



Climatic efficiency index (CEI): a multi-scale diagnostic for energy–water–climate interactions in semi-arid regions

Erkan Karakoyun¹

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Abstract

Climate change and increasing demand for energy require the use of comprehensive indicators that consider atmospheric, hydrological, and energy system dynamics. Degree-day indices, such as Cooling Degree Days (CDD) and Heating Degree Days (HDD), have long been used to estimate energy demand in response to climatic variability. However, because CDD and HDD only consider near-surface air temperature, they ignore critical processes like radiative forcing, evaporative cooling, and surface energy balance, limiting their ability to fully represent climatic constraints on energy efficiency. In this study, we created and used the Climatic Efficiency Index (CEI), a compound index that combines three important components: thermal penalty, Bowen ratio, and evaporative fraction. CEI was calculated at multiple timescales (CEI-1 (monthly), CEI-3 (three-monthly), CEI-6 (semi-annual), and CEI-12 (annual) and compared to degree-day indicators using data from Southeastern Anatolia (1950–2024). The results show a strong positive correlation between CEI and CDD ($\rho > 0.90$) and a strong negative correlation with HDD ($\rho < -0.85$) at short timescales (CEI-1). However, the magnitude of these correlations decreases at longer time scales, reflecting the smoothing of climatic variability over multi-month periods. Despite this attenuation, significant associations persist at all scales, confirming CEI's robustness as an energy-climate indicator. From an energy standpoint, CEI is a more comprehensive and mechanistic measure than CDD alone, as it explains why and under what climatic conditions energy stress occurs. By combining evaporative and radiative dynamics, CEI can capture both immediate thermal stress and long-term climatic inefficiencies, connecting energy demand to drought processes and climate change impacts. This makes CEI an important addition to the water-energy-climate nexus, providing new insights into energy system planning and adaptation in semi-arid areas.

Keywords Climatic efficiency index (CEI) · Cooling degree days (CDD) · Heating degree days (HDD) · Energy demand · Bowen ratio · Thermal penalty · Evaporative fraction · Climate change

1 Introduction

Climate change and rapidly rising energy demand have highlighted the importance of comprehensive indicators that bridge the gap between atmospheric dynamics, water availability, and energy system performance. Global warming increases not only the frequency and magnitude of extreme weather events, but also the thermal and hydrological stresses placed on energy from renewable sources technologies, particularly photovoltaic (PV) systems. The

Southeastern Anatolia Project (GAP) region of Türkiye is a critical hotspot where these challenges intersect. The region, with semi-arid to arid climatic conditions, significant inter-annual rainfall variability, and recurring summer heatwaves (Önol & Semazzi 2009; Yürekli 2015), is a natural laboratory for testing climate-energy-water interactions. Such conditions have a direct impact on both the availability of water resources for agriculture and hydropower, as well as the potential operational efficiency of PV systems, which are sensitive to increases in temperature and evaporative cooling limitations (Krauter 2004; Van Vliet et al. 2016).

Traditional climate indices, such as the Standardized Precipitation Index (SPI) (McKee et al. 1993) and the Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al. 2012), have been widely used to assess droughts over multiple time scales. While SPI

✉ Erkan Karakoyun
e.karakoyun@alparslan.edu.tr

¹ Faculty of Engineering and Architecture, Mus Alparslan University, Muş, Türkiye

measures precipitation anomalies and SPEI accounts for evaporative demand, their primary focus remains hydrological drought. These indicators do not explicitly account for the partitioning of surface energy fluxes or the thermal penalties that occur at high temperatures and intense solar radiation. Similarly, heat stress metrics such as Cooling Degree Days (CDD) quantify cooling demand, while evapotranspiration-based indices reflect water stress, but each is one-dimensional, focusing on one aspect of climate-energy interactions rather than providing a comprehensive measure of climatic efficiency. Recent studies emphasize that evapotranspiration and the partitioning of surface energy fluxes (net radiation, sensible heat, and latent heat) are central to understanding climate–water–energy dynamics yet remain insufficiently represented in traditional indices (Katul et al. 2012; Yuan et al. 2022). Furthermore, research on hydrologic–energy partitioning shows that energy balance processes impose strong constraints on climate system behavior, highlighting the need for integrative approaches that move beyond single-variable indicators (Yin et al. 2019).

Recent literature reinforces these limitations from various angles. For example, dynamic drought monitoring frameworks that incorporate energy fluxes show that net radiation, sensible heat, and latent heat anomalies can provide early-warning signals of drought propensity, demonstrating the predictive power of energy balance processes for hydrological stress (Wu et al. 2025). At the same time, energy system studies show that climate change-induced increases in cooling demand can put additional strain on electricity grids, though these effects can be mitigated with distributed photovoltaics and passive cooling strategies (Kapeller et al. 2024). These findings emphasize how climate variability affects both water availability and energy infrastructure resilience.

A large body of degree-day research confirms the growing imbalance between heating and cooling requirements. EURO-CORDEX simulations for 2021–2050 show a significant decrease in HDD and a sharp increase in CDD, particularly under RCP8.5, with topography and coastal proximity influencing local outcomes (Karagiannidis et al. 2024). Degree-day mapping in Türkiye has revealed stark regional contrasts, with maximum HDDs in the high-altitude northeast (Ardahan) and maximum CDDs in the semi-arid southeast (Şanlıurfa), highlighting the country's spatial energy heterogeneity (Dombayci 2009). Overall, these studies show that while HDD/CDD indices are useful for estimating energy demand, they are insufficient to capture the coupled thermal, hydrological, and radiative dynamics that define climatic efficiency.

The Bowen Ratio (B) (Bowen 1926) provides an important diagnostic of surface energy balance by describing the relative partitioning of sensible and latent heat fluxes. Elevated Bowen ratios indicate dry, energy-limited environments with limited evaporative cooling, whereas lower values indicate greater water availability and land–atmosphere coupling. The Evaporative Fraction (EF), defined as the contribution of latent heat flux to the total surface energy budget, has been identified as a reliable indicator of hydrological and ecosystem stress (Crago & Qualls 2014; Shuttleworth et al. 1989). B and EF work together to capture the hydrological efficiency of the climate system. In parallel, the Thermal Penalty (TP) concept addresses the energy efficiency dimension by quantifying performance losses in PV systems when operating cell temperature exceeds reference conditions ($T_{\text{ref}}=25\text{ }^{\circ}\text{C}$), which are typically modeled using the Nominal Operating Cell Temperature (NOCT) framework (Skoplaki & Palyvos 2009). TP thus serves as a proxy for the potential degradation in energy yields, quantifying how atmospheric and radiative stress may constrain the operational performance of energy systems.

Despite the established importance of B, EF, and TP, there is no integrated index that combines the three complementary dimensions of hydrological balance, evaporative cooling potential, and thermal stress into a single, standardized measure of climate efficiency. Existing approaches treat these processes separately, which limits their applicability to the energy–water–climate nexus, where interactions are inherently linked. The proposed Climatic Efficiency Index (CEI) bridges this critical gap by combining TP, B, and EF into a single, multi-scale framework. CEI uses robust normalization, geometric aggregation, and z-score standardization to condense complex climate interactions into an interpretable classification ranging from "Very Efficient" to "Very Inefficient."

The need for such an index is especially acute in areas like GAP, where irrigation for agriculture, hydropower generation, and rapidly expanding PV installations is all simultaneously vulnerable to climatic stress. Efficient climate metrics are critical for forecasting seasonal to interannual variations in water and energy supply, optimizing PV system design, and directing climate adaptation strategies. Furthermore, CEI's multi-scale structure (1-, 3-, 6-, and 12-month windows) allows for the simultaneous assessment of short-term anomalies (e.g., heatwave-induced PV losses) and long-term regime shifts (rising aridity trends), making it a decision-support tool for both operational management and strategic planning.

In this context, traditional climate indicators such as SPI, SPEI, CDD, and HDD are inherently one-dimensional

and thus inadequate to capture the multifaceted nature of climate-energy-water interactions. The CEI bridges this gap by combining the thermal penalty, the Bowen ratio, and the evaporative fraction into a comprehensive, multidimensional framework. CEI reflects variations in energy demand while also incorporating surface energy balance and hydro-meteorological processes, resulting in a more comprehensive evaluation. In semi-arid regions like GAP, where agricultural irrigation, hydropower, and rapidly expanding PV installations are all subjected to climatic stress, the development and application of CEI is especially important.

In this study, CEI was not only developed and computed for the GAP region, but it was also systematically compared to traditional degree-day indices such as CDD and HDD. While CDD and HDD are commonly used to estimate energy demand, they only consider air temperature and thus cannot fully account for the complex climatic drivers of energy stress. By contrasting CEI with CDD and HDD, this study shows how CEI incorporates additional dimensions such as thermal penalty, Bowen ratio, and evaporative fraction, capturing both the intensity of climatic inefficiency and the underlying physical mechanisms. Existing temperature-based indices (e.g., CDD and HDD) do not capture the role of evaporative cooling, moisture limitation, and land-atmosphere feedbacks. CEI is introduced to bridge this gap by incorporating climatic energy balance dynamics alongside temperature anomalies, offering a more physically grounded metric for climate-energy interaction. The comparative analysis reveals that CEI is more closely aligned with energy demand dynamics, as well as links to drought intensification and long-term climate change.

Accordingly, this study pursues four main objectives: 1) To develop and formalize the CEI, integrating TP, B, and EF into a coherent, multi-dimensional indicator.

2) To compute CEI across multiple timescales for the GAP region from 1950 to 2024. 3) To systematically compare CEI with established indices such as CDD, and HDD, thereby demonstrating its added value for energy-water-climate nexus applications. 4) To assess the implications of CEI for short-term energy demand variability, long-term climatic inefficiency, and regional climate resilience.

By introducing CEI and benchmarking it against degree-day metrics, this research contributes an innovative diagnostic tool that captures the intertwined thermal, hydrological, and radiative processes driving climatic efficiency. Its ability to provide both regional insights and global transferability highlights its novelty and scientific contribution. The results are expected to have broad implications for PV system planning, integrated water-energy management, and climate resilience in semi-arid and arid regions, while also

offering a framework adaptable to other geographic and sectoral contexts.

2 Materials and methods

2.1 Study area

The research focuses on the Southeastern Anatolia Project (GAP) region of Türkiye, encompassing the provinces of Siirt, Gaziantep, Şanlıurfa, Batman, Diyarbakır, Adıyaman, Kilis, and Mardin (Fig. 1). This region is characterized by a semi-arid to arid climate, with hot, dry summers and relatively mild, wetter winters (Gumus et al. 2021). The combination of high solar irradiance, elevated summer air temperatures, and significant variability in evapotranspiration processes makes the GAP region a critical case study for assessing climatic efficiency in relation to photovoltaic (PV) system performance and energy-water interactions.

2.2 Data sources

Climatic variables were obtained from the ERA5 reanalysis dataset produced by the European Centre for Medium-Range Weather Forecasts (ECMWF), covering the period 1950–2024 (Hersbach et al. 2020). Two types of temporal aggregation were employed:

Monthly means, extracted for:

Sensible heat flux ($\text{W}\cdot\text{m}^{-2}$) from ERA5 variable *hfss*. Latent heat flux ($\text{W}\cdot\text{m}^{-2}$) from ERA5 variable *hfls*. Near-surface air temperature (T_{amb} , °C) from ERA5 variable *tas_mean*. Surface shortwave radiation ($\text{W}\cdot\text{m}^{-2}$) from ERA5 variable *rsds_mean*. 10 m wind speed ($\text{m}\cdot\text{s}^{-1}$) from ERA5 variable *windspeed_mean*.

Daily near-surface air temperature (*tas_mean*) was additionally retrieved to compute CDD and HDD. Daily CDD and HDD values were calculated using base temperatures of 25 °C and 18 °C, respectively, and then aggregated to monthly totals for consistency with CEI indices (Isaac & van Vuuren 2009; Spinoni et al. 2015). Although the ERA5 product provides hourly resolution, CEI was constructed at monthly and aggregated time scales to align with regional drought monitoring practices in the arid GAP region. Future studies may explore daily CEI applications to support short-term extreme event detection and operational decision-making.

For photovoltaic (PV) performance modeling, a Nominal Operating Cell Temperature (NOCT) of 45 °C, representative of crystalline silicon modules, was assumed (Skoplaki & Palyvos 2009). In accordance with Standard

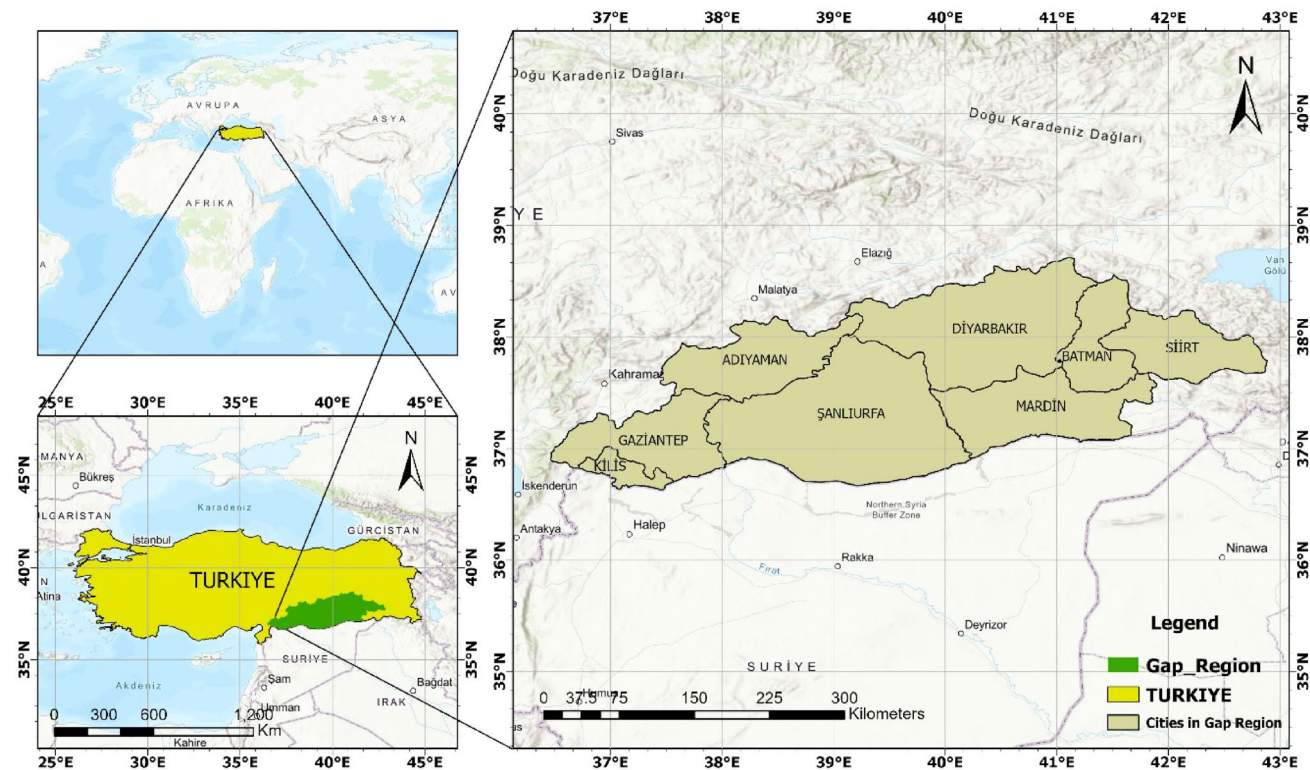


Fig. 1 Study area

Test Conditions, the reference cell temperature (T_{ref}) was fixed at 25 °C.

2.3 Calculation process of CEI

2.3.1 PV cell temperature and thermal penalty

PV cell temperature was modeled as (Skoplaki & Palyvos 2009):

$$T_{cell} = T_{amb} + \frac{(NOCT - 20)}{800} \left(\frac{rsds}{1 + \alpha_v} \right) \quad (1)$$

in which T_{cell} is the PV cell temperature (°C), T_{amb} is the 2 m air temperature (°C), NOCT is the nominal operating cell temperature (°C), $rsds$ is the incoming shortwave radiation (W/m^2), and α_v is an empirical wind cooling coefficient set to 0.1.

The thermal penalty (TP) is calculated as:

$$TP = \frac{T_{cell} - T_{ref}}{T_{ref}} \times 100 \quad (2)$$

in which TP is the relative efficiency loss due to elevated cell temperature (%), and T_{ref} is the reference temperature of 25 °C.

2.3.2 Bowen ratio

$$B = \frac{|H|}{|LE|} \quad (3)$$

In which B is the Bowen ratio (dimensionless), H is the sensible heat flux (W/m^2), and LE is the latent heat flux (W/m^2). High B values indicate dry and hot conditions, while low B values reflect moist and evaporatively active conditions (Bowen 1926).

2.3.3 Evaporative fraction

$$EF = \frac{|LE|}{|LE| + |H|} \quad (4)$$

in which EF is the evaporative fraction (dimensionless), representing the partitioning of available energy into latent heat flux. High EF values indicate strong evaporative cooling capacity, while low EF values signal surface dryness and limited evapotranspiration (Shuttleworth et al. 1989).

2.3.4 Normalization of indicators

Each indicator (TP, B, and EF) was normalized using a robust min–max scaling between the 5th and 95th percentiles of their long-term distribution to reduce sensitivity to outliers (Wilks 2011). For TP and B, high values indicate inefficiency; therefore, normalization preserved the original direction of the data. For EF, high values are favorable; therefore, an inverted form $EF^* = 1 - EF_n$ was used so that all indicators aligned in direction (higher=less efficient).

2.3.5 Climatic efficiency index (CEI)

The CEI was defined as the geometric mean of the normalized indicators:

$$CEI = (TP_n \times B_n \times EF_n^*)^{\frac{1}{3}} \quad (5)$$

in which TP_n , B_n , and EF_n^* are the normalized thermal penalty, Bowen ratio, and inverted evaporative fraction, respectively. The geometric means ensures that an extreme inefficiency in any component strongly penalizes the overall index.

To evaluate uncertainty, CEI was recomputed under multiple perturbation assumptions: alternative percentile bounds (10th–90th), arithmetic aggregation, $\pm 10\%$ and $\pm 15\%$ perturbation of both sensible and latent heat fluxes, and $\pm 10\%$ modification of the wind-cooling coefficient. Sensitivity was assessed through correlation, RMSE, and CEI-category transition metrics, enabling quantification of how parameter and flux uncertainty propagate into CEI outcomes.

CEI is constructed from ERA5 surface sensible (hfss) and latent (hfls) heat fluxes, 2-m air temperature (tas), surface shortwave radiation (rsds) and 10-m wind speed, which are first combined into Bowen ratio, evaporative fraction and a NOCT-based thermal penalty term. All components are then transformed using a robust percentile normalization (5th–95th percentile) and standardized to SPI-type z-scores, as implemented in the CEI code. Consequently, CEI captures the relative hydroclimatic state (position within the local climatological distribution) rather than absolute flux magnitudes, thereby mitigating but not eliminating potential systematic biases in ERA5 reanalysis fields.

Recent validation studies in Türkiye demonstrate that ERA5 reliably captures the temporal evolution and spatial coherence of climate surface energy components (Çetin et al. 2024; Tatli 2025; Tulger Kara & Elbir 2025; Yilmaz 2023). According to their results, the evaluations show strong agreement between ERA5 and station-based observations in seasonal and interannual temperature variability. Besides, to assess the influence of ERA5 structural biases, a perturbation-based uncertainty experiment was performed

in which sensible and latent heat fluxes were systematically increased and decreased by $\pm 10\%$ and $\pm 15\%$. These scenarios represent the approximate maximum range of reported flux uncertainty in reanalysis products. The resulting CEI time series presented near-perfect correlation with the baseline formulation ($r \approx 1.00$) and no classification differences across all temporal scales. This indicates that the CEI is statistically robust to potential flux bias propagation and that the contribution of Bowen ratio uncertainties does not destabilize the index dynamics.

2.3.6 Multi-scale extension

To assess short-, medium-, and long-term variability, CEI values were aggregated using moving averages of 3, 6, and 12 months, denoted as CEI_3 , CEI_6 , and CEI_{12} . This approach parallels multi-scale drought indices such as SPI (McKee et al. 1993) and SPEI (Vicente-Serrano et al. 2012).

2.3.7 Standardization and classification

The CEI time series is standardized using z-scores:

$$Z = \frac{CEI - \mu}{\sigma} \quad (6)$$

in which Z is the standardized score, μ is the long-term mean, and σ is the standard deviation for each station.

2.4 Degree-day indices

To quantify the thermal energy demand associated with temperature variability, CDD and HDD were calculated.

Cooling Degree Days (CDD) Computed relative to a base temperature of 25 °C, which has been widely used in energy and climate applications in warm climatic zones (Isaac & van Vuuren 2009; Spinoni et al. 2015).

$$CDD = \max(T_{mean} - 25, 0) \quad (7)$$

Heating Degree Days (HDD) Computed relative to a base temperature of 18 °C, a threshold extensively applied in building energy and climatological studies across Europe and globally (Spinoni et al. 2015).

$$HDD = \max(18 - T_{mean}, 0) \quad (8)$$

Daily values of CDD and HDD were derived for each station and then aggregated into monthly totals to allow direct comparison with the monthly Climate Efficiency Index (CEI). This approach follows widely accepted methodologies in energy climatology.

2.5 Statistical analysis

The statistical association between CDD/HDD and CEI indices was assessed using Spearman's rank correlation coefficient (Spearman 1904). This non-parametric measure is appropriate for climatological time series as it does not assume linearity and is less sensitive to outliers than Pearson's correlation (Wilks 2011).

For each station and each CEI timescale (CEI-1, CEI-3, CEI-6, CEI-12), the following were computed:

Spearman's ρ (rho) indicating the strength and direction of the monotonic association.

p-value testing the null hypothesis that no correlation exists between the two variables.

A correlation was considered statistically significant when $p < 0.05$, consistent with common practices in climate and hydrological analyses.

The CEI integrates multiple climatic components that jointly influence climate–energy interaction, and therefore the geometric mean was adopted as the aggregation operator to reflect their multiplicative interaction and to avoid dominance of extreme values, consistent with previous drought and energy-balance metrics (Vicente-Serrano et al., 2010; Shukla & Wood, 2008; Hobbins et al., 2016). Additionally, normalization using the 5th and 95th percentile bounds was applied to reduce the influence of heavy-tailed distributions, which are common in arid regions, and to allow comparability across temporal aggregation scales, following established percentile-based anomaly treatment recommended for operational drought monitoring (McKee et al. 1993; Svoboda et al., 2012; Svoboda and Fuchs 2016). Finally, the threshold categories for CEI were aligned with widely implemented drought-severity classification frameworks used in SPI and SPEI to maintain interpretability, enable cross-index comparison, and facilitate integration with existing decision-support systems without the need for a new categorical scheme (McKee et al. 1993; Vicente-Serrano et al., 2010; Svoboda et al., 2012).

Finally, temporal CEI statistics were evaluated by computing period-based mean values for three historical windows (1950–1980, 1981–2000, 2001–2024), enabling a quantitative assessment of long-term changes in climatic efficiency.

3 Results

3.1 Temporal variability of CEI

Figure 2 depicts the temporal variability of CEI-1 in the eight provinces of Southeastern Anatolia from 1950 to 2024. The dashed red lines represent the ± 1.5 thresholds, indicating

very efficient (≤ -1.5) and very inefficient ($\geq +1.5$) climatic conditions. Across all stations, CEI-1 values are frequently greater than $+1.5$, indicating that short-term climatic conditions are generally unfavorable for maintaining optimal to energy efficiency. CEI-1 values < -1.5 , indicating highly favorable conditions, are rare. Elevated CEI-1 values reflect not only the thermal stress associated with high near-surface temperatures thermal penalty (Skoplaki & Palyvos 2009), but also the dominance of sensible over latent heat flux high Bowen ratio (Bowen 1926; Seneviratne et al. 2010) and a low evaporative cooling potential (Gentine et al. 2007; Shuttleworth et al. 1989).

Spatial differences are obvious. Adıyaman and Şanlıurfa have consistently high CEI-1 values, indicating persistent thermal penalties and limited evaporative moderation, resulting in chronically elevated cooling loads. The Bowen ratio in Batman and Diyarbakır is influenced by alternating wet and dry years, resulting in inefficient phases despite higher variability. Gaziantep and Kilis have lower CEI-1 values between 1970 and 1990, which could be attributed to periods of increased soil moisture and higher evaporative fractions, which temporarily reduced climatic inefficiency. In contrast, Mardin and Siirt have consistently high CEI-1, with Mardin exhibiting long periods of inefficiency, implying a sustained imbalance between heat input and evaporative dissipation. From an energy standpoint, these patterns highlight a compound stressor: not only does elevated CEI-1 correspond to higher CDD (and thus increased electricity demand), but it also occurs during times when natural climatic buffers (evapotranspiration) are weakest. This suggests that energy demand peaks coincide with reduced atmospheric resilience, putting additional strain on the energy system. These findings emphasize the importance of renewable integration and adaptive energy planning, especially in semi-arid climates where CEI indicates chronic inefficiency. While traditional indices such as Cooling Degree Days (CDD) and the Standardized Precipitation Evapotranspiration Index (SPEI) provide valuable insights into thermal demand and hydrological stress, they often overlook the mechanistic coupling between surface energy fluxes and atmospheric efficiency. The CEI fills this gap by integrating the thermal penalty, Bowen ratio, and evaporative fraction into a single diagnostic framework. Unlike CDD, which relies solely on air temperature, CEI identifies 'climatic inefficiency' by accounting for evaporative cooling losses and the intensification of sensible heat flux. This allows the detection of compound stress events—where high thermal demand coincides with a weakened ecosystem capacity to buffer heat—that are not captured by individual flux metrics or one-dimensional climate indices. The CEI-1 patterns presented in Fig. 2 elucidate surface energy partitioning and hydroclimatic stress across different atmospheric conditions. Elevated

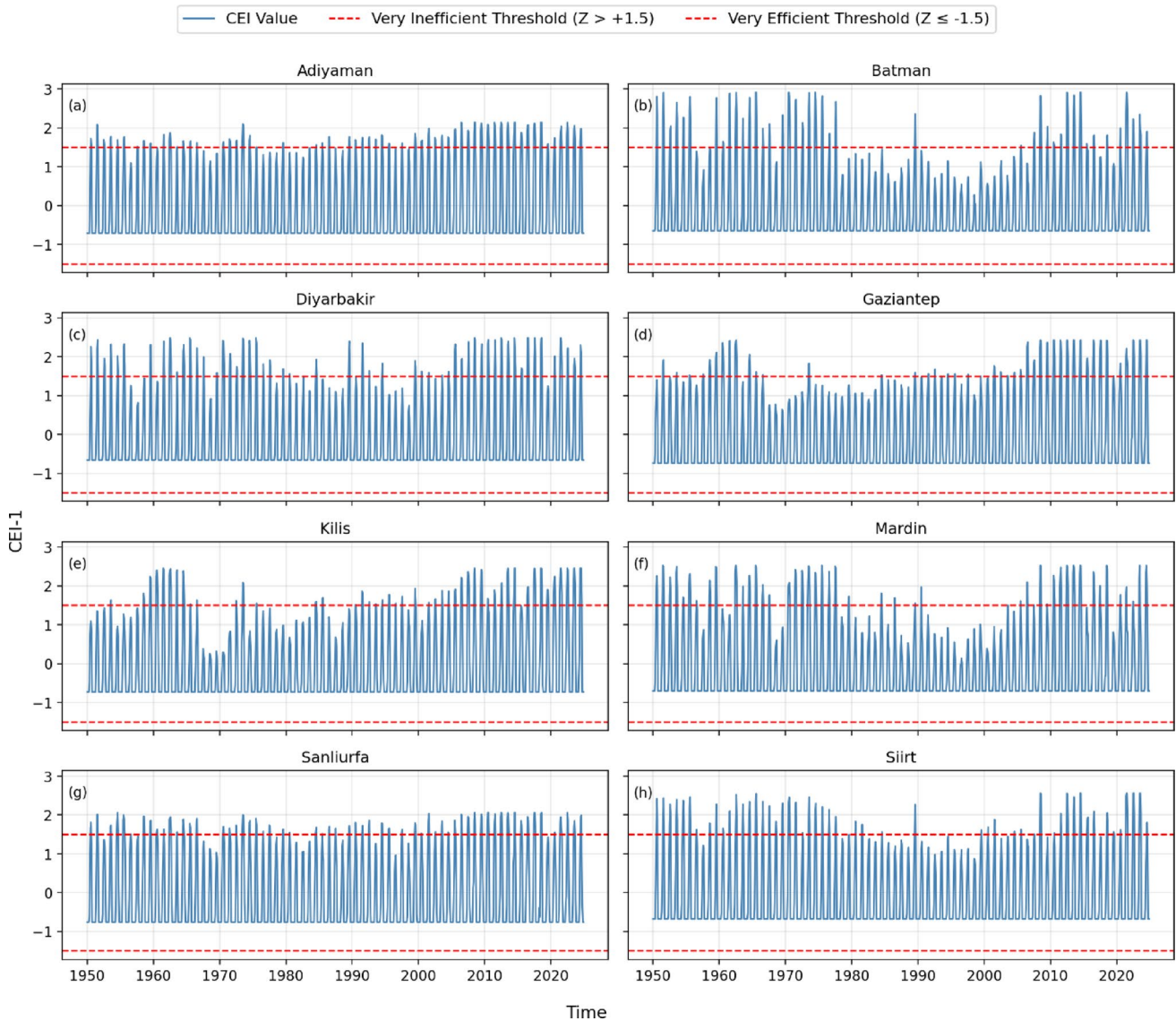


Fig. 2 Temporal variability of CEI-1 during 1950–2024: **a** Adiyaman, **b** Batman, **c** Diyarbakir, **d** Gaziantep, **e** Kilis, **f** Mardin, **g** Şanlıurfa, **h** Siirt

CEI values are associated with periods characterized by a high Bowen ratio and a low evaporative fraction, indicating heat-dominated surface energy partitioning and diminished evaporative efficiency. Such conditions can occur in both moisture-limited regimes and during radiation-driven heat extremes, thereby representing energy-driven aridity rather than solely precipitation-based drought. (Miralles et al. 2019; Seneviratne et al. 2010). These conditions are consistent with known drought signatures, implying that CEI can act as a proxy for drought-related stress on ecosystems and energy systems. Furthermore, the consistent upward shifts in CEI-1 since the late twentieth century reflect the impact of climate change (Arias et al. 2021), with rising air temperatures increasing thermal penalties and exacerbating the imbalance between sensible and latent heat fluxes. This convergence of climatic inefficiency potential, drought risk,

and long-term climate change highlights the vulnerability of semi-arid regions like Southeastern Anatolia to interconnected water-energy-climate challenges.

Figure 3 shows the CEI-3 time series for Southeastern Anatolia from 1950 to 2024. Compared to CEI-1, the 3-month aggregation reveals long-term seasonal inefficiencies rather than transient fluctuations. From an energy standpoint, high CEI-3 values indicate extended periods of elevated thermal penalties, reduced evaporative cooling capacity, and high Bowen ratios. In practice, this refers to months when CDD accumulate rapidly, resulting in sustained peaks in electricity demand for air conditioning. At the same time, the land surface's natural ability to offset heat through evapotranspiration is reduced, limiting resilience. This dual stressor is critical for energy planning because it implies that energy demand peaks and reduced natural

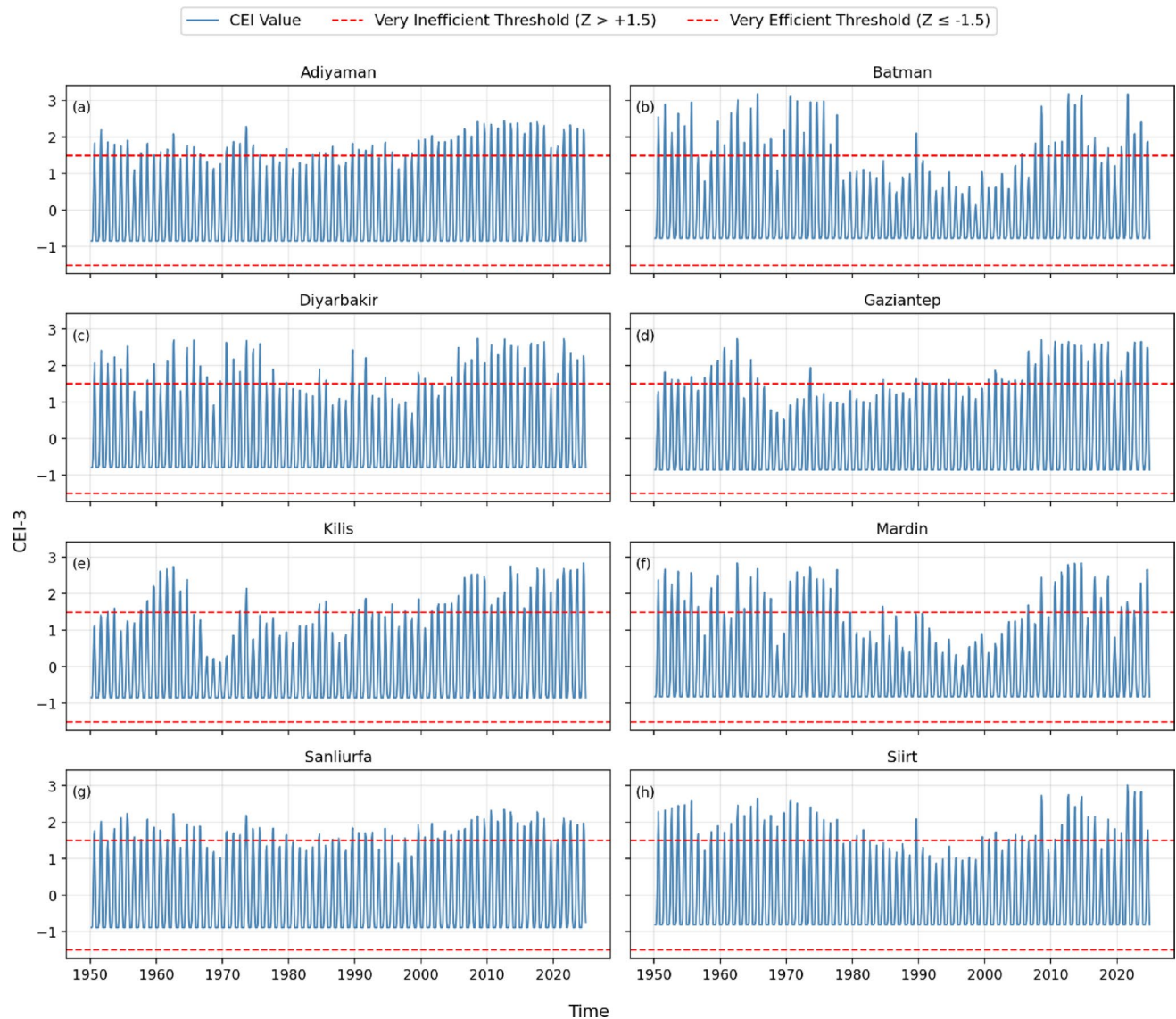


Fig. 3 Temporal variability of CEI-3 during 1950–2024: **a** Adiyaman, **b** Batman, **c** Diyarbakır, **d** Gaziantep, **e** Kilis, **f** Mardin, **g** Şanlıurfa, **h** Siirt

cooling occurs during the same season, increasing grid vulnerability. Spatial patterns support this picture. Adiyaman, Şanlıurfa, and Mardin exhibit consistently high CEI-3 levels, indicating structural inefficiency and seasonal stress on energy systems. Batman and Diyarbakır exhibit alternating efficient and inefficient phases, indicating that energy demand is more susceptible to interannual climate variability. Gaziantep and Kilis experienced relative relief during the 1970–1990 period, when stronger evaporative buffering temporarily alleviated seasonal energy stress. In contrast, Siirt has shown persistently elevated inefficiency since the 1990s, mirroring regional warming and signaling intensifying seasonal cooling loads. CEI-3 is important in the context of climate change and drought because it captures stress persistence. Elevated values correspond to decreased evapotranspiration and increased sensible heating, both of

which are common during droughts (Miralles et al. 2019; Seneviratne et al. 2010). The long-term upward trend since the late twentieth century reflects regional warming (Arias et al. 2021), implying that seasonal-scale energy demand, drought risk, and climate change are becoming more intertwined in semi-arid regions such as Southeastern Anatolia.

Figure 4 depicts CEI-6 variability across Southeastern Anatolia from 1950 to 2024. Compared to CEI-1 and CEI-3, the 6-month scale smoothes out short-term fluctuations, revealing persistent inefficiency phases that last throughout the warm or cold seasons. This timescale is especially important for assessing energy planning risks because it identifies when high cooling demand and limited evaporative buffering persist for several months. From an energy standpoint, high CEI-6 values indicate long periods of cumulative thermal stress, during which CDD accumulates over entire half-year

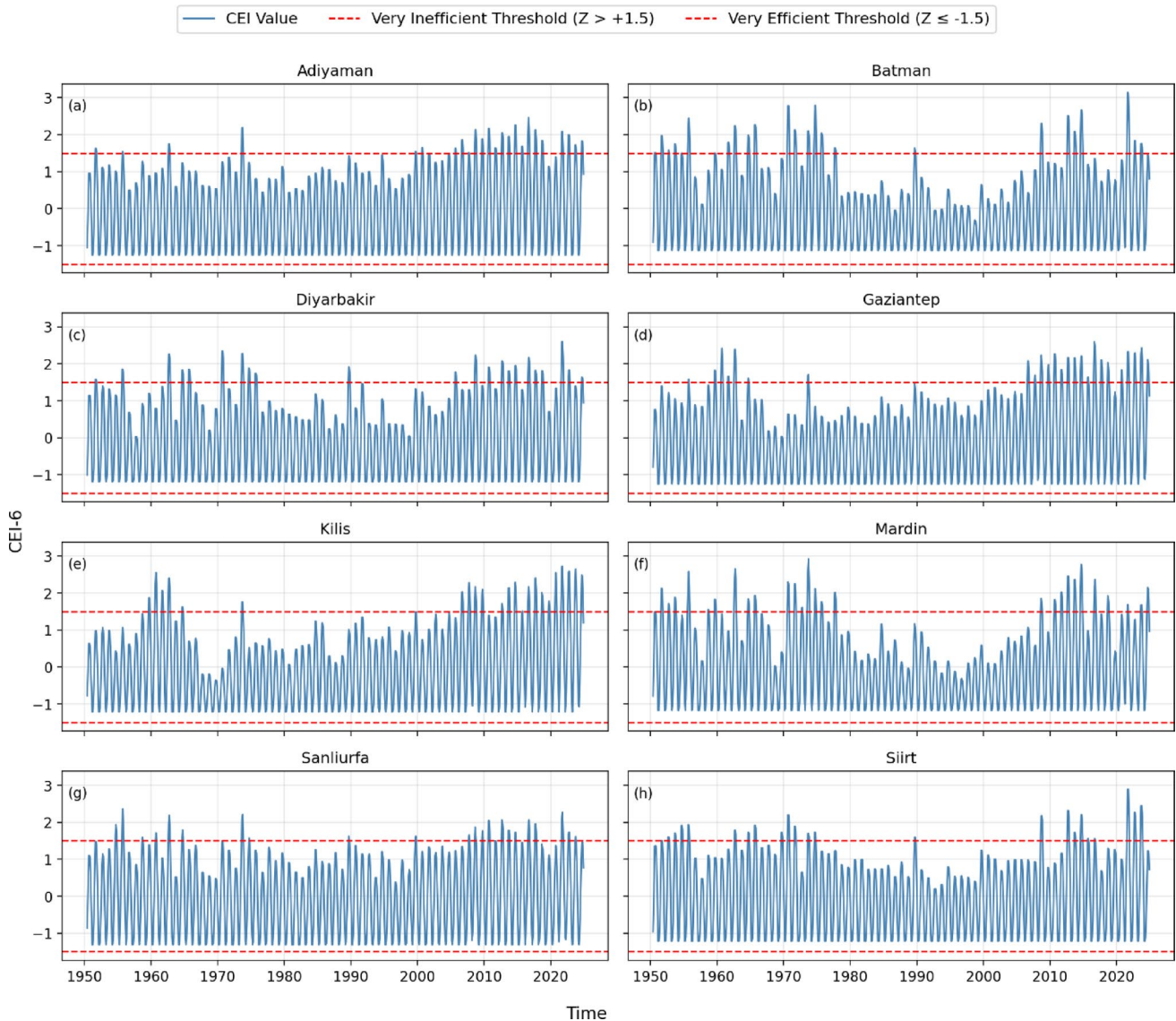


Fig. 4 Temporal variability of CEI-6 during 1950–2024: **a** Adiyaman, **b** Batman, **c** Diyarbakir, **d** Gaziantep, **e** Kilis, **f** Mardin, **g** Şanlıurfa, **h** Siirt

windows. If renewable supply is insufficient, this will result in prolonged electricity demand surges, putting a strain on grid reliability and increasing reliance on fossil-fuel backup generation. The spatial variability remains clear. Adiyaman and Şanlıurfa exhibit extended periods of inefficiency, indicating prolonged exposure to high seasonal cooling loads. Batman and Diyarbakir have alternating efficient and inefficient multi-month phases, indicating strong modulation by wet-dry cycles. Gaziantep and Kilis have relatively moderate inefficiency until the early 1990s, after which CEI-6 steadily rises, in line with regional warming signals. Mardin and Siirt stand out for their sustained inefficiency in recent decades, with Mardin demonstrating a persistent imbalance between heat input and evaporative dissipation. In terms of climate change and drought, CEI-6 captures the shift toward long-term inefficient states. Extended periods

of high Bowen ratio and suppressed evaporative fraction indicate soil moisture deficits and drought intensification (Miralles et al. 2019; Seneviratne et al. 2010). The rise in CEI-6 values since the 1990s corresponds to the warming trend reported in IPCC AR6 (Arias et al. 2021), demonstrating that multi-seasonal drought conditions and rising energy demand are increasingly linked in semi-arid regions such as Southeastern Anatolia.

Figure 5 shows CEI-12 variability in Southeastern Anatolia from 1950 to 2024. CEI-12 emphasizes long-term climatic balance over short-term or seasonal anomalies by averaging conditions over a 12-month period. These smoothing reveal clear multi-decadal patterns of inefficiency, with marked upward shifts since the late twentieth century, which are consistent with regional climate warming and increased drought stress. In terms of energy, elevated

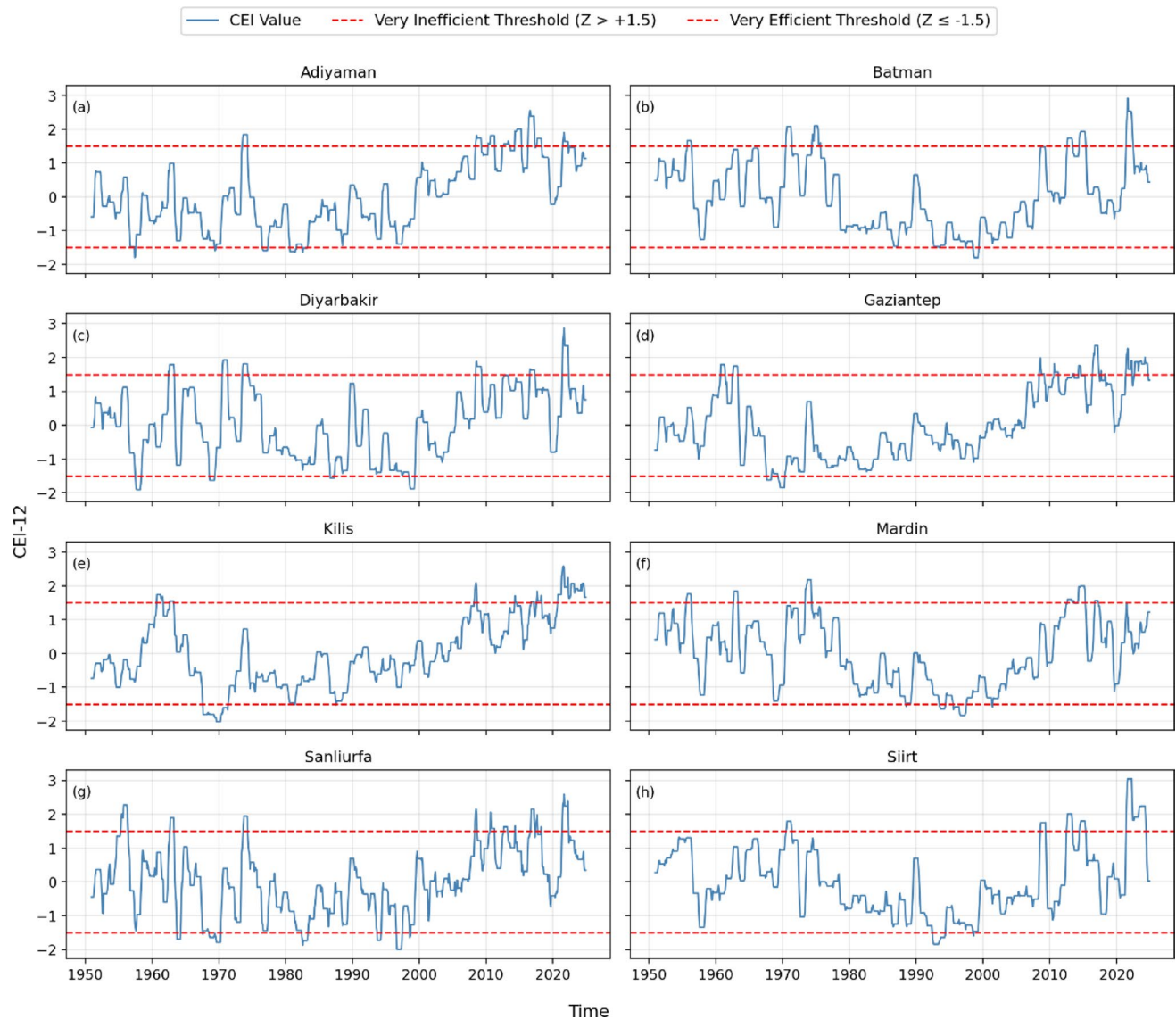


Fig. 5 Temporal variability of CEI-12 during 1950–2024: **a** Adiyaman, **b** Batman, **c** Diyarbakır, **d** Gaziantep, **e** Kilis, **f** Mardin, **g** Şanlıurfa, **h** Siirt

CEI-12 values indicate years when CDD consistently accumulate above normal, resulting in sustained annual electricity demand for cooling. Unlike CEI-1 and CEI-3, which measure short-term demand spikes, CEI-12 demonstrates how inefficiency becomes a structural condition that strains energy systems over time. This is especially important for long-term energy planning and infrastructure investment, as persistent inefficiency results in higher baseload cooling requirements, reduced hydropower reliability due to drought-induced water stress, and increased reliance on fossil or renewable backup. Adiyaman, Kilis, and Gaziantep have shown a clear upward trajectory since the 1980s, indicating a shift toward chronic inefficiency. In Mardin and Şanlıurfa, elevated CEI-12 levels indicate a combination of heat stress and reduced evaporative buffering. After 2000, Batman and Diyarbakır show higher CEI-12, indicating that

inefficient years are more persistent. Siirt, while exhibiting some variability, has also shifted toward inefficient states in recent decades, reinforcing the regional pattern. High annual inefficiency is associated with sustained soil moisture deficits, high Bowen ratios, and suppressed evaporative fractions, all of which are typical of multi-year droughts (Miralles et al. 2019; Seneviratne et al. 2010). The consistent rise in CEI-12 values since the late twentieth century corresponds to the IPCC AR6 (Arias et al. 2021) findings of accelerated warming in the Mediterranean and Middle Eastern regions, highlighting the growing link between energy demand, drought persistence, and climate change (Table 1).

The sensitivity experiment expanded beyond normalization and aerodynamic assumptions to explicitly include structural flux uncertainty. CEI was recomputed using three uncertainty dimensions: (i) altered normalization percentiles

Table 1 Classification of Z values

Categories	Range
Very Efficient	$Z \leq -1.5$
Efficient	$-1.5 < Z \leq -0.5$
Normal	$-0.5 < Z \leq 0.5$
Inefficient	$0.5 < Z \leq 1.5$
Very Inefficient	$Z > 1.5$

(10–90), (ii) alternative aggregation (arithmetic mean), (iii) $\pm 10\%$ and $\pm 15\%$ perturbation simultaneously applied to sensible and latent heat fluxes (representing upper-bound uncertainty reported for reanalysis land-surface fluxes), and (iv) $\pm 10\%$ adjustments of the wind-cooling coefficient in the thermal penalty formulation. Sensitivity was quantified using correlation (r), RMSE, and classification transition metrics, and the results are given in Table 2.

The sensitivity experiments demonstrate that CEI is highly robust to parameter uncertainties. Adjusting the normalization bounds (5–95 vs. 10–90) results in minor deviations ($r > 0.98$ and $< 3\%$ change in classification), whereas replacing the geometric aggregation with an arithmetic mean yields greater sensitivity while maintaining overall consistency in classification. More critically, perturbing ERA5 sensible and latent heat fluxes by $\pm 10\%$ and $\pm 15\%$ — representing structural reanalysis uncertainty — produced near-perfect correlation with the baseline ($r \approx 1.00$) and no classification changes (100% identical CEI category assignments). This confirms that CEI's integration of Bowen ratio and evaporative fraction is statistically stable and not driven by marginal flux biases, indicating strong resilience to land-surface model artifacts and energy balance closure errors.

Flux uncertainty showed the highest stability. Perturbing both flux components by $\pm 10\%$ and $\pm 15\%$ resulted in a perfect correlation with baseline CEI ($r = 1.00$) and zero classification changes at both CEI-3 and CEI-12 (Table 2).

This demonstrates that CEI is structurally insensitive to plausible magnitudes of reanalysis flux uncertainty. The percentile normalization variant (10–90 vs. 5–95) maintained very high correlation with the baseline ($r = 0.997$ for CEI-3; $r = 0.989$ for CEI-12), with $> 97\%$ and $\sim 90\%$ class agreement, respectively, and no major category transitions. Adjusting the wind-cooling coefficient produced near-perfect consistency ($r > 0.999$; $\text{RMSE} < 0.013$) and $> 99.6\%$ classification stability without major transitions, indicating negligible uncertainty propagation. The only scenario showing moderate divergence was the arithmetic mean. Despite high correlation ($r = 0.973$ for CEI-3; $r = 0.946$ for CEI-12), classification changes were more pronounced (12.7% minor for CEI-3; 23.3% for CEI-12). This supports the conceptual rationale for the geometric mean, which preserves asymmetric stress contributions rather than allowing one component to compensate linearly for others.

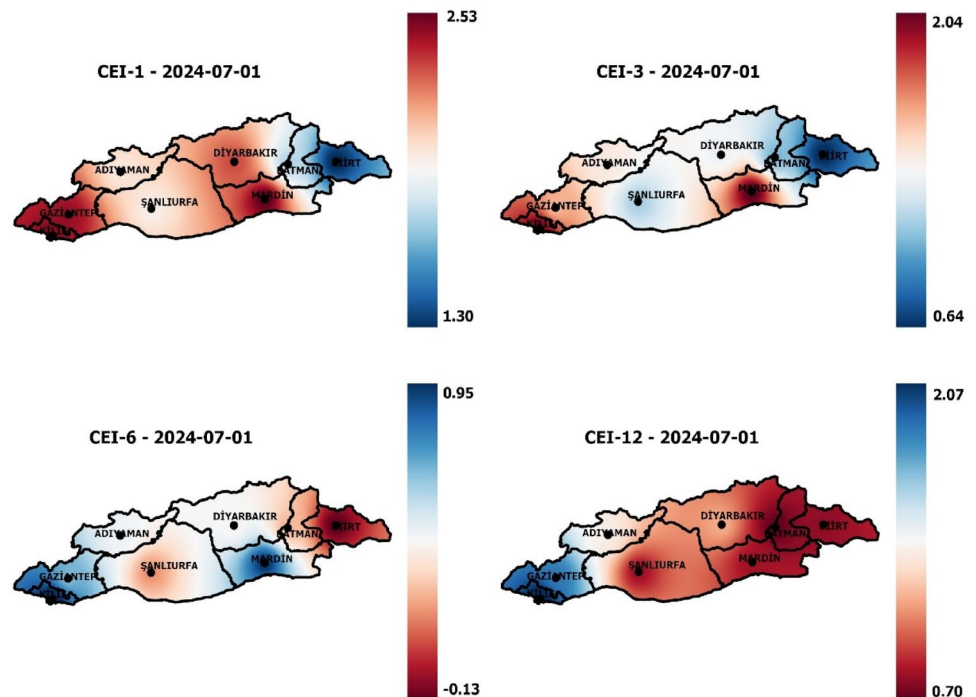
3.2 Spatial analysis of CEI

Figure 6 depicts the spatial distribution of CEI values across Southeastern Anatolia in July 2024 at four temporal scales (CEI-1, CEI-3, CEI-6, and CEI-12). Most provinces (Diyarbakır, Gaziantep, Mardin) have elevated CEI-1 values (> 1.5), indicating significant thermal penalties from high near-surface air temperatures and high Bowen ratios. At the seasonal scale (CEI-3 and CEI-6), spatial contrasts become more apparent. Provinces like Kilis and Gaziantep continue to have moderately high CEI values, indicating that climatic inefficiency persists throughout the warm season. Areas like Şanlıurfa and Batman have lower CEI-3/6 values, indicating short-term relief due to transient moisture availability. CEI-12 values are declining across much of the region, with the exception of localized hotspots (Kilis, Gaziantep). This reflects the smoothing effect of long-term averaging, but

Table 2 Comparing the current CEI methodology under different data-increase or data-decrease scenarios

Variant	Scale	$r_{\text{with_Base}}$	$\text{RMSE}_{\text{with_Base}}$	Same_Class_%	Minor_Change (± 1)_%	Major_Change (> 1)_%
Pct10_90	CEI_3	0.997	0.074	97.180	2.819	0
Pct10_90	CEI_12	0.989	0.146	89.861	10.139	0
Arithmetic	CEI_3	0.974	0.229	87.305	12.666	0.027
Arithmetic	CEI_12	0.946	0.328	76.5	23.333	0.166
WindPlus10	CEI_3	0.999	0.004	99.944	0.055	0
WindPlus10	CEI_12	0.999	0.008	99.652	0.347	0
WindMinus10	CEI_3	0.999	0.006	99.944	0.055	0
WindMinus10	CEI_12	0.999	0.013	99.889	0.111	0
FluxPlus10	CEI_3	1	$3.36\text{E}-16$	100	0	0
FluxPlus10	CEI_12	1	$5.86\text{E}-16$	100	0	0
FluxMinus10	CEI_3	1	$2.94\text{E}-16$	100	0	0
FluxMinus10	CEI_12	1	$6.01\text{E}-16$	100	0	0
FluxPlus15	CEI_3	1	$2.66\text{E}-16$	100	0	0
FluxPlus15	CEI_12	1	$6.43\text{E}-16$	100	0	0
FluxMinus15	CEI_3	1	$3.23\text{E}-16$	100	0	0
FluxMinus15	CEI_12	1	$7.03\text{E}-16$	100	0	0

Fig. 6 Spatial distribution of CEI values across Southeastern Anatolia provinces: **a** CEI-1, **b** CEI-3, **c** CEI-6, **d** CEI-12



it also highlights how chronic warming trends continue to impose higher baseline thermal penalties. Persistent inefficiency at CEI-12 suggests that the climate system is shifting toward hotter, drier states, which is consistent with observed climate change impacts in the Mediterranean and semi-arid regions (Arias et al. 2021; Diffenbaugh & Giorgi 2012). In terms of energy, high CEI values indicate an increase in CDD and electricity demand during summer peaks. Simultaneously, the strong association between CEI, high Bowen ratios, and low evaporative fractions establishes CEI as an indicator of energy-driven hydroclimatic stress. This association reflects heat-dominated surface energy partitioning and reduced evaporative efficiency at the land–atmosphere interface, rather than direct soil water limitation or precipitation-based drought. (Seneviratne et al. 2010). This convergence of climatic inefficiency potential, drought risk, and climate warming indicates that Southeastern Anatolia faces a multifaceted challenge: energy demand peaks are likely to coincide with worsening hydrological stress, exacerbating vulnerability to further climate change (Arias et al. 2021; Giorgi & Lionello 2008).

3.3 CEI mechanism decomposition and seasonal phase-shift analysis

In order to evaluate the relative contribution of each climatic stress mechanism to the CEI, the monthly thermal penalty (TP), Bowen ratio (B), and evaporative fraction (EF) components were normalized to percentage contribution

and averaged for each region across the 1950–2024 period (Fig. 7).

To investigate temporal transitions in the timing of peak climatic inefficiency, the 1950–2024 record was separated into two climatological epochs (1950–1985 and 1986–2024). The month with the maximum CEI value was identified for each period, and the phase shift was quantified as the difference between the recent and baseline peak month (Recent – Baseline).

A negative shift denotes earlier occurrence of climatic inefficiency conditions, while positive values indicate a delayed peak. This analysis enabled evaluation of long-term alterations in the seasonality of climatic stress drivers.

A notable temporal transition is observed when comparing the early (1950–1985) and recent (1986–2024) periods. Four regions (Adiyaman, Kilis, Mardin, Sanliurfa) experienced an earlier peak of CEI by approximately one month, suggesting that thermal-driven inefficiency emerges earlier in the season under recent climatic conditions. Other regions show little or no shift, indicating spatial heterogeneity in the timing of atmospheric energy imbalance.

3.3.1 Mechanism contributions

Figure 7 shows the contribution matrix of CEI components: thermal penalty, Bowen ratio, and evaporative fraction. In all regions studied, thermal penalty makes up the largest part of CEI (33–41%), followed by evaporative limitations (32–36%) and sensible heat dominance from the Bowen ratio (27–31%). These results suggest that thermal stress is

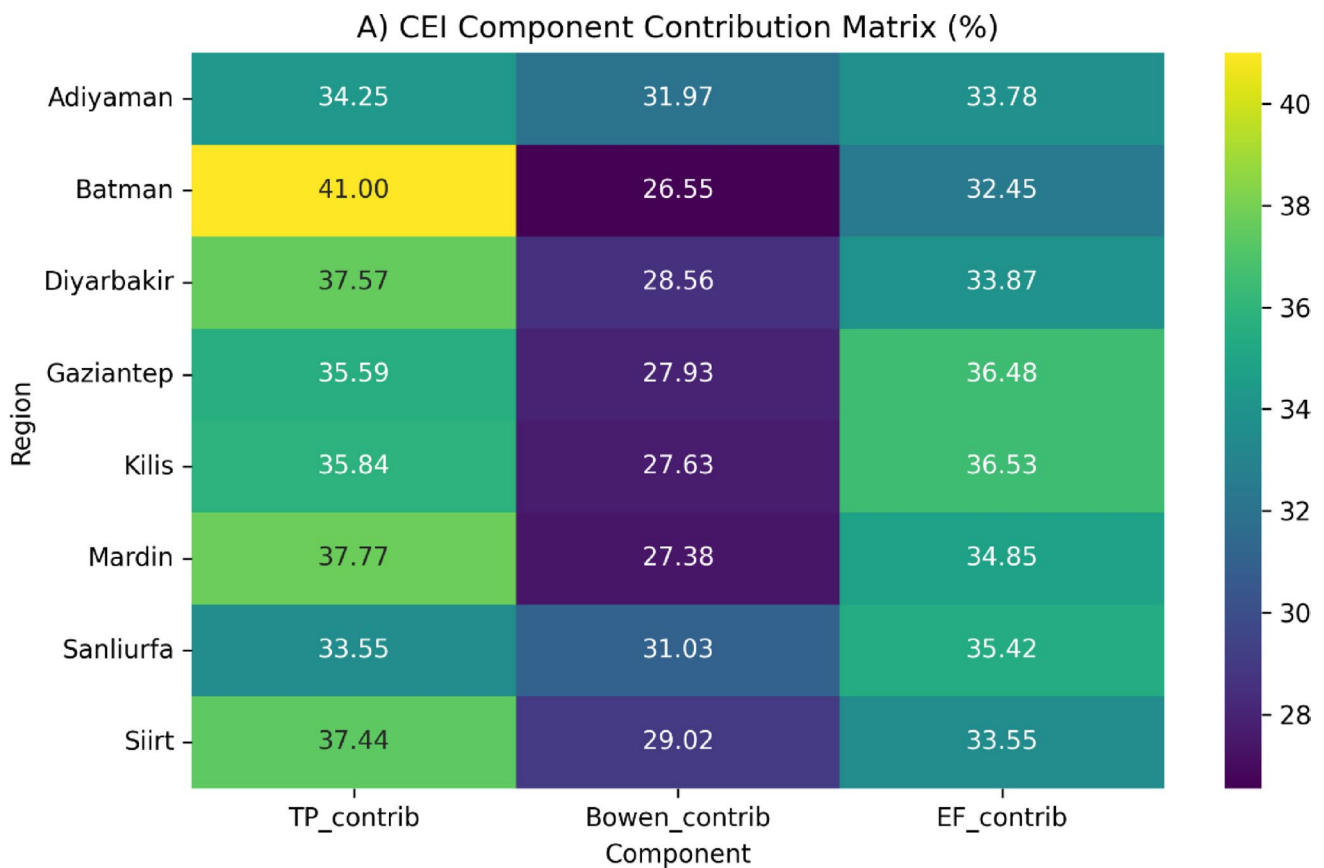


Fig. 7 CEI Component contribution matrix

the main factor in climatic inefficiency, but evaporative and sensible heat processes are also important. The observed associations between CEI and surface energy fluxes are consistent with previous studies linking surface moisture availability to evaporative fraction and Bowen ratio variability (Gentine et al. 2007; Seneviratne et al. 2010). Differences between regions may be due to interactions between the land and the atmosphere. For instance, Batman's higher thermal contribution may point to more temperature-related stress, while Sanliurfa's higher evaporative fraction may reflect more surface moisture, possibly from irrigation.

3.3.2 Spatial differences

Spatially, eastern inland provinces (Siirt, Diyarbakır, Mardin) display a stronger Bowen-ratio contribution, consistent with lower land-surface moisture availability and higher dependency on sensible heat flux (Fig. 8). In contrast, provinces with extensive irrigated plains (Sanliurfa, Gaziantep) present higher evaporative fractions and lower Bowen ratios, indicating that land-management practices partially mitigate climatic inefficiency in these areas.

To provide an objective numerical interpretation beyond visual inspection, mean CEI values were computed for three

representative climate periods (1950–1980, 1981–2000, 2001–2024) (Table 3). Across all regions, CEI values transition from predominantly negative z-scores in 1950–1980 to strongly positive values in 2001–2024. For example, Gaziantep shifts from -0.38 (1950–1980) to $+0.97$ (2001–2024), Kilis from -0.40 to $+0.93$, and Adiyaman from -0.43 to $+1.04$. This indicates a statistically measurable intensification of thermal and evaporative inefficiency in recent decades.

3.4 Temporal evolution of degree-day indices

Figures 9 and 10 show the contrasting temporal trajectories of CDD and HDD in Southeastern Anatolia from 1950 to 2024. CDD is on the rise, particularly in provinces like Şanlıurfa, Mardin, and Diyarbakır where monthly totals have surpassed 200–250 °C·days in recent decades. This reflects increased summer heat extremes, which are consistent with broader Mediterranean warming signals (Arias et al. 2021; Diffenbaugh & Giorgi 2012). HDD has steadily decreased since the 1980s, especially in colder provinces like Siirt and Adiyaman, where monthly totals once exceeded 600 °C·days. This downward trend is due to warmer winters, which reduce heating demand while also

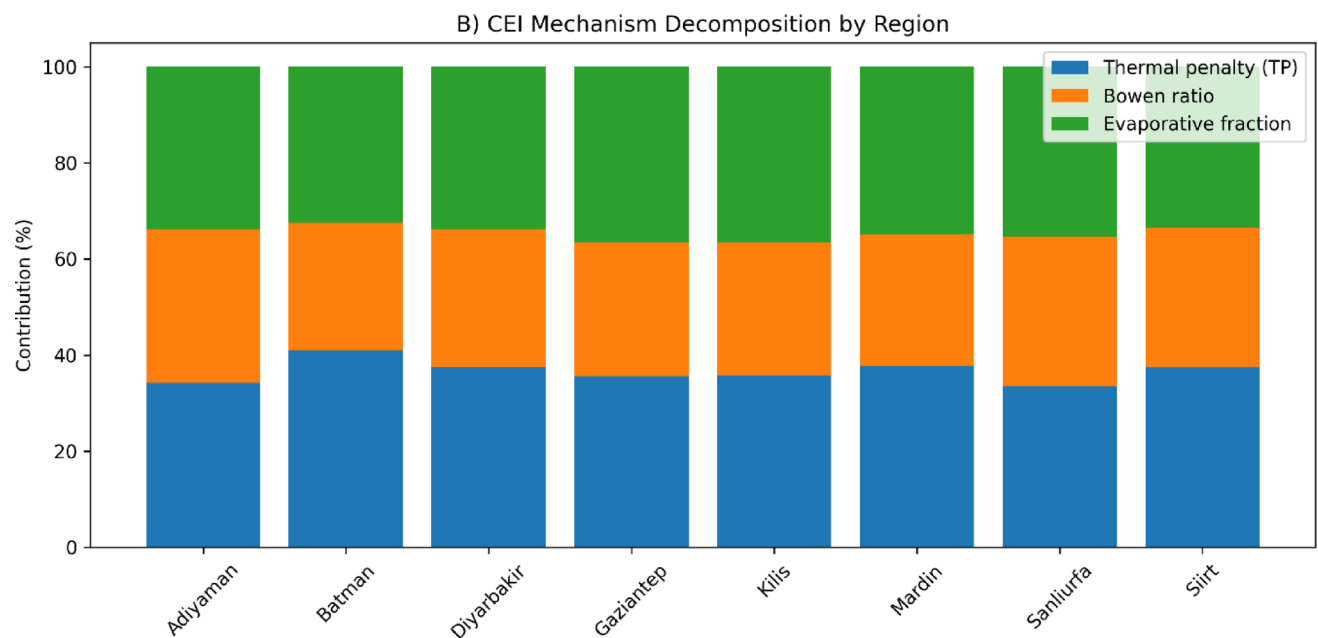


Fig. 8 CEI Mechanism Decomposition by region

Table 3 Temporal evolution of CEI (1950–2024)

Region	Period	Mean_CEI_3	Mean_CEI_12
Adiyaman	1950–1980	−0.075	−0.429
Adiyaman	1981–2000	−0.097	−0.608
Adiyaman	2001–2024	0.177	1.045
Batman	1950–1980	0.117	0.445
Batman	1981–2000	−0.260	−0.931
Batman	2001–2024	0.067	0.219
Diyarbakir	1950–1980	0.009	0.053
Diyarbakir	1981–2000	−0.153	−0.766
Diyarbakir	2001–2024	0.116	0.572
Gaziantep	1950–1980	−0.087	−0.374
Gaziantep	1981–2000	−0.134	−0.607
Gaziantep	2001–2024	0.223	0.975
Kilis	1950–1980	−0.114	−0.403
Kilis	1981–2000	−0.138	−0.519
Kilis	2001–2024	0.262	0.937
Mardin	1950–1980	0.123	0.456
Mardin	1981–2000	−0.295	−1.015
Mardin	2001–2024	0.089	0.274
Sanliurfa	1950–1980	−0.010	−0.065
Sanliurfa	1981–2000	−0.110	−0.692
Sanliurfa	2001–2024	0.105	0.657
Siirt	1950–1980	0.056	0.306
Siirt	1981–2000	−0.165	−0.895
Siirt	2001–2024	0.066	0.362

limiting opportunities for soil moisture recharge, exacerbating summer drought exposure (Spinoni et al. 2015).

From an energy standpoint, the divergent evolution of CDD and HDD suggests a shift from heating-dominated to cooling-dominated energy demand regimes. While reduced heating needs may reduce winter energy demands, rising

summer loads put additional strain on electricity systems, particularly during heatwaves (Isaac & van Vuuren 2009; Santamouris et al. 2015a, b). This seasonal imbalance is exacerbated by CEI dynamics, which capture the combined effects of increased thermal penalty, strong Bowen ratios, and weakened evaporative fractions, amplifying summer energy stress. Elevated CDD is also associated with drought-prone states, where low soil moisture reduces evaporative cooling and causes higher Bowen ratios (Shuttleworth et al. 1989; Spinoni et al. 2015). Meanwhile, declining HDD reflects regional warming trends, which are consistent with observed and projected reductions in cold extremes in Europe and the Middle East (Arias et al. 2021). Together, these patterns reveal a climate change fingerprint in South-eastern Anatolia: decreased demand for heating, increased reliance on cooling, and a stronger link between drought, heat stress, and energy demand.

3.5 Correlation analysis to evaluate the relationship between CEI and drought related variables

Partial correlation analysis was given in Table 4 to evaluate the relationships between CEI and drought-related variables (SPI, SPEI) as well as surface energy components (HFSS – sensible heat flux; HFLS – latent heat flux; RSDS – shortwave radiation; and wind speed), while controlling for temperature. The results reveal that CEI retains strong positive associations with latent heat flux (HFLS) and sensible heat flux (HFSS), particularly at 3–6 month timescales (e.g., >0.70 in Gaziantep, Kilis, and Mardin). In contrast, correlations with drought proxies (SPI, SPEI) remain weak

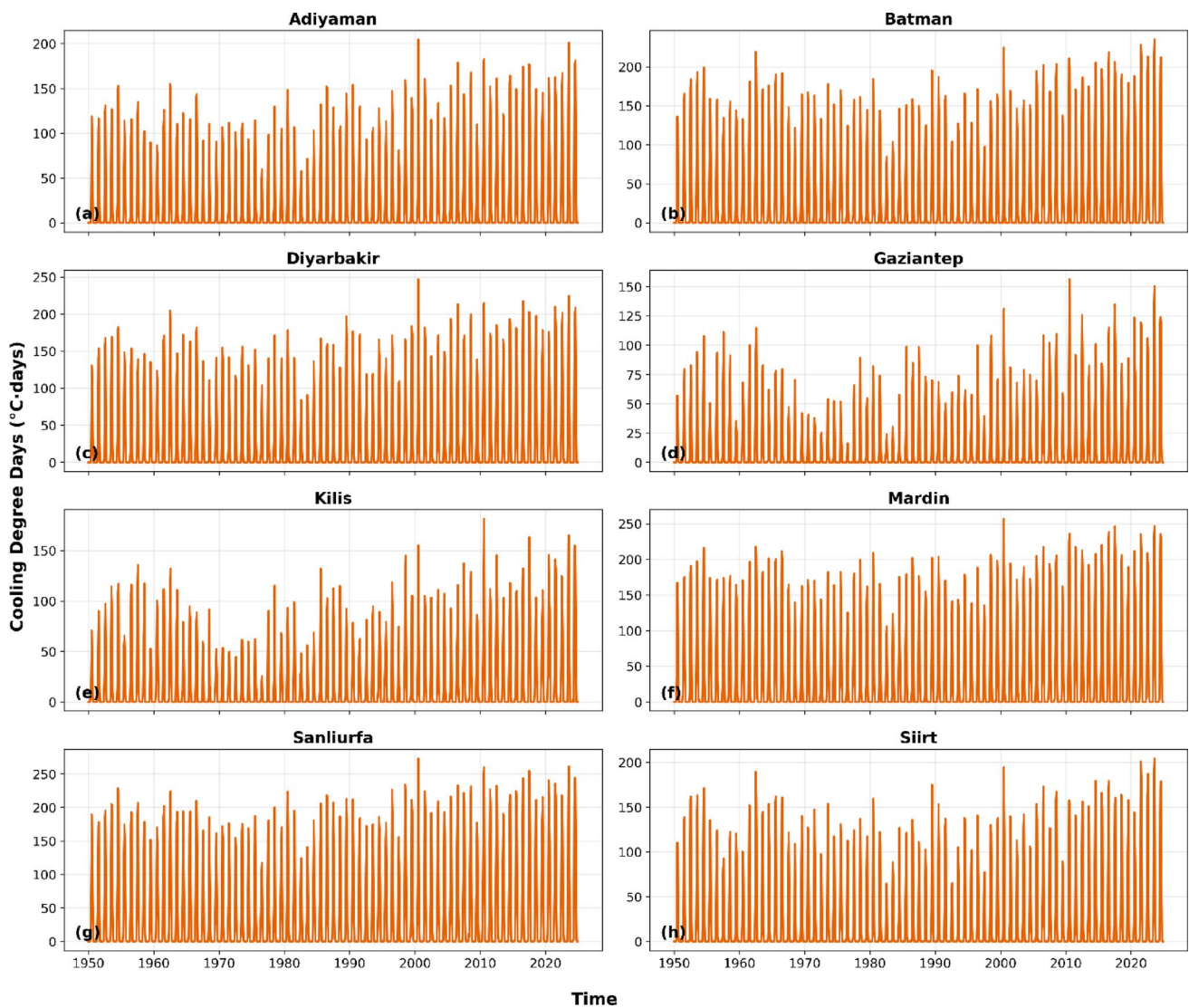


Fig. 9 Temporal evolution of CDD aggregated to monthly totals: **a** Adiyaman, **b** Batman, **c** Diyarbakir, **d** Gaziantep, **e** Kilis, **f** Mardin, **g** Şanlıurfa, **h** Siirt

at short timescales. These findings indicate that CEI is strongly linked to surface energy exchange processes and does not function merely as a temperature derivative, supporting its role as a multidimensional indicator that captures evaporative demand and land–atmosphere coupling components beyond those represented by CDD and HDD.

3.6 Correlation analysis of CEI and degree-day indices

Figures 11 and 12 demonstrate the correlation between CEI-1 with HDD, and CEI-1 with CDD, respectively, along with the appendix correlations for CEI-3, CEI-6, and CEI-12 (Figs. 14, 15, 16, 17, 18 and 19), show a statistical relationship between CEI values and degree-day indicators in Southeastern Anatolia. CEI has a strong negative correlation

with HDD ($\rho \approx -0.85$ to -0.88 , $p < 0.001$), and a strong positive correlation with CDD ($\rho \approx 0.90$ to 0.95 , $p < 0.001$). This duality highlights the climatic asymmetry embedded in the CEI framework: inefficient climatic states (high CEI values) correspond to increased cooling demand, whereas efficient states (low CEI values) correspond to heating requirements. Moreover, the strength of the CEI–CDD relationship declines with increasing temporal aggregation, indicating that multi-scale CEI reflects longer-term evaporative and radiative imbalances rather than short-term temperature changes. These results show that, even with high collinearity at short timescales, CEI maintains independent explanatory value related to land–atmosphere coupling and surface energy partitioning. CEI's robustness stems from its multidimensional design, which incorporates three critical components: thermal penalty (reflecting heat stress on PV and

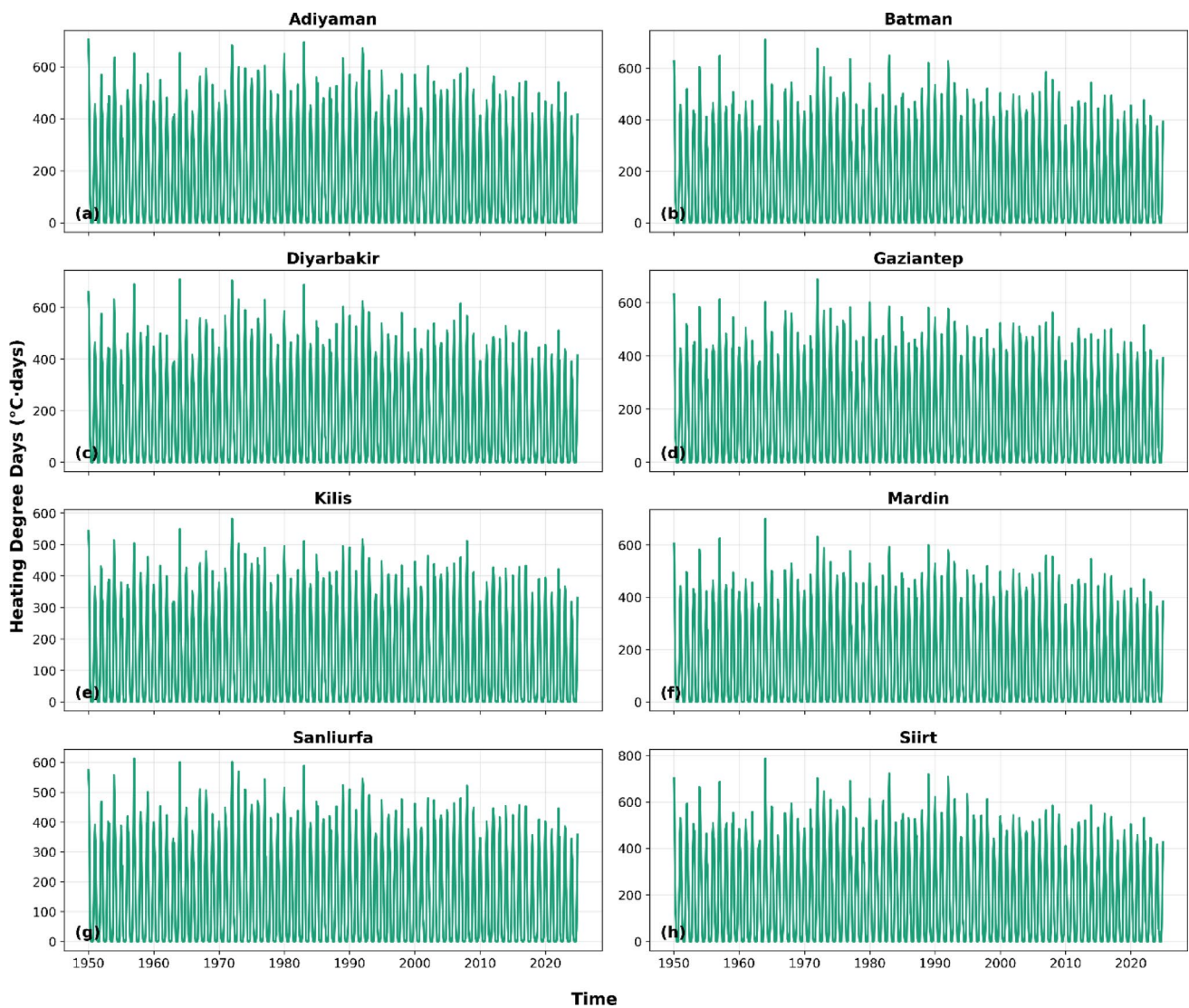


Fig. 10 Temporal evolution of HDD aggregated to monthly totals: **a** Adiyaman, **b** Batman, **c** Diyarbakır, **d** Gaziantep, **e** Kilis, **f** Mardin, **g** Şanlıurfa, **h** Siirt

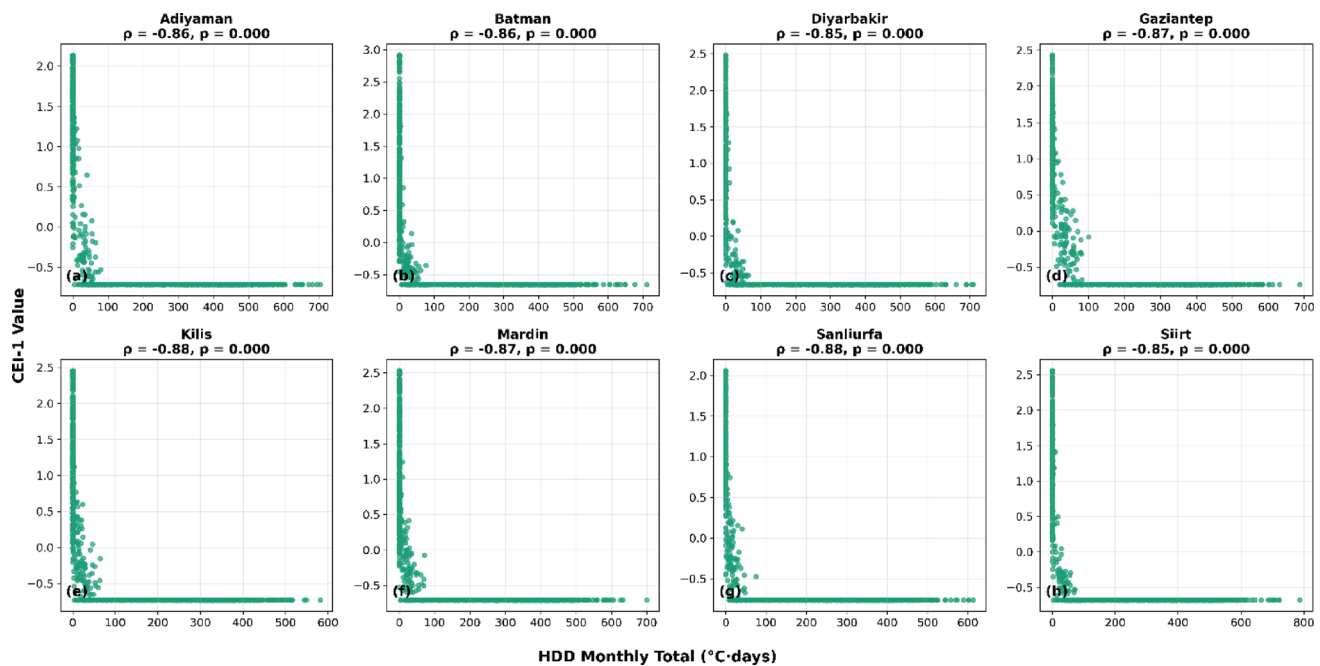
cooling systems), the Bowen ratio (capturing the balance between sensible and latent heat flux), and the evaporative fraction (indicating the land surface's cooling capacity via evapotranspiration). By combining these variables, CEI not only tracks temperature anomalies but also captures the processes that directly govern both energy demand and hydroclimatic stress. Elevated CEI values indicate not only increased electricity loads for cooling, but also a weakening of natural climatic buffers against heat, making the index a composite proxy for energy inefficiency and drought exposure (Spinoni et al. 2015). These relationships are strongest on short timescales (CEI-1 and CEI-3), where the index directly captures episodic heat extremes and their impact on cooling energy demand. At longer timescales (CEI-6 and CEI-12), the correlations become weaker but still statistically significant, reflecting the smoothing effects of seasonal

transitions and interannual variability. This scaling behavior highlights CEI's dual role: in the short term, it serves as an early warning signal for acute energy system stress during heatwaves, while in the long term, it reflects background inefficiency trends relevant to infrastructure planning and climate adaptation (Isaac & van Vuuren 2009; Spinoni et al. 2015).

From an energy standpoint, the positive CEI-CDD alignment indicates that peak inefficiency corresponds with the highest electricity demand for cooling, exacerbating grid stress and vulnerability to supply shortages. In contrast, the negative CEI-HDD relationship reflects the reduced importance of evaporative fraction and Bowen ratio in colder conditions, when energy demand shifts toward heating. The broader implication is that CEI serves as a compound nexus indicator, connecting energy demand, drought processes,

Table 4 Partial Correlation after Removing Temperature Effect

Station	Scale	Partial_CEI SPI_TAS	Partial_CEI SPEI_TAS	Partial_CEI HFSS_TAS	Partial_CEI HFLS_TAS	Partial_CEI RSDS_TAS	Partial_CEI WindSpeed_TAS
Adiyaman	1	-0.031	0.037	-0.220	0.312	0.170	0.535
Adiyaman	3	-0.040	0.013	0.205	0.767	-0.629	-0.152
Adiyaman	6	-0.075	0.030	0.398	0.859	-0.812	-0.239
Adiyaman	12	-0.342	0.048	-0.219	0.235	-0.102	-0.004
Diyarbakir	1	-0.041	-0.068	-0.304	0.503	0.072	0.335
Diyarbakir	3	-0.072	-0.086	-0.035	0.725	-0.628	-0.268
Diyarbakir	6	-0.104	-0.132	0.200	0.835	-0.765	-0.279
Diyarbakir	12	-0.387	-0.485	-0.152	0.230	-0.052	-0.026
Gaziantep	1	-0.009	0.023	-0.248	0.434	0.131	0.448
Gaziantep	3	-0.034	0.037	0.354	0.730	-0.662	-0.457
Gaziantep	6	-0.063	0.058	0.541	0.793	-0.810	-0.510
Gaziantep	12	-0.226	0.228	-0.094	0.242	-0.121	-0.002
Kilis	1	-0.070	-0.048	-0.265	0.428	0.113	0.372
Kilis	3	-0.032	-0.028	0.361	0.769	-0.659	-0.451
Kilis	6	-0.086	-0.040	0.535	0.825	-0.785	-0.444
Kilis	12	-0.368	-0.193	-0.119	0.339	-0.110	0.075
Mardin	1	-0.051	-0.041	-0.383	0.429	0.174	0.333
Mardin	3	-0.079	-0.063	0.149	0.749	-0.604	-0.355
Mardin	6	-0.098	-0.105	0.353	0.828	-0.750	-0.325
Mardin	12	-0.243	-0.280	-0.270	0.372	-0.047	0.121
Sanliurfa	1	-0.065	-0.103	-0.295	0.573	0.142	0.411
Sanliurfa	3	-0.061	-0.080	0.335	0.675	-0.662	-0.405
Sanliurfa	6	-0.109	-0.107	0.529	0.718	-0.812	-0.475
Sanliurfa	12	-0.516	-0.553	-0.055	0.166	-0.070	0.015
Siirt	1	-0.025	-0.081	-0.238	0.479	0.145	0.385
Siirt	3	-0.030	-0.060	0.094	0.723	-0.588	-0.159
Siirt	6	-0.062	-0.088	0.262	0.803	-0.769	-0.207
Siirt	12	-0.288	-0.358	-0.182	0.193	-0.074	0.067

**Fig. 11** Spearman correlation between CEI-1 and HDD across provinces: **a** Adiyaman, **b** Batman, **c** Diyarbakir, **d** Gaziantep, **e** Kilis, **f** Mardin, **g** Sanliurfa, **h** Siirt

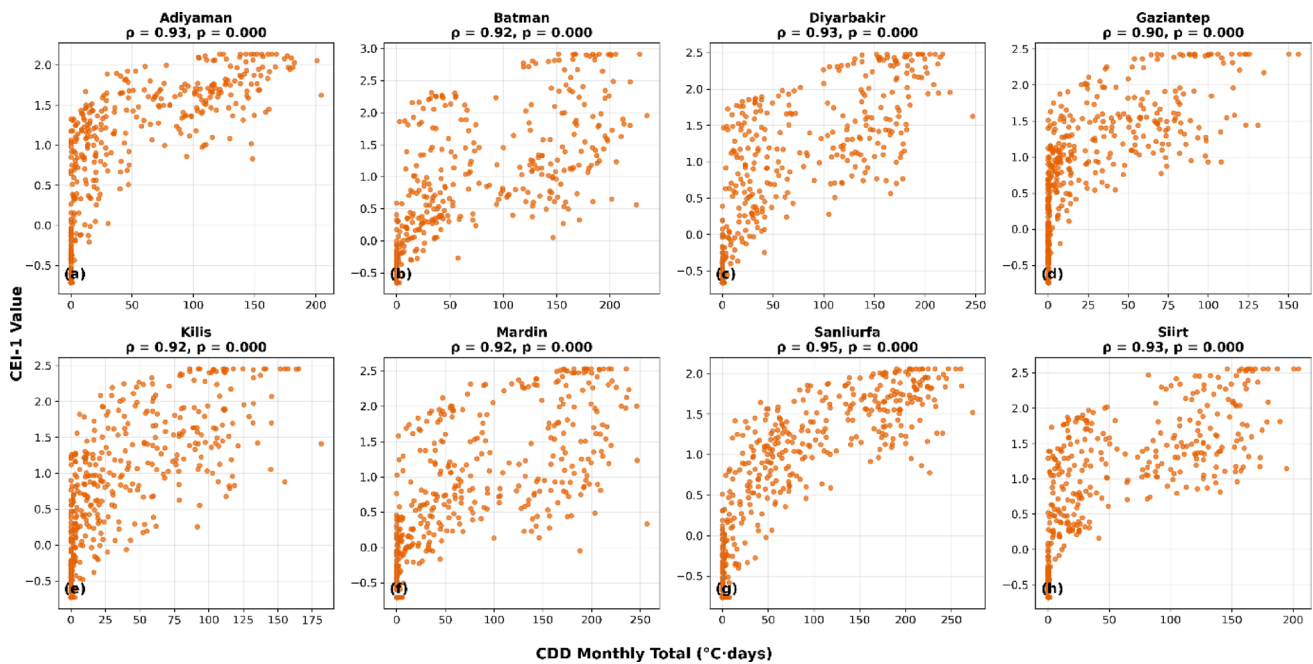


Fig. 12 Spearman correlation between CEI indices and CDD across provinces: **a** Adiyaman, **b** Batman, **c** Diyarbakır, **d** Gaziantep, **e** Kilis, **f** Mardin, **g** Şanlıurfa, **h** Siirt

Table 5 Scale-dependent Spearman correlations between the CEI and temperature-based indices (CDD and HDD)

	Scale	Adiyaman	Batman	Diyarbakır	Gaziantep	Kilis	Mardin	Sanliurfa	Siirt
		CEI-CDD	CEI-CDD	CEI-CDD	CEI-CDD	CEI-CDD	CEI-CDD	CEI-CDD	CEI-CDD
CEI-CDD	1	0.93	0.92	0.93	0.90	0.92	0.92	0.95	0.93
	3	0.73	0.70	0.69	0.71	0.73	0.75	0.76	0.70
	6	0.22	0.21	0.17	0.25	0.24	0.25	0.21	0.20
	12	0.06	0.05	0.05	0.09	0.08	0.04	0.06	0.04
CEI-HDD	1	−0.86	−0.86	−0.85	−0.87	−0.88	−0.87	−0.88	−0.85
	3	−0.82	−0.79	−0.78	−0.83	−0.82	−0.81	−0.82	−0.79
	6	−0.18	−0.09	−0.08	−0.20	−0.19	−0.17	−0.19	−0.11
	12	−0.05	−0.03	−0.03	−0.06	−0.06	−0.03	−0.04	−0.03

and climate change. Persistent upward shifts in CEI, particularly at longer timescales, signal a climate trajectory marked by rising thermal penalties, suppressed evapotranspiration, and increased aridity. These dynamics are consistent with regional projections of hotter, drier summers across the Mediterranean and semi-arid regions, which are expected to reduce heating needs while significantly increasing cooling loads (Arias et al. 2021; Jacob et al. 2014). As a result, CEI's integrative design makes it particularly useful for quantifying climatic inefficiency and guiding adaptation strategies across the water-energy-climate nexus.

Table 5 summarizes the scale-dependent correlation between CEI and temperature-based indices across all stations. The results show that CEI is strongly correlated with CDD ($\rho=0.90\text{--}0.95$) and HDD ($\rho=-0.85$ to -0.88) when measured over one month. As the time scale increases, these correlations drop sharply, reaching almost zero at the 12-month scale ($\rho=0.04\text{--}0.09$ for CDD and -0.03 to -0.06

for HDD). The size ($\Delta\rho\approx0.84\text{--}0.90$) and consistency of this drop across all stations show that CEI acts differently from additive temperature indices when data is averaged over time. This means the way CEI changes with scale is due to unique multi-scale dynamics, not just a statistical effect.

3.7 Correlation analysis of CEI and hydroclimatic variables

A significance-filtered Spearman correlation analysis was performed across 1-, 3-, 6-, and 12-month scales for all stations. In the visualization presented (Fig. 13a–d), only statistically significant coefficients ($p<0.05$) are color-coded, while non-significant relationships remain neutral. The results reveal that CEI maintains strong and significant correlations with latent and sensible heat fluxes (HFLS and HFSS) at short aggregation windows. In contrast, correlations with drought-related indices (SPI and SPEI) become

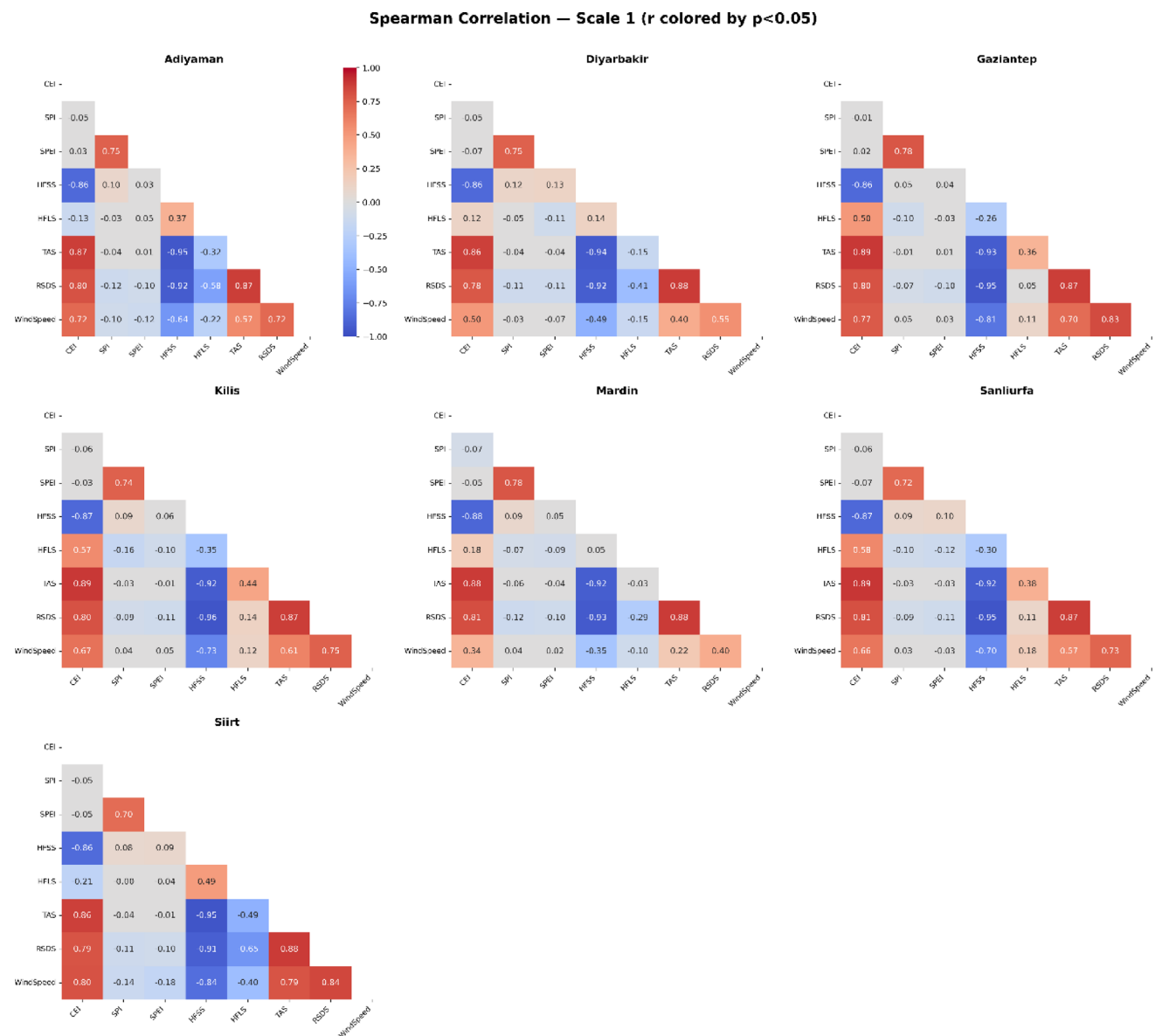


Fig. 13 **a** Scale-1 Dependent Significance-Filtered Spearman Correlations Between CEI and Hydroclimatic Variables. **b** Scale-3 Dependent Significance-Filtered Spearman Correlations Between CEI and Hydroclimatic Variables. **c** Scale-6 Dependent Significance-Filtered Spear-

man Correlations Between CEI and Hydroclimatic Variables. **d** Scale-12 Dependent Significance-Filtered Spearman Correlations Between CEI and Hydroclimatic Variables

more pronounced at longer timescales. This pattern demonstrates that temporal smoothing interacts with seasonal transition dynamics and confirms that CEI responds to both surface energy exchange processes and slower hydrological signals, thereby supporting its multidimensional behavior.

To evaluate CEI's proposed function as a drought–energy nexus indicator, CEI was compared directly with the Standardized Precipitation Index (SPI) and Standardized Precipitation Evapotranspiration Index (SPEI) across multiple temporal scales (1, 3, 6, and 12 months). The results show that CEI maintains relatively weak relationships with SPI and SPEI at shorter timescales (< 0.10), while correlations

increase moderately during longer aggregation periods, consistent with hydrological memory. The CEI demonstrates weak correlations with SPI and SPEI at short timescales. This outcome is anticipated because SPI and SPEI quantify precipitation-driven drought, while CEI reflects energy-driven aridity related to surface energy balance and evaporative limitations. This pattern indicates that CEI retains sensitivity to drought conditions while simultaneously capturing short-term land–atmosphere energy dynamics not represented in traditional drought metrics. These findings suggest that CEI complements rather than replaces existing drought indices by integrating thermal

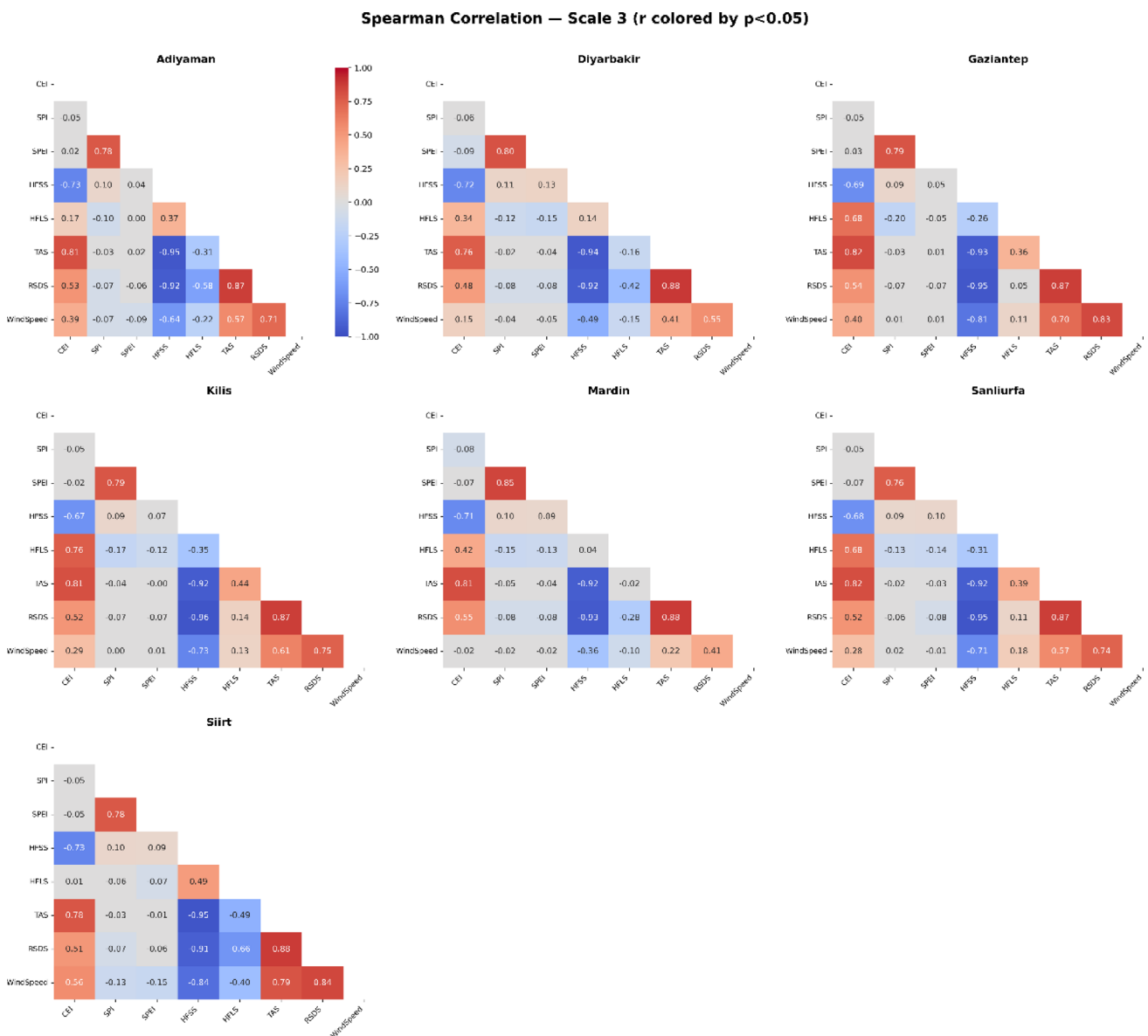


Fig. 13 (continued)

penalty and evaporative demand components within the same framework.

4 Discussion

It is important to clarify what 'efficiency' means in the context of the Climatic Efficiency Index (CEI). In energy engineering, efficiency usually describes how well a technology converts input to output, such as the efficiency of a PV cell. In this study, though, CEI does not measure how energy hardware performs. Instead, it looks at the environment's 'Climatic Inefficiency Potential.' The index measures the thermodynamic state at the land-atmosphere boundary

and highlights times when the environment cannot release thermal stress well, often because of a lower evaporative fraction and a higher Bowen ratio. In this way, CEI acts as a marker of environmental limits that can affect how energy systems work. While indices like CDD show demand-side stress, CEI gives a broader view of how well the land-surface system handles energy and water flows.

The results show that CEI values are strongly related to temperature-driven energy demand, with a positive correlation with CDD and a negative correlation with HDD. This dual relationship confirms CEI's ability to capture the redistribution of energy demand in response to climate variability. At high CEI values, the combination of thermal penalties, elevated Bowen ratios, and decreased evaporative fractions

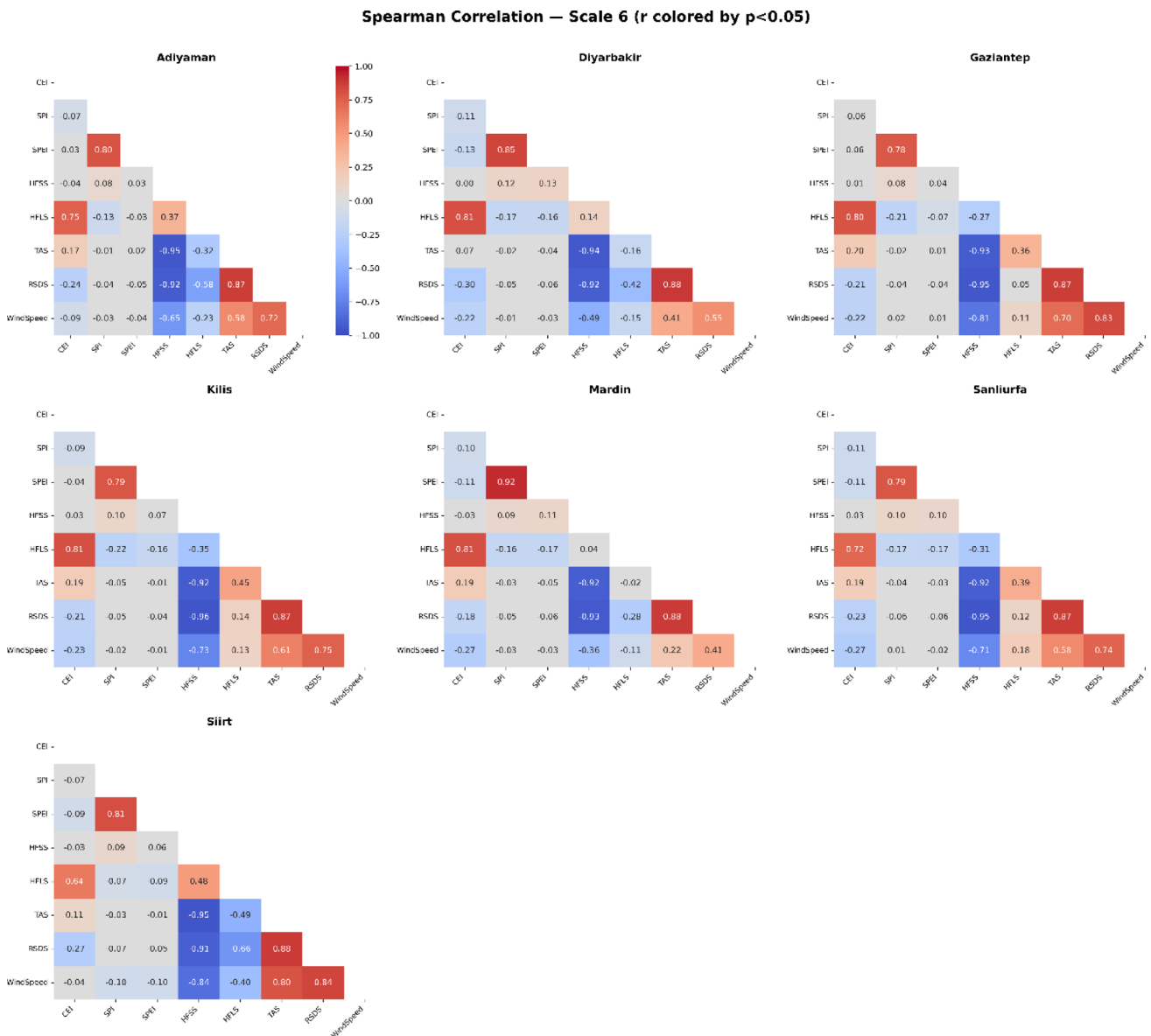


Fig. 13 (continued)

indicates a climatic state in which electricity demand for cooling increases while natural heat-moderating mechanisms weaken. Low CEI values, on the other hand, correspond to heating periods in which evaporative stress is less relevant, and HDD dominates energy requirements. However, while CDD has been widely used as an energy index (Isaac & van Vuuren 2009), it is entirely dependent on air temperature. CDD does not consider surface-atmosphere energy exchanges, evaporative cooling potential, or the thermal stress on buildings and photovoltaic systems. As a result, CDD alone may misrepresent actual energy requirements in conditions where humidity, radiation, and land-atmosphere coupling are important. In this context, it should be noted that while the TP component of the CEI is

formulated using PV cell temperature parameters, its implications extend beyond solar energy harvesting. TP serves as an integrated thermodynamic indicator of atmospheric loading. In semi-arid regions, elevated TP values indicate a state in which high radiative forcing and ambient heat converge, exerting simultaneous pressure on both the supply and demand sides. Therefore, within the CEI framework, TP is used not merely as a PV performance metric but also as a proxy for the total thermal stress imposed on the regional energy infrastructure and the broader energy-water-climate nexus. Unlike drought indices like SPI and SPEI, which are intended to capture moisture deficits that accumulate over weeks to months, CEI is inherently sensitive to short-term climatic anomalies. Elevated CEI-1 values reflect

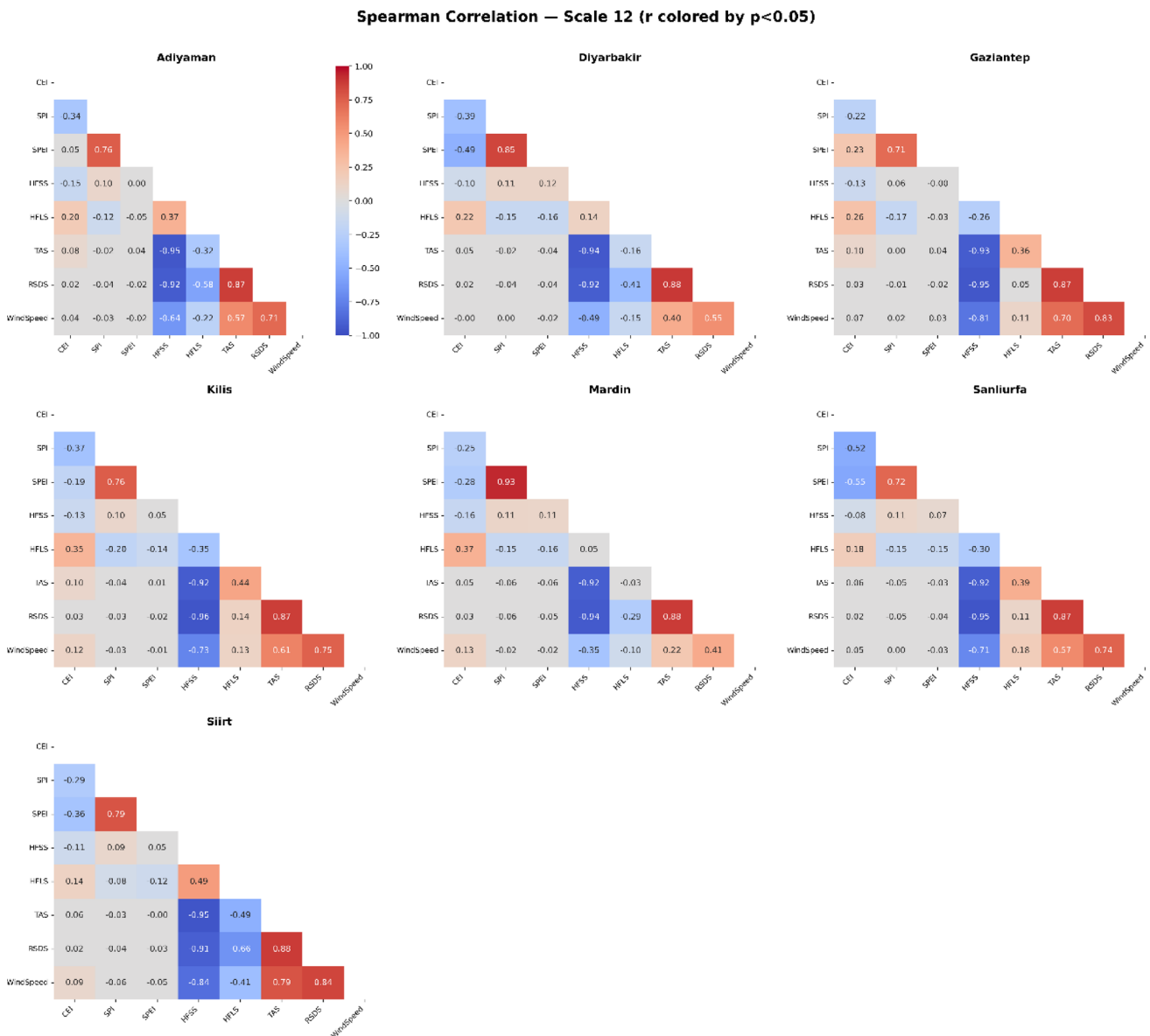


Fig. 13 (continued)

immediate inefficiencies in energy balance that occur within a month, often during heatwaves, whereas drought processes typically unfold over longer time scales. This distinction emphasizes CEI's importance as a short-term indicator of acute energy stress, which complements drought indices that track cumulative water deficits. The CEI framework presented here addresses these shortcomings by incorporating thermal penalty, Bowen ratio, and evaporative fraction, moving beyond pure temperature-based indices. This multi-dimensional approach distinguishes CEI as a novel methodology that bridges the gap between traditional energy climatology metrics (CDD/HDD) and the larger water-energy-climate nexus. The sensitivity analysis confirms that CEI performance is insensitive to realistic magnitudes of

land-surface flux uncertainty, suggesting that the Bowen-ratio component is stable enough for climatic and planning applications. The expanded sensitivity analysis shows that CEI is highly robust to uncertainty in normalization bounds, aerodynamic cooling assumptions, and—critically—structural flux uncertainty. Flux perturbation of $\pm 10\%$ and $\pm 15\%$ produced no change in classification and perfect correlation with the baseline CEI, confirming that Bowen-ratio-derived structural errors do not propagate meaningfully into index outcomes. Conversely, replacing the geometric mean with an arithmetic mean generated the largest divergence, empirically validating the geometric formulation for preserving multiplicative climatic stress interactions. It not only gives a more accurate picture of climatic inefficiency, but it also

explains why cooling loads rise under certain conditions and how evaporative suppression, and energy partitioning exacerbate both energy and drought stress. These quantitative results demonstrate that CEI does not simply reflect instantaneous environmental stress but captures a structural regime shift consistent with long-term warming and evaporative demand intensification. The transition from negative CEI values (efficient) to positive values (inefficient) after 2000 aligns with known regional warming trends in southeastern Türkiye and supports the interpretation that CEI behaves as a multi-dimensional climatic stress indicator rather than a short-term variability metric. The strong, statistically significant relationships with latent and sensible heat fluxes on short timescales demonstrate that CEI reflects land–atmosphere coupling and evaporative demand. The moderate but increasing correlation with drought indices at longer aggregation windows indicates sensitivity to hydrological stress. These results collectively support CEI's multidimensional role as a metric that integrates both surface energy exchange and drought-related dynamics, without implying that CEI replaces conventional drought indicators. Instead, CEI offers complementary information that links atmospheric energy demand to water stress signals, contributing to a broader understanding of climate–energy–drought interactions. To our knowledge, this is one of the first systematic attempts to move away from CDD as a single energy indicator and toward a compound index capable of capturing both the causes and consequences of inefficiency. The link between CEI and drought processes strengthens this added value. Elevated CEI values correspond to high Bowen ratios and low evaporative fractions, indicating heat-dominated surface energy partitioning and reduced evaporative efficiency. Consequently, CEI primarily serves to characterize energy system stress and energy-driven hydroclimatic vulnerability rather than to directly diagnose soil moisture deficits or precipitation-based drought. This duality is especially useful in semi-arid regions, where water scarcity and energy demand are inextricably linked. In terms of climate change, the long-term trends are clear. Declining HDD values reflect regional winter warming, while rising CDD values indicate intensifying summer extremes, in line with Mediterranean climate projections (Arias et al. 2021; Diefenbaugh & Giorgi 2012). Importantly, because CEI incorporates both thermal penalties and hydrological constraints, it can be used as an integrated climate–energy diagnostic tool, with far greater scope and explanatory power than degree-day indices. The CEI was applied in the GAP region of Türkiye, which is characterized as an arid and water-limited climate zone. In such environments, evapotranspiration demand strongly influences climate stress, and CEI responds accordingly to temperature increases and moisture deficits. However, CEI may behave differently in other

hydroclimatic regions. In humid climates, water availability is less constrained and energy limitations rather than moisture deficits can dominate climate anomalies, which may reduce the relative role of evapotranspiration in CEI variability. In temperate climates, the controlling factors may shift seasonally, suggesting that CEI may require local evaluation or calibration to capture periodic transitions between energy-limited and water-limited conditions. Therefore, extending CEI to other climate zones represents an important future research direction to assess the index's transferability, stability, and potential adaptation for global use. The study region is characterized by extensive irrigation, which can substantially alter evaporative fraction and Bowen ratio by supplementing soil moisture independently of precipitation. Consequently, CEI behavior in irrigated landscapes reflects combined climatic and anthropogenic controls on surface energy partitioning, and its transferability to non-irrigated or humid regions should be evaluated with caution. These results demonstrate that CEI provides not only a magnitude-based indicator of climatic inefficiency but also diagnostic insight into the dominant underlying mechanisms and their seasonal evolution. The earlier onset of peak inefficiency in several regions aligns with long-term warming trends and advancing heat seasonality observed across semi-arid climates. The mechanism-level decomposition improves the interpretive value of CEI, enabling differentiation between thermal, aerodynamic, and evaporative controls. Compared to previous literature, our findings support Isaac & van Vuuren, (2009) and Santamouris et al., (2015a, b)'s findings about the increasing role of cooling energy demand under climate change, but CEI adds explanatory power by incorporating evaporative and energy balance processes. Unlike traditional drought indices like SPI (McKee et al. 1993) and SPEI (Beguería et al. 2010), CEI integrates directly with energy-relevant variables, putting it in a unique position to bridge climate, water, and energy research. Furthermore, while degree-day indices only account for one aspect of demand (temperature), CEI can explain how and why inefficiencies arise, providing a methodological innovation that directly addresses gaps in current energy climatology.

4.1 Data uncertainty and reanalysis limitations

Access to plant-level solar energy production or real electricity demand data in the GAP region is limited and not publicly available. Therefore, the present study relied on ERA5-based meteorological variables that can be accessed and reproduced by other users. Future research could incorporate power generation models, PV efficiency simulations, or measured output from renewable energy facilities to validate CEI directly in the energy sector. Such analyses would

allow a more comprehensive assessment of CEI's operational advantages relative to temperature-based indices such as CDD and HDD. While the study does not include direct electricity consumption or plant-level production data due to data availability constraints, the consistent and statistically robust relationships between CEI, degree-day indices, and physically based PV efficiency losses demonstrate that CEI variability has clear and interpretable operational energy implications.

Furthermore, it should be noted that the CEI, as presented in this study, serves as a top-down climatic diagnostic tool rather than an operational performance metric. A key limitation of the current framework is the absence of empirical validation against observed PV output, grid load, or electricity demand data. While the index successfully characterizes the thermodynamic and hydrological constraints of the environment, its direct sensitivity to actual energy production remains to be quantified. Future research should focus on integrating site-specific operational data to bridge the gap between climatic inefficiency potential and observed energy system performance, thereby transitioning the CEI from a diagnostic indicator to a predictive tool for energy management.

The perturbation experiments are intended to assess the CEI's sensitivity to plausible ranges of reanalysis flux uncertainty, rather than to determine the absolute accuracy of ERA5 surface fluxes. The near-perfect correlation observed under uniform perturbations demonstrates the structural stability of the index formulation, which results from the relative and percentile-based construction of the CEI. Nevertheless, this robustness should not be construed as evidence that ERA5 flux uncertainties are insignificant. The lack of long-term in-situ flux validation remains a significant limitation. In addition, the CEI is not intended to replace precipitation-based drought indices such as SPI or SPEI. Instead, it serves as a complementary indicator that captures energy-controlled aridity and hydroclimatic stress.

The use of ERA5 reanalysis fluxes introduces uncertainty related to land-surface modelling, flux partitioning and energy-budget closure. In this study, ERA5 is employed to describe the relative variability of hydroclimatic conditions relevant to climatic efficiency, not to reproduce site-specific power generation in an absolute sense. The exclusive reliance on ERA5 represents a practical limitation of this study. Future applications of the CEI should evaluate its performance using alternative reanalysis products and available station-based flux observations to more comprehensively assess dataset-dependent uncertainty. The CEI formulation relies on percentile-based normalization and z-score standardization of Bowen ratio, evaporative fraction and the thermal penalty component, which reduces

the influence of systematic biases in flux magnitudes. However, residual structural errors in ERA5 and the absence of long-term flux-tower or plant-level validation data in the study region remain important limitations, and future work should include direct comparison with in-situ observations where available. The temporal variation of CEI presented in this study reflects changes observed across the study period; however, it is not intended as a full trend attribution analysis. While these variations appear consistent with documented regional warming and drought intensification, establishing causal attribution would require dedicated trend statistics, breakpoint assessment, and integration with external warming indicators. Such an analysis falls outside the scope of the present work, which focuses on understanding the multidimensional and scale-dependent characteristics of CEI. Future studies may incorporate formal trend attribution frameworks to assess long-term changes in CEI more comprehensively. Furthermore, the CEI provides a solid framework for identifying how climate affects energy and water systems. However, this study is limited because it does not use real-world PV output data or detailed electricity demand data. Right now, the index mainly serves as a broad climate diagnostic that points out when conditions are tough for energy infrastructure. Future studies should use specific operational data to precisely measure how energy yields respond to changes in the CEI. Validating the index with this kind of data would help turn the CEI from a general climate tool into a practical metric for managing energy operations.

Although the CEI demonstrates long-term changes that align with documented regional warming and increasing aridity, this study does not perform formal trend detection or attribution analyses. Therefore, references to climate change serve as contextual interpretation rather than explicit attribution.

5 Conclusions

This study developed the Climatic Efficiency Index (CEI) as a compound assessment tool for assessing climatic inefficiency in Southeastern Anatolia in Türkiye. By incorporating thermal penalty, Bowen ratio, and evaporative fraction, CEI captures not only the direct effect of air temperature, but also the underlying land-atmosphere energy balance processes that shape cooling and heating demand. The findings revealed a consistent pattern: CEI correlates strongly and positively with CDD and negatively with HDD, demonstrating its ability to track seasonal redistributions of energy demand. Importantly, correlations weakened at longer time scales, indicating that CEI-1 and CEI-3 are best suited to

detecting acute, short-term energy stress, whereas CEI-6 and CEI-12 capture broader background inefficiency trends. Unlike drought indices, which capture long-term moisture anomalies, CEI responds primarily to short-term energy imbalances, making it especially effective for detecting acute stresses in cooling demand while remaining relevant for broader climate-energy interactions. From an energy standpoint, these findings show that CEI is a more reliable measure than traditional temperature-based indices like CDD. While CDD has long been used as a proxy for cooling demand, its reliance on near-surface air temperature limits its explanatory power, especially in conditions where evaporative dynamics and radiation loads are significant. CEI closes this gap by explicitly incorporating evaporative fraction and Bowen ratio, accounting for natural cooling efficiency and the balance of sensible and latent heat fluxes. This makes CEI more than just an indicator of energy inefficiency; it also serves as a mechanistic framework for explaining why energy stress occurs. In addition to energy demand, CEI provides critical information on drought and climate change impacts. Elevated CEI values correspond to hot and dry periods with high Bowen ratios and low evapotranspiration, which both increase cooling energy requirements and reflect meteorological drought processes. Over time, rising CEI values reflect the impact of climate warming, with decreasing HDD and rising CDD indicating a shift toward a climate dominated by chronic cooling demand. The convergence of energy stress, drought vulnerability, and climate change emphasizes CEI's unique role as a multidimensional index in the water-energy-climate nexus. Consequently, CEI is an innovative step beyond degree-day indices. It provides a comprehensive measure of climatic inefficiency by combining key energy balance components with temperature-based thresholds, making it directly applicable to energy planning, drought monitoring, and climate adaptation. Future research

should broaden this framework to include other semi-arid regions, test its applicability across various energy sectors, and investigate its incorporation into operational early-warning systems for both energy and drought management.

6 Recommendations

- (1) CEI-1 and CEI-3 can alert utilities and planners to sudden increases in cooling demand during heatwaves, allowing for proactive load management and renewable integration.
- (2) Long-term resilience: CEI-6 and CEI-12 can inform infrastructure and policy planning by highlighting inefficiencies and climate stress.
- (3) CEI can integrate with drought monitoring systems to assess both energy and hydrological risks, especially in semi-arid regions.
- (4) To adapt to climate change, policymakers should invest in low-carbon cooling technologies and demand-side management strategies to meet future cooling energy demands.
- (5) Further research in drought-prone regions could validate the utility of CEI as a cross-regional tool for assessing energy-climate-drought relationships. Furthermore, more work is required to refine CEI thresholds for various climatic zones and to directly link CEI outputs to energy system operational data.

Appendix

See Figs. 14, 15, 16, 17, 18 and 19.

Fig. 14 Spearman correlation between CEI-3 and CDD across provinces: **a** Adıyaman, **b** Batman, **c** Diyarbakır, **d** Gaziantep, **e** Kilis, **f** Mardin, **g** Şanlıurfa, **h** Siirt

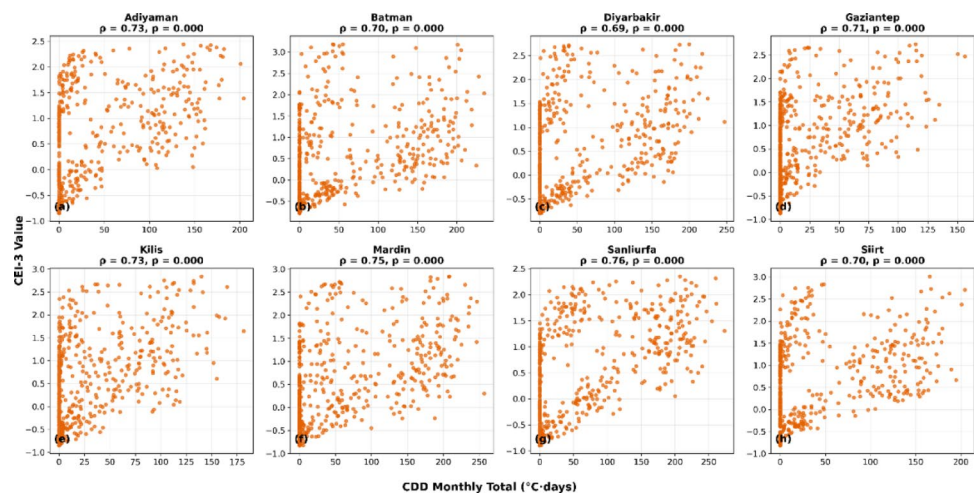


Fig. 15 Spearman correlation between CEI-3 and HDD across provinces: **a** Adıyaman, **b** Batman, **c** Diyarbakır, **d** Gaziantep, **e** Kilis, **f** Mardin, **g** Şanlıurfa, **h** Siirt

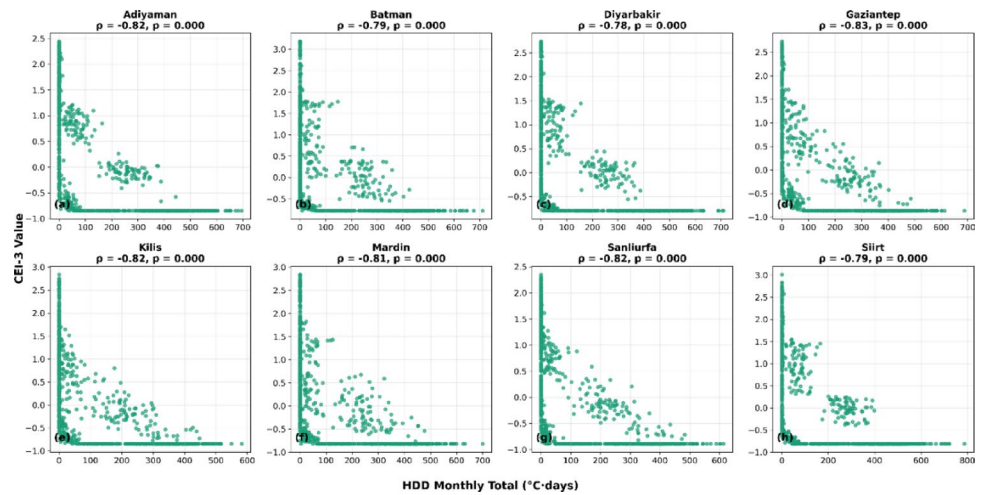


Fig. 16 Spearman correlation between CEI-6 and CDD across provinces: **a** Adıyaman, **b** Batman, **c** Diyarbakır, **d** Gaziantep, **e** Kilis, **f** Mardin, **g** Şanlıurfa, **h** Siirt

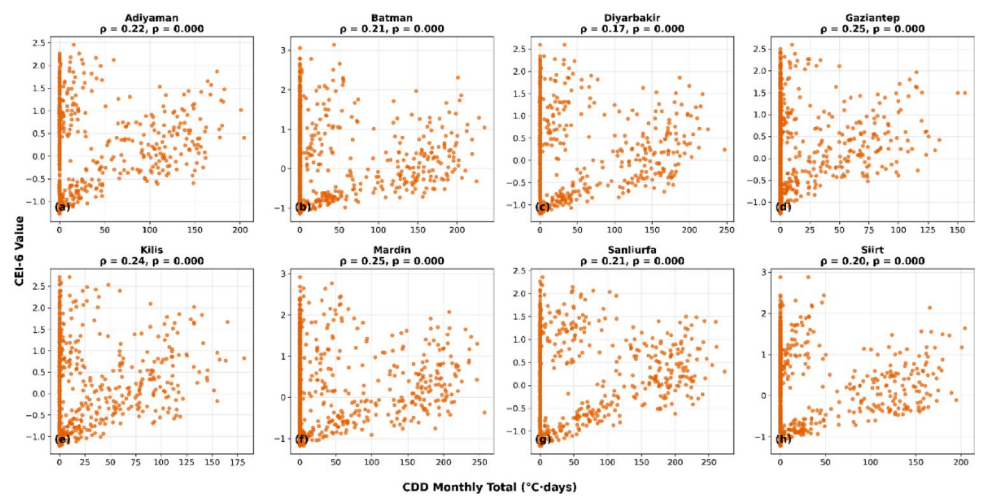


Fig. 17 Spearman correlation between CEI-6 and HDD across provinces: **a** Adıyaman, **b** Batman, **c** Diyarbakır, **d** Gaziantep, **e** Kilis, **f** Mardin, **g** Şanlıurfa, **h** Siirt

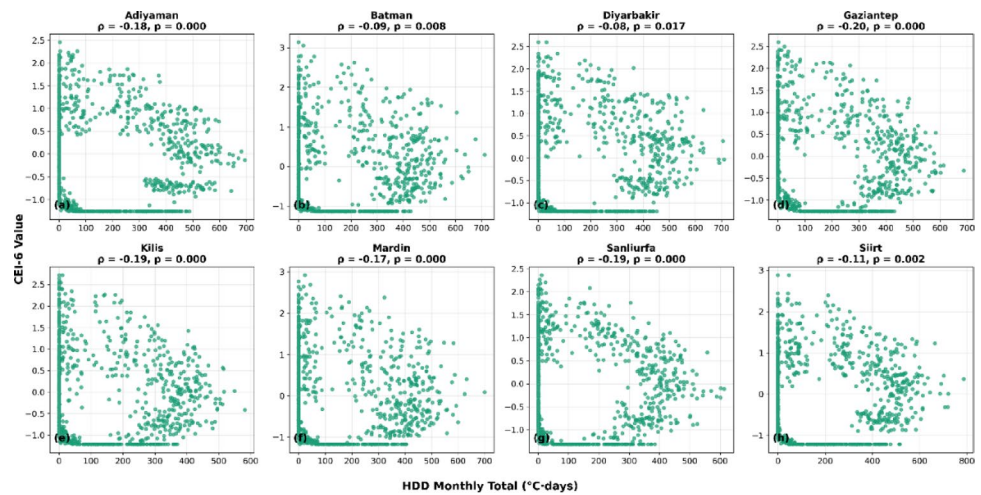


Fig. 18 Spearman correlation between CEI-12 and HDD across provinces: **a** Adiyaman, **b** Batman, **c** Diyarbakır, **d** Gaziantep, **e** Kilis, **f** Mardin, **g** Şanlıurfa, **h** Siirt

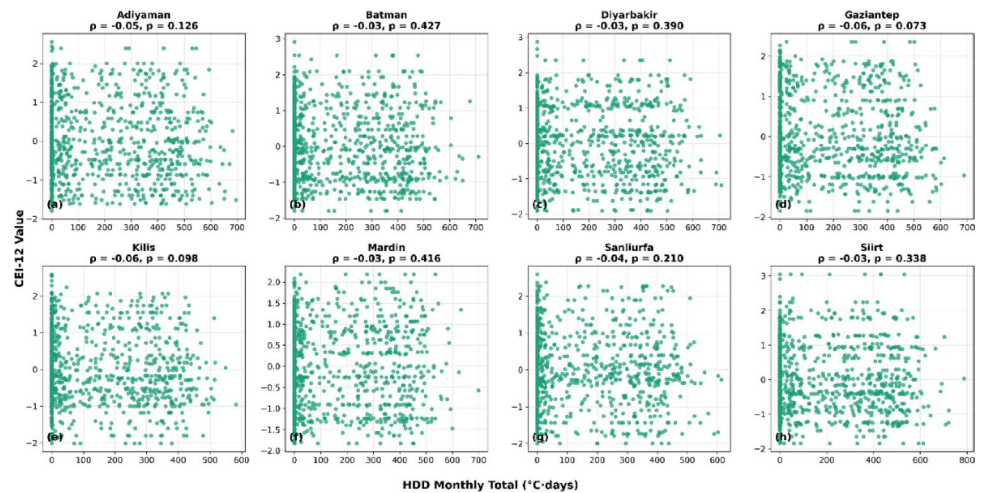
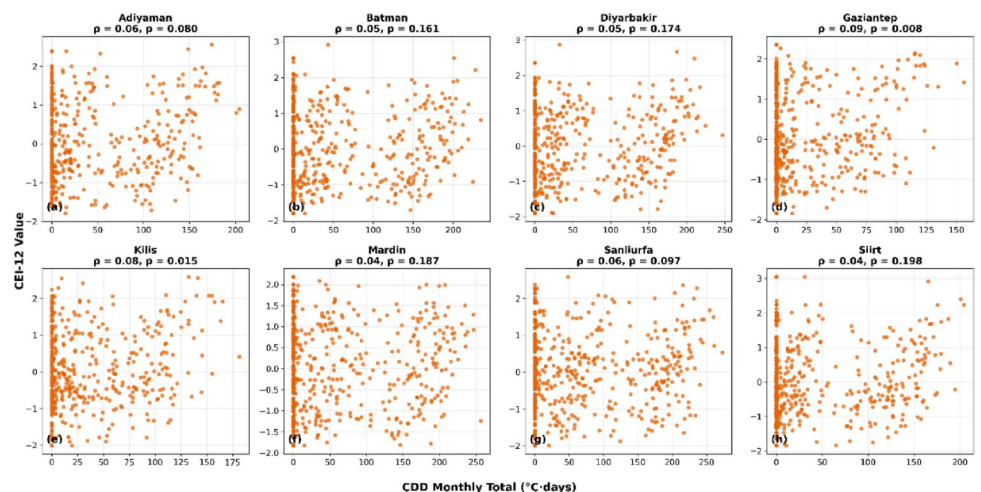


Fig. 19 Spearman correlation between CEI-12 and CDD across provinces: **a** Adiyaman, **b** Batman, **c** Diyarbakır, **d** Gaziantep, **e** Kilis, **f** Mardin, **g** Şanlıurfa, **h** Siirt



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Data availability The datasets used and/or analyzed in the present study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest The author declares no conflict of interest.

Consent to publish The author declares that this work has not been published before, and it is not under consideration for publication elsewhere.

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