DoI: https://doi.org/10.58537/jorangrau.2026.54.2.11

J. Res. ANGRAU 54 (2) 76-83, 2026

DIURNAL TEMPERATURE RANGE VARIABILITY OVER KARNATAKA, INDIA: SPECTRAL EVIDENCE OF INTERANNUAL AND DECADAL CLIMATE MODES (1958–2024)

SRINIVASA SASDHAR PONNALURU*

Department of Economics, Vijayanagara Srikrishnadevaraya University,
Bellary - 583105, Karnataka, India

Date of Receipt : 06-05-2026 Date of Acceptance : 18-06-2026

ABSTRACT

Diurnal temperature range (DTR), defined as the difference between daily maximum and minimum temperatures, is an important indicator of climatic variability and land–atmosphere interactions. This study examines the temporal variability of DTR over Karnataka, India, using monthly temperature data for 1958–2024. Monthly DTR anomalies were analysed using Welch and Lomb–Scargle spectral techniques with statistical significance assessed against an AR(1) red-noise background. The results reveal variability across multiple timescales, including interannual (H=2–5 years), sub-decadal (H=8–9 years), and a statistically significant decadal cycle near 16–17 years. Additional low-frequency variability around 30 years indicates gradual climatic modulation of DTR. These findings highlight the presence of multi-timescale climate variability influencing diurnal temperature behaviour in southern India, with potential implications for agricultural planning and climate adaptation.

Keywords: Climate Variability, Diurnal temperature range, ENSO, Karnataka, Spectral analysis.

INTRODUCTION

Temperature variability plays an important role in agricultural productivity and environmental processes, particularly in regions where climate strongly influences crop growth and water availability. In addition to mean temperature levels, differences between daytime and night-time temperatures affect plant respiration, phenology, and grain filling. The diurnal temperature range (DTR), defined as the difference between daily maximum and minimum temperatures, is therefore a useful indicator of climatic variability and land–atmosphere interactions.

Recent studies show that climate change often affects daytime and night-time temperatures asymmetrically, with minimum temperatures increasing more rapidly than maximum temperatures in many regions. Such changes modify the diurnal temperature cycle and influence regional climate behaviour (Donat *et al.*, 2016; Zhang *et al.*, 2019). Temperature variability is controlled by multiple processes, including atmospheric circulation, land–surface interactions, soil moisture conditions, and cloud cover (Sun *et al.*, 2017). Large-scale climate assessments further indicate that these processes operate across a wide range of temporal scales from

*Corresponding Author Email: sasdhar@vskub.ac.in

interannual oscillations to multi-decadal variability (IPCC, 2021).

In the Indian region, several studies have reported increasing temperature variability and changing climatic conditions associated with monsoon dynamics and long-term warming (Krishnan *et al.*, 2020). High-resolution climate datasets also reveal substantial spatial heterogeneity in temperature and rainfall patterns across the Indian peninsula (Pai *et al.*, 2021). Within Karnataka, climatic conditions vary considerably due to contrasts between humid coastal regions, the Western Ghats, and the semi-arid interior plateau (Simpson *et al.*, 2024).

Temperature variability also has important implications for agricultural systems. Crop growth and productivity depend not only on average temperature but also on fluctuations in day–night temperature differences. Elevated night-time temperatures can increase crop respiration and reduce grain filling, thereby affecting yields (Lobell *et al.*, 2015). Climate variability has also been shown to account for a significant portion of global crop yield fluctuations (Ray *et al.*, 2015; Lesk *et al.*, 2016).

While many studies have examined long-term trends in temperature and climate extremes, comparatively little attention has been given to the temporal structure of temperature variability itself. Climatic variables often exhibit variability across multiple timescales associated with large-scale climate modes and land–atmosphere feedbacks. Spectral analysis provides a useful approach for identifying such periodic components by decomposing time-series variance into frequency bands.

While previous studies have primarily focused on long-term temperature trends and extremes, the temporal structure of diurnal temperature variability across multiple climatic timescales remains relatively underexplored, particularly at sub-national scales in India. This study addresses this gap by applying spectral analysis to identify dominant periodicities in DTR over Karnataka.

This study examines the temporal variability of diurnal temperature range over Karnataka during 1958–2024 using spectral analysis techniques. Specifically, Welch and Lomb–Scargle periodograms are used to identify dominant interannual, sub-decadal, and decadal modes of variability in DTR. Understanding these temporal patterns can improve regional climate characterization and provide insights relevant for agricultural planning in southern India.

MATERIAL AND METHODS

The study focuses on Karnataka in southern India, which extends from the humid coastal plains along the Arabian Sea to the elevated Western Ghats and the semi-arid interior Deccan plateau. These physiographic contrasts produce substantial spatial variation in temperature and rainfall regimes. Coastal districts generally exhibit smaller diurnal temperature ranges due to maritime influence, whereas interior districts experience larger day–night temperature contrasts typical of semi-arid climates.

Temperature data and DTR calculation

Monthly maximum (Tmax) and minimum (Tmin) temperature data were obtained from the TerraClimate dataset, a high-resolution global climate dataset widely used in climatological research (Abatzoglou *et al.*, 2018). The dataset provides monthly climate variables at approximately 4km spatial resolution and covers the period from 1958–2024.The TerraClimate dataset is quality-controlled and contains negligible missing values. Standard consistency checks were

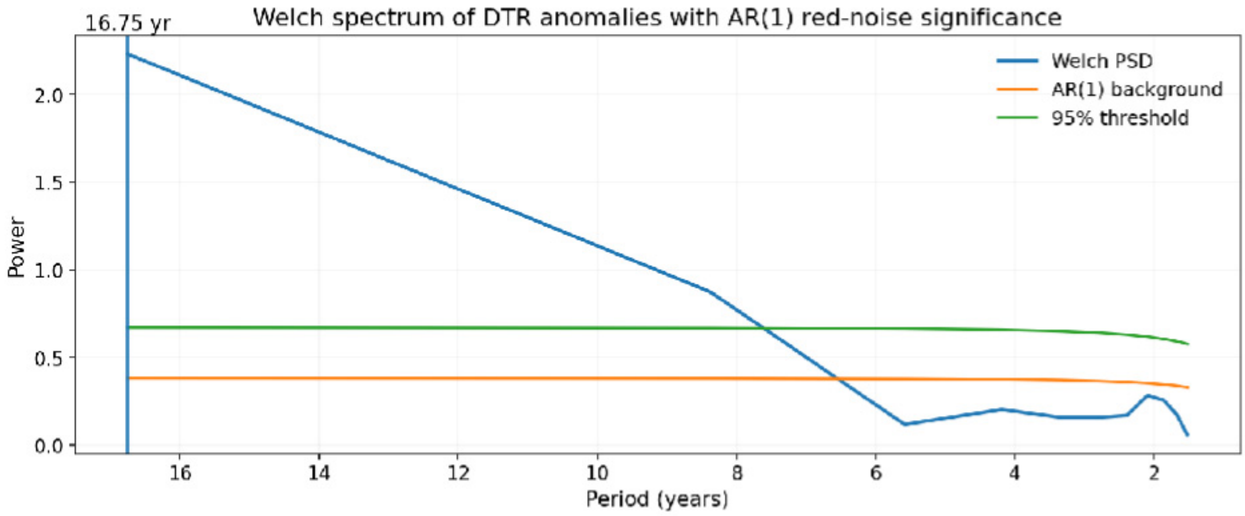

Fig.1.Welch power spectrum of deseasonalized DTR anomalies over Karnataka (1958–2024) with AR(1) red-noise background and 95% confidence threshold. The dominant decadal peak (~16–17 years) exceeds the red-noise threshold, indicating statistically significant low-frequency variability.

performed prior to analysis, and no interpolation was required.The data processing workflow involved aggregation of gridded temperature data to monthly district-level values, computation of DTR (T_{max} - T_{min}), removal of the seasonal cycle to obtain anomalies, linear detrending, and standardization to ensure comparability across time prior to spectral analysis.

Diurnal temperature range was calculated as: $DTR = T_{max} - T_{min}$

DTR anomaly construction

To isolate variability beyond the seasonal cycle, monthly DTR anomalies were calculated by removing the mean annual cycle. Monthly climatological means were first computed for each calendar month across the study period, and these values were subtracted from the original DTR series.The resulting anomaly series was linearly detrended and standardized prior to spectral analysis to ensure that the estimated spectra reflect intrinsic variability rather than seasonal or long-term linear trends.

Spectral analysis

Temporal variability in DTR was examined using two complementary spectral techniques.Spectral analysis is particularly suited for identifying periodic components in climate time series that are not readily observable in the time domain. First, the Welch periodogram was applied to the monthly anomaly series. The Welch method estimates power spectra by dividing the time series into overlapping segments, computing spectra for each segment, and averaging the results. This procedure reduces variance in spectral estimates and improves the stability of detected periodicities.

Second, the Lomb–Scargle periodogram was used to examine lower-frequency variability and verify spectral features identified using the Welch method. The Lomb–Scargle approach is widely used in geophysical time-series analysis for detecting periodic signals.

Statistical significance of spectral peaks was assessed against a first-order autoregressive [AR(1)] red-noise background.

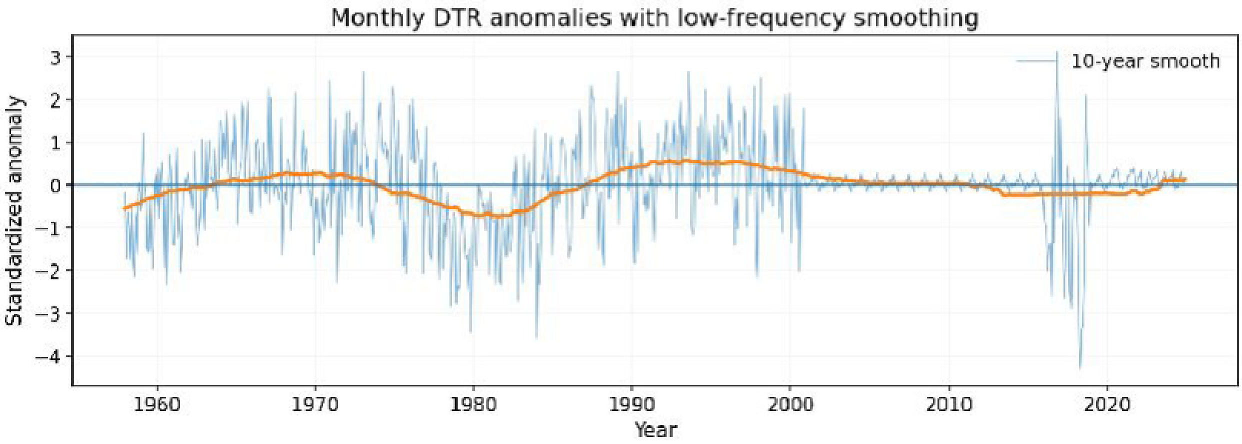

Fig.2. Monthly DTR anomalies over Karnataka (grey) and smoothed low-frequency component (bold), illustrating non-stationary decadal variability.

The lag-1 autocorrelation coefficient of the anomaly series was used to construct the theoretical red-noise spectrum, and peaks exceeding the 95% confidence level were considered statistically significant.The analysis is conducted at the state level to capture broad-scale climatic variability; however, sub-regional heterogeneity within Karnataka may exist and warrants further investigation.

Spectral computations were performed using Python scientific libraries including NumPy, SciPy, and Astropy.

RESULTS AND DISCUSSION

Temporal variability of DTR anomalies

The deseasonalized diurnal temperature range (DTR) anomaly series for Karnataka during 1958–2024 shows pronounced interannual variability together with slower multi-year fluctuations (Fig. 2). Positive anomalies indicate periods when daytime warming dominates relative to night-time warming, whereas negative anomalies reflect relatively stronger increases in minimum temperatures.

The anomaly series exhibits clear multi-year oscillatory behaviour rather than purely random variability. Such patterns are consistent with the influence of interacting atmospheric and land–surface processes that modulate the balance between daytime heating and nocturnal cooling. In monsoon-dominated regions such as southern India, these processes are further affected by variability in large-scale ocean–atmosphere systems. The presence of slow oscillations in the anomaly series suggests that DTR variability is influenced by climatic processes operating across multiple temporal scales.

Spectral characteristics of DTR variability

The Welch power spectrum of the DTR anomaly series reveals several distinct peaks corresponding to different timescales of variability (Fig. 1). The strongest peak occurs at approximately 16–17 years, indicating a pronounced decadal-scale component in DTR variability across Karnataka. This peak exceeds the 95% confidence threshold derived from the AR(1) red-noise background, confirming that the signal is statistically significant and unlikely to arise solely from autocorrelated climate noise.

Additional spectral peaks occur within the sub-decadal band near 8–9 years and the interannual band between approximately 2 and

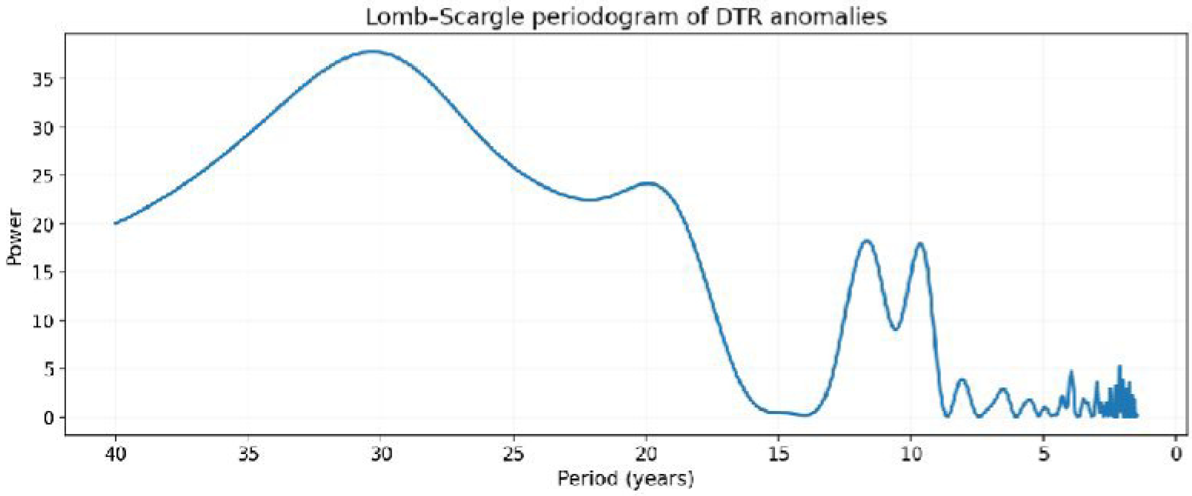

Fig.3. Lomb–Scargle periodogram of DTR anomalies highlighting enhanced low-frequency power associated with long-term climate modulation.

5 years. Although these peaks do not exceed the red-noise significance threshold, they indicate moderate variability at shorter timescales. Together, these results suggest that DTR variability over Karnataka is characterized by a hierarchy of temporal scales rather than by a single dominant oscillation.

Low-frequency variability

The Lomb–Scargle periodogram provides additional insight into longer-period variability (Fig.3). The spectrum shows enhanced power at periods of roughly 30 years, indicating substantial low-frequency variability in the DTR series. Rather than representing a discrete oscillatory cycle, this broad low-frequency signal likely reflects gradual modulation of the regional temperature regime.

Such behaviour is consistent with observational evidence from India indicating asymmetric warming between daytime and night-time temperatures, with minimum temperatures increasing more rapidly in several regions. These gradual shifts can generate persistent low-frequency variability in DTR that appears in spectral analysis as enhanced power at long periods.

Interpretation of dominant climatic timescales

The interannual variability observed in the 2–5 year band broadly coincides with the characteristic periodicity of the El Niño–Southern Oscillation (ENSO). ENSO influences atmospheric circulation and monsoon dynamics across the Indian subcontinent, affecting cloud cover, radiation balance, and surface moisture conditions. These factors influence both daytime heating and nocturnal cooling and can therefore modulate DTR behaviour.

The sub-decadal variability near 8–9 years may reflect interactions among ocean–atmosphere processes such as the Indian Ocean Dipole (IOD) and longer-term modulation of ENSO activity. Persistence in land-surface conditions, including soil moisture and vegetation cover, may also contribute to multi-year temperature variability through land–atmosphere feedback mechanisms.

The strongest spectral signal identified in this study, near 16–17 years, suggests the presence of decadal-scale modulation in diurnal temperature behaviour. Such variability may arise from gradual adjustments in the regional climate system, including land-use change, irrigation expansion, and aerosol influences, which can alter the surface energy balance and preferentially affect night-time cooling.

Implications for agricultural systems

Variability in diurnal temperature range has important implications for agricultural systems. Crop growth depends not only on mean temperature conditions but also on the balance between daytime and night-time temperatures. Elevated night-time temperatures can increase plant respiration and reduce grain filling in several crops, while larger diurnal temperature ranges may increase evapotranspiration and crop water demand.In Karnataka, crops such as paddy, maize, and pulses are particularly sensitive to night-time temperature increases during critical growth stages.

The presence of multi-timescale variability in DTR suggests that agricultural temperature conditions in Karnataka may be influenced by climate oscillations operating over several years or decades. Periods characterized by sustained increases in night-time temperatures may therefore influence crop productivity and heat stress conditions, particularly in semi-arid regions with limited irrigation resources. Recognizing these temporal patterns can support improved climate risk assessment and agricultural planning.

Robustness and limitations of spectral analysis

Spectral techniques provide valuable insights into the temporal structure of climatic variability but require careful interpretation. The identification of dominant periodicities depends on the statistical properties and length of the underlying time series as well as assumptions regarding background noise behaviour. In this study, spectral significance was evaluated against a first-order autoregressive [AR(1)] red-noise model. The dominant peak near 16–17 years exceeds the 95% confidence level, confirming the statistical robustness of the decadal signal (Table 1).

Table 1. Welch power spectrum of DTR anomalies over Karnataka (1958–2024) with AR(1) red-noise significance threshold.

Period (years)	Power
16.8	2.23
8.4	0.87
4.2	0.2
3.4	0.16
2.1	0.28

Lower-amplitude peaks in the interannual and sub-decadal ranges do not exceed the significance threshold and should therefore be interpreted cautiously. These peaks may reflect weak climatic signals combined with residual autocorrelation in the time series. Additionally, the broad low-frequency power detected in the Lomb–Scargle spectrum likely reflects non-stationary climatic behaviour associated with gradual changes in the regional temperature regime rather than a strictly periodic oscillation.

Association with ENSO and IOD variability

To examine whether the interannual variability in DTR is associated with large-scale climate modes, monthly DTR anomalies were compared with the Oceanic Niño Index (ONI) and Dipole Mode Index (DMI) at lags of 0–6 months (Table 2).The results indicate a weak but statistically significant negative association between DTR anomalies and ONI at a lag of six months ($r = -0.098$, $p < 0.01$), suggesting a delayed ENSO influence on diurnal

Table 2. Association between DTR anomalies and ENSO/IOD indices

Model	Lag (months)	Corre-lation	p-value	NW Coefficient	NW p-value
ONI	6	- 0.098	0.005	- 0.116	0.085
DMI	0	0.064	0.068	0.176	0.183
ONI (joint)	6	—	—	- 0.113	0.09
DMI (joint)	0	—	—	0.15	0.241

temperature variability. In contrast, the association with DMI is weak and statistically insignificant across all lags.

Newey–West regression estimates confirm these findings, with the ENSO coefficient remaining marginally significant at the 10% level, while the IOD effect is not statistically significant. These results suggest that ENSO contributes modestly to interannual variability in DTR, whereas IOD influence is minimal.Overall, the statistical evidence supports interpreting the interannual spectral variability as consistent with ENSO timescales, although ENSO explains only a small proportion of the observed variability.

CONCLUSION

This study examined the temporal variability of diurnal temperature range (DTR) over Karnataka using spectral analysis of monthly temperature data for the period 1958–2024. The results reveal that DTR variability is characterized by multiple temporal scales, including interannual fluctuations near 2–5 years, sub-decadal variability around 8–9 years, and a statistically significant decadal signal near 16–17 years. Complementary Lomb–Scargle analysis further indicates strong low-frequency variability near 30 years, indicating gradual climatic modulation of diurnal temperature behaviour.

These findings indicate that DTR variability over Karnataka reflects the combined influence of short-term climate oscillations and longer-term structural changes in the regional climate system. Because day–night temperature differences influence crop respiration, evapotranspiration, and heat stress conditions, multi-timescale variability in DTR may have important implications for agricultural systems in semi-arid and monsoon-dominated regions. Incorporating such climatic signals into agricultural advisories and seasonal planning frameworks could improve preparedness for temperature-related risks and support climate-resilient agricultural strategies in Karnataka.

Future research may extend the present analysis using wavelet methods or climate-mode correlation studies to further investigate the drivers of diurnal temperature variability in the region.

ACKNOWLEDGEMENT

The author acknowledges financial support from The Indian Council of Social Science Research (ICSSR) New Delhi under major Research Project Grant G133.

REFERENCES

Abatzoglou, J. T., Dobrowski, S. Z., Parks, S. A., and Hegewisch, K. C. 2018. TerraClimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958–2015. Scientific Data, 5, 170191. https://doi.org/10.1038/sdata.2017.191

Donat, M. G., Lowry, A. L., Alexander, L. V., O'Gorman, P. A., and Maher, N. 2016. More extreme precipitation in the world's dry and wet regions. Nature Climate Change, 6, 508–513. https://doi.org/10.1038/nclimate2941

IPCC (2021). Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge. https://doi.org/10.1017/9781009157896

Krishnan, R., Sanjay, J., Gnanaseelan, C., Mujumdar, M., Kulkarni, A., and Chakraborty, S. 2020. Assessment of Climate Change over the Indian Region. Springer Nature, Singapore. https://doi.org/10.1007/978-981-15-4327-2

Lesk, C., Rowhani, P., and Ramankutty, N. 2016. Influence of extreme weather disasters on global crop production. Nature, 529, 84–87. https://doi.org/10.1038/nature16467

Lobell, D. B., Hammer, G. L., McLean, G., Messina, C., Roberts, M. J., and Schlenker, W. 2015. The critical role of extreme heat for maize production in the United States. Nature Climate Change, 3, 497–501. https://doi.org/10.1038/nclimate1832

Pai, D. S., Sridhar, L., Rajeevan, M., Sreejith, O. P., Satbhai, N. S., and Mukhopadhyay, B. 2021. Development of a new high spatial resolution rainfall data set for India and its long-term climatological analysis. Mausam, 72(1), 1–20. https://doi.org/10.54302/mausam.v72i1.82

Ray, D. K., Gerber, J. S., MacDonald, G. K., and West, P. C.2015. Climate variation explains a third of global crop yield variability. Nature Communications, 6, 5989. https://doi.org/10.1038/ncomms6989

Simpson, R., Abhilash, K. P., Kavya, R., and Hiremath, S. 2024. Examining Two Decades of Climate Variability in Karnataka: Insights from Temperature and Rainfall Trends. International Journal of Environment and Climate Change, 14(2), 97–109.https://doi.org/10.9734/ijecc/2024/v14i74255

Sun, Y., Zhang, X., Zwiers, F. W., Song, L., Wan, H., Hu, T., Yin, H., and Ren, G. 2017. Rapid increase in the risk of extreme summer heat in Eastern China. Nature Climate Change, 7, 320–324. https://doi.org/10.1038/nclimate3279

Zhang, X., Alexander, L., Hegerl, G., Jones, P., Tank, A. K., Peterson, T., Trewin, B., and Zwiers, F. 2019. Indices for monitoring changes in extremes based on daily temperature and precipitation data. Climate Dynamics, 52, 4245–4259. https://doi.org/10.1007/s00382-018-4366-2

Srinivasa Sasdhar, P. 2026. Diurnal temperature range variability over Karnataka, India: Spectral evidence of interannual and decadal climate modes (1958–2024).
The Journal of Research ANGRAU,54(2) : 76-83