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Geospatial Intelligence for Peri-Urban Land-Use Conflicts: Evaluating Agricultural Suitability against Rapid Urbanisation Using the Analytic Hierarchy Process and Cloud Computing

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ABSTRACT

This paper presents a geospatial multi-criteria evaluation of agricultural potential in the suburban region of Bapatla using eight physical and land-use characteristics: elevation, slope, road accessibility, proximity to water bodies, Land Surface Temperature (LST), Normalised Difference Vegetation Index (NDVI), Land Use/Land Cover (LULC), and soil texture, processed using Google Earth Engine. The Analytic Hierarchy Process (AHP) was used to determine the relative weights of each criterion. NDVI received the highest weight (26.33%), followed by LST, slope, and proximity to water bodies (14.96% each), while elevation received the lowest weight (4.6%) due to the region's flat terrain. Weighted overlay analysis classified the 142.25 km² study area into Suitable (108.90 km²; 76.55%), Not Suitable (32.60 km²; 22.92%), and Highly Suitable (0.75 km²; 0.53%) categories. Suitable areas are mainly distributed across the southern and peripheral agricultural zones, whereas unsuitable areas are concentrated within Bapatla Urban and its surroundings. The limited extent of highly suitable land highlights the scarcity of optimal agricultural sites. The results reveal land-use conflicts driven primarily by urbanisation rather than environmental constraints. The AHP-weighted suitability map provides an evidence-based tool for agricultural land conservation, water-resource management, and sustainable urban expansion.

1. Introduction

Urbanisation has grown substantially during the twenty-first century. It has had significant and lasting implications on land use and land cover in a global context. The outward expansion of cities has impacted fertile agricultural land, converting it into residential, industrial, and infrastructural development. The changes to the biosphere, which pose significant threats to urban food security, have been regarded as largely irreversible by the Food and Agriculture Organisation (FAO), Seto et al. [36] and the United Nations. The percentage of the world's population living in cities is projected to exceed 68% by 2050 as a consequence of continued urbanisation, putting considerable pressure

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on urban areas to develop sustainable food-production systems by United Nations [39]. Urban agriculture has therefore become an important component of strategies addressing food security, environmental sustainability, and socioeconomic resilience in rapidly urbanising regions.

Urban agriculture consists of the cultivation, processing, and marketing of food products using spaces such as vacant lots, rooftops, and community gardens which are otherwise unused or underutilised. Beyond food production, it provides several ecosystem services such as microclimate regulation, flood mitigation, biodiversity conservation, and carbon sequestration [9 – 21], as well as improvements to the quality of life of urban residents [30]. Previous studies have therefore seen urban agriculture identified as an important strategy for strengthening food security while promoting environmental sustainability and socioeconomic resilience in rapidly urbanising communities [2, 7, 28, 29].

Identifying suitable locations for urban agriculture in such rapidly changing environments has been a complex spatial-planning challenge where environmental, socioeconomic, infrastructural, and policy-related factors interact to constrain agricultural development (McClintock et al. [26]; Mok et al. [27]). Geographic Information System (GIS) and raster-based approaches have been widely integrated into land-use decision-making and site-suitability assessment by incorporating environmental, socioeconomic, and infrastructural datasets [6, 16, 17, 20, 23, 24, 40, 41]. Such assessments commonly consider biophysical factors such as soil characteristics, landform, Land Surface Temperature (LST), vegetation indices, rainfall, and water availability [11, 37]. Multi-Criteria Decision Analysis (MCDA), Analytical Hierarchy Process (AHP), and Fuzzy Decision Analysis have further enhanced GIS-based suitability assessment by allowing multiple criteria to be integrated into spatial decision-making frameworks [10, 22, 33, 34]. These approaches are particularly useful for urban agriculture as suitability depends not on a single environmental variable but on the combined influence of several spatially varying factors.

The increasing availability of Earth-observation data has further strengthened the application of Remote Sensing (RS) and GIS in agricultural and land-use assessment. Satellite programmes such as Landsat, Sentinel, and the Moderate Resolution Imaging Spectroradiometer (MODIS) provide continuous and timely observations for monitoring land-use changes and agricultural conditions [8, 18, 31]. Vegetation indices, particularly the Normalised Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and Soil Adjusted Vegetation Index (SAVI), are widely used to characterise vegetation condition based on spectral reflectance properties [14, 15, 38]. In addition to assessing vegetation health, such indices provide useful information for evaluating the agricultural potential of land. Digital Elevation Models (DEMs), including the Shuttle Radar Topography Mission (SRTM), Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), and Light Detection and Ranging (LiDAR) datasets, provide information on terrain characteristics and are useful for deriving slope, relief, and surface-drainage characteristics [13].

The application of GIS-based multi-criteria approaches has demonstrated their practical value in different geographical settings. In Amman, Jordan, GIS-based suitability assessment showed that rapid urban growth had restricted the proportion of land available for agricultural purposes [1]. In Dharmapuri District, India, the integration of remote-sensing data, geospatial field surveys, and machine-learning algorithms, including Naïve Bayes, Extra Trees, Random Forest, k-nearest neighbours, and Support Vector Machines, improved the prediction of areas suitable for agriculture [35]. These studies demonstrate the importance of incorporating environmental conditions, pollution, transportation, and other relevant factors into agricultural suitability models [4, 29, 30, 32]. At the same time, advances in Artificial Intelligence (AI) and deep learning have further improved the accuracy of suitability assessment and land-use planning [5, 19, 25].

The emergence of cloud-based geospatial platforms such as Google Earth Engine (GEE) has further enhanced the efficiency of spatial suitability mapping by enabling the rapid processing and integration of large volumes of geospatial datasets [12]. The combination of GEE with AHP and multiple spatial criteria has demonstrated the capability of cloud-based platforms to support large-scale multi-criteria analysis. For example, Atalla et al. [3] integrated thirteen criteria, including NDVI, land surface temperature, slope, and land-use characteristics, within GEE and an AHP framework to identify areas suitable for groundwater exploration in Kuwait. Although the application was focused on groundwater rather than urban agriculture, it demonstrates the capacity of GEE to integrate multiple spatial datasets within a consistent multi-criteria decision-making framework. Recent urban-agriculture research has applied GIS-based spatial approaches to identify suitable sites by incorporating factors such as soil quality, land accessibility, and proximity to underserved communities, thus supporting more effective planning of urban food systems [42, 43] assessed the potential for urban agriculture in Cape Town using environmental and accessibility criteria within an AHP-based weighted framework, while Ding et al. [44] examined urban agriculture potential at the community scale by considering spatial heterogeneity, influencing factors, and planning implications.

These recent developments demonstrate a growing shift towards integrated geospatial and multi-criteria approaches for identifying urban agricultural potential. Despite these developments, integrated assessments combining Remote Sensing, GIS, and Google Earth Engine for urban agricultural suitability remain limited, particularly in Indian suburban environments. The Bapatla suburban region of Andhra Pradesh represents a rapidly changing urban–rural interface where agricultural land is increasingly exposed to competing demands associated with urban expansion. Therefore, the present study applies a geospatial multi-criteria approach within Google Earth Engine to assess urban agricultural suitability in Bapatla City. The assessment integrates eight criteria, namely elevation, slope, road accessibility, proximity to water bodies, LST, NDVI, Land Use/Land Cover (LULC), and soil texture. The AHP is used to determine the relative importance of these criteria, followed by weighted overlay analysis to generate a spatial suitability map. The study provides a localised assessment of urban agricultural potential and contributes evidence for agricultural land conservation, sustainable urban food-system planning, and balanced urban expansion in Bapatla, Andhra Pradesh.

2. Methodology

2.1 Data Used

The Urban Agricultural Suitability Assessment for the Bapatla Suburban Area was conducted using multi-source geospatial datasets processed on the Google Earth Engine (GEE) cloud platform. All datasets were clipped to the same study area boundary (Bapatla Suburban Area) to ensure spatial consistency throughout the analysis.

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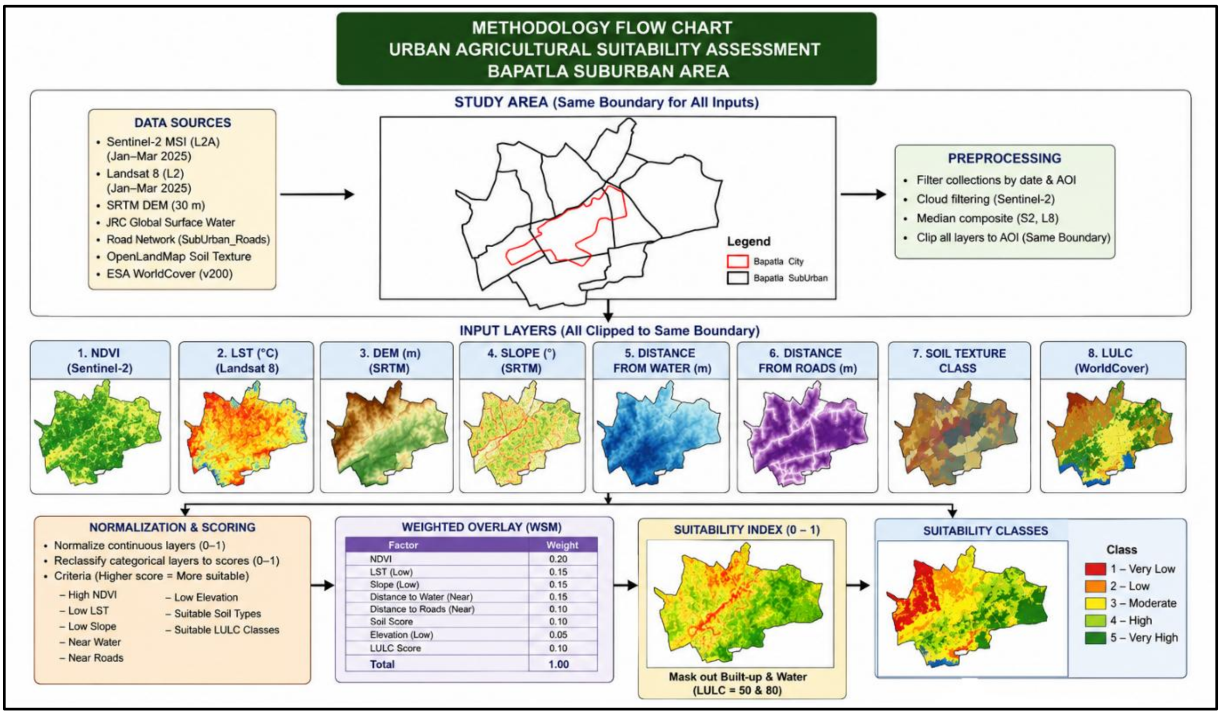

Fig. 1. Methodological Flow Chart

Table 1
Data Sets Used for Analysis

Sl. No.	Data Layer	Source	Resolution	Purpose
1	Sentinel-2 Multi-Spectral Instrument (MSI) (L2A)	COPERNICUS -S2	10 m	NDVI
2	Landsat 8 Level-2	LANDSAT - LS8 OLI	30 m	LST
3	SRTM DEM	United States Geological Survey (USGS) - SRTMGL1_003	30 m	Elevation and Slope
4	Global Surface Water	JRC/GSW1_4	30 m	Distance from Water Bodies
5	Road Network	Road network shapefile	Vector	Distance from Roads
6	Soil Map	NBSS & LUP	2.5 m	Soil Suitability
7	ESA World Cover	ESA World Cover	10 m	LULC Classification

2.2 Preparation of Input Factors

Eight thematic layers influencing urban agricultural suitability were generated.

a) Normalised Difference Vegetation Index (NDVI)

NDVI was derived from Sentinel-2 imagery using:

$$\text{NDVI} = \frac{\text{NIR}-\text{RED}}{NIR+RED} \qquad (1)$$

Where: Near-Infrared (NIR) = Band 8 and Red = Band 4

Higher NDVI values indicate healthier vegetation and better agricultural potential.

a) Land Surface Temperature (LST)

LST was derived from Landsat 8 Thermal Infrared Sensor (Band ST_B10) using:

$$\text{LST} = (\text{ST\_B10}\times 0.00341802+149) - 273.15 \qquad (2)$$

Three temperature zones were considered more suitable for urban agriculture.

b) Digital Elevation Model (DEM))

Elevation information was extracted from the SRTM DEM. Lower elevations were assigned higher suitability scores because they generally possess deeper soils and easier cultivation conditions.

a) Slope

Slope was derived from the DEM using the terrain analysis function in GEE:

Slope = f (DEM) (3)

Areas with gentle slopes were considered highly suitable due to the reduced risk of erosion and the ease of cultivation.

b) Distance from Water Bodies

Water bodies were extracted from the Joint Research Centre (JRC) Global Surface Water dataset. Euclidean distance analysis was performed to generate a distance-to-water map.

Areas closer to water sources received higher suitability scores because of easier irrigation access.

c) Distance from Roads

The suburban road network shapefile was rasterised and converted into a distance raster using the Fast Distance Transform algorithm.

Areas closer to roads were assigned higher suitability scores because of improved accessibility and transportation facilities.

d) Soil Texture

Soil texture information was obtained from the National Bureau of Soil Survey and Land Use Planning (NBSS & LUP). Different soil classes were assigned suitability scores ranging from 0.1 to 1.0 based on their agricultural productivity and water-holding capacity.

e) Land Use/Land Cover (LULC)

European Space Agency (ESA) World Cover 2025 was used to classify land cover.

Agricultural and vegetation classes received higher suitability values, while built-up and waterbody classes received lower scores.

2.3 Normalisation of Factors

To eliminate differences in measurement units, all continuous variables were normalised between 0 and 1 using Min-Max normalisation:

$$X_n = \frac{\mathrm{X - X\,min}}{Xmax - Xmin} \quad \ldots \quad (4)$$

Where: Xn = Normalized value

X = Original value

Xmin= Minimum value

Xmax= Maximum value

For inverse criteria such as LST, slope, elevation, road distance, and water distance, suitability scores were reversed so that lower values corresponded to higher suitability.

3. Study Area

The present study was carried out in the suburbs of Bapatla City in Bapatla District, on the southeastern coast of Andhra Pradesh, India. The study site is Bapatla City with its urban fringe and peri-urban zones, and the total geographical coverage is approx 142.25 sq km. (Figure 2). It is located in a fertile coastal plain that is influenced by the Bay of Bengal. The terrain is mainly level except for the gentle rolling hills that make agricultural activities possible, along with the development of urban areas.

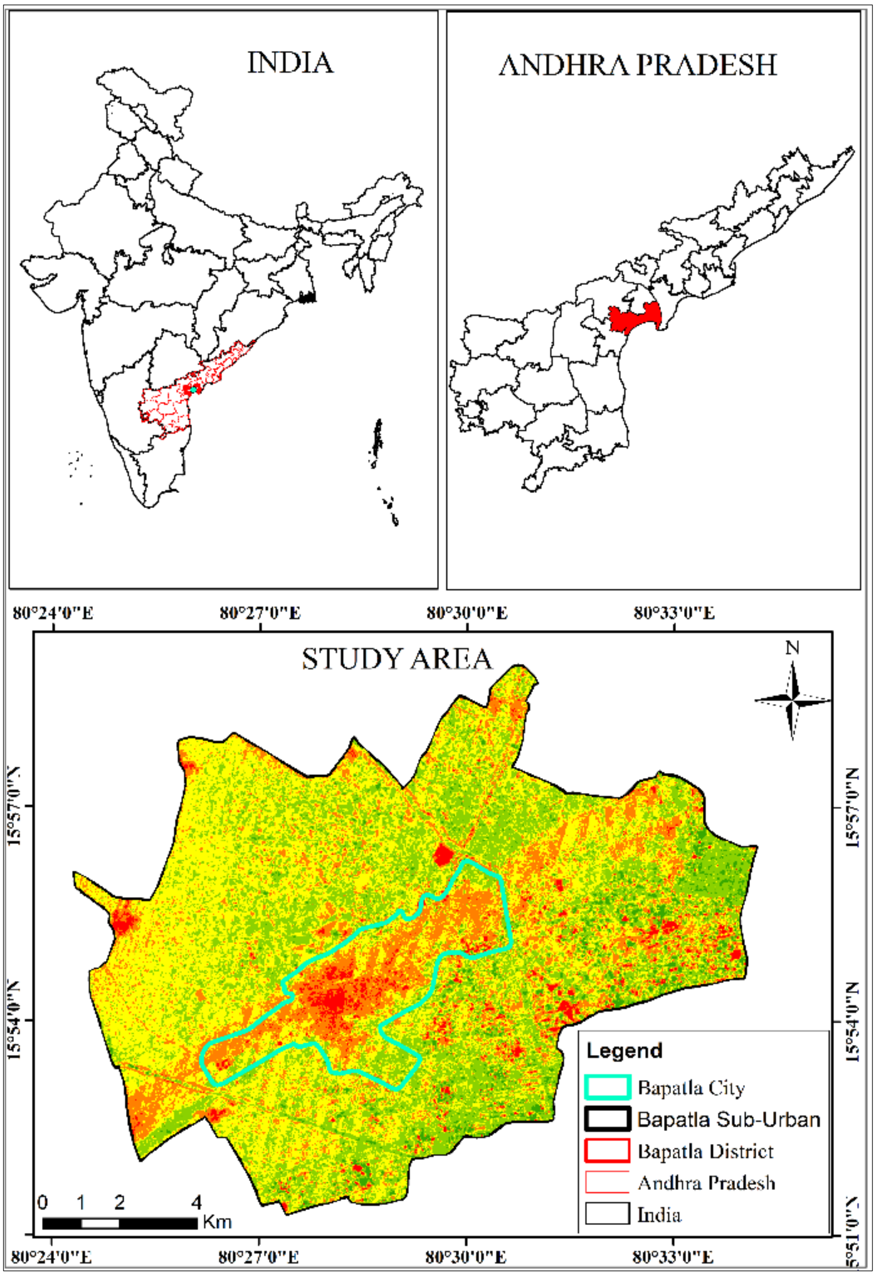

Fig. 2. Location map of the Study Area

It's a tropical monsoon climate zone in the region with characteristics such as hot summers, quite cold winters, and rains brought by the Southwest and Northeast monsoons during different seasons. The annual rainfall in most localities is within the 850 to 1, 000 mm range that supports cultivation of a range of different crops. The maximum and the minimum values of mean annual temperature range from 33°C to 25°C. But the summer temperature is often above 40°C in the hottest month. The area is geologically an intricate mix of coastal alluvium, sand, clay, silt, and mud that come from fluvial and coastal activities. These materials form the basis of productive and well-irrigated soils which are ideal for agriculture and horticulture. In terms of geomorphology, the region is largely dominated by flat coastal plains, tidal flats, river valleys such as floodplains, beach ridges, etc. This low-relief area, however, together with its ability to support the growth of a wide diversity of plant species, has contributed to the agricultural richness of the province.

At the edge of Bapatla, there's a mosaic of land uses and covers: farmlands, human settlements, transport networks, open or fallow plots, areas of woods or trees in blocks or patches, lakes or waterbodies, and urban areas; all of these have been growing fast while still being parts of a complex urban landscape. With land use rapidly shifting and the population growing, the agricultural farmlands as well as the natural resources of this part have been severely put in danger; therefore, there is a need to consider the sustainability of land management and food security, in general.

It was essential then to choose proper sites for the introduction of urban agriculture. The selection of the study site was based on the limits of the administrative division, and such divisions quite accurately define the functional outskirts of Bapatla city. Because of the location's advantage in terms of having cultivable and fertile soil and being accessible via transport corridors and proximity to urban centres, this area is suitable for urban farming. Hence, the suburban area of Bapatla might become an operational area that is a good model for evaluating urban agriculture suitability with a mix of Remote Sensing (RS) and Geographic Information System (GIS) techniques; this would aid well-informed decisions on agricultural and urban sustainable growth.

4. Result and Discussion

4.1 Agricultural Suitability Parameter

After integrating vegetative, thermal, topographical, hydrological, structural, soils, and land-use/land-cover layers through remote sensing techniques with the aid of Google Earth Engine, this segment presents the geospatial assessment results of Bapatla suburban areas using multi-criteria evaluation. The spatial patterns and agricultural potential correlation of each factor are evaluated through analysis before being combined to produce a composite suitability surface using the Analytic Hierarchy Process (AHP) weighted overlay method.

The suitability classification derived from these overlays is further compared to maps of Bapatla Urban and Sub-Urban boundaries in order to assess agriculturally rich lands that coincide with urban expansion or are at risk. Finally, all the points are presented as a whole in a discussion on sustainable land use planning and food security as well as urban agricultural development in quickly growing coastal communities like Bapatla.

Figure 3. depicts the Agricultural Suitability Parameters: Elevation (a), Slope (b), Distance from Roads (c), Distance from Water (d), LST (e), NDVI (f), LULC (g) and Soil Texture (h).

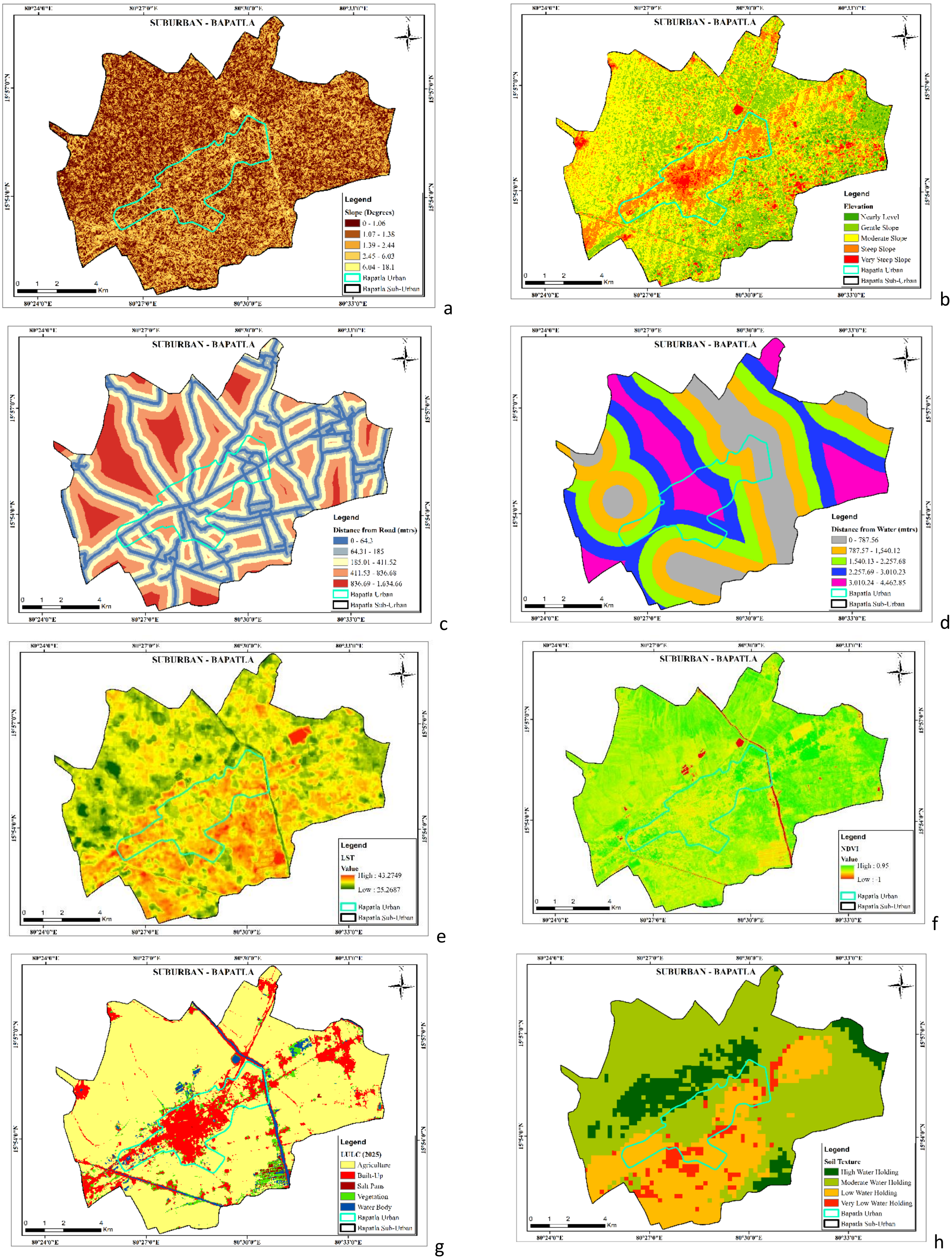

Fig. 3. Agricultural Suitability Parameters

Elevation: The elevation map (Fig No: 3a) reveals that the Bapatla suburban area is largely composed of low-lying coastal lands with a gentle slope, which is also typical of the larger geomorphological setup of the southeast plain of Andhra Pradesh. Except for a few elevated pockets, most of the surveyed area is at or slightly above sea level, although moderately elevated regions are scattered across central and peripheral parts. The prime Bapatla urban area is on a largely flat to gently sloping terrain; that is, the elevation does not really hinder the use of land, either urban or agricultural. The small rise in elevation makes the whole landscape suitable for agricultural activities, as the runoff is very mild on such surfaces; however, at the same time, this low-lying nature makes these areas vulnerable to flooding when the rainfall becomes heavy or when it is accompanied by cyclonic rains. To sum up, the topography of elevation is basically flat, like a coastal plain, with small hills causing differences in soil drainage as well as land suitability.

Slope: The slope map (Fig No: 3b) shows that the Bapatla sub-urban region consists mainly of a very gentle slope, and that is why geologically it is a flat, coastal, and plain-type location. Most of the area belongs to the lowest slope levels, which means the slope variation is the least. Slope values significantly higher than this are only found in a very small number of places, which are isolated topographic breaks and stream channels, and their combined share of the total land area is really negligible. Most of the area of the city of Bapatla lies on a low-gradient terrain, which reduces the constraints and erosion risks for construction and at the same time offers good agricultural conditions; though it is a flat terrain which also slows runoff and can lead to flooding in localities. This kind of slope formation through coastal depositional processes indicates a general set of land conditions, which can support different kinds of land use, i.e. agricultural as well as urban. However, one should not forget that the effective drainage of the area is extremely important, because if something goes wrong, it will be the first to be affected.

Distance from Roads: The road-proximity map (Fig No: 3c) is actually a quantification of the Euclidean distance of a point in the research area from the nearest major road. The distance ranges from zero at intersections of the street or road network of a city to 1, 634.66 m at locations that are the farthest from urban areas or cities. The proximity of a farmer's farm to the nearest road determines the likelihood/ degree of success or failure to a great extent, as the farmer will have to access various agricultural goods through his/her vehicle on one hand and will rely heavily on the physical presence of his/her workers (labourer/s). In this way, the road distance gradient has provided an opportunity for measuring the availability of transport (logistical accessibility) of each plot individually. This road-proximity map is also being used for delineating the administrative boundary zones of the Bapatla Urban and Sub-Urban areas, thereby paving the way for the direct evaluation of road connectivity of the urbanised centre with the peri-urban and rural areas. The road distance layer thus plays an important role not only as the input of the suitability model but also as a single reference tool for the planning of infrastructure. Generally, through road proximity measures, an objective accessibility parameter is created which supplements the physical criteria related to suitability.

Distance from Water: The distance-from-water map (Fig No: 3d) indicates how close water sources are to each location, giving a continuous measure of distance for surface water. The availability of water is the primary consideration when determining the agricultural potential of the soils, especially in the areas where there is reliance on irrigation as the water source. Therefore, such a map will have an influence on the whole suitability assessment and must therefore be treated as an input. Overlaying Bapatla Urban and Sub-Urban boundaries on the distance-from-water surface gives a water availability comparison directly between the developed land use type and surrounding areas that are mainly rural and peri-urban. The separation of areas close to the water and those distant from it can help planners identify places where water is more readily available to the local population and the agricultural land users.

Land Surface Temperature: The surface temperature (LST) map (Fig No: 3e) provides a visual of the temperature differences in surface radiant heat between different places within the study area; the measurements obtained show a range of 25.27°C to 43.27°C. Primarily, land cover and land use influence these temperature variations, as areas such as barren, sparsely vegetated land and densely built-up surfaces regularly appear warmer than green areas and land used for agriculture. Overlaying the Bapatla Urban and Sub-Urban boundaries on the LST map clearly demonstrates the urban heat island effect, with the inner part of the city having significantly higher temperatures compared to the surrounding regions at the edges of the city. The distribution of temperature data is an indicator of the risk of heat stress to crops or those being grown nearby within the city limits. Hence, the land surface temperature (LST) is considered one of the important climatic factors in the assessment of agricultural productivity at the study level.

Normalised Difference Vegetation Index (NDVI): The Normalized Difference Vegetation Index (NDVI) map (Fig No: 3f) characterizes the vegetation cover in terms of density and physiological condition in the study area, and it is calculated from the differential reflectance of near-infrared, and red spectral bands The index values start with a minimum of -1, representing water, bare soil or built-up surfaces and reach a maximum of 0.95 which corresponds to very dense and vigorous vegetation. As a measure of vegetative vigour, the NDVI surface is a useful tool for evaluating agricultural productivity, which usually follows NDVI values: the higher the value, the more productive the crop fields. Combining the spatial layers of Bapatla Urban and Sub-Urban regions with that of NDVI brings to light an evident difference in the quality of vegetation between the built-up city centre and the surrounding rural and semi-natural land. This further supports the importance of NDVI as a key biophysical parameter in a multi-criteria suitability model.

Land Use/Land Cover: The LULC map (Fig No: 3g) shows six classes of thematic features: agriculture, built-up, salt pans, vegetation, water bodies, and the nested Bapatla Urban boundary within the Sub-Urban extent. Agricultural land dominates the scene, covering large parts of the east, west, and south of the study area, reflecting its past as a primarily rice- and aquaculture-based region. The built-up class is found within the Bapatla Urban boundary and the surrounding areas, with secondary, more widely dispersed built-up clusters extending along the major road routes that reflect a transport-driven, linear peri-urban growth. Vegetation and water-body classes are relatively small and scattered, with water bodies following a diagonal drainage corridor and salt pans confined to the southeastern margin. The contrast between large expanses of agricultural land and a compact yet rapidly growing built-up core highlights how critical the suitability assessment is in addressing future land-use pressure.

Soil Texture: The soil texture map (Fig No: 3h) shows what the soil types are over an area of study. It is a property which determines the performance of soils in their most significant role in supporting plant life and hence a primary criterion for suitability. The dataset classifies soil texture, which shows that soil physical properties vary in different locations even within the suburban area. Overlapping the Bapatla Urban and Sub-Urban boundaries map with the soil texture model helps in understanding variations in the physical properties of soil from the built-up areas versus agricultural lands surrounding them. Soil texture, as a parameter, is relatively more static when compared to dynamic variables, such as NDVI and LST. Hence, by reflecting the land's native ability to sustain crops, it provides a stable baseline through the years. Based on soil texture, the paper assesses the agricultural activity's long-term viability in the research area.

4.2 Agricultural Suitability Map

The suitability classification quantifies the spatial extent of each class across the 142.25 km² study area. The Suitable class occupies the largest share at 108.90 km² (76.55%), confirming its dominant, near-continuous distribution across the southern, south-eastern, and outer peripheral portions of the study area.

Table 2
Agricultural Suitability Classification

Sl. No.	Suitability Index	Area (Sq. Km.)	Area (%)
1	Highly Suitable	0.75	0.53
2	Suitable	108.90	76.55
3	Not Suitable	32.60	22.92
Total		**142.25**	**100**

The Not Suitable class accounts for 32.60 km² (22.92%), concentrated within and radiating outward from the Bapatla Urban boundary, indicating that unsuitability is driven primarily by existing urbanisation rather than environmental constraints.

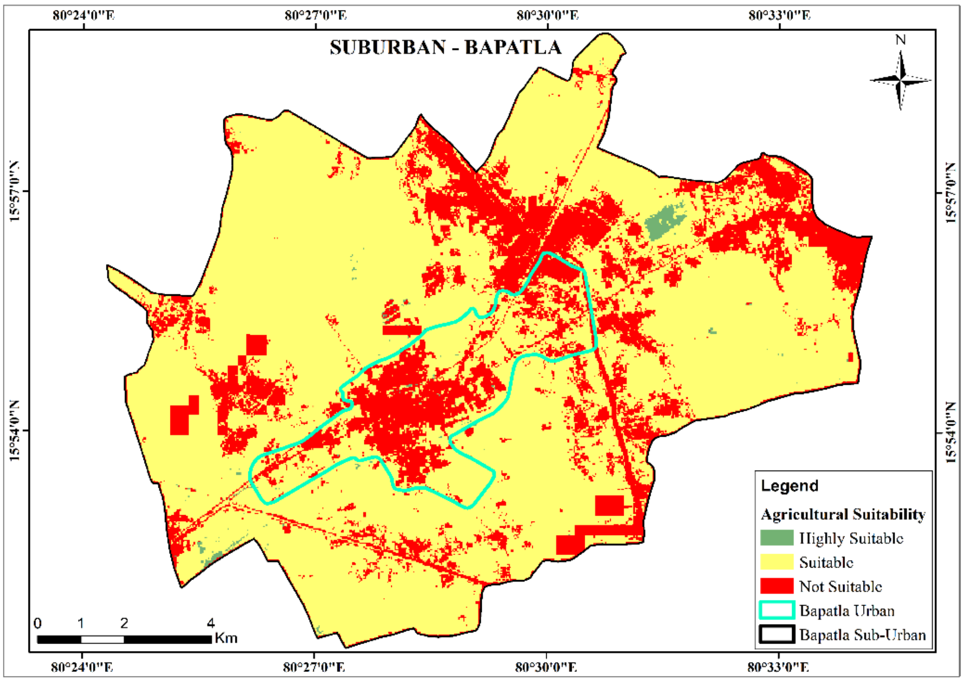

Fig. 4. Agricultural Suitability Map

The Highly Suitable class occupies just 0.75 km² (0.53%), reflecting an extremely limited and spatially isolated distribution of optimal agricultural land. Collectively, while 77.08% of the suburban landscape remains agriculturally viable, less than 1% meets the full combined criteria for optimal suitability, highlighting both the scale of preservable land and the scarcity of top-priority parcels.

4.3. Agricultural Suitability Map (AHP-Based)

The AHP weight table presents the relative importance of the eight biophysical and infrastructural criteria, derived through pairwise comparison. NDVI received the highest weight (0.263, 26.33%), reflecting vegetation strength as the primary determinant of suitability. LST, slope, and distance from water were each weighted 0.150 (14.96%), reflecting comparable secondary importance of thermal stress, terrain gradient, and irrigation-water accessibility. Distance from roads, soil texture, and LULC were each weighted 0.081 (8.06%), forming a tertiary tier of accessibility, edaphic, and land-cover refinement. Elevation received the lowest weight (0.046, 4.6%), consistent with the area's minimal topographic variation, and the weights sum to 1.00, satisfying AHP's normalisation requirement.

Table 3
AHP-Based Agricultural Suitability Weight

AHP Weightage			
Sl. No.	**Criterion**	**Weight**	**Weight (in %)**
1	NDVI	0.263	26.33
2	LST	0.150	14.96
3	Slope	0.150	14.96
4	Water	0.150	14.96
5	Road	0.081	8.06
6	Soil	0.081	8.06
7	Elevation	0.046	4.6
8	LULC	0.081	8.06
Total		**1.00**	**100.0**

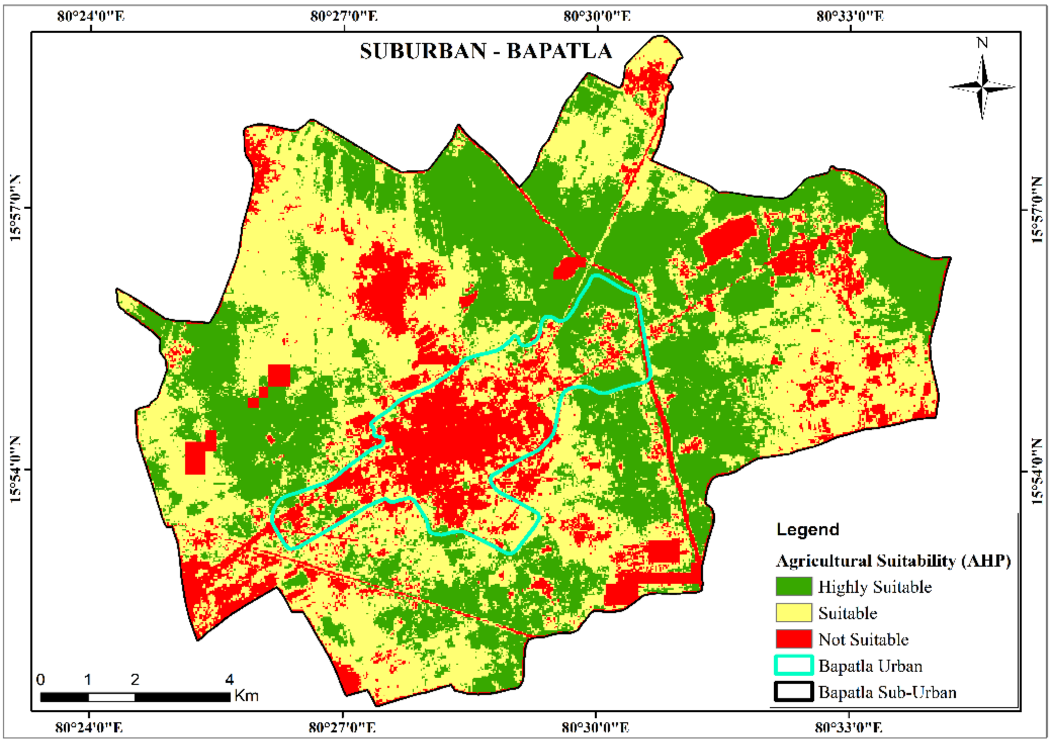

Fig. 5. AHP-Based Agricultural Suitability Map

The final suitability map integrates the biophysical and infrastructural layers through an AHP-weighted overlay, classifying the study area into Highly Suitable, Suitable, and Not Suitable categories. The Bapatla Urban and Sub-Urban administrative units were excluded from classification given their existing developed status. The spatial distribution of suitability classes provides a direct basis for identifying land-use conflicts, particularly where Highly Suitable or Suitable land lies near expanding urban boundaries. By consolidating multiple criteria, weighted according to the AHP hierarchy in Table 1, into a single decision-support surface, the map offers planners an evidence-based tool for prioritising agricultural land preservation. It thereby supports sustainable land-use decision-making across the Bapatla suburban region.

5. Conclusion

The study demonstrated a geospatial multi-criteria evaluation approach, which was done by implementing it through Google Earth Engine and used the Analytic Hierarchy Process (AHP). The urban agricultural suitability of the Bapatla suburban area in Andhra Pradesh was thus assessed. Eight biophysical and infrastructural factors, NDVI, land surface temperature, slope, elevation, soil texture, land use/land cover, and proximity to water and roads, were mapped together, and the analysis showed that the flat coastal plain topography of the study area, along with the gentle slopes and relatively good road and water accessibility, allowed for a majority of the 142.25 km² area to be used for cultivation, with the limitations mainly coming from inherent terrain and drainage. The weighted results obtained from the AHP confirmed that the Vegetation condition (NDVI) was the most significant criterion in the determination of suitability. This was closely followed by three other major factors that were a result of thermal stress, terrain gradient, and water accessibility. Compared to these three other factors, elevation did not contribute much because this area has almost no relief.

Using suitable and highly suitable as the two categories for suitability, these accounted for about 77% and 53%, respectively. This suggests that Bapatla suburban areas are still largely agrarian and there is much potential in agriculture, which is a big plus. As a result, the study showed that the land categorised as not suitable (which is 22.92%) mostly overlaps with the existing built-up land and does not seem to have any significant environmental issue that has limited it. These results will be beneficial in urban planning and in other urbanising cities with similar features. The fact that unsuitable land in Bapatla City mainly lies near and around it, together with the vast area of suitable and highly suitable land near the urban hub, clearly shows that further expansion of the city without some restrictions can eat into land good for agriculture.

Consequently, suitability-based zoning needs to be embedded in both municipal and peri-urban planning frameworks to not only protect high-value agricultural lands from being prematurely turned into built environments but also to find best-fit locations for urban and peri-urban agriculture projects. At the same time, the paper presents one practical method for doing so by taking advantage of cloud geospatial processing and a multi-criteria decision-making approach together with a framework to get evidence-based, repeatable suitability assessment at the suburban scale. To increase the effectiveness of this framework as a decision tool for sustainable urban planning with agriculture, future studies should expand it by introducing multi-time land cover analysis, socio-economic accessibility indexes, and making the pairwise comparisons part of the stakeholder-informed process.

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Author Contributions
Sreerama Naik S R: Conceptualisation, methodology, data collection, data processing, analysis, interpretation of results, and manuscript preparation. T K Prasad: Supervision, methodological guidance, and critical revision of the manuscript. Feba Jose Jasmine: Data analysis, interpretation, and manuscript review. Jayapal G: Research guidance, critical evaluation, and manuscript review. All authors reviewed and approved the final version of the manuscript.

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Conflicts of Interest
The authors declare that they have no conflicts of interest related to this research, its findings, or the publication of this manuscript.

References
[1] Al-Johari, E. E., & Sharaf, F. M. (2024). A land suitability model of urban agriculture: The case of Amman City in Jordan. Universal Journal of Agricultural Research, 12(2), 211–224. https://doi.org/10.13189/ujar.2024.120201
[2] Artmann, M., & Sartison, K. (2018). The role of urban agriculture as a nature-based solution: A review for developing a systemic assessment framework. Sustainability, 10(6), 1937. https://doi.org/10.3390/su10061937
[3] Atalla, M. A., Shebl, A., Đurin, B., Kranjčić, N., & AlMetwaly, W. M. (2024). Assessment of groundwater potential zones in Kuwait's semi-arid region: A hybrid approach of multi-criteria decision making, Google Earth Engine, and geospatial techniques. Scientific Reports, 14, Article 29938. https://doi.org/10.1038/s41598-024-76989-4
[4] Aubry, C., Ramamonjisoa, J., Dabat, M. H., Rakotoarisoa, J., Rakotondraibe, J., & Rabeharisoa, L. (2012). Urban agriculture and land use in cities: An approach with the multifunctionality and sustainability concepts in the case of Antananarivo. Land Use Policy, 29(2), 429–439. https://doi.org/10.1016/j.landusepol.2011.08.009
[5] Belgiu, M., & Drăguţ, L. (2016). Random forest in remote sensing: A review of applications and future directions. ISPRS Journal of Photogrammetry and Remote Sensing, 114, 24–31. https://doi.org/10.1016/j.isprsjprs.2016.01.011
[6] Burrough, P. A., & McDonnell, R. A. (1998). Principles of geographical information systems. Oxford University Press.
[7] De Zeeuw, H., Van Veenhuizen, R., & Dubbeling, M. (2011). The role of urban agriculture in building resilient cities in developing countries. The Journal of Agricultural Science, 149(S1), 153–163. https://doi.org/10.1017/S0021859610001279
[8] Drusch, M., Del Bello, U., Carlier, S., Colin, O., Fernandez, V., Gascon, F., Hoersch, B., Isola, C., Laberinti, P., Martimort, P., Meygret, A., Spoto, F., Sy, O., Marchese, F., & Bargellini, P. (2012). Sentinel-2: ESA's optical high-resolution mission for GMES operational services. Remote Sensing of Environment, 120, 25–36. https://doi.org/10.1016/j.rse.2011.11.026
[9] Eigenbrod, C., & Gruda, N. (2015). Urban vegetable production for food security in cities. Agronomy for Sustainable Development, 35(2), 483–498. https://doi.org/10.1007/s13593-014-0273-y

[10] Feizizadeh, B., & Blaschke, T. (2013). Land suitability analysis for Tabriz County, Iran: A multi-criteria evaluation approach using GIS. Journal of Environmental Planning and Management, 56(1), 1–23. https://doi.org/10.1080/09640568.2011.646964
[11] Food and Agriculture Organisation. (1976). A framework for land evaluation. Food and Agriculture Organisation of the United Nations.
[12] Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote Sensing of Environment, 202, 18–27. https://doi.org/10.1016/j.rse.2017.06.031
[13] Hengl, T., & Reuter, H. I. (Eds.). (2009). Geomorphometry: Concepts, software, applications. Elsevier. https://doi.org/10.1016/S0166-2481(08)00001-9
[14] Huete, A. R. (1988). A soil-adjusted vegetation index (SAVI). Remote Sensing of Environment, 25(3), 295–309. https://doi.org/10.1016/0034-4257(88)90106-X
[15] Huete, A., Didan, K., Miura, T., Rodriguez, E., Gao, X., & Ferreira, L. (2002). Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sensing of Environment, 83(1–2), 195–213. https://doi.org/10.1016/S0034-4257(02)00096-2
[16] Jankowski, P. (1995). Integrating geographical information systems and multiple criteria decision-making methods. International Journal of Geographical Information Systems, 9(3), 251–273. https://doi.org/10.1080/02693799508902036
[17] Jensen, J. R. (2007). Remote Sensing of the Environment: An Earth Resource Perspective (2nd ed.). Pearson.
[18] Justice, C. O., Townshend, J. R. G., Vermote, E. F., Masuoka, E., Wolfe, R. E., Saleous, N., Roy, D. P., & Morisette, J. T. (2002). An overview of MODIS land data processing and product status. Remote Sensing of Environment, 83(1–2), 3–15. https://doi.org/10.1016/S0034-4257(02)00084-6
[19] Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. Sensors, 18(8), 2674. https://doi.org/10.3390/s18082674
[20] Longley, P. A., Goodchild, M. F., Maguire, D. J., & Rhind, D. W. (2015). Geographic Information Systems and Science (4th ed.). Wiley.
[21] Lovell, S. T. (2010). Multifunctional urban agriculture for sustainable land-use planning. Landscape and Urban Planning, 97(4), 220–229. https://doi.org/10.1016/j.landurbplan.2010.06.004
[22] Malczewski, J. (1999). GIS and Multicriteria Decision Analysis. Wiley.
[23] Malczewski, J. (2003). GIS-based land-use suitability analysis: A critical overview. Progress in Planning, 62(1), 3–65. https://doi.org/10.1016/j.progress.2003.09.002
[24] Malczewski, J. (2006). GIS-based multicriteria decision analysis: A survey of the literature. International Journal of Geographical Information Science, 20(7), 703–726. https://doi.org/10.1080/13658810600661508
[25] Maxwell, A. E., Warner, T. A., & Fang, F. (2018). Implementation of machine-learning classification in remote sensing: An applied review. International Journal of Remote Sensing, 39(9), 2784–2817. https://doi.org/10.1080/01431161.2018.1433343
[26] McClintock, N., Mahmoudi, D., Simpson, M., & Santos, J. P. (2016). Socio-spatial differentiation in urban agriculture. Landscape and Urban Planning, 148, 33–44. https://doi.org/10.1016/j.landurbplan.2015.12.004
[27] Mok, H. F., Williamson, V. G., Grove, J. R., Burry, K., Barker, S. F., & Hamilton, A. J. (2014). Strawberry fields forever? Urban agriculture in developed countries. Agronomy for Sustainable Development, 34(1), 21–43. https://doi.org/10.1007/s13593-013-0156-7
[28] Mougeot, L. J. A. (2000). Urban agriculture: Definition, presence, potentials and risks. In N. Bakker, M. Dubbeling, S. Guendel, U. Sabel Koschella, & H. de Zeeuw (Eds.), Growing cities, growing food: Urban agriculture on the policy agenda (pp. 1–42). DSE.
[29] Orsini, F., Kahane, R., Nono-Womdim, R., & Gianquinto, G. (2013). Urban agriculture in the developing world: A review. Agronomy for Sustainable Development, 33(4), 695–720. https://doi.org/10.1007/s13593-013-0143-z
[30] Pulighe, G., & Lupia, F. (2019). Mapping spatial patterns of urban agriculture in Europe. Landscape and Urban Planning, 187, 1–9. https://doi.org/10.1016/j.landurbplan.2019.03.004
[31] Roy, D. P., Wulder, M. A., Loveland, T. R., Woodcock, C. E., Allen, R., Anderson, M., Helder, D., Irons, J., Johnson, D., Kennedy, R., Scambos, T., Schaaf, C., Schott, J., Sheng, Y., Vermote, E., Belward, A., Bindschadler, R., Cohen, W., Gao, F., ... Zhu, Z. (2014). Landsat-8: Science and product vision for terrestrial global change research. Remote Sensing of Environment, 145, 154–172. https://doi.org/10.1016/j.rse.2014.02.001
[32] Russo, A., & Cirella, G. T. (2018). Modern compact cities and urban agriculture. Smart Cities, 1(1), 160–177. https://doi.org/10.3390/smartcities1010011
[33] Saaty, T. L. (1980). The Analytic Hierarchy Process. McGraw-Hill.

[34] Saaty, T. L., & Vargas, L. G. (2013). Decision Making with the Analytic Hierarchy Process. Springer. https://doi.org/10.1007/978-1-4614-3597-6

[35] Sathiyamurthi, S., Subbarayan, S., Ramya, M., Sivasakthi, M., Gobi, R., Qaysi, S., Praveen Kumar, S., Lee, J., Alarifi, N., Wahba, M., & Youssef, Y. M. (2024). Advancing agricultural land suitability in urbanized semi-arid environments: Insights from geospatial and machine learning approaches. ISPRS International Journal of Geo-Information, 13(12), Article 436. https://doi.org/10.3390/ijgi13120436

[36] Seto, K. C., Güneralp, B., & Hutyra, L. R. (2012). Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools. Proceedings of the National Academy of Sciences, 109(40), 16083–16088. https://doi.org/10.1073/pnas.1211658109

[37] Sys, C., Van Ranst, E., Debaveye, J., & Beernaert, F. (1991). Land Evaluation: Part I. Principles in Land Evaluation and Crop Production Calculations (Agricultural Publications No. 7). General Administration for Development Cooperation.

[38] Tucker, C. J. (1979). Red and photographic infrared linear combinations for monitoring vegetation. Remote Sensing of Environment, 8(2), 127–150. https://doi.org/10.1016/0034-4257(79)90013-0

[39] United Nations. (2019). World Urbanization Prospects 2018: Highlights. United Nations Department of Economic and Social Affairs.

[40] Weng, Q. (2012). Remote sensing of impervious surfaces in urban areas: Requirements, methods, and trends. Remote Sensing of Environment, 117, 34–49. https://doi.org/10.1016/j.rse.2011.02.030

[41] Xie, Y., Sha, Z., & Yu, M. (2008). Remote sensing imagery in vegetation mapping: A review. Journal of Plant Ecology, 1(1), 9–23. https://doi.org/10.1093/jpe/rtm005

[42] Kamali, M. I., Nazari, R., Karimi, M., & Nikoo, M. R. (2025). Mapping the future of urban agriculture: A GIS-based spatial framework for food equity. Sustainable Cities and Society, 131, Article 106786. https://doi.org/10.1016/j.scs.2025.106786

[43] Kanosvamhira, T. P., Musasa, T., & Mupepi, O. (2025). The potential for urban agriculture (UA) in Cape Town, South Africa: A suitability analysis. Annals of GIS, 31(1), 107–122. https://doi.org/10.1080/19475683.2025.2455430

[44] Ding, X., Li, W., Sun, X., & Peng, Y. (2026). Assessing the potential of urban agriculture at the community scale: Spatial heterogeneity, influencing factors, and planning implications. Journal of Environmental Management, 409, Article 130046. https://doi.org/10.1016/j.jenvman.2026.130046