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Urban Expansion, Entropy Dynamics, and Ecological Quality: A District-Based Assessment

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Abstract

Urban expansion in rapidly developing metropolitan regions reshapes not only the spatial structure of built environments but also the ecological functioning of surrounding landscapes. This study examines district-level urban expansion and ecological change between 2007, 2018, and 2025 in a rapidly growing region of north-west Sydney, Australia. Multi-temporal Landsat imagery was classified to extract built-up land, and Shannon’s entropy was used to quantify the spatial dispersion of development. In parallel, ecological conditions were assessed using the Remote Sensing Ecological Index (RSEI), while temporal differences (ΔRSEI) and Getis–Ord Gi hotspot analysis were applied to identify spatial clusters of improvement or degradation. Results show that entropy increased from 0.88 (2007) to 0.91 (2018), indicating a phase of suburban expansion, then stabilised at 0.90 by 2025 as development became more uniform across districts. Ecological quality declined steadily, with mean RSEI decreasing from 0.72 to 0.70 and further dropping to 0.61 in the final period. Hotspot patterns reveal ecological improvement in central districts during early development (2007–2018), whereas a distinct cold spot emerges in the southern district between 2018–2025, associated with intensified construction activity and vegetation loss. These spatial patterns are further supported by socio-economic indicators. Population grew by over 50%, housing prices tripled, and transport investments such as the Sydney Metro Northwest contributed to increasing development pressure, accelerating suburbanisation and ecological stress. Overall, the integrated entropy-RSEI hotspot approach provides a framework for linking urban with ecological quality and offers insights to support planning and management in rapidly growing metropolitan regions.

1. Introduction

Urbanization represents one of the most significant land transformation processes of the twenty-first century. Rapid urban expansion not only alters land cover but also modifies ecological processes and reshapes the spatial structure of metropolitan regions (Seto et.al, 2012). As cities grow, natural landscapes are increasingly converted into built-up areas, leading to vegetation loss, increased surface temperature, and greater environmental pressure on surrounding ecosystems (Oli et al., 2025; Ullah et al., 2024). Monitoring these changes is therefore essential for sustainable urban planning and environmental management. In this context, remote sensing has emerged as a key tool for observing and analysing urban growth, as it enables consistent long-term monitoring of land-cover dynamics across large geographic areas (Weng, 2012).

Satellite imagery has been widely used to monitor land-cover change and urban expansion dynamics in rapidly developing regions. Landsat imagery, in particular, has been extensively applied for urban growth studies due to its long historical archive and suitable spatial resolution for regional-scale analysis (Schneider et al., 2010). Previous studies have demonstrated that remote sensing techniques can effectively detect urban expansion patterns and quantify the environmental impacts associated with land-cover transformation (Seto et al., 2012; Herold et al., 2003).

However, beyond simply mapping urban growth, it is equally important to characterise the spatial configuration of this expansion. Spatial metrics such as Shannon’s entropy have been widely used to quantify the dispersion or compactness of urban development. Entropy values close to zero indicate compact urban patterns, whereas values approaching one represent more dispersed or fragmented urban structures. Yeh and Li (2001) applied entropy analysis to examine urban sprawl in Chinese cities, while Sudhira et al. (2004) used the approach to analyse urban expansion patterns in Bangalore, India. These studies demonstrate that entropy analysis provides an effective way to measure spatial urban growth dynamics and identify the transition from compact to dispersed development.

While spatial metrics capture the form of urban expansion, assessing its environmental consequences requires the integration of ecological indicators. One widely used approach is the Remote Sensing Ecological Index (RSEI), which combines multiple environmental variables derived from satellite imagery to evaluate ecological quality (Xu et al., 2019). The index typically integrates vegetation greenness, land surface temperature, and built-up or bare soil indicators to provide a comprehensive assessment of environmental conditions. Several studies have successfully applied RSEI to monitor ecological changes associated with urbanization and land-use transformation (Jing et al., 2020; Liu et al., 2023). These studies show that increasing urban development often corresponds with declining ecological quality due to vegetation loss and increasing thermal stress.

In addition to these indicators, spatial statistical techniques enable the identification of localized patterns of ecological change. The Getis–Ord Gi* statistic is commonly used to detect spatial clusters of high or low values within geographic datasets (Ord and Getis, 1995). When applied to ecological indices, hotspot analysis can reveal areas where ecological deterioration or improvement is spatially concentrated. This approach has been increasingly used in environmental monitoring studies to identify spatial patterns of ecological stress and environmental change (Mondal et al., 2024).

Although research on urban expansion and ecological quality has grown considerably, most studies remain focused on city-wide assessments, which may mask spatial variability at finer administrative scales. District-level approaches can provide a more detailed understanding of how urban growth affects ecological conditions at local scales. Suburban growth corridors within metropolitan regions are particularly important to investigate, as these areas often experience rapid land-use transitions and environmental pressure.

Sydney, Australia, is currently experiencing substantial metropolitan expansion, particularly in its north-western growth corridors. The Hills Shire Local Government Area (LGA) has become one of the fastest growing suburban districts in Greater Sydney due to population growth, infrastructure development, and housing demand. Despite this rapid growth, the associated ecological impacts at the district level remain insufficiently quantified.

Therefore, this study aims to examine the relationship between urban expansion patterns and ecological quality change in the Hills Shire LGA between 2007, 2018, and 2025 using remote sensing and spatial analysis techniques. Specifically, the study aims to (1) map built-up expansion and quantify urban spatial structure using Shannon’s entropy, (2) assess ecological quality using RSEI, and (3) identify spatial clusters of ecological change using hotspot analysis.

By integrating spatial metrics with ecological indicators, this study investigates how rapid suburban development affects ecological conditions at the district level within a growing metropolitan region.

2. Study Area and Data

2.1 Study Area

The Hills Shire LGA, located in the north-western part of Sydney, Australia, is recognised as one of the key metropolitan regions experiencing rapid urban expansion (Figure 1). Over the past two decades, the area has undergone extensive residential and commercial development, driven by demographic growth, major transport infrastructure investments, and strategic urban planning initiatives. These dynamics make the Hills Shire an appropriate case study for examining the environmental implications of peri-urban development.

One of the primary drivers of this expansion is steady population growth. The region has shown a continuous increase in population, accompanied by rising housing demand and intensified development pressure. According to the Australian Bureau of Statistics, the population grew from approximately 138,000 in 2007 to nearly 208,000 in 2025 (Australian Bureau of Statistics (ABS), 2025; idCommunity, 2025). At the same time, large-scale infrastructure projects—particularly the Sydney Metro Northwest railway— have facilitated residential expansion and influenced urban growth patterns (Transport for NSW, 2019).

This urban growth has taken place within a spatially heterogeneous landscape. The Hills Shire LGA comprises a mix of urban settlements, agricultural land, and remnant forested areas, resulting in clear contrasts between built-up and natural environments. Such heterogeneity provides a suitable setting for analysing ecological variation and evaluating how different levels of development pressure affect environmental quality.

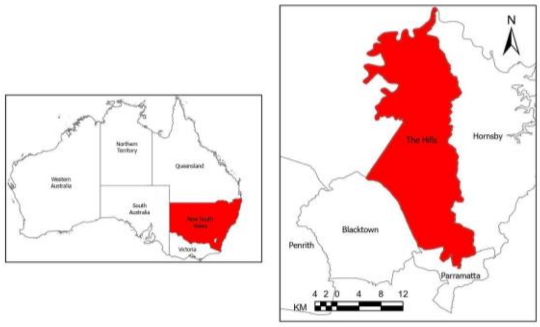

Figure1. Hills Shire LGA boundary, Sydney, Australia.

2.2 Satellite Imagery and Ancillary Data

Landsat 5 TM (05.01.2007), Landsat 8 OLI (19.01.2018), and Landsat 9 OLI (05.01.2025) images were obtained from the USGS Earth Explorer platform. All datasets were selected to represent comparable seasonal conditions and low cloud cover, ensuring temporal consistency across the analysis. In addition, ancillary datasets were incorporated, including administrative boundaries for district-level aggregation, population and housing data from the Australian Bureau of Statistics, and information on major transport infrastructure developments.

3. Methodology

The methodological framework consisted of several key steps. First, satellite imagery was pre-processed to ensure radiometric and spatial consistency. Land Use/Land Cover (LULC) classification was then performed to extract built-up areas. Subsequently, district-level Shannon entropy was calculated to evaluate patterns of urban expansion. Ecological quality was then assessed for each year using RSEI. Changes in ecological conditions were quantified using ΔRSEI, followed by Getis–Ord Gi hotspot analysis to identify spatial clusters of change. Finally, all results were interpreted in relation to demographic and socio-economic characteristics of the study area.

3.1 Image Pre-processing

All satellite images were Level 2 surface reflectance products with a spatial resolution of 30 m. Pre-processing steps included band stacking, clipping to the study area, and quality assessments to ensure geometric consistency across datasets.

3.2 Land Use/Land Cover Classification

A supervised classification was performed using the Maximum Likelihood Classification (MLC) algorithm, a widely applied parametric method that assumes normally distributed spectral responses (Richards and Jia, 1999). MLC is one of the most used supervised classification techniques and is known to achieve accuracy levels of approximately 80–90% (Bharath et al., 2017; Roy and Kasemi, 2021). Training samples were selected using high-resolution reference maps, expert knowledge of local land characteristics, and visual interpretation of spectral signatures. Five LULC classes were identified: built-up areas, forest, agricultural land, water, and quarry (Azabdaftari and Sunar, 2024). Among these, built-up areas were specifically extracted for subsequent spatial and ecological analysis.

Classification accuracy was evaluated using randomly distributed validation points, with overall accuracies exceeding 85% across all years, consistent with values reported in the literature for similar land-cover classification studies (Azabdaftari and Sunar, 2024).

3.3 Shannon’s Entropy Calculation

Shannon’s entropy was calculated to evaluate the spatial structure of urban expansion using concentric buffer zones centred on the urban core. Shannon’s entropy measures the degree of dispersion or concentration of built-up areas across spatial units and is widely used in urban studies. Entropy values range from 0, indicating a highly compact urban form, to 1, representing a fully dispersed pattern (Tewolde and Cabral, 2011; Azabdaftari and Sunar, 2022). The relative entropy was calculated as follows:

$$H_n' = \sum_i^n P_i \log\left(\frac{1}{P_i}\right) / \log(n) \tag{1}$$

where:
$P_i = x_i / \sum x_i$
x_i = built-up area in the i th zone
$\sum x_i$ = total built-up area across all n zones
n = number of zones

3.4 Remote Sensing Ecological Index (RSEI)

Ecological conditions were evaluated using RSEI, a composite indicator of environmental quality derived from satellite imagery. This index integrates key ecological components representing different environmental dimensions, including vegetation greenness, surface wetness, built-up intensity, and thermal conditions.

In this study, four indicators derived from Landsat imagery were used: the Normalized Difference Vegetation Index (NDVI) representing vegetation greenness and ecological productivity, the Tasseled Cap Wetness (WET) component reflecting surface moisture conditions, the Normalized Difference Built-up and Soil Index (NDBSI) representing built-up intensity and dryness conditions, and Land Surface Temperature (LST) representing thermal characteristics associated with urban heat effects. NDVI and NDBSI were calculated using standard spectral indices, WET was derived using the Tasseled Cap transformation, and LST was estimated from Landsat thermal bands following established algorithms (Colak and Sunar, 2020; Azabdaftari and Sunar, 2022).

NDVI and Wetness are positively related to ecological quality, whereas LST and NDBSI represent heat and dryness conditions and are negatively related to ecological quality. Therefore, LST and NDBSI were inverted so that all indicators follow the same direction, with higher values representing better environmental conditions.

To integrate these indicators, all variables were first normalized to ensure comparability. Principal Component Analysis (PCA) was then applied to synthesize the indicators into a single composite index. PCA transforms correlated variables into a set of uncorrelated components, that capture the main variability in the dataset. In the RSEI framework, the first principal component (PC1) typically represents the majority of ecological information and is therefore used as the basis of the index. The resulting PC1 values were normalized to a range between 0 and 1, where higher values indicate better ecological quality and lower values represent degraded ecological conditions (Jing et al., 2020; Liu et al., 2023; Azabdaftari and Sunar, 2025).

3.5 Ecological Change Detection Using ΔRSEI

To analyse temporal ecological dynamics, changes in ecological quality were quantified using differences in RSEI values between the selected time periods (Xu et al., 2019). The change in ecological conditions was expressed as ΔRSEI:

$$\Delta RSEI = RSEIt_2 - RSEIt_1 \tag{2}$$

where $RSEIt_1$ and $RSEIt_2$ represent the ecological index values at two time periods. Positive ΔRSEI values indicate an improvement, whereas negative values indicate ecological degradation. In this study, ΔRSEI was calculated for the periods 2007–2018 and 2018–2025 to evaluate ecological changes associated with urban expansion.

3.6 Spatial Hotspot Analysis Using Getis–Ord Gi*

To identify spatial clusters of ecological change, hotspot analysis was performed using the Getis–Ord Gi* statistic. This local indicator of spatial association detects statistically significant clusters of high or low values within spatial datasets. This statistic is calculated as:

$$G_i^* = \frac{\sum_j w_{ij} x_j - \bar{X} \sum_j w_{ij}}{S \sqrt{\left[\frac{n \sum_j w_{ij}^2 - \left(\sum_j w_{ij}\right)^2}{n-1}\right]}} \tag{3}$$

where:
x_j represents the attribute value at location j
w_{ij} represents the spatial weight between features iii and jjj
n is the number of spatial observations
X¯ is the mean of the dataset
S is the standard deviation

The statistic evaluates whether high or low values are spatially clustered beyond what would be expected under spatial randomness. The resulting z-scores indicate the intensity and direction of clustering, while p-values reflect the statistical significance of these patterns. Positive z-scores represent hotspots, whereas negative z-scores indicate cold spots (Ord and Getis, 1995).

In this study, these clusters correspond to ecological improvement (high ΔRSEI) and degradation (low ΔRSEI), respectively. Statistical significance levels of 90%, 95%, and 99% confidence were used to classify hotspot intensity (ESRI, 2023). This approach allows the identification of spatial variation in ecological conditions across the study area. Unlike global measures such as Moran’s I, which summarize overall spatial autocorrelation, the Gi* statistic identifies localized patterns of change, allowing the detection of areas with concentrated ecological degradation or recovery (Anselin, 1995; Mondal et al., 2024).

4. Results and Discussion

4.1 Urban Expansion and Spatial Structure

The classified Landsat images for 2007, 2018, and 2025 provided a clear representation of land-cover distribution across the study area. Following supervised classification using MLC approach, the results were reclassified into two primary categories—built-up and non-built-up areas—to facilitate the analysis of urban expansion patterns. The resulting built-up maps formed the basis for analysing urban spatial structure and calculating Shannon's entropy for each year.

Urban development patterns in the Hills Shire LGA changed markedly between 2007 and 2025, as reflected in both the spatial structure of built-up areas and overall development trends. Shannon's entropy increased from 0.88 in 2007 to 0.91 in 2018, indicating a shift from a relatively compact urban form toward a more dispersed development pattern, with expansion extending into peripheral and newly developing districts. By 2025, entropy slightly decreased to 0.90, suggesting that although outward expansion continued, built-up areas became more evenly distributed across the district. These changes are illustrated in Figure 2, which shows the distribution of built-up areas across the study period.

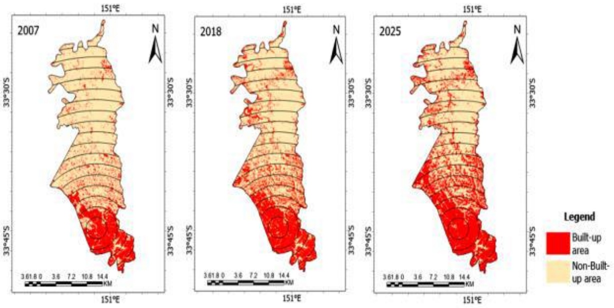

Figure 2. Spatial distribution of built-up areas.

Population growth accompanied these spatial changes. According to data from the Australian Bureau of Statistics (ABS), the population of the Hills Shire LGA increased from 138,034 in 2007 to 173,067 in 2018, and further to 207,959 in 2025, representing growth rates of approximately 25% and 20% during the two study periods (Australian Bureau of Statistics (ABS), 2025).

This demographic growth was reflected in the housing market. Median house prices rose from $599,346 in 2007 to $1,212,115 in 2018, and further to $2,029,689 in 2025, indicating increasing housing demand and development pressure across the region (idCommunity, 2025).

At the same time, infrastructure investments contributed to shaping these development patterns. Major projects—particularly the Sydney Metro Northwest rail line introduced in 2019, along with improvements to the road network—enhanced accessibility and supported further residential expansion. Such infrastructure-driven growth patterns are well documented in urban development studies, where improvements in transportation accessibility often stimulate suburban expansion (Giuliano and Hanson, 2017).

4.2 Ecological Quality Assessment

RSEI was computed for 2007, 2018, and 2025 using normalized NDVI, TC wetness, LST, and NDBSI layers, with LST and NDBSI inverted to reflect their negative ecological effects. The input indicator maps are presented in Figure 3. The indicators were combined and analysed using PCA, and the first principal component (PC1) was normalized to derive the final RSEI. Detailed PCA results are provided in Table 1.

Ecological conditions in the Hills Shire LGA declined over the study period based on RSEI results. The mean RSEI value decreased from 0.72 in 2007 to 0.70 in 2018, and further to 0.61 in 2025, indicating a progressive reduction in ecological quality associated with urban development. Although the decrease during the first period was relatively small, the more pronounced decline observed between 2018 and 2025 points to increasing environmental pressure.

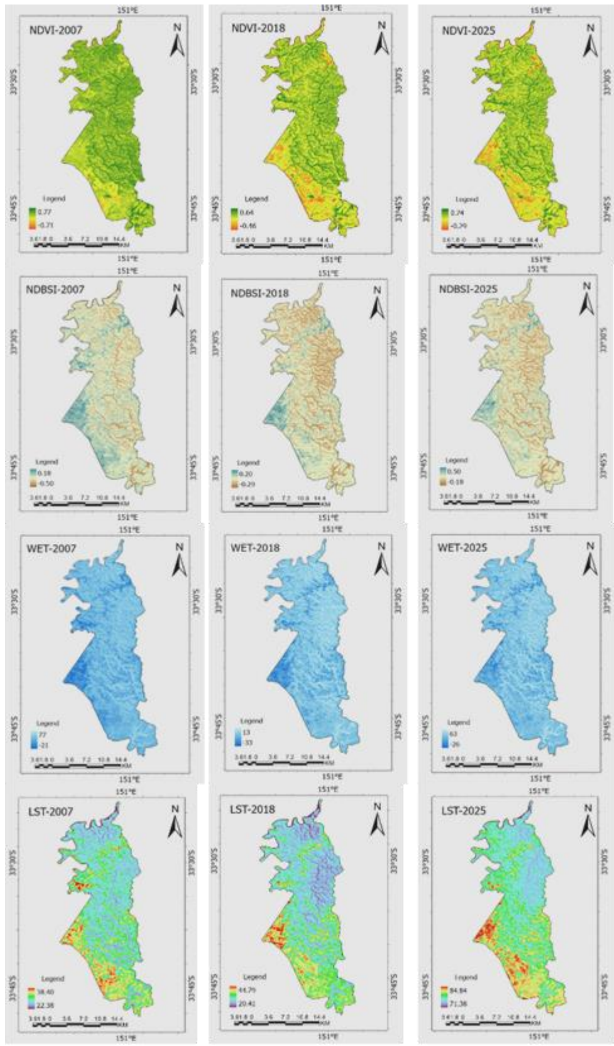

Figure 3. NDVI, LST, Tasseled Cap Wetness and NDBSI maps used for RSEI calculation.

Table1. Summary of PCA results.

Year	Indicators	PC1	PC2	PC3	PC4
2007	NDVI	0.240	0.605	0.696	0.300
	WET	0.709	-0.629	0.314	-0.030
	LST	0.564	0.479	-0.369	-0.560
	NDBI	0.345	0.087	-0.527	0.771
	Eigenvalue	0.020	0.003	0.002	0.000
	%eigenvalue	77.41	12.439	8.457	1.692
2018	NDVI	0.241	0.596	0.724	0.246
	WET	0.697	-0.649	0.302	-0.000
	LST	0.632	0.468	-0.454	-0.417
	NDBI	0.233	0.552	-0.420	0.874
	Eigenvalue	0.014	0.002	0.001	0.000
	%eigenvalue	78.43	14.37	6.431	0.756
2025	NDVI	0.189	0.675	-0.663	0.258
	WET	0.908	-0.392	-0.142	-0.003
	LST	0.291	0.546	0.369	-0.692
	NDBI	0.232	0.300	0.634	0.672
	Eigenvalue	0.012	0.002	0.000	0.000
	%eigenvalue	80.14	13.85	5.764	0.240

This decline is consistent with the observed expansion of built-up areas and the associated loss of vegetation and increase in impervious surfaces. The calculated ΔRSEI values of –0.02 for 2007–2018 and –0.11 for 2018–2025 further confirm that ecological deterioration intensified during the later phase of urban expansion.

These findings are consistent with previous studies that report declining ecological quality in rapidly urbanizing regions. For example, Xu (2013) showed that increasing urban development leads to reduced RSEI values due to vegetation loss and rising surface temperatures. Similar trends have been observed in different urban contexts, where the conversion of natural land cover to built-up areas results in measurable declines in ecological quality (Jing et al., 2020; Liu et al., 2023).

The sharper decline observed in the 2018–2025 period likely reflects the cumulative impacts of rapid suburban development in the Hills Shire LGA, including large-scale residential construction and infrastructure expansion. Such accelerated degradation during later stages of urban growth has also been reported in metropolitan expansion corridors where vegetated and agricultural land is progressively replaced by built environments (Weng, 2012; Seto et al., 2012). These results indicate increasing ecological pressure associated with ongoing population growth and urban development.

Overall, the RSEI results indicate that ecological conditions remained relatively stable during the earlier phase of development, whereas a stronger decline occurred in the recent period. This pattern suggests that continued urban expansion may further increase environmental pressure if not carefully managed.

4.3 Hotspot Analysis

Spatial patterns of ecological change differed between the two study periods. Figure 4 presents hotspot analysis maps derived from the Getis–Ord Gi* statistic for ΔRSEI, illustrating the spatial clustering of ecological improvement and deterioration across the Hills Shire LGA.

For the 2007–2018 period, results indicate a zone of ecological improvement across several central districts, identified as statistically significant hotspots at the 90–95% confidence level. These areas may be associated with vegetation establishment and landscaping in newly developed residential zones, where planted vegetation can temporarily enhance local ecological conditions. At the same time, a small cold spot in the northern part of the study area indicates localized ecological degradation, possibly related to land clearing and site preparation prior to development.

In contrast, the 2018–2025 period shows a different spatial pattern. A cold spot emerges in the southern part of the district, significant at the 90% confidence level, indicating a concentration of ecological decline during this later stage of suburban expansion. This pattern is consistent with intensified construction activities, increasing impervious surfaces, and continued vegetation removal. Only a small hotspot appears in the far northern area, indicating limited ecological improvement within the study area during this period.

The transition from central ecological improvement zones in the earlier period to more widespread ecological deterioration in the later period reflects the cumulative environmental pressures associated with ongoing urban expansion. Similar spatial patterns have been reported in other rapidly developing metropolitan regions, where early phases of development may show temporary ecological improvements due to landscaping or vegetation establishment, followed by broader ecological decline as urbanization intensifies (Weng, 2012; Liu et al., 2023). Studies using hotspot analysis further show that urban growth produces localized clusters of ecological degradation, particularly in areas with concentrated land conversion and infrastructure development (Mondal et al., 2024).

Overall, the hotspot analysis shows that ecological change within the Hills Shire LGA is not spatially uniform. Instead, ecological improvement and deterioration occur in distinct spatial clusters, reflecting the heterogeneous nature of suburban development. These results emphasize the importance of spatial environmental monitoring to identify areas under greater ecological pressure and to support more targeted urban planning and management strategies.

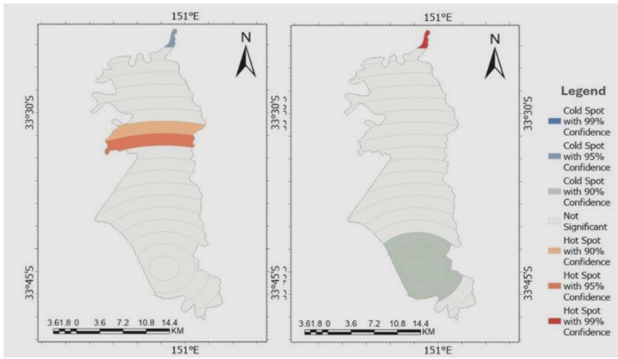

Figure 4. Hotspot maps of ΔRSEI for
(a) 2007–2018 and (b) 2018–2025.

5. Conclusion

Urban expansion in the Hills Shire LGA was associated with a clear decline in ecological quality, particularly during the 2018–2025 period. While earlier development showed relatively stable conditions, recent changes indicate increasing environmental pressure linked to intensified suburban growth.

The main findings of the study can be summarized as follows:

- Entropy results indicate an initial outward expansion followed by a more uniform distribution of built-up areas across the district.
- RSEI and ΔRSEI values consistently show a decline in ecological conditions, with a stronger decrease in the later period.
- Hotspot analysis reveals that ecological change is not spatially uniform, with clusters of degradation emerging in areas of concentrated development.

These findings show that ecological impacts of urban growth are both temporal and spatial and should be evaluated together rather than separately. Integrating spatial metrics with remote sensing–based indicators provide a practical basis for identifying areas under higher ecological pressure and supporting more effective and evidence-based planning decisions.

Future research can extend this approach by incorporating higher-resolution satellite data and additional ecological indicators to improve the sensitivity of environmental assessments. Integrating socio-economic variables and infrastructure data would also help to better explain the drivers of ecological change observed across the study area. Furthermore, applying the framework to other rapidly developing districts within metropolitan regions could provide a comparative perspective on how different urban growth patterns influence ecological conditions.

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