

# Distance & Directional Based Assessment of Urban Sprawl in Eluru City, Andhra Pradesh, Using GEE and ArcGIS

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## ARTICLE INFO

## ABSTRACT

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This study evaluates two decades of urban expansion in Eluru city using multi-temporal Landsat imagery processed in Google Earth Engine and spatial analyses in ArcGIS. Three time series from 2004, 2014, and 2024 were mapped using a Random Forest classifier to determine the dynamics of land use and land cover. Achieving overall accuracies above 85 % and Kappa coefficient values over 0.80. Concentric buffers at radii of 5 km, 10 km, 14 km created around the center of the city. combined these buffers with 16 directional segments, computed both radial and compass-oriented growth. Results show urban area increasing from 12.7 km<sup>2</sup> in 2004 to 39.0 km<sup>2</sup> in 2024, with the fastest expansion between 2004 and 2014. The zonal assessment revealed the most significant expansion occurred in the west-northwest and northeast quadrants. These growth patterns align with major transport corridors and areas well-suited for peri-urban development. Buffer statistics reveal a core to periphery shift. Where the 5 km zone's built-up cover rose by 13.34 km<sup>2</sup> while the outer 14 km ring exhibited emerging sprawl. These spatial trends signal ongoing conversion of agricultural lands, degradation of riparian buffers, and reinforce flood risk. By combining cloud-based classification in Google Earth Engine with detailed GIS buffering, this approach provides a remarkable method for tracking urban expansion. These findings underscore the importance of strategic, sustainable land-use policies and recommend implementing green infrastructure and robust flood-mitigation strategies to ensure that the development of Eluru and its peri-urban areas aligns with ecosystem conservation.

**Keywords:** Urban Expansion, GEE, ArcGIS, Direction and Distance, LULC, Eluru city.

## 1. INTRODUCTION:

Eluru city is situated at 16.70° N latitude and 81.10° E longitude close by National Highway 5. Previously, this city serving as the administrative headquarters of the West Godavari district. However, On 2 April 2022, Eluru District was officially formed as part of an administrative reorganization. Eluru was designated as the district headquarters. The city is located on the fertile alluvial plains between the Godavari and Krishna rivers in the state of Andhra Pradesh. A canal linking these two rivers and bisects the city into southern Town 1 and northern Town 2. This setup makes Eluru prone to spasmodic flooding and poor drainage (Sharma et al., 2023). This city originally constituted as a selection grade municipality, then upgraded to a Municipal Corporation on 9 April 2005 and now covers 14.55 km<sup>2</sup> (Kumar et al., 2011). In recent years, both registered and floating populations have increased steadily due to rural-to-urban migration and expanding local economic opportunities (Cui & Shi, 2012). Although peri-urban areas remain dominated by paddy fields, most residents earn a living as daily wage labourers. Only 60 % of households have basic sanitation, open-field defecation persists, and drinking water is supplied via communal taps and shallow wells (Vardhani, 2013).

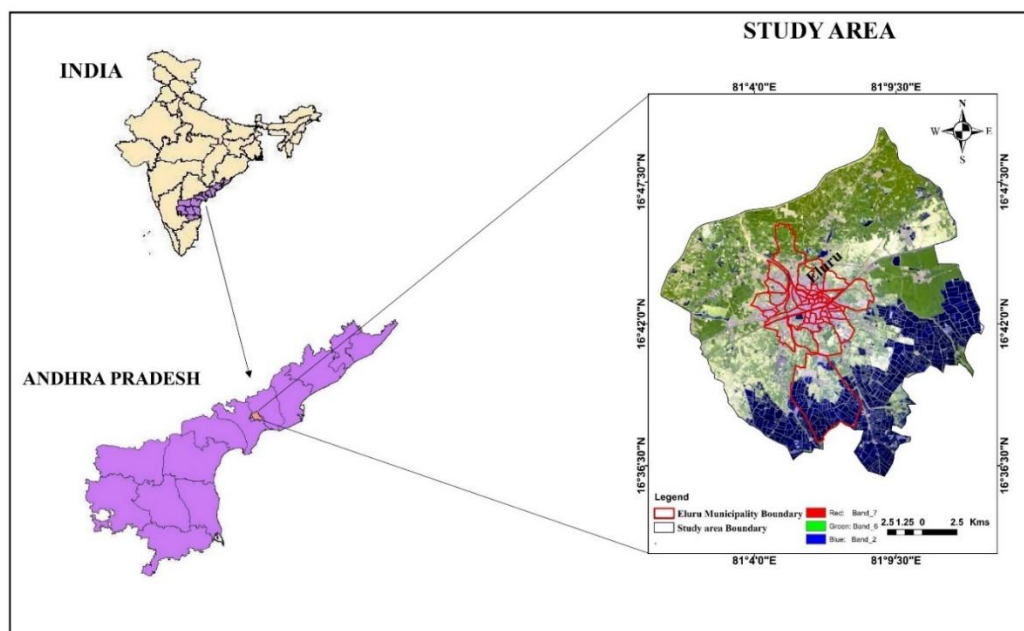
Kolleru Lake lies nearly 15 km from Eluru city. It is the biggest shallow freshwater wetland in Asia, with a total size of 245 km<sup>2</sup>. The lake was designated a Ramsar site in recognition of its global ecological importance. (Amaraneni, 2002; Jayanthi et al., 2006). The lake receives water from the seasonal Budameru and Tammileru streams and over

68 minor drains. Acting as a natural flood-balancing reservoir for the Krishna–Godavari system and supports aquatic plants and trees such as *Borassus flabellifer* and *Acacia nilotica* provides critical habitat for spoonbill sandpipers, grey pelicans, and both greater and lesser flamingos. Kolleru Lake is also a source of strength to fisheries and aquaculture, Support the livelihoods of riparian communities (Karanam et al., 2013; Kolli et al., 2020).

Global urban area covers about 3 % of Earth's land surface (Sabet Sarvestani et al., 2011). Over 55 % of the world's population lived in cities in 2018. By 2050, that percentage is predicted to rise to 68% (Karimi et al., 2019). Cities expand spatially and demographically, natural and agricultural lands are converted to built-up areas, altering local climate, hydrology, and water quality through increased temperatures, reduced humidity and wind speeds, and elevated nutrient loading (Cerqueira et al., 2020; Cui & Shi, 2012). The outskirts of the city are known as peri-urban zones. In this areas farmland quickly turns into homes, shops and offices. These zones usually grow without planning, lack basic services like roads and water, and mostly provide cheap rentals for middle- and low-income families (Sahana et al., 2023).

Such transformations also tend to bring down species richness of mammals, reptiles, amphibians, invertebrates, and plants, especially under extreme urbanization gradients (Fidino et al., 2021; Mckinney, 2008). Understanding these patterns is indispensable to resilient urban planning, flood mitigation, and biodiversity conservation (Rastandeh et al., 2018).

This study employs multi-temporal satellite imagery processed through Google Earth Engine (GEE) and ArcGIS spatial analyst tools to identify, quantify, and interpret directional and distance based trends in urban growth across Eluru city. By mapping the spatial distribution of urban density and analyzing sectoral expansion dynamics provide actionable insights for sustainable land-use planning and the protection of this ecologically sensitive delta region.



**Fig.1. Location Map of the study area**

## 2. STUDY AREA:

Eluru city is the principal administrative and commercial center of Eluru district. It includes the Eluru Municipal Corporation and the adjoining area. Over recent decades, demographic pressures and economic opportunities have drawn substantial inflows of residents to the municipality. These conditions driving urban sprawl into adjacent rural and agricultural zones (Cui & Shi, 2012). Its strategic location along National Highway 5 and within the fertile Godavari–Krishna delta has further accelerated built-up expansion into formerly paddy-dominated landscapes (Sharma et al., 2023). The Study of spatial growth patterns is critical for understanding the implications of land-use change on regional hydrology, flood risk, and ecological integrity.

### **3. METHODOLOGY**

#### **3.1. Google Earth Engine (GEE)**

The Google Earth Engine (GEE) is a cloud-computing platform designed to store and process petabyte-scale datasets for large-scale environmental monitoring and analysis, ultimate decision-making (Puissant et al., 2014). The free-to-use GEE platform offers: (1) access to petabytes of publicly available remote sensing imagery and ready to use products (2) high-speed parallel processing and machine learning capabilities implement in Google's computational infrastructure (3) An application programming interface (API) library that includes Python and JavaScript development environments (Tamiminia et al., 2020).

#### **3.2. ArcGIS**

ArcGIS is a comprehensive geographic information system (GIS) software suite developed by Esri (Environmental Systems Research Institute). It facilitating the creation, management, analysis, and visualization of spatial data (Khan & Mohiuddin, 2018). In this study, ArcGIS spatial analyst tools were employed to compute distance based urban density gradients, generate sectoral buffers, and produce directional rose diagrams to elucidate patterns of built-up growth.

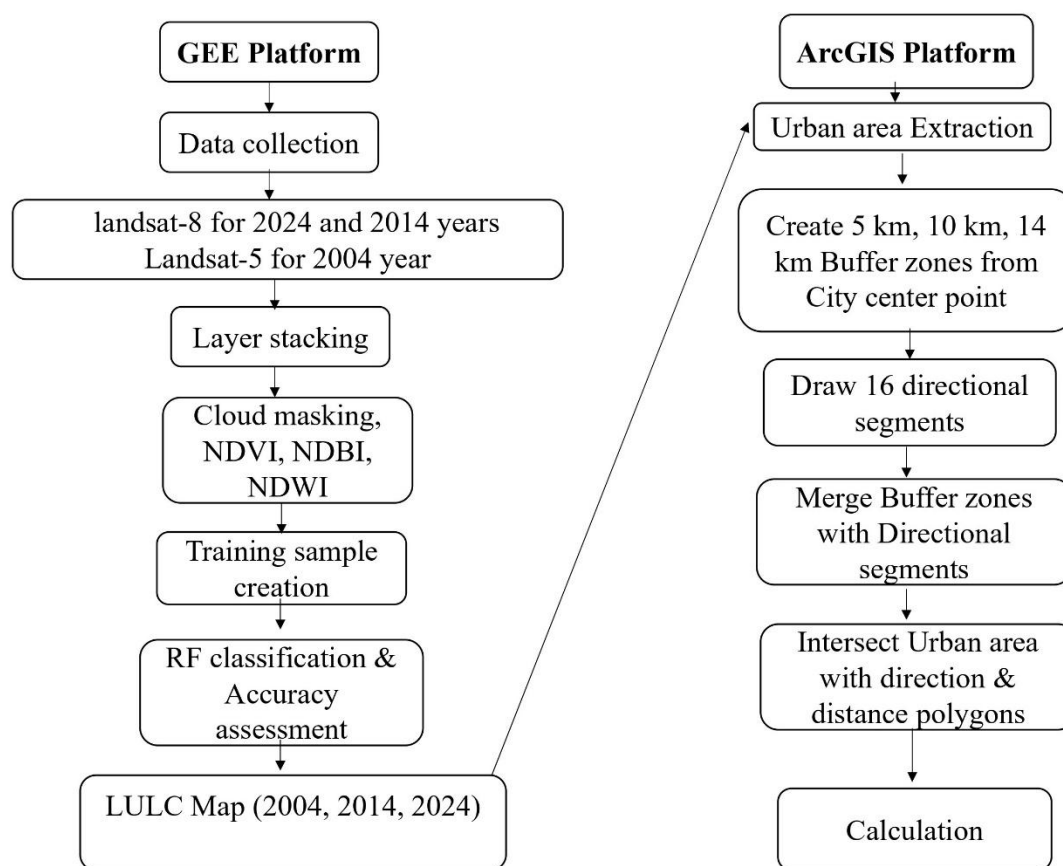
#### **3.3. Data Collection and Image Processing**

Satellite imagery data for the years of 2004, 2014, and 2024 was added from the USGS Collection 1 Tier 2 Top of Atmosphere (TOA) dataset (Table.1), is directly accessed via Google Earth Engine (GEE). Landsat 5 imagery was utilized for the 2004 dataset, while Landsat 8 provided the 2014 and 2024 images (Amindin et al., 2024). All scenes were clipped to the study area boundary in GEE. For removal of cloud shadows and clouds using the QA pixel band bit mask approach in Landsat images (Yan et al., 2022). A median reducer was then applied across each image to minimize noise and produce cloud-free composites suitable for classification (Rajendiren & Ram, 2023).

For each composite image, ten spectral bands were selected for analysis. It including blue, green, red, near-infrared (NIR), shortwave infrared (SWIR<sub>1</sub> and SWIR<sub>2</sub>), and thermal bands. (Gumma et al., 2020). To enhance discrimination between built-up, vegetation, water, and bare soil classes, four spectral indices, Normalized Difference Built-up Index (NDBI), the Normalized Difference Water Index (NDWI), the Normalized Difference Vegetation Index (NDVI) used. Training data were collected by digitizing representative sample sites for each land-cover category using false colour composites. These reference samples were randomly partitioned into training (70 %) and validation (30 %) subsets. The training set was used to calibrate a supervised classification algorithm, while the validation set assessed map accuracy through confusion matrix metrics (Rajendiren & Ram, 2023).

**Table.1. data sources utilized for LULC classification**

<b>S. No</b>	<b>Year</b>	<b>Dataset</b>	<b>Resolution (m)</b>	<b>Revisit interval</b>
1	2004	USGS Landsat 8 Level 2, collection 2, Tier 1	30	16 days
2	2014	USGS Landsat 8 Level 2, collection 2, Tier 1	30	16 days
3	2024	USGS Landsat 5 Level 2, collection 2, Tier 1	30	16 days



**Fig.2. Flowchart depicts the methodology used in this study.**

### 3.4. LULC Classification and Extraction of Urban Area

Land-use and land-cover (LULC) classification (Fig.3) was performed using the Random Forest (RF) algorithm within the Google Earth Engine (GEE) environment. RF is one of the broadly used nonparametric and supervised machine learning classifier. RF has been widely applied across diverse fields such as genetics, medical imaging, pharmacology, and ecology, and has proven effective in remote-sensing tasks including the mapping of landslides, agricultural lands, and urban extents (Puissant et al., 2014). For each target year (2004, 2014, and 2024), the RF classifier was trained on 70 % of the reference samples and validated against the remaining 30 % to generate an error matrix in GEE. Overall accuracy and kappa coefficient were computed to quantify agreement between classified outputs and validation data (Amindin et al., 2024).

After LULC classification this image was imported into ArcGIS. Classified urban pixels were converted into polygon features for each time period using the Raster to Polygon conversion tool. Then Urban area layers were extracted for the years 2004, 2014, and 2024, give a basis for subsequent spatial analysis. To investigate spatial patterns of urban expansion, a ring-buffer and directional sector framework was applied. A central point representing the Eluru municipal centroid was derived from the municipal boundary shapefile. Concentric buffers of 5 km, 10 km, and 14 km radii were generated around this point using ArcGIS Spatial Analyst tools. Simultaneously, sixteen equal-angle directional sectors were created to partition the surrounding landscape. By intersecting buffer rings with directional sectors and overlaying the urban-area layers, the area of urban cover within each buffer-sector combination was computed. By using following formula (Vivekananda et al., 2020).

$$C = N_y - B_y \text{ -----(1)}$$

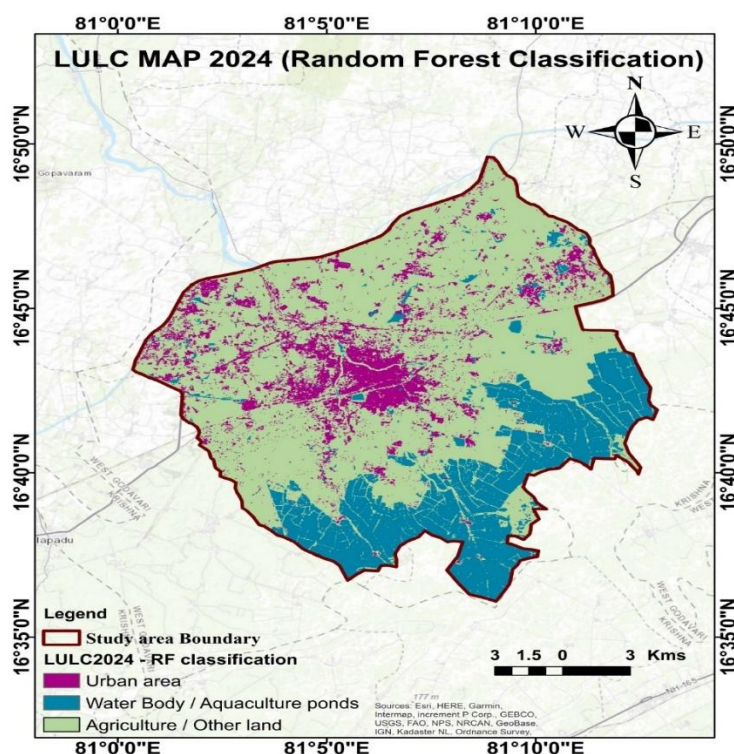
C = Change in area



$N_y$  = New year value

$B_y$  = Base year value

It revealed growth patterns by both radial distance and compass direction, identifying which sectors falls in the fastest built-up expansion over the twenty-year period.



**Fig.3. Representative 2024 LULC Map Derived from Random Forest Analysis**

#### 4. RESULTS AND DISCUSSION

##### 4.1. Overall Urban Growth Dynamics

The extent and pattern of urban expansion, along with its quantitative and spatial implications, are summarized in Table 2, Table 3, and illustrated in Figure 3. The total built-up area of Eluru increased by 26.3 km<sup>2</sup> between 2004 and 2024 i.e. from 12.7 km<sup>2</sup> to 39.0 km<sup>2</sup>. The urban area had nearly doubled to 24.75 km<sup>2</sup> in the first decade of this gain, and by 2024, it had grown by an additional 14.25 km<sup>2</sup>. The Surface water bodies, vegetation, and agricultural land have all been converted as a result of this rapid urban growth (Shikary & Rudra, 2020). In the Godavari–Krishna deltaic region, these land-use changes have increased flood risk and disturbed natural drainage regimes.

##### 4.2. Directional Patterns of Expansion

Sectoral analysis reveals that growth was not uniform in all directions. The west-northwest (WNW) sector exhibited the most dramatic increase, from 0.70 km<sup>2</sup> in 2004 to 5.10 km<sup>2</sup> in 2024. This is because of development along major transport and peri-urban zones. Significant gains were also observed in the west (W) and northeast (NE) sectors, where urban cover grew by 3.19 km<sup>2</sup> and 2.83 km<sup>2</sup> respectively. In contrast the south-southeast (SSE), south (S), and east-southeast (ESE) directions recorded more modest increases (<1.5 km<sup>2</sup> over twenty years). These findings align with broader observations that urban expansion often follows infrastructure axes and land suitability gradients (Cerqueira et al., 2020; Fidino et al., 2021)

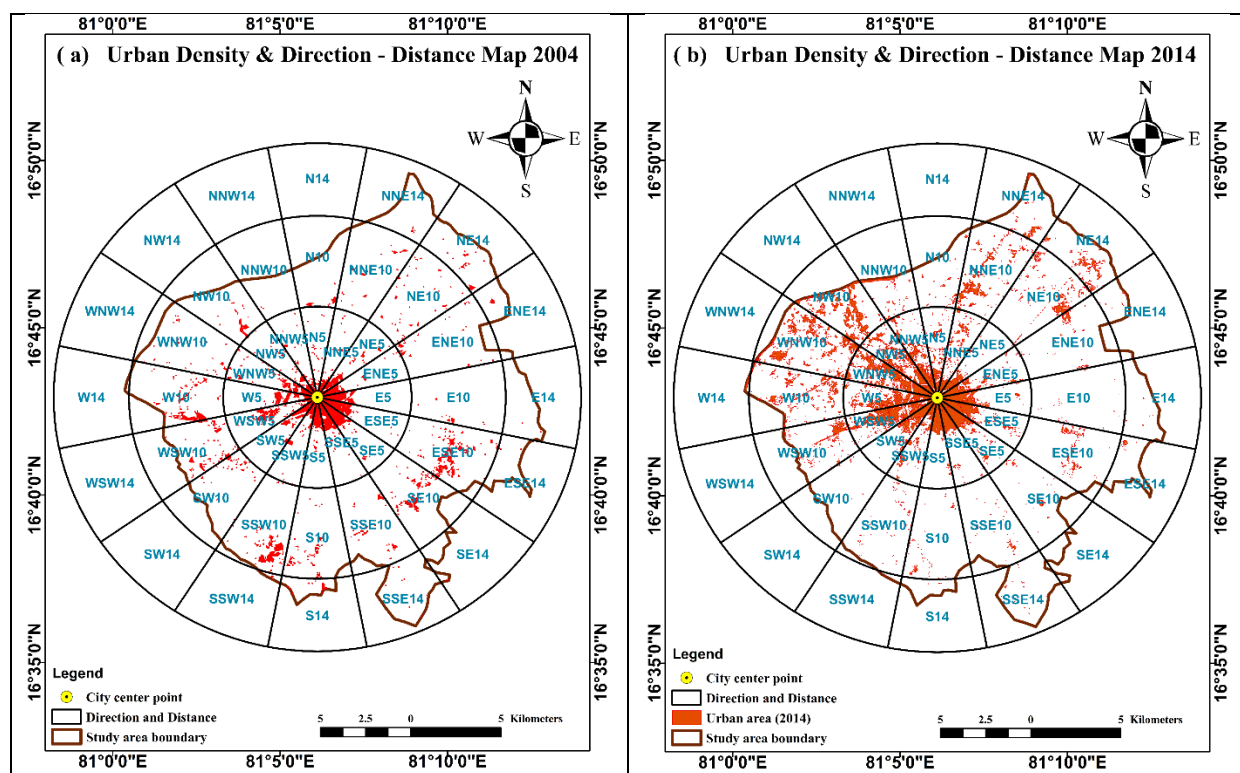
##### 4.3. Radial Spread Across Buffers

The concentric-buffer analysis encapsulates a core to periphery diffusion pattern. Within 5 km of the city center, built-up area raised from 7.66 km<sup>2</sup> in 2004 to 21.0 km<sup>2</sup> in 2024. This indicates densification in the 5 km urban core.

In the 10 km buffer, urban extent rose from 4.68 km<sup>2</sup> to 15.0 km<sup>2</sup>, with accelerated growth between 2014 and 2024. The outermost 14 km zone, while accounting for only 0.34 km<sup>2</sup> of urban cover in 2004, expanded to 2.0 km<sup>2</sup> by 2024, showing new development at the city periphery. This outward sprawl highlights a shift towards peripheral growth in the latter decade, development followed the familiar trend of core saturation driving expansion toward the urban fringe (Jaysawal & Saha, 2014).

#### 4.4. Implications for Planning and Ecology

Rapid horizontal expansion into agricultural and riparian zones threatens local food security, water quality, and wetland integrity. Increased impervious surfaces alter runoff volumes and hydroperiods, impacting Kolleru Lake flood attenuation function (White & Greer, 2006). Moreover, the loss of vegetated buffers in peri-urban zones reduces habitat connectivity, potentially suppressing terrestrial and aquatic biodiversity (Mckinney et al., 2008; Rastandeh et al., 2018). These dynamics underscore the need for integrated land-use and flood management strategies, such as green infrastructure deployment, buffer-zone restoration, and stricter regulation of peri-urban development to balance growth with ecosystem resilience.



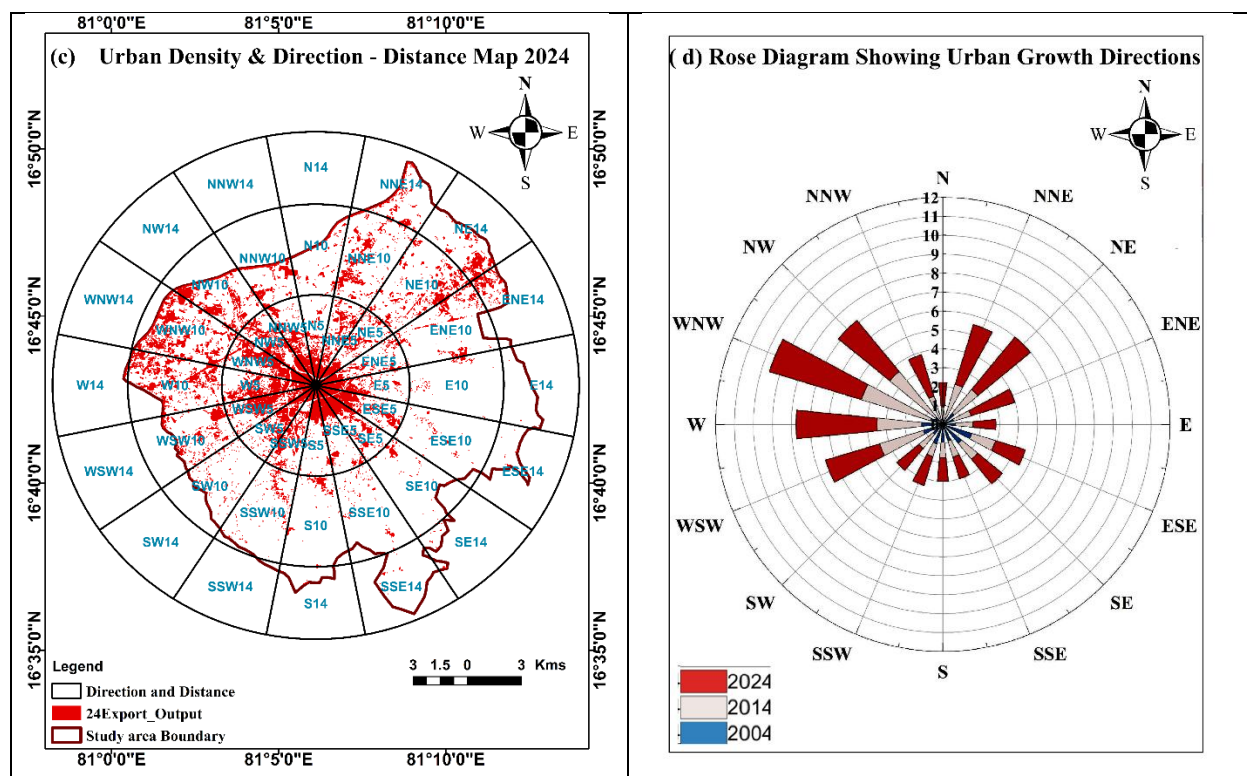


Fig.3. Urban density map with direction and distance (a) 2004 (b) 2014 (c) 2024, (d) Urban growth direction in Rose diagram

Table.2. Direction wise urbanized area calculation in km<sup>2</sup>

S. No	Direction	Area in km <sup>2</sup>		
		Year 2004	Year 2014	Year 2024
1	E	0.68	0.9	1.23
2	ENE	0.6	0.95	2.43
3	ESE	1.6	1.3	1.66
4	N	0.22	0.7	1.3
5	NE	0.78	1.61	3.61
6	NNE	0.36	1.85	3.33
7	NNW	0.18	1.38	2.3
8	NW	0.51	3.1	3.53
9	S	0.94	0.81	1.25
10	SE	1.28	1.1	1.69
11	SSE	0.91	0.88	1.21
12	SSW	1.07	0.7	1.6
13	SW	0.67	0.96	1.52
14	W	1.11	2.35	4.3

15	WNW	0.70	3.77	5.1
16	WSW	1.08	2.4	3
<b>Total area</b>		12.7	24.75	39

**Table.3. Distance wise urbanized area calculation in km<sup>2</sup>**

S. No	Buffer Distance in kms	Area in km <sup>2</sup>			Area change		
		Year 2004	Year 2014	Year 2024	From 2004-2014	2014-2024	2004- 2024
1	5	7.66	16.1	21	8.44	4.9	13.34
2	10	4.68	7.75	15	3.07	7.25	10.32
3	14	0.34	0.94	2	0.6	1.06	1.66

## 5. CONCLUSION

This study demonstrates that Eluru city, its peri-urban fringes, and the surrounding deltaic landscape have undergone significant and multidirectional urban growth between 2004 and 2024. Using multi-temporal Landsat data processed in Google Earth Engine combined with Random Forest classification, and detailed spatial analyses in ArcGIS, quantified a more than three times increase in built-up area from 12.7 km<sup>2</sup> to 39.0 km<sup>2</sup>. Sectoral analysis revealed the west-northwest and northeast strip of land as primary axes of expansion, while buffer-based metrics highlighted a clear progression from core densification to peripheral sprawl. These spatial dynamics carry critical environmental and planning implications. The conversion of agricultural lands, riparian buffers, and peri-urban green spaces threatens Kolleru Lake's flood-balancing functions, degrades water quality, and fragments habitats for both aquatic and terrestrial species. Our findings underscore the urgency of integrating green infrastructure in urban and peri-urban zones, enforcing buffer-zone protections, and adopting land-use policies that steer growth toward underutilized cores. The combination of GEE and ArcGIS offers a reliable and repeatable way to track urban growth in peri-urban, deltaic, and other environmentally sensitive areas. More frequent time-based data, social and economic considerations, and water flow models should all be incorporated into future studies to help with better planning. It is important to balance Eluru development with environmental protection in both urban and peri-urban areas to ensure sustainable growth in the Godavari–Krishna delta.

### Ethics approval

Not applicable

### Informed consent

Not applicable

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### CRedit authorship contribution statement:

**BKR:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Visualization and Writing -Original draft.

**YSR:** Conceptualization, methodology, Review & Editing of Original draft.



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### Data Availability:

Data will be made available upon request.

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