	0

Table 4: Optimal light intensity (PPFD) and photoperiod for carrot (Daucus carota L.)

PPFD Range [μmol $\cdot$ m^{-2} $\cdot$ s^{-1}]	Photoperiod [h]	Rating
<200	0–12	0
200–250	12–16	2
250–400	16	3
400–800	16	2
>1000	16	0

Tomato (Solanum lycopersicum L.)

Table 5: Temperature ranges for tomato (Solanum lycopersicum L.) in a temperate climate

Temperature Range [°C]	Rating
<18	0
18–20	2
20–24	3
24–26	2
26–30	1
>30	0

Table 6: Optimal light intensity (PPFD) and photoperiod for tomato (Solanum lycopersicum L.)

PPFD Range [μmol $\cdot$ m^{-2} $\cdot$ s^{-1}]	Photoperiod [h]	Rating
170–249	16	1
250	16	3
251–520	16	1
>520	16–24	0

Sugar Beet (Beta vulgaris L.)

Table 7: Temperature ranges for sugar beet (Beta vulgaris L.) in a temperate climate

Temperature Range [°C]	Rating
<10	0
10–15	1
15–18	2
18–24	3
24–25	2
25–30	1
>30	0

Table 8: Optimal light intensity (PPFD) and photoperiod for sugar beet (Beta vulgaris L.)

PPFD Range [μmol $\cdot$ m^{-2} $\cdot$ s^{-1}]	Photoperiod [h]	Rating
<150	0–12	0
150–199	12–13	2
200	14	3
201–250	14	2
250–300	14–16	1
>300	16–24	0

Results

Thermal and Solar Conditions

Based on data from the study *Optimizing Microclimatic Conditions for Lettuce, Tomatoes, Carrots, and Beets* Oana Alina Nitu, n.d., optimal temperature ranges, PPFD, and photoperiods were determined for the studied species. Comparing these with real data showed that the laboratory-defined ranges are very restrictive – most days during the study period fall into the lowest rating category (0).

Figure 1 shows a heatmap displaying the distribution of condition ratings for each species on consecutive days. Colors correspond to the simplified 0–3 scale:

- 0 – unsuitable conditions
- 1 – plant stress
- 2 – acceptable conditions
- 3 – optimal

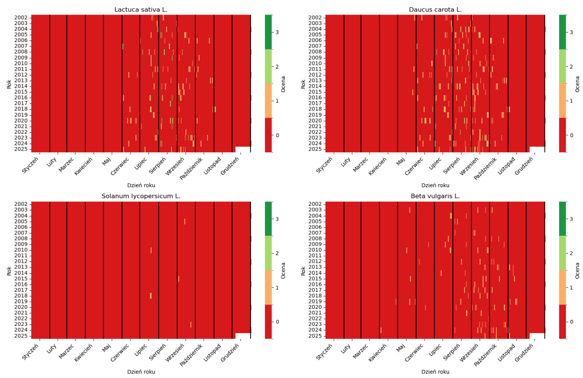

Figure 1: Heatmap showing the rating of thermal and solar conditions for the studied species. X-axis: days, Y-axis: plant species, colors: rating on a 0–3 scale.

Results of the Runs Test The runs test was performed for the thermal and solar condition ratings (0–3) for the studied plant species. The results are presented in tables, with test statistics and corresponding p-values for each rating.

Table 9: Runs test results for lettuce

Rating	Column 0	Column 1	Column 2
Statistic	1.81	0.63	0.56
p-value	0.07	0.53	0.58

Table 10: Runs test results for carrot

Rating	Column 0	Column 1	Column 2
Statistic	0.41	0.22	0.35
p-value	0.68	0.82	0.73

Table 11: Runs test results for tomato

Rating	Column 0	Column 1	Column 2
Statistic	0.41	0.12	$-\infty$
p-value	0.68	0.90	0

Table 12: Runs test results for sugar beet

Rating	Column 0	Column 1	Column 2
Statistic	0.32	-0.14	2.11
p-value	0.75	0.89	0.035

The analysis of the runs test results indicates that ratings 0 and 1 generally show a random distribution over time for all studied species. Ratings of 2, corresponding to medium-quality conditions, exhibit non-random distribution for tomato and sugar beet, which may be due to the limited number of observations or seasonal patterns in conditions. Ratings of 3 did not occur in the data, so no test statistics could be calculated. Overall, the results suggest that most ratings are randomly distributed, confirming the absence of systematic deviations over time for the dominant values (0–1), while medium ratings (2) may reveal some seasonal patterns.

Precipitation

Estimating plant water requirements precisely is challenging because it depends on many factors, including temperature, soil properties, and groundwater levels. The amount of water available in the soil varies over time and space depending on soil permeability and local groundwater levels, which complicates precise modeling of plant water needs.

Therefore, the analysis focused on extreme conditions that best reflect the risk of drought or excessive water. Both the intensity of precipitation on rainy days and the number of days with heavy or intense rainfall were examined. This allows assessing whether rainfall is weak but regular, favorable for agriculture, or occurs in concentrated downpours, which can lead to waterlogging and soil erosion.

Temperature/Precipitation Ratio A linear trend analysis was performed on the average annual temperature/precipitation ratio over the 24-year study period. This ratio indicates the relationship between average temperature and annual precipitation sum.

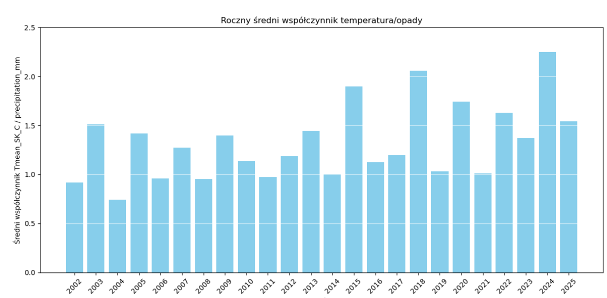

Figure 2: Average annual temperature/precipitation ratio for the study period. The trend line shows an increasing ratio over time.

Table 13: Linear regression results of temperature/precipitation ratio versus years

Parameter	Value	P-value
Constant (const)	1.015	0.000
Annual trend (x1)	0.0269	0.014

The analysis indicates a moderate increasing trend in the average temperature/precipitation ratio.

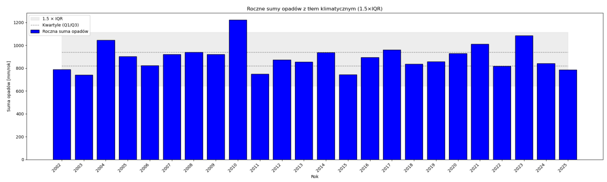

Figure 3: Annual precipitation sums with 1.5×IQR climate background. Gray background shows typical variability range; blue bars show annual precipitation sums.

Table 14: Trend analysis results for annual precipitation sums versus years

Method / Parameter	Value	P-value
OLS – Constant (const)	-176.66	0.980
OLS – Annual trend (x1)	0.532	0.879
Spearman ρ	0.043	0.84

Annual Precipitation Sums Annual precipitation sums remain relatively stable, and the observed trend is not statistically significant (OLS: slope 0.532 mm/year, $p = 0.879$; Spearman $\rho = 0.043$, $p = 0.84$).

SDII – Mean Intensity of Rainy Days (>1 mm) Figure 4 shows SDII – mean intensity of days with precipitation over 1 mm. Two outlier years were removed: 2010 (flood – extreme value) and 2025 (incomplete data).

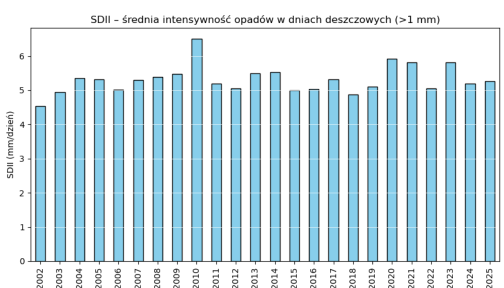

Figure 4: SDII – mean precipitation intensity on rainy days (>1 mm).

Table 15: Linear regression results of SDII versus years (after removing 2010 and 2025)

Parameter	Value	P-value
Constant (const)	1.234	0.002
Annual trend (x1)	0.0184	0.0804

The annual SDII trend shows a subtle increasing tendency, though it is not statistically significant. The data show high interannual variability.

Number of Heavy Rain Days (precipitation > 10 mm/day) The number of days with precipitation above 10 mm from 2002–2024 was analyzed using OLS linear regression. Year 2025 was excluded due to missing data.

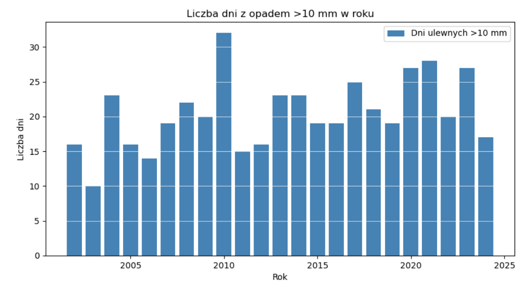

Figure 5: Number of days with precipitation above 10 mm in 2002–2024.

Table 16: Regression results for the number of heavy rain days versus years

Parameter	Value	P-value
Constant (const)	-639.913	0.045
Annual trend (x1)	0.328	0.039

The analysis indicates a mild but statistically significant upward trend in the number of heavy rain days. Kendall's test confirms the increasing trend direction ($\tau = 0.329$, $p = 0.031$). Interannual variability remains considerable.

General Conclusions Regarding Precipitation

Analysis of all precipitation indicators shows that annual precipitation sums remain essentially stable and do not exhibit statistically significant trends, confirmed by both Spearman's test ($\rho = 0.043$, $p = 0.84$) and OLS linear regression (slope 0.532 mm/year, $p = 0.879$). This means that the total annual precipitation over the study period did not change significantly.

On the other hand, changes in the nature of precipitation are more pronounced. The mean intensity of rainy days (SDII) shows a subtle upward tendency (0.018 mm/day per year), although it is not statistically significant ($p = 0.0804$). This indicates a possible increase in precipitation intensity on rainy days.

The most pronounced trend concerns the number of heavy rain days (precipitation > 10 mm/day), which increases on average by 0.33 days per year, and the trend is statistically significant ($p = 0.039$, Kendall $\tau = 0.329$, $p = 0.031$). This suggests that extreme precipitation events are becoming more frequent, even though the annual sum remains stable.

Overall, these results suggest that the studied area is experiencing a shift toward more extreme precipitation conditions:

the number and intensity of short, heavy rainfall events are increasing, while the annual precipitation sum remains stable. This trend may have significant implications for agriculture as well as flood and soil erosion risk.

Discussion

The analysis of thermal and solar conditions revealed significant limitations stemming from the nature of the input data. Temperature ranges, solar radiation, and photoperiods were developed for industrial production in tunnels or greenhouses, which prevents their direct application to assess conditions in natural outdoor environments. Consequently, most days in the study period received the lowest rating (0), limiting the practical use of these data in the analysis.

Despite the relatively short observation period (24 years), the analysis of precipitation indicators provided consistent conclusions regarding changes in precipitation characteristics. Annual precipitation sums remained stable, yet the mean intensity of precipitation on rainy days (SDII) showed a subtle increasing trend, and the number of heavy rain days increased on average by 0.33 days per year.

These changes indicate a shift toward more extreme precipitation conditions, which may reduce soil water infiltration, increase the risk of erosion and local flooding, and simultaneously hinder soil water storage, favoring droughts during dry periods. Although the total annual precipitation did not change, shifts in precipitation patterns may have significant implications for agriculture and water management.

Limitations of the Analysis and Possible Improvements

The analysis presented in this study has several important limitations that should be considered when interpreting the results. The main issues are outlined below:

- **Limited spatial representativeness of the data:** The study relied on a single time series from one location, which limits the ability to capture microclimatic variability in the area. Expanding measurements to several or a dozen sensors distributed across different points would allow a more comprehensive assessment of climatic conditions and their impact on plants.
- **Temperature and solar radiation ranges adapted for tunnel production:** The temperature and radiation ranges used in the analysis were developed for tunnel or greenhouse cultivation, and therefore do not fully reflect actual outdoor conditions. Using wider and better-adjusted ranges would allow more effective use of these data for assessing conditions for open-field crops.
- **Lack of soil properties and groundwater level consideration:** The current analysis did not include soil parameters or groundwater levels, which are crucial for plant water availability. Incorporating these data into water demand modeling would allow more precise assessment of drought or water excess risks in the soil, enabling better prediction of crop conditions.
- **Short observation period:** The analyzed time series covers a relatively short period, limiting the ability to detect long-term climatic trends. Extending the observation period would better distinguish natural fluctuations from actual changes in precipitation intensity and characteristics, and allow a more reliable assessment of extreme weather risk.

Conclusions

The analysis of climatic data indicates that annual precipitation in the studied area remains stable, but the nature of precipitation is changing. The mean intensity of rainy days (SDII) shows a slight increase, and the number of heavy rain days rises significantly by approximately 0.33 days per year. This indicates that extreme precipitation events are becoming more frequent, which may increase the risk of local floods and soil erosion, even though the total annual precipitation remains unchanged.

Limitations in the analysis of thermal and solar conditions arise from using ranges developed for tunnel production, which do not directly translate to outdoor conditions.

Based on the available data, it is possible to consider attempts to estimate plant water requirements using machine learning (ML) techniques. Potential model targets could be indicators of extreme precipitation (e.g., SDII or number of heavy rain days), with input features including temperature, precipitation sums, and other meteorological variables. Such an analysis could support crop planning and water management in the context of changing climatic conditions.

References

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