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Long-term changes in fire weather conditions in Ukraine

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Abstract

This study investigates spatiotemporal changes in fire-dangerous weather conditions across Ukraine during the period 1960–2023. Daily temperature and relative humidity data from ERA5 reanalysis were used to calculate Ångström index, which reflect the level of potential fire danger based on meteorological conditions. Trend analysis revealed a consistent decrease in Ångström index values across regions of the country and in all seasons, indicating an overall increase in fire danger during the study period. An assessment of the frequency of fire danger classes based on the threshold values of the Ångström index revealed significant positive trends in the frequency of days with extreme and high fire hazard in most of Ukraine during the warm season (April–October), with the greatest increase observed in the southern and southwestern regions. The average number of extreme fire danger days has increased by more than 1.5 times since 1960, reaching 51 days in the recent decade. The analysis of the relationship between burned areas and number of days in different fire danger classes in warm period of the year revealed clear regional differentiation depending on index thresholds. In forested regions, the largest burned areas were associated with extreme and high fire danger classes. By contrast, in steppe and forest-steppe zones, the greatest burned areas occurred under less severe weather conditions corresponding to the moderate fire danger class. The results of the study demonstrate the potential of using the Ångström index both for the operational assessment of fire weather danger and for the development of a comprehensive system for assessing and forecasting fire risk in various landscape zones of Ukraine.

Keywords: wildfires; Ångström index; fire weather; fire danger class; burned area

1 Introduction

Wildfires are an integral component of terrestrial ecosystem functioning under stable climatic conditions (*Hantson et al.*, 2024). However, observations over recent decades indicate an increase in the annual number of wildfires in various parts of the world (*Flannigan et al.*, 2013; *Abatzoglou and Williams*, 2016; *Jones et al.*, 2022; *Torres-Vázquez et al.*, 2025), as well as the occurrence of very large events, the so-called 'megafires' (*San-Miguel-Ayanz et al.*, 2013; *Farid et al.*, 2024). While the causes of wildfires are highly diverse and, in most cases, linked to human activity (*Ganteaume et al.*, 2013), the persistence and spread of fire are largely determined by weather conditions (*Bowman et al.*, 2017), which, as a result of climate change, are becoming drier and hotter in many regions, including Europe (*Sutanto et al.*, 2020) and the Arctic (*Rantanen et al.*, 2022).

An assessment of fire risk based on weather conditions is commonly conducted using indicators or indices that incorporate key atmospheric variables such as temperature,

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humidity, wind, and precipitation. National meteorological services may apply entire systems or individual indices. The most widely known and advanced system for evaluating fire danger risk based on weather conditions is the Canadian Forest Fire Weather Index (FWI) System, which forms part of the Canadian Forest Fire Danger Rating System (CFFDRS), developed in Canada in 1968 (*Van Wagner*, 1987). The FWI is based on two key components: the Initial Spread Index (ISI) and the Buildup Index (BUI), both of which are related to the amount and condition of combustible fuel, as determined by prevailing weather conditions (`https://cwfis.cfs.nrcan.gc.ca/background/summary/fwi`). The adapted fire danger levels of the FWI are also used as the basis for fire danger assessment and forecasting in the European Forest Fire Information System (EFFIS) (`https://forest-fire.emergency.copernicus.eu/about-effis/technical-background/fire-danger-forecast`).

Numerous meteorological indices developed in different countries for assessing fire danger are more convenient and effective for operational use, as they take into account the characteristics of specific geographic regions (*Zacharakis and Tsihrintzis*, 2023). Among the simplest of these indices are the Chandler Burning Index and the Ångström index (*Chandler et al.*, 1983), which are based on air temperature and relative humidity as key indicators of fuel flammability. A relatively recent development in the United States, the Hot-Dry-Windy Index (HDWI), also appears promising, as it incorporates wind in addition to temperature and humidity (*Srock et al.*, 2018). This makes it a versatile and effective tool under rapidly changing atmospheric conditions across different regions (e.g., *Semenova et al.*, 2022). Beyond their direct use for assessing current fire danger conditions, these indices can also be successfully applied in evaluating regional climate changes (*McDonald et al.*, 2018; *Abatzoglou et al.*, 2019), as they include key Essential Climate Variables (ECVs) (*Bojinski et al.*, 2014).

In Ukraine, the national hydrometeorological service currently uses the Nesterov Composite Index (NCI) to assess fire danger based on weather conditions. This index categorizes fire risk into five classes depending on the index range (*Balabukh and Malytska*, 2017). The NCI is cumulative index, taking into account the number of days since the last precipitation event exceeding 3 mm, as well as current air temperature and dew point temperature, and is therefore considered more suitable for evaluating ignition potential rather than fire spread (*Venevsky et al.*, 2002). Studies for various regions indicate that the Nesterov Index generally exhibits relatively low correlation with fire activity metrics compared to other indices and tends to overestimate fire danger severity (*Arpaci et al.*, 2013; *Torres et al.*, 2017; *Tošić et al.*, 2019).

This article presents the results of a spatiotemporal analysis of fire-prone weather conditions in Ukraine and their changes over the period 1960–2023, based on the Ångström index. One of the advantages of simple indices such as the Ångström index is the ability to quickly assess local fire danger risk using readily available temperature and humidity observations. This offers certain benefits compared to cumulative indices like the Nesterov Index, which is commonly used in Ukraine. To achieve this, the study: (i) examined the spatiotemporal distribution and trends of the Ångström index;

(ii) assessed the dynamics of the number of days across different fire danger classes; and (iii) evaluated the seasonal relationship between burned areas and the frequency of days within various fire danger classes.

2 Data and methods

The Ångström index is calculated daily using only meteorological parameters, without taking into account fuel moisture (*Ångström*, 1949). The degree of fire danger depends on the index value: the lower it is, the higher the risk of fire. Although this index depends only on atmospheric variables, its values show a high correlation with litter moisture, which expands its capabilities in assessing fire weather conditions (*Ganatsas et al.*, 2011). The Ångström index (AI) is calculated using the formula:

$$\mathrm{AI} = \frac{\mathrm{RH}_{13}}{20} + \frac{27 - T_{13}}{10} \,, \tag{2.1}$$

where RH_{13} is relative air humidity (%) and T_{13} is air temperature (°C) at 13 h.

Table 2.1 shows classes from 1 to 4 of fire danger severity in accordance with the values of the Ångström index and their abbreviations, which will be further used in the article.

Table 2.1: Fire danger classes and their criteria in accordance with the Ångström index.

Fire danger class	**AI values**	**Fire danger severity**
AI1	$\mathrm{AI} > 4.0$	Fire occurrence unlikely (low level of danger)
AI2	$2.5 < \mathrm{AI} \leq 4.0$	Fire conditions unfavorable (moderate level of danger)
AI3	$2.0 < \mathrm{AI} \leq 2.5$	Fire conditions favorable (high level of danger)
AI4	$\mathrm{AI} \leq 2.0$	Fire occurrence very likely (extreme level of danger)

To calculate the Ångström index, daily 2-m air temperature and dew point data with a grid resolution of $0.25° \times 0.25°$ from the ERA5 reanalysis provided by Copernicus Climate Change Service (C3S) were taken for the period from 1960 to 2023, at 13 UTC (*Hersbach et al.*, 2020). This term was chosen because the daily maximum temperature in Ukraine occurs around 15 h local time (*Lipinsky and Dyakun*, 2003). To assess the relationship between the Ångström index and fire activity in Ukraine, the monthly Burned Area product with a spatial resolution of $0.25° \times 0.25°$ was used, which was also extracted from the C3S land cover dataset for the period 2001 to 2021. This product is obtained using medium-resolution sensors (Terra MODIS, Sentinel-3 OLCI) and characterizes the burned areas from all types of fires (*Chuvieco et al.*, 2016).

To quantify the relative contributions of air temperature and air humidity to the variation of the Ångström index (AI), we applied a multiple linear regression combined with a moving-window approach. When constructing a model, dew point temperature as a humidity-related predictor was used. Relative humidity is a metric that is highly dependent on temperature, and in our case, it is calculated using air temperature and dewpoint temperature. Dewpoint temperature is a direct indicator of the water vapor content of the air (*Lawrence*, 2005; *Sjöström et al.*, 2025).

There was used 10-year moving window to capture potential temporal non-stationarity in the drivers of AI. For each period, a separate regression is fit, enabling analysis of how the relative importance of predictors changes over time. Within each time window, the Ångström index is approximated by a linear regression model:

$$\mathrm{AI} = \beta_0 + \beta_1 T + \beta_2 T_{\mathrm{d}} \ , \tag{2.2}$$

where: AI is the Ångström index; T is the air temperature; T_{d} is the dew point temperature; β_0, β_1, and β_2 are regression coefficients.

The contribution of temperature and dew point to explaining the variance of AI is quantified using the Lindeman–Merenda–Gold (LMG) method, as implemented in the `relaimpo` R-package (*Grömping*, 2006). The LMG method decomposes the overall coefficient of determination (R^2) of a multiple linear regression model into additive components attributed to each predictor. For each possible order of predictor inclusion, the increase in R^2 is computed, and the final relative importance of predictor is the average of its contributions across all orderings. With normalization, these contributions in total are 100 %, allowing direct comparison of the proportion of variance in AI explained by temperature and dew point. Time series of temperature and dew point temperature at 11 UTC, averaged across the territory of Ukraine, were used as the initial data for the model.

The nonparametric Mann–Kendall test was used to identify trends in the time series of variables, and the Theil–Sen estimator was used to estimate the magnitude of changes (*Zade et al.*, 2023). The processing of initial data and all calculations were performed using standard R packages. Some analysis and visualization were also performed using CM SAF R Toolbox (v. 3.5.2), which is part of the R-package `cmsaf` (*cmsaf*, 2024).

3 *Study area*

Ukraine is located in the eastern part of Europe, on the southwestern edge of the East European Plain. The terrain is predominantly flat, with lowlands and uplands covering about 95 % of the country's territory (*National Atlas of Ukraine* 2007). The main mountain system, the Eastern Carpathians, is located in the far west, while the southern tip of the Crimean Peninsula is occupied by the Crimean Mountains. Within Ukraine, four main natural zones are distinguished: steppe, forest-steppe, mixed forests (Polissia), and mountainous areas (Fig. 3.1a). The most fertile soils, chernozems, are concentrated in the steppe regions. Forests cover about 10 million hectares, or 15.9 % of the national territory, with the highest density in the northern and western regions, particularly in Polissia and the Carpathians (Fig. 3.1b). Pine (35 %) and oak (28 %) are the dominant forest species. Beech, spruce, fir, birch, and aspen each account for 7–9%, while other species are less common.

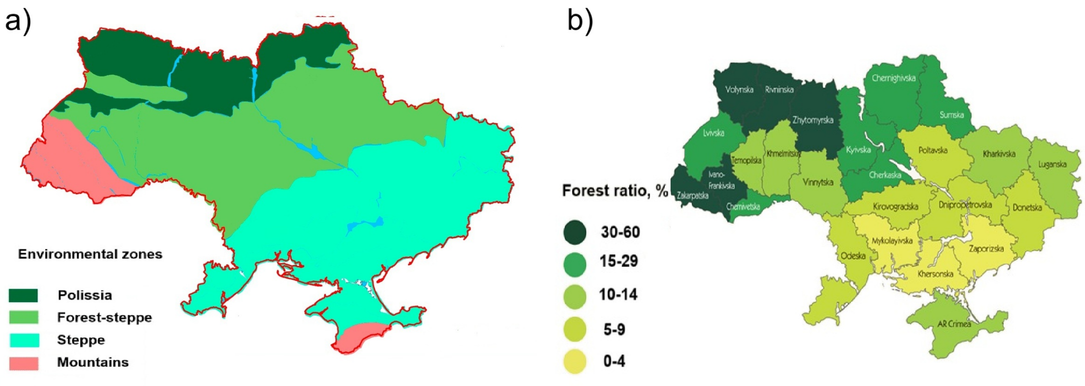

Fig. 3.1: (a) Environmental zones of Ukraine. *Credit: BioModel.Info* (`https://biomodel.info`). (b) Forest ratio by administrative regions. *Credit: State Forest Resources Agency of Ukraine* (`https://forest.gov.ua/en/areas-activity/forests-ukraine/general-characteristic-ukrainian-forests`).

Between 2000 to 4000 forest fires are recorded annually in Ukraine (during the period 1990–2020), and the average annual burned area reached 7000 hectares following the anomalous year 2020, when several catastrophic fires occurred in different regions of the country (*Zibtsev et al.*, 2019; *Soshenskyi et al.*, 2021).

The climate is temperate, with cold winters and warm summers, and its degree of continentality increases from west to east. Over the last 30 years, Eastern Europe and Ukraine in particular have experienced significant changes in air temperature, with the mean temperature rising by almost 1.5 °C compared to the 1961–1990 reference period (*Wilson et al.*, 2021; *Boychenko and Maidanovych*, 2024). At the same time, no significant changes in precipitation amounts or patterns have been observed, leading to an increased frequency of droughts in many regions of the country (*Semenova and Vicente-Serrano*, 2024). These climatic changes are also affecting agricultural production by shifting cultivation zones northward and altering the range of crops (*Nikolayeva*, 2012; *King et al.*, 2018).

Since the onset of military hostilities in February 2022, forests located within combat zones in Ukraine have experienced substantial damage and destruction, with the most pronounced losses reported in Kherson region in the south of the country and Kharkiv region in the east (*Tomchenko et al.*, 2023; *Matsala et al.*, 2024). During 2022–2023, an estimated 66–80 % of all wildfires in Ukraine occurred within a 30-km corridor along the front line. Furthermore, during periods of the most intense fire activity, many cities across Ukraine experienced significant increases in air pollutants (NO_2, CO, aerosols), with temporary concentrations comparable to those from industrial emissions (*Malytska et al.*, 2025).

4 Results

4.1 Spatiotemporal distribution and trends of the Ångström index

The spatial distribution of the Ångström index (AI) across Ukraine is characterized by a decrease in values from the west and northwest toward the south and southeast (Fig. 4.1a). Maximum AI values are observed in the Ukrainian Carpathians, while the minimum values occur in Kherson region and the central part of the Crimean Peninsula. The mean annual AI values across Ukraine range between 4.0 to 5.9.

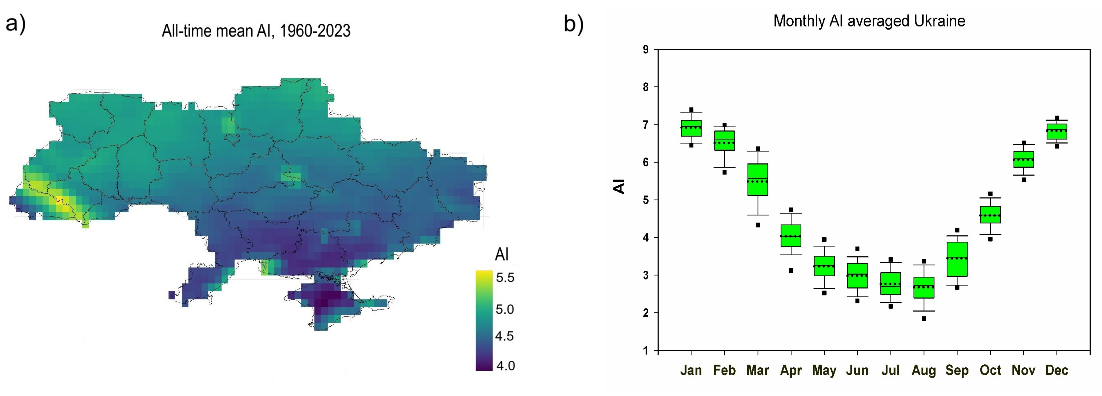

Fig. 4.1: Spatial distribution of: (a) all-time mean AI, and (b) annual distribution of monthly mean AI averaged over the territory of Ukraine, both for the period 1960–2023. Boxplot displays: the 90th and 10th percentile at the whiskers; the 75th and 25th percentiles both side of the box; the median line is in the centre; dotted line marks the mean; squares both side of the error bars shows 95th (top) and 5th (bottom) percentiles.

The AI index has pronounced seasonal variation, in accordance with changes in temperature and humidity throughout the year, while retaining a latitudinal gradient in its spatial distribution throughout all seasons (Fig. 4.1b). The highest seasonal AI values are observed in the winter, with a maximum in January, the lowest are in the summer, with a minimum in August. On average, spring AI values are lower than autumn ones. The greatest variability of the AI values is observed at the beginning of spring and autumn, and August is characterized by the greatest spread of extreme values against the low interannual variability.

In the spatial distribution of the index, the lowest AI values are consistently observed in the southern regions throughout all seasons (Fig. 4.2). As for the maximum values, with the exception of the Carpathians where the maximum AI is persistent, areas of high values exhibit seasonal variability. During winter, the highest values are concentrated in the northeastern regions; in spring and summer, the maxima shift to the western regions of the country; and in autumn, they are located in the northwestern and northern regions. Among the geographical features of the AI spatial distribution is the presence of stable elevated values compared to the surrounding areas in the coastal zones of the Black and Azov Seas, as well as along the Dnipro River basin. Local maxima are concentrated near reservoirs, with the most pronounced one over the Kremenchuk reservoir in the center of the country. These maxima are primarily driven by increased humidity near water bodies.

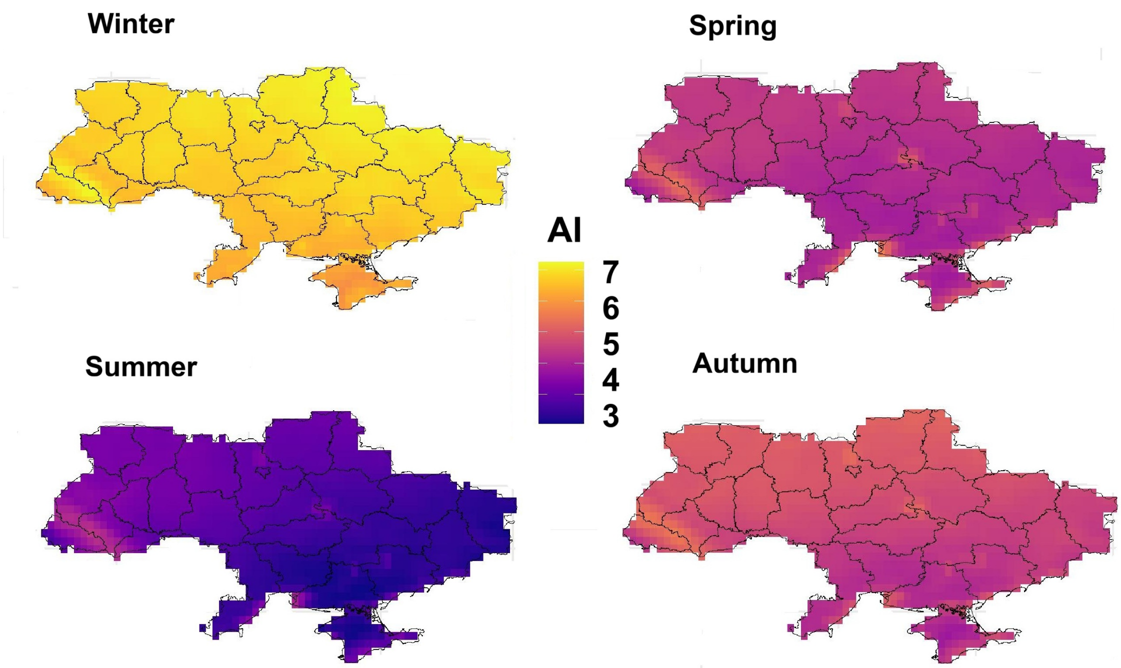

Fig. 4.2: Spatial distribution of the seasonal mean AI, for the period 1960–2023.

To assess the dynamics of the Angstrom index (AI) over the period 1960–2023, we used time series of mean annual AI values averaged over the territory of Ukraine. Despite minor interannual variability, two distinct periods with different temporal patterns can be identified in the AI time series (Fig. 4.3a). During 1960–1996, the trend in AI changes was negligible. However, from 1997 onwards until the end of the study period, a clear decreasing trend in the index is observed. The time course of anomalies in mean annual AI values (Fig. 4.3b) demonstrates a marked shift from predominantly positive anomalies in the first half of the study period (1960–1998) to negative anomalies in the second half (1999–2023). The trend is statistically significant at the 95 % confidence level. To illustrate the changes in the Ångström index (AI) over the 63-year period, mean fields for the first and last decades of the study period are shown in Fig. 4.3c–d. A substantial expansion of the low-index area in the southern half of Ukraine can be observed. The constructed linear regression model for assessing the contributions of air temperature and dew point temperature to the Ångström index was statistically significant for both variables. The temporal variations in the contributions of these metrics, shown in Fig. 4.3e, clearly indicate that the dominant contribution belongs to air temperature (on average, 80 %), with an increasing trend toward the end of the study period. The contribution of atmospheric moisture, represented by dew point temperature, decreased correspondingly. This result is consistent with global findings on the impact of rising air temperatures and decreasing air humidity on increasing fire danger and dry conditions (*Jain et al.*, 2022; *Gebrechorkos et al.*, 2025).

The analysis of the spatial distribution of seasonal AI trends showed that the trends

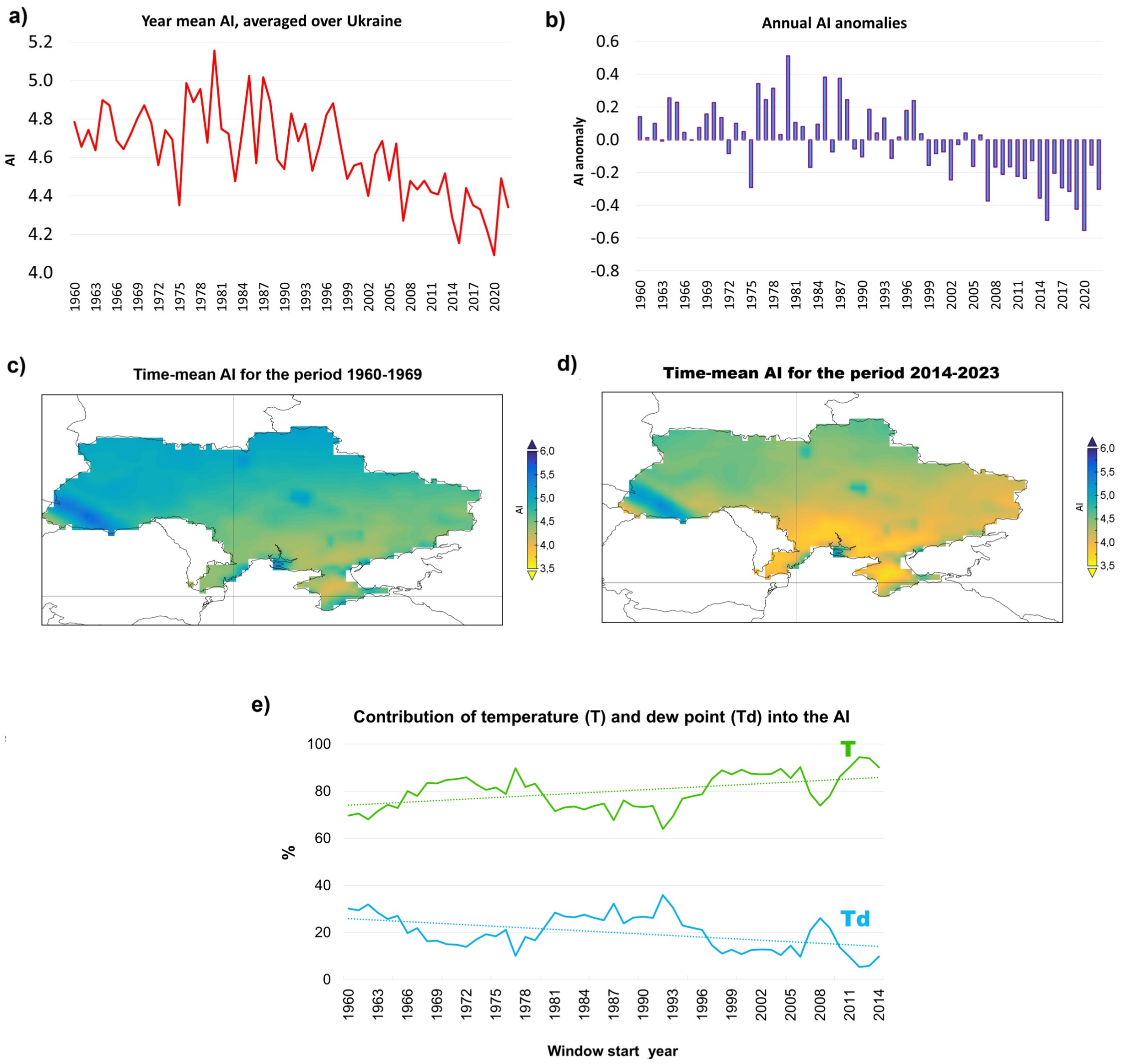

Fig. 4.3: (a) Time series of year-mean AI, averaged over Ukraine for the period 1960–2023; (b) annual AI anomalies (base period 1981–2010); (c) and (d) spatial distribution of time-mean AI for the periods 1960–1969 and 2014–2023, respectively; (e) dynamics of contribution (%) the temperature and dew point temperature to the AI.

are negative throughout Ukraine and in all seasons (Fig. 4.4), indicating an increase in the risk of fire hazard. The greatest changes are typical for the southwestern regions, especially in spring and summer (Odesa and Mykolaiv regions), and for the Crimean Peninsula in all seasons. Also, the center of substantial AI changes is observed in the Carpathian region (Ivano-Frankivsk and Ternopil regions). In the autumn, the greatest negative trends are concentrated in the eastern half of Ukraine, and in the west of the country, they are close to zero. The analysis of the statistical significance of trends showed that in winter, spring and autumn, negative trends are statistically significant throughout Ukraine. In autumn, the trends are not significant in the western regions, as well as in the center of Ukraine (Dnipropetrovsk region).

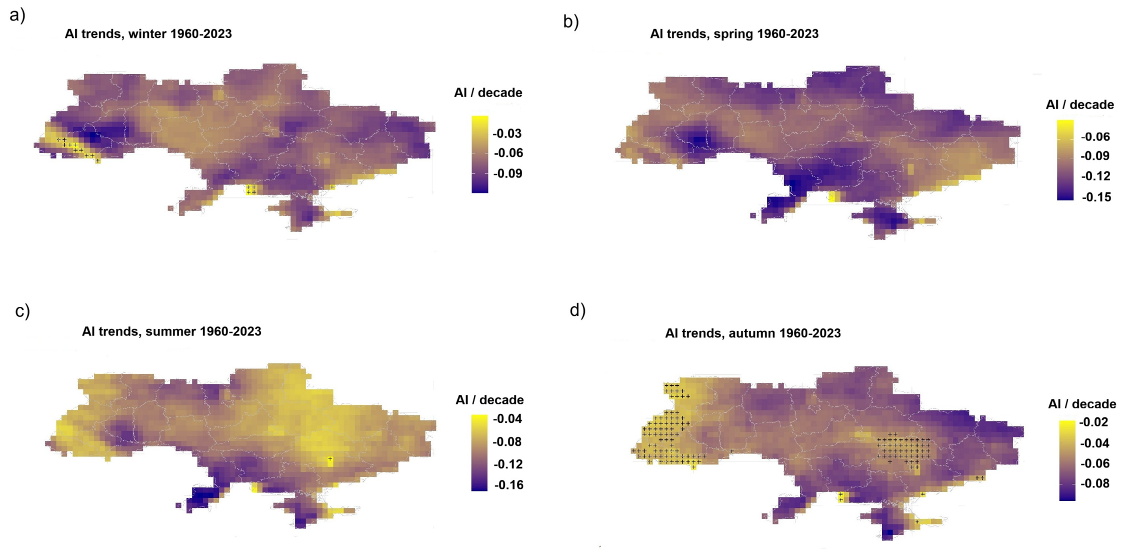

Fig. 4.4: Seasonal AI trends (AI value per decade): (a) winter; (b) spring; (c) summer; (d) autumn. The areas of non-significant trends marked by '+'.

4.2 *Occurrence of Fire Danger Classes*

First, we analysed time series of the annual number of days in each fire danger class, averaged across the territory of Ukraine (Fig. 4.5). The changes in the annual number of days within different AI classes indicate a marked redistribution in their frequency since the late 1990s. Over the entire study period, the annual frequency of days in the AI1 class averaged 58 %, while the AI2 class occurred on average 25 % of days per year. Days classified as high (AI3) or extreme (AI4) fire danger were observed on average in 7.6 % and 9.0 % of cases, respectively. During the period 1960–1995, the average frequency of days in the extreme AI4 class was 26 days per year (7.1 %), whereas from 1996 to 2023, this number increased to almost 42 days per year (11.4 %). Consequently, the combined frequency of days in classes AI3 and AI4 rose from 14.1 % in 1960–1995 to 19.7 % over the last 28 years.

In the subsequent analysis, we focused on the warm season (April–October), examining the number of days in each fire danger class and the trends in their changes across different regions of the country (Fig. 4.6).

Analysis of mean seasonal frequency of days in each fire danger class showed that the highest number of days in the extreme fire danger class (AI4) is concentrated in the southern and southeastern regions of Ukraine, as well as on the Crimean Peninsula, averaging 60–65 days over the warm season. In the north of Ukraine, in the Carpathians, along the coastal areas, and over river basins, the number of days with extreme fire danger sharply decreases, not exceeding 10–15 days per year. A similar spatial pattern is observed for the high fire danger class (AI3), although the average number of days in this class is substantially lower, not exceeding 35–39 days in the southern regions of the country. For the moderate fire danger class (AI2), the highest number of days (90–110 days per year) is observed in the northern and western regions, as well as along the coasts of the Crimean

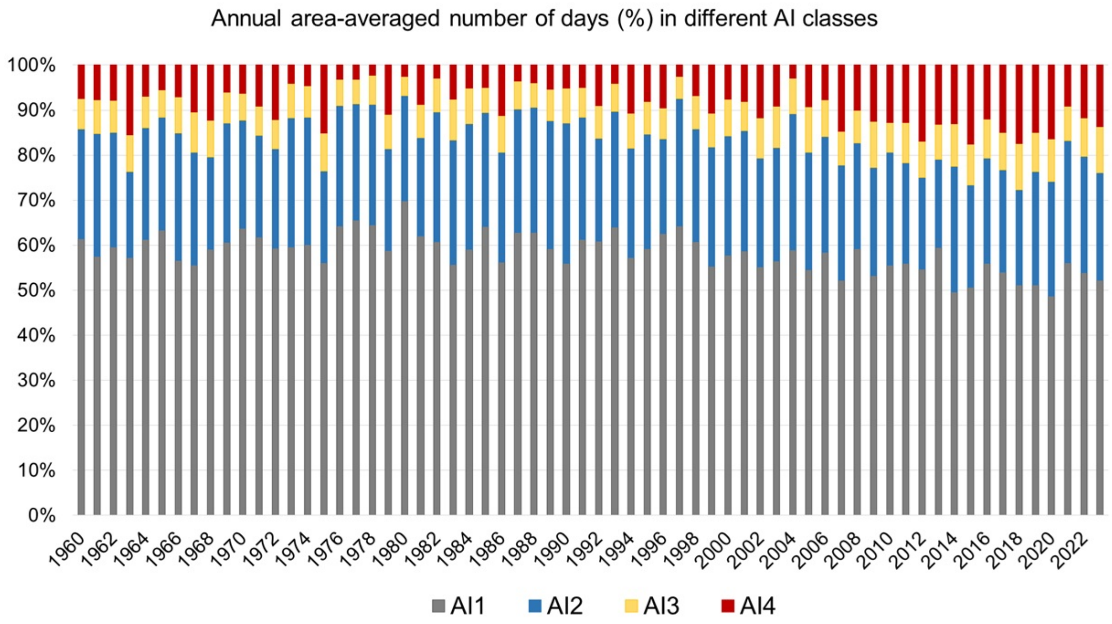

Fig. 4.5: Time series of the annual number of days (%) in different AI classes, averaged over Ukraine for 1960–2023, with ranges shown for each class.

Peninsula and Odesa region. The maximum frequency of days with low fire danger (AI1) occurs in the Carpathians and along the coastal areas, increasing from south to north on average from 50–60 to 100–120 days per year.

The obtained results on the spatial distribution and number of days with high and extreme fire danger according to the Ångström index are comparable to estimates derived using the Nesterov Composite Index (NCI). According to *Balabukh and Malytska* (2017), during the warm season (April–October) of 1981–2010, the maximum number of days with extreme fire danger in the southern half of Ukraine reached 40–50 days, while days with high fire danger reached 75–85 days, totaling 115–135 days for the two classes. These values are comparable to our estimates of mean frequency, which sum to 90–104 days for the AI3 and AI4 classes in the southern regions during the warm season.

Trends in the number of days across different fire danger classes vary and clearly reflect adverse changes in fire hazard conditions (Fig. 4.6). Positive and statistically significant trends in the extreme fire danger class (AI4) are observed throughout the country, with particularly strong increases in the southwestern regions. In contrast, trends in the low fire danger class (AI1) are all negative, though smaller in magnitude. For the high fire danger class (AI3), positive and significant trends predominate in the northern and western parts of the country. In the steppe regions, trends are near zero or slightly negative and statistically insignificant. For the moderate fire danger class (AI2), negative insignificant trends dominate in the northern and eastern regions. Of particular note are trends in the Eastern Carpathians, which show an increase in the frequency of days in AI2 class, while trends for the higher fire danger classes AI3 and AI4 remain near zero.

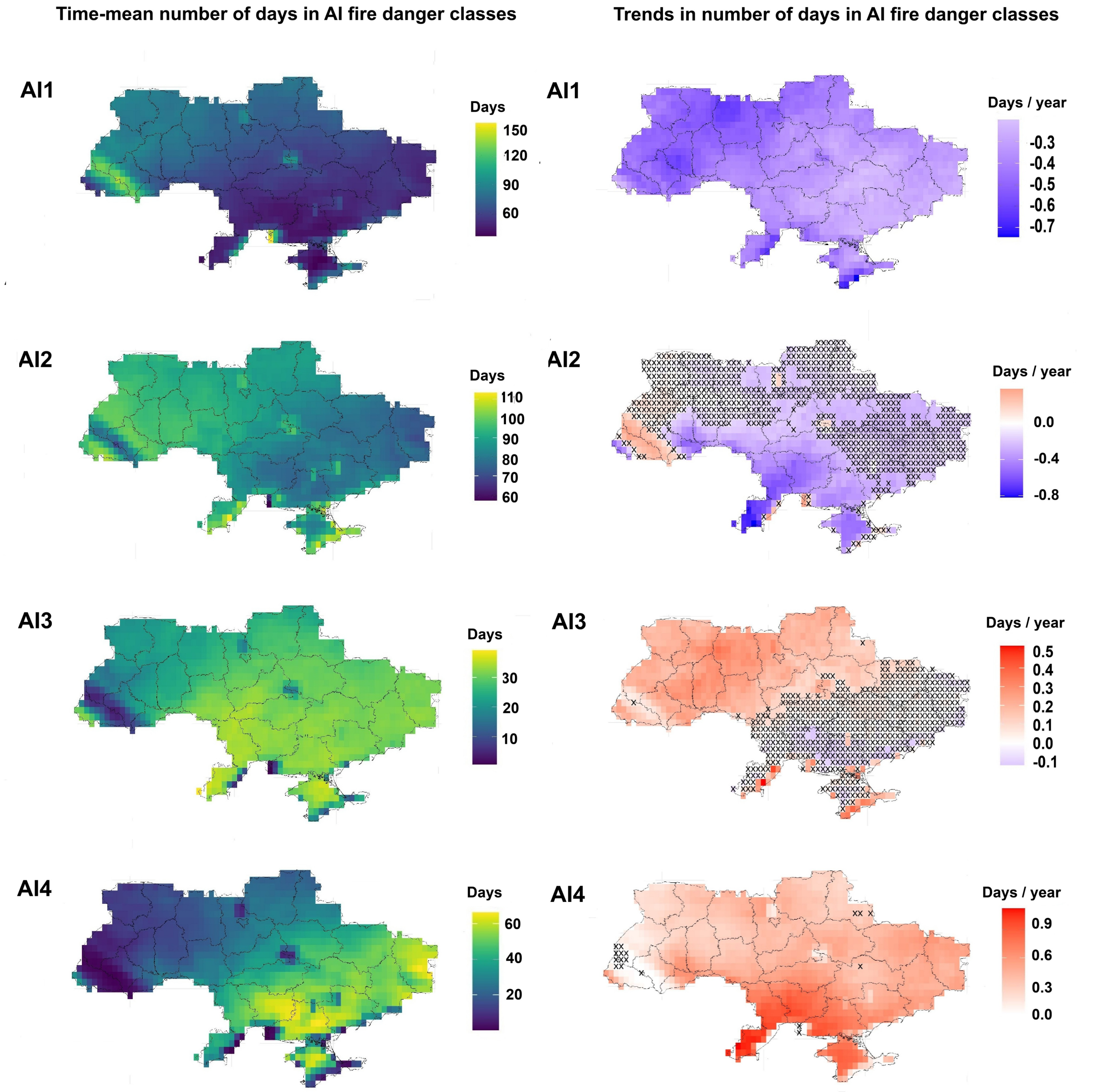

Fig. 4.6: Average annual frequency of days in different fire danger classes and trends in frequency (days per year) in the warm period 1960–2023. The areas of non-significant trends are marked by '+'.

4.3 Relationship between burned areas and the number of days in different AI classes

To investigate the relationship between the Ångström index and fire activity in Ukraine, the correlation between the burned area sums during warm seasons and the seasonal mean Ångström index was first assessed. Fig. 4.7a shows the spatial distribution of seasonal mean BA sums across Ukraine for the study period. The largest burned areas are concentrated in the southwestern and eastern regions of the country within the steppe zone, while the smallest values are typical for the western and northwestern parts. The spatial distribution of Pearson correlation coefficients between seasonal mean AI and BA values reveals a negative relationship in the northern and western regions, as well as on the Crimean Peninsula (Fig. 4.7b). The correlation coefficients are statistically significant mainly in the Polissia. In the central and southern parts of the country, a positive correlation prevails, with significant r-values observed only in a limited area at the border between Mykolaiv and Kirovohrad regions.

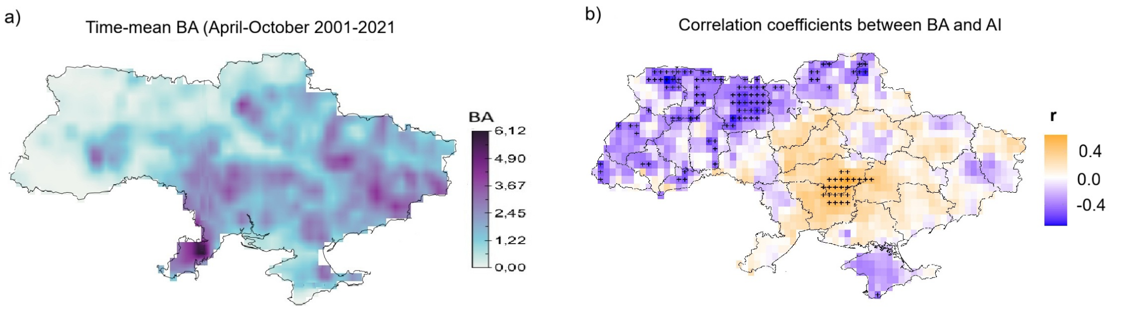

Fig. 4.7: (a) Time-mean BA sums (10^7 ha) for the warm season (April–October) of 2001–2021; (b) spatial distribution of correlation coefficients (r) between seasonal BA sums and seasonal mean AI for the period 2001–2021. The '+' indicates grid points with statistically significant correlation coefficients (at the 95 % confidence level).

Next, the statistical relationship between the burned area during warm seasons and the number of days in each fire danger class was examined. Fig. 4.8 presents the spatial distribution of the Pearson correlation coefficients and their statistical significance at the 95 % confidence level for each of the four classes. As can be seen, the spatial distribution of correlation coefficients varies significantly depending on the fire danger class.

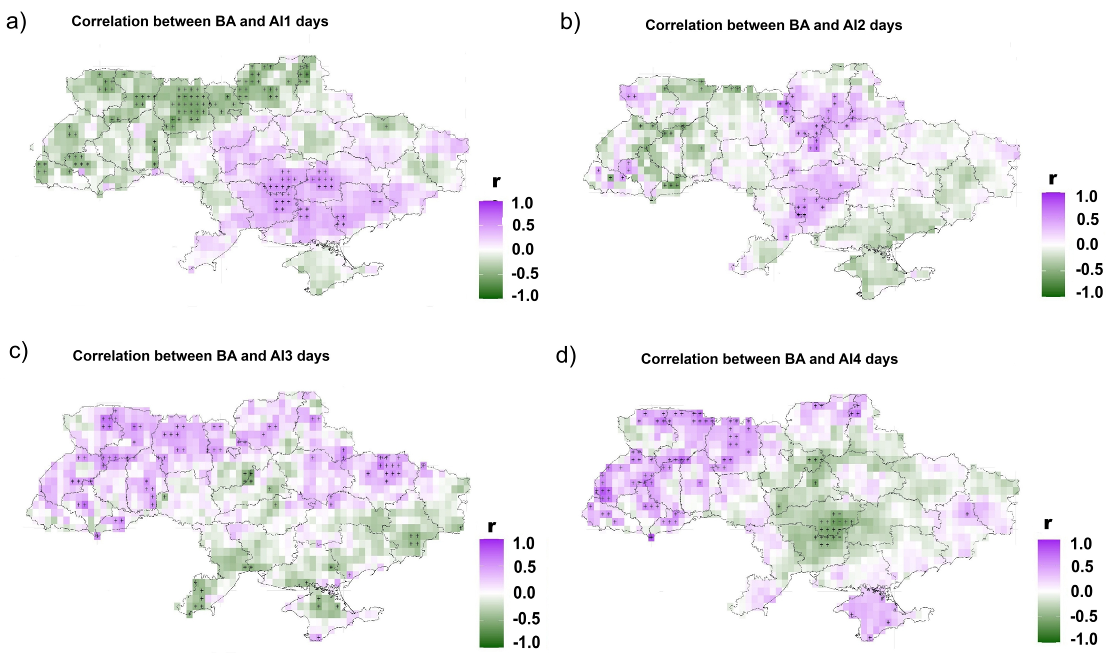

Fig. 4.8: Spatial distribution of Pearson correlation coefficients between burned areas (BA) and the number of days in each fire danger class. '+' symbols indicate statistically significant correlation coefficients (at the 95 % confidence level).

For the AI1 class, which indicates low fire danger, a negative and statistically significant correlation ($r = -0.6$ to -0.7) is typical for the most forested regions in the north and west of the country, as well as for the Crimean Peninsula (Fig. 4.8a). For the AI2 class, representing moderate fire danger, the spatial pattern of correlation coefficients changes: a positive and statistically significant relationship ($r = 0.5$ to 0.7) is observed mainly in the central part of the country, while negative correlations dominate in other regions (Fig. 4.8b). In the AI3 class, which indicates high fire danger, positive and statistically significant correlation coefficients ($r = 0.5$ to 0.7) are typical for the northern half of Ukraine and the western regions (Fig. 4.8c). However, in the steppe zone and central parts of the country, negative correlations prevail. Finally, in the AI4 class, representing extreme fire danger, positive correlation coefficients ($r = 0.4$ to 0.8) dominate in many areas, except for the central part of the country and the northeastern regions (Fig. 4.8d). Statistically significant relationships are mainly observed in the western and central regions of Ukraine. Summarizing these results, it can be noted that in the classes with high fire danger (AI3 and AI4), an increase in the number of fire-dangerous days leads to an increase in burned areas in the most forested regions of the country. At the same time, in the steppe and forest-steppe zones, the expansion of burned areas is associated with less severe fire danger conditions, as described by the AI1 and AI2 classes.

5 *Discussion*

Meteorological indices for assessing fire danger based on weather conditions are a convenient tool for evaluating the risk of fire ignition and spread across different regions and with varying lead times. Existing studies on the use of the simple Ångström index in various geographic settings, in comparison with other fire danger indices, have demonstrated a high level of agreement with observed fire activity (*Eastaugh and Hasenauer*, 2014; *Pérez-Sánchez et al.*, 2017; *Todorova et al.*, 2023).

Our analysis showed that, under Ukrainian conditions, the Ångström index at the seasonal scale provides clear differentiation in fire danger risk assessment across different natural zones, depending on the index's threshold values. While in forested regions of the country, classes with high and extreme fire danger (AI3 and AI4) are expectedly associated with increased burned areas, an inverse relationship was found in the steppe and forest-steppe zones. The emergence of negative correlations in high fire danger classes in the central regions of Ukraine may be explained by the fact that an increase in days with high temperatures and low humidity, especially during spring and early summer, leads to reduced development of ground vegetation, thereby reducing the amount of potential fuels. At the same time, less severe weather conditions, described by the thresholds of AI1 and AI2 classes, are more favorable for the accumulation of vegetative biomass in steppe and forest-steppe areas. This can result in larger burned areas due to the presence of abundant fuel, which is reflected in the positive correlation observed in these fire danger classes. A similar pattern has been noted, for example, in Portugal, where it was found that in shrub-covered areas, large fires tend to occur under less extreme weather conditions than in forested regions (*Calheiros et al.*, 2022).

Studies have shown (*Turco et al.*, 2017a; *Wasserman and Mueller*, 2023; *Lai et al.*, 2025) that preceding and current dry and hot conditions lead to increased fuel dryness, primarily affecting its flammability. However, fire spread may be limited by the amount of available fuel, depending on whether the vegetation is forest, shrubland, or grassland (*Turco et al.*, 2017b). As noted by (*Stavi*, 2019), fuel loads in grasslands and shrublands are significantly lower than in forests, but the fuel is drier and tends to burn almost completely. Additionally, it is important to consider that Ukraine has a very high degree of agricultural land use. In the steppe and forest-steppe zones, the share of arable land reaches 70–80 % (*Holovachko et al.*, 2021), and the annual burning of agricultural residues remains widespread (*Hall et al.*, 2021), which may influences the statistics of burned areas and number of fires. Unlike in forested regions, where fire occurrence is closely linked to meteorological conditions, in croplands ignition largely depends on agricultural cycles. This situation can alter the fire regime of specific areas (*Dara et al.*, 2020) and distort statistical assessments of the relationship between burned areas and meteorological conditions (*Forrest et al.*, 2024). On the other hand, the spatial and temporal scales of agricultural burning are relatively small, which leads to their underestimation in satellite monitoring using medium-resolution instruments such as MODIS (*Hall et al.*, 2016), the BA product of which we used in this study. Moreover, during dry and hot seasons, a reduction in biomass also occurs in crops, resulting in fewer and smaller agricultural fires, which evidently minimizes their influence on the overall burned area statistics. Considering the somewhat contradictory results, we obtained regarding the inverse relationship between burned areas and the number of fire-prone days in the highest fire danger classes AI3 and AI4 in steppe regions, it becomes evident that further research on the impact of weather conditions on fire danger requires either filtering out agricultural fires or selecting study areas with minimal agricultural impact.

Overall, the results obtained regarding the nature of the relationship between weather conditions described by the Ångström index, and burned areas across different natural zones appear consistent and reflect the varying impact of similar temperature and humidity conditions on different types of vegetation. However, it should be noted that our estimates are based on seasonal-scale analysis, which accounts for the vegetation cycle. For short-term applications (up to 7–10 days), the effectiveness of the Ångström index in Ukraine should be evaluated using appropriate datasets and statistics on actual fire occurrences (e.g., *Mavrakis and Salvati*, 2015).

Since the Ångström index was originally developed for the climatic conditions of Sweden, which differ significantly from those in Ukraine, it may be reasonable to reconsider the criteria defining the fire danger classes for practical implementation. For example, the AI3 class is defined by a very narrow range compared to other classes (see Table 2.1) and has low recurrence, as shown earlier. If a percentile-based approach is used to identify thresholds of extremity, it can be demonstrated that, for example, in summer, the 5^{th} and 10^{th} percentile values across most of Ukraine are within AI values of 2.5 or lower (Fig. 10). This supports the idea of potentially merging AI3 and AI4 into a single class with a threshold of AI ≤ 2.5 for daily operational use of the index. At the same time, the spatial distribution of correlation signs for seasonal values in both classes shows substantial differences, indicating the need to keep them separate when assessing fire danger risk at larger temporal scales. Additionally, the AI2 class is defined by a relatively wide interval. However, in some studies (e.g., *Tošić et al.*, 2019), this class is split into two subcategories: $4.0 < \mathrm{AI} < 3.0$ (Unfavorable) and $3.0 < \mathrm{AI} < 2.5$ (Favorable). This approach also requires further investigation regarding its relationship with actual fire occurrences in Ukraine.

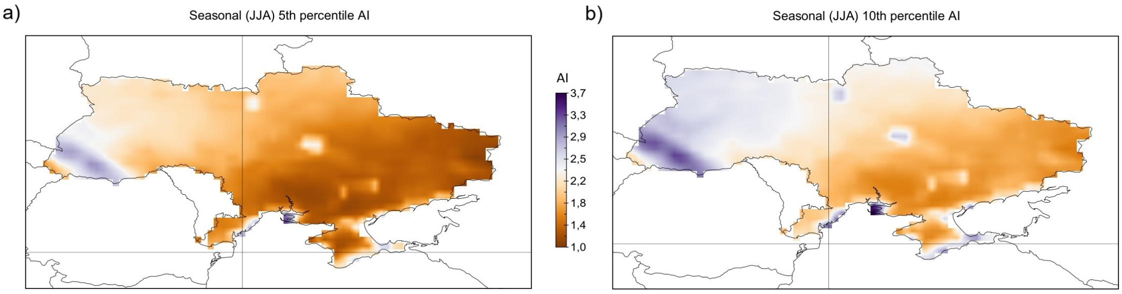

Fig. 5.1: Spatial distribution of the 5th (a) and 10th (b) percentile values of the Ångström index for the summer period (June–August), 1960–2023.

6 *Conclusion*

In this study, a comprehensive spatiotemporal analysis of fire-prone weather conditions in Ukraine was conducted for the first time using the Ångström index over a long-term period from 1960 to 2023.

The obtained estimates of temporal changes in the spatial distribution of the Ångström index revealed that, due to the observed increase in air temperature across all seasons, there has been a consistent trend toward decreasing AI values in all regions of Ukraine that indicating an increased risk of fire-prone conditions. The most important changes were observed during spring and summer in the southern regions of the country. The dynamics of annual average AI values across Ukraine showed that persistent changes began in the late 1990s. Since 2007, the annual average AI has exhibited only negative anomalies, which corresponds to the trend of rising air temperatures in recent decades. Using threshold values of the Ångström index), we assessed the recurrence of fire danger days across four different classes, ranging from low to extreme fire danger. The analysis showed that the frequency of days with extreme fire danger has increased across Ukraine on average by more than 1.5 times since 1960. In the most recent decade (2014–2023), the average number of days in extreme class reached 51 days per warm season.

Considering the relatively short period of the study with burned area product (21 years), the results we obtained regarding the correlation relationships between BA and recurrence of different AI fire danger classes can be considered preliminary, which require confirmation over longer period of study and taking into account the possible impact of agricultural burning. Following this, it will be possible to recommend incorporating these relationships into seasonal fire risk assessment schemes for various landscape zones in Ukraine using climate modelling data. The use of the Ångström index may be beneficial in the development of fire risk models that incorporate a comprehensive assessment of risk factors to support the design of adaptation and fire management strategies under changing climate conditions.

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Data availability

1. ERA5 hourly data on single levels from 1940 to present. Copernicus Climate Change Service (C3S). Climate Data Store (CDS). DOI: `10.24381/cds.adbb2d47`

2. Fire Burned Area product from 2001 to present derived from satellite observation. Copernicus Climate Change Service (C3S). Climate Data Store (CDS). DOI: `10.24381/cds.f333cf85`

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