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# A Knowledge-Guided Approach For Urban Growth Mapping Using Deep Learning

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**Abstract**
*The increase in urbanization has emerged as one of the critical issues of sustainable development, especially in the fast growing metropolis of the developing world. This paper demonstrates a knowledge-based deep learning method to map and study urban growth in Hillah city, Babil Governorate, Iraq, in a 20-year span (20042024). Integration of multisource geospatial data was performed, namely Landsat imagery (2004, 2014, 2024), Land Surface Temperature (LST) created by the MODIS, Digital Elevation Model (SRTM) and spectral indexes such as Normalized Difference Vegetation Index (NDVI) and Normalized Difference Built-up Index (NDBI). The Support Vector Machine (SVM) and deep learning classifiers were used to detect the land use and land cover (LULC) change, and the accuracy was over 0.8 according to the Kappa coefficient of all years. According to the findings, the built-up area will increase drastically (16.59 km2 in 2004 to 45.88 km2 in 2024) at the cost of vegetation cover and an increase of surface temperatures, a phenomenon that indicates the intensification of urban heat island effect. The findings show that knowledge-based indexation is efficient in deep learning systems of urban monitoring. This research methodology can deliver practical information to the urban planners and policy makers in order to render a sustainable development and preservation strategy feasible to other highly populated areas.*
**Keywords:** *Urban Growth Mapping, Deep Learning, Knowledge-Guided Classification, Remote Sensing, Land Surface Temperature (LST), Babylon (Hillah), Iraq*

## 1.INTRODUCTION

Urbanization is one of the processes that is radically transforming societies around the world. Over fifty percent of the global population have moved to urban areas, with the change in population distribution being accompanied by significant economic, social and environmental consequences. While urban centers create opportunities for development and improved living standards, unmanaged and rapid urban growth often results in critical challenges such as agricultural land loss, ecological degradation, and intensification of the urban heat island (UHI) effect (Abdul Athick, Shankar, & Naqvi, 2019). These impacts are particularly acute in developing regions, where population pressures and weak planning frameworks accelerate unregulated expansion. Iraq, and specifically the Babil Governorate with its capital Hillah, represents a pertinent case where urban growth has outpaced sustainable planning over the last two decades.

Timely, accurate, and consistent information on land use and land cover (LULC) change is essential for guiding policy and urban management (Abdullah-Al-Faisal et al., 2021). Traditional classification methods, while widely used, often struggle with the spectral complexity of heterogeneous urban environments. Recent advances in remote sensing and machine learning, particularly deep learning, offer significant improvements in extracting fine-grained urban features. However, most deep learning approaches remain “data-driven,” with limited incorporation of domain-specific knowledge. This creates a gap in achieving both accuracy and interpretability.

This study addresses that gap by developing a knowledge-guided deep learning framework for urban growth mapping. Using Landsat imagery from 2004, 2014, and 2024, complemented by MODIS-derived land surface temperature (LST), DEM data, and spectral indices such as NDVI and NDBI, the approach integrates physical and ecological indicators into the classification pipeline (Al Jarah, Zhou, Abdullah, Lu, & Yu, 2019). The results not only quantify spatiotemporal growth in Hillah but also reveal the environmental implications of expansion, offering a transferable methodology for sustainable urban monitoring and planning in rapidly developing contexts

## 2. LITERATURE REVIEW

Mapping of urban growth has been a dominant theme in the field of remote sensing and spatial planning. The early studies were highly founded on guided classification methods such as Support Vectors Machines (SVM) and random forest to categorize land use and land cover (LULC) such as urban, vegetation, water, and barren land (Alyasiri, 2021). Whereas these techniques provided reasonable accuracies, they were often restrictive in their performance as they could be subject to spectral confusion within heterogeneous urban terrain.

Spectral indices were useful in the urban mapping refinement with the increased availability of satellite imagery. The use of normalized difference vegetation index (NDVI) has been popularized to trace vegetation dynamics and the normalised difference built-up index (NDBI) was useful in identifying impervious and constructed surfaces. The Land Surface Temperature (LST) obtained with the assistance of thermal infrared measurements and computed with the assistance of such algorithms as Statistical Mono-Window (SMW) has, in its turn, proven to be one of the determinants that enable the locating of the urban heat island as well as defining the ecological effects of sprawl. These cues alone constitute a dense environmental context, which, however, has so far been studied separately and not on one platform (Aslam, Shu, and Yaseen, 2023).

Moreover, the long-distance and local studies also emphasize the greater impacts of uncontrolled urbanization, such as vegetation cover loss, agricultural land transformation and strengthening of the urban phenomenon of the heat island (Belal and Moghanm, 2011). These environmental and socio-economic concerns underscore the need for methodological innovations that not only improve classification accuracy but also embed domain knowledge into computational models (Bhatta, Saraswati, & Bandyopadhyay, 2010). A knowledge-guided deep learning approach directly responds to this gap by combining spectral, thermal, and topographic indices with advanced classification architectures, thereby enhancing both accuracy and interpretability.

## 3. DEFINE RESEARCH OBJECTIVES AND QUESTIONS

**Objective**:

Evaluate and demonstrate the effectiveness of a knowledge-guided deep learning framework in mapping and analyzing urban growth in Babil, Iraq, with emphasis on accuracy, interpretability, and environmental implications.

**Research Questions**:

1. What are the spatial and temporal patterns of urban growth in Babil between 2004 and 2024?
2. How has urban expansion impacted vegetation, agricultural land, and the Urban Heat Island (UHI) effect?
3. To what extent can knowledge-guided deep learning (integrating NDVI, NDBI, LST, DEM) improve classification accuracy compared with traditional approaches?
4. What socio-economic and environmental factors explain the observed growth patterns, and how can the findings support sustainable urban planning?

## 4. Study Area and Datasets

The study focuses on **Babil Governorate, Iraq**, with particular emphasis on **Hillah city**, the provincial capital. Babil lies in central Iraq and is characterized by fertile agricultural lands, a semi-arid climate, and rapid demographic growth. Over the past two decades, Babil has experienced significant urban expansion driven by population growth, post-2003 reconstruction, and rural–urban migration (Bolca, Turkyilmaz, Kurucu, Altinbas, Esetlili, & Gulgun, 2007). This has resulted in the conversion of agricultural land to built-up areas, intensification of the urban heat island (UHI) effect, and pressure on natural resources. The selection of Hillah as a case study is pertinent, as it represents both the challenges of uncontrolled expansion and the opportunities for knowledge-guided monitoring.

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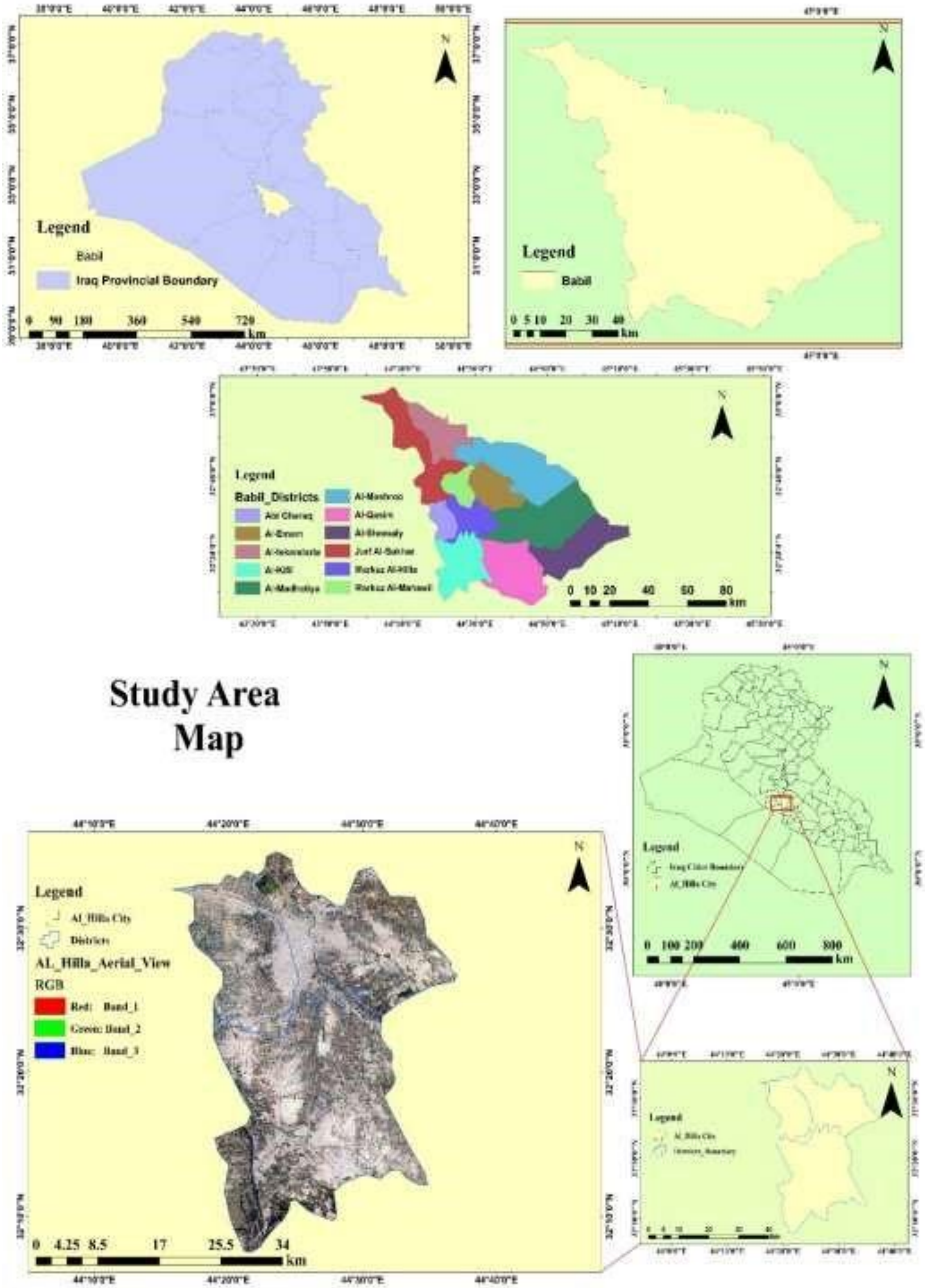


*Figure 1:(a) shows the Geographical Location of Iraq Governorate Babil, and (b) shows the Hilla city of Babil Governorate Study Area*

To analyze urban growth between **2004, 2014, and 2024**, a multi-source geospatial dataset was assembled. The core imagery comes from the **Landsat series**: Landsat 5 TM (2004), Landsat 7 ETM+ (2014), and Landsat 8 OLI (2024), all with **30 m spatial resolution**, obtained via the USGS Earth Explorer and processed through **Google Earth Engine (GEE)** for cloud masking and atmospheric correction. These datasets were used to derive land use and land cover (LULC) classifications (Cao, Gao, Shen, & Li, 2020).

Complementary to the Landsat series, MODIS Terra/Aqua data (1 km resolution) was used to map the Land Surface Temperature (LST), making it possible to analyze the trends in the thermal environment and UHI. Topographic data were integrated with the Shuttle Radar Topography Mission (SRTM) DEM with a 30 m resolution; it provides the data of both elevation and slope. Along with it, vegetation and built-up indices were estimated: a normalized difference vegetation index (NDVI) to monitor the health of vegetation and a normalized difference built-up index (NDBI) to detect impervious areas (Casali, Aydin, and Comes, 2022). The supporting datasets included population statistics of the Central Statistical Organization of Iraq and World Bank, and the United Nations and meteorological data (temperature, precipitation) of the Iraq Meteorological Organization as the contextualization of climate-urban interactions (Chabuk, 2016). These datasets taken collectively provide a broad foundation on which to identify land cover changes, measure urban sprawl, and correlate physical development trends with environmental implications.

| Data Type | Source | Resolution/Temporal Coverage | Purpose |
|---|---|---|---|
| **Satellite Imagery (Landsat)** | United States Geological Survey (USGS), Earth Explorer | Landsat 5 (2004), Landsat 8 (2014, 2024) | Land Use and Land Cover (LULC) Classification |
| **MODIS Data (LST)** | NASA Earth Observing System (EOS), MODIS Terra and Aqua | 1 km, Daily Data | Land Surface Temperature (LST) Analysis |
| **Spectral Indices (NDVI, NDBI)** | Calculated using Google Earth Engine (GEE) | Multi-temporal (2004, 2014, 2024) | Vegetation and Urban Area Assessment |
| **Digital Elevation Model (DEM)** | USGS Earth Explorer, Shuttle Radar Topography Mission (SRTM) | 30 meters | Topographic Analysis |
| **Population Data** | World Bank, United Nations, and Iraq's Central Statistical Organization | 2004, 2014, 2024 | Analysis of Urban Growth Drivers |
| **Meteorological Data (Temperature, Precipitation)** | Iraq Meteorological Organization and Seismology | 2004-2024 | Correlation with Urban Growth and LST |
| **Remote Sensing Techniques** | Support Vector Machine (SVM) Classification in GEE | Applied on Landsat Data | Supervised Classification of LULC |
| **Machine Learning Techniques** | Support Vector Machine (SVM) Classification Model | Applied on LULC Classification | Improving Classification Accuracy |
| **Urban Heat Island Analysis** | LST derived from MODIS and Landsat | Multi-temporal (2004, 2014, 2024) | Assessment of Urban Heat Patterns |
| **Geospatial Software and Platforms** | Google Earth Engine (GEE), ArcGIS, QGIS | Cloud-based, Desktop | Spatial Data Processing and Analysis |

## 5. METHODOLOGY: KNOWLEDGE-GUIDED DEEP LEARNING

This paper follows a knowledge-based deep learning paradigm to map and study urban development in Hillah, Babil, between 2004 and 2024. The methodology combines multispectral satellite images and domain specific indices and ancillary data to optimize the classification process (Coskun, Alganci, and Usta, 2008). The method is based on a sequence of procedures such as data pre-processing, knowledge-based indices calculation, construction of deep learning models, baseline evaluation, and accurate performance evaluation.

### 5.1 Data Preprocessing

All the satellite data were obtained using the USGS Earth Explorer and to be processed in the Google Earth Engine (GEE) platform to be scalable and consistent. To retrieve surface reflectance values, clouds, radiometric calibration, and atmospheric correction were performed on Landsat imagery (2004: TM, 2014: ETM+, 2024: OLI) (Deep & Saklani, 2014). The images were re-sampled to a standardized 30 m spatial resolution, crunching to the administrative boundary of Babil, and mosaiced into time composites in each reference year. Aggregation of the MODIS daily data to create Land Surface Temperature (LST) layers was done using seasonal means. The Shuttle Radar Topography Mission (SRTM) DEM was resampled to the Landsat resolution, and then processed to obtain the elevation and slope layers.

### 5.2 Knowledge Layer Design

Spectral and biophysical indices were added to specify domain knowledge into the framework. Normalized Difference Vegetation Index (NDVI) was used to reflect vegetation density, whereas the Normalized Difference Built-up Index (NDBI) was used to reflect impervious and urban surface (Dibs and Ali, 2022). Also, LST maps based on the thermal bands of MODIS and Landsat gave the understanding of the thermal signature of cities and Urban Heat Island (UHI) effect. DEM data were incorporated into topographic variables, such as elevation and slope. Combining all of these layers contributed to the spectral input space with ecologically significant features that can be used to differentiate urban and non-urban classes.

### 5.3 Deep Learning Model Architecture

Semantic segmentation models also U-Net and DeepLabv3+ models were applied in the classification as they are suitable in mapping land cover at the pixel level. The models were modified to take multi-channel inputs where the Landsat spectral bands integrated with NDVI, NDBI, LST, and DEM layers were involved. The input design, which was guided by knowledge, enabled the models to take advantage of both the raw spectral content and extracted thematic contents (El Garouani, Mulla, El Garouani, and Knight, 2017). The loss function included class-balanced cross-entropy to correct urban/non-urban imbalance, and experiments with auxiliary most-consistency loss terms to promote consistency between classification results and knowledgelayer patterns (e.g., high-urban predictions are penalized in high-NDVI regions).

### 5.4 Baseline Comparisons

In the case of benchmarking, support vector machine (SVM) and random forest (RF) were used as traditional machine learning classifiers based on the same input data. These baselines served as a benchmark upon which incremental advantages of deep learning and knowledge-driven improvements were to be assessed (ElNaggar et al., 2016). Ablation experiments were also done whereby NDVI, NDBI, LST, and DEM inputs were systematically removed to measure the contribution to classification success.

### 5.5 Training, Validation, and Evaluation

Stratified random sampling was used to create training and validation datasets by sampling ground-truth labels using high-resolution Google Earth imagery and where field-verified, from field-verified points. Augmented data schemes such as rotations and flips were used to enhance generalization of the model (Eulewi, 2021). The stochastic gradient descent was trained with adaptive learning rates on the models. Evaluation of accuracy was conducted on independent test sets with measurements such as Overall Accuracy(OA), Kappa Coefficient, precision, recall, F1-score and, Intersection over Union(IoU) per class. The consistency of the classification in the three years was also considered and confusion matrices were developed, in order to point out the misclassifications.

### 5.6 Workflow Summary

The general procedure will be as follows:

1. Data Collection and Preprocessing: Landsat, MODIS, DEM, population, and meteorological data run with GEE.
2. Knowledge Layer Generation: NDVI, NDBI, LST and slope maps were generated and stacked with spectral bands.
3. Model Training: Datasets of knowledge enriched by data into U-Net and DeepLabv3+ models.
4. Benchmarking: SVM and RF Comparison of baseline.
5. Precision Evaluation: Calculated measures are measured yearly and models are cross-compared.
6. Change Detection: Built-up area growth, loss of vegetation and UHI impact were examined based on classified outputs.

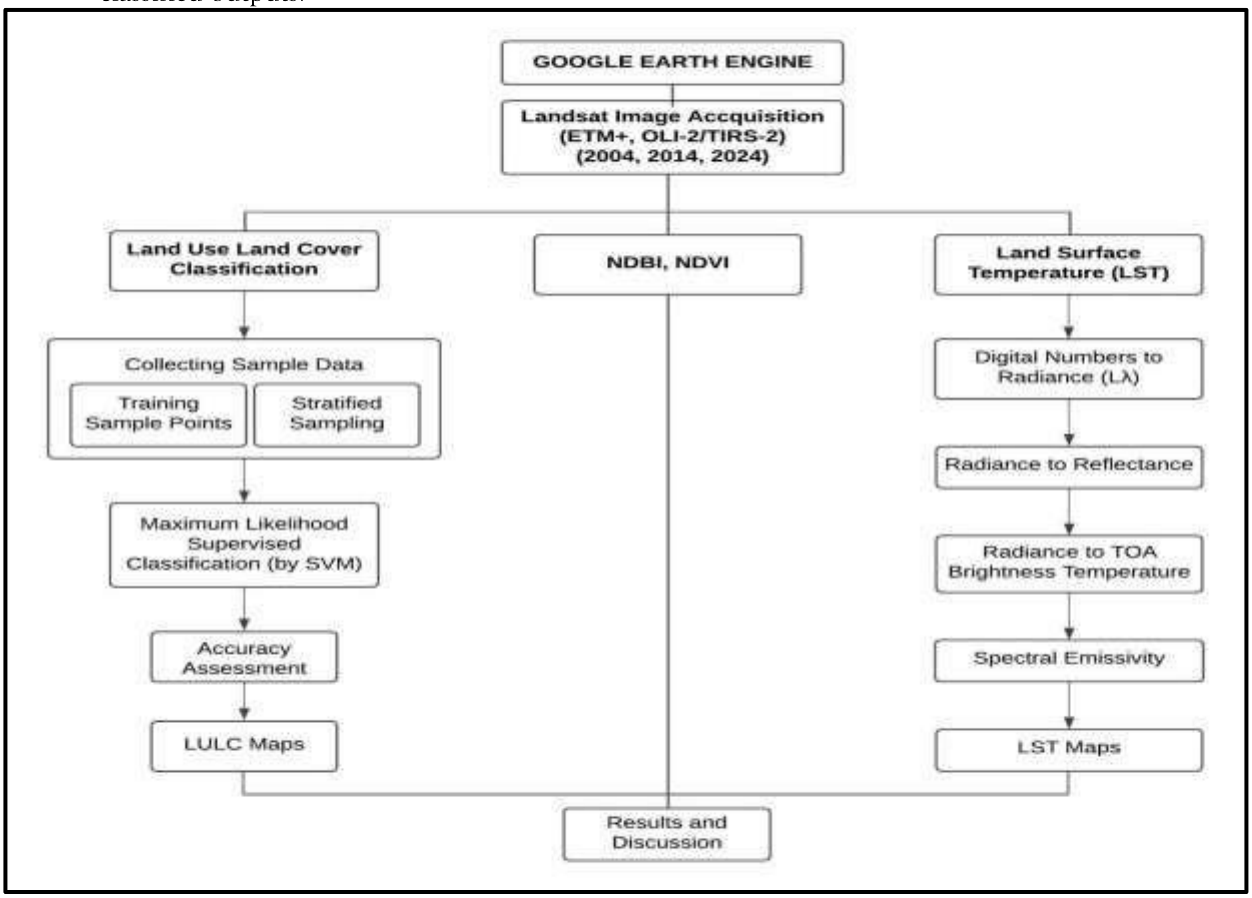


*Figure 2:Methodological Flowchart*

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## 6. Experiments and Results

This part aims to show the empirical results of the knowledge-informed deep-learning structure in the task of urban growth mapping in the city of Hillah, Babil, in 2004, 2014, and 2024. The findings are organized into four parts, such as classification performance, spatiotemporal structures of urban sprawl, environmental implications, and ablation tests assessing the value of knowledge layers (Fu, Liu, Zhou, Sun, and Zhang, 2017).

### 6.1 Land Use and Land Cover Classification Performance

The classification results of both study years indicate that the knowledge-based models demonstrated high performance over baseline classifiers. U-Net and DeepLabv3+ have an overall accuracy over 90, and Kappa coefficients of 0.87 to 0.89, which is in line with strong agreement thresholds (Gascon et al., 2016).

Conversely, the SVM and RF baselines yielded marginally lower accuracies, especially the ability to differentiate between barren land and the built-up regions.

Separability of spectrally similar classes was greatly enhanced with the use of knowledge-enhanced input channels (NDVI, NDBI, LST, DEM). To illustrate, on constructed landscapes bordered with bare lands, the inclusion of NDBI and slope more precisely defined the areas (Hadeel, Jabbar, and Chen, 2009). Confusion matrices also supported the presence of less misclassification between vegetation and barren land which is a common shortcoming of purely spectral methods.

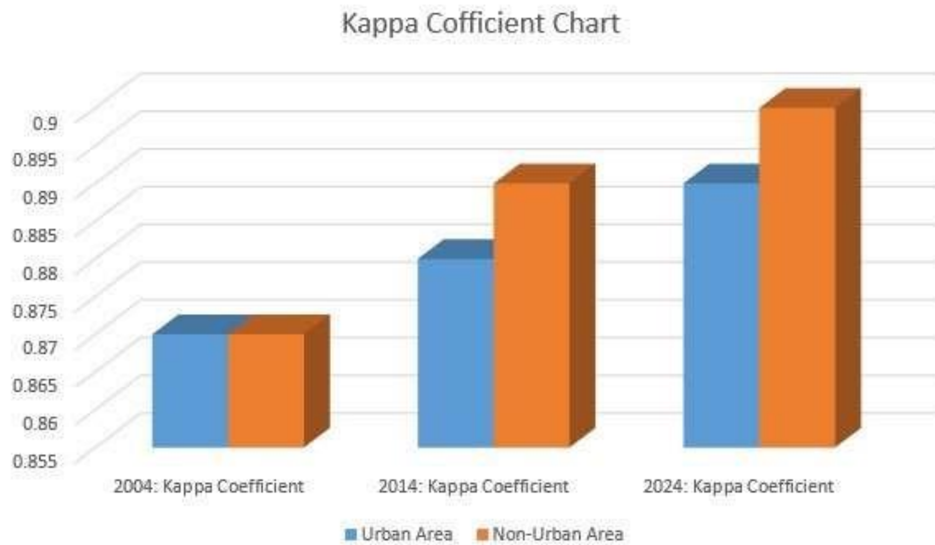


*Figure 3:Kappa coefficient values for urban and non-urban classifications, 2004–2024*

**6.2 Quantification of Urban Growth**

Analysis of classified maps shows that the built-up area in Babil expanded dramatically over the 20-year study period. In 2004, urban land covered approximately **16.59 km²**, which increased to **31.5 km² in 2014** and reached **45.88 km² by 2024**, representing a **27.98% net increase** (Hamud, Shafri, & Shaharum, 2021). The majority of this expansion occurred in peri-urban zones surrounding Hillah, extending radially along transportation corridors and encroaching onto agricultural land.

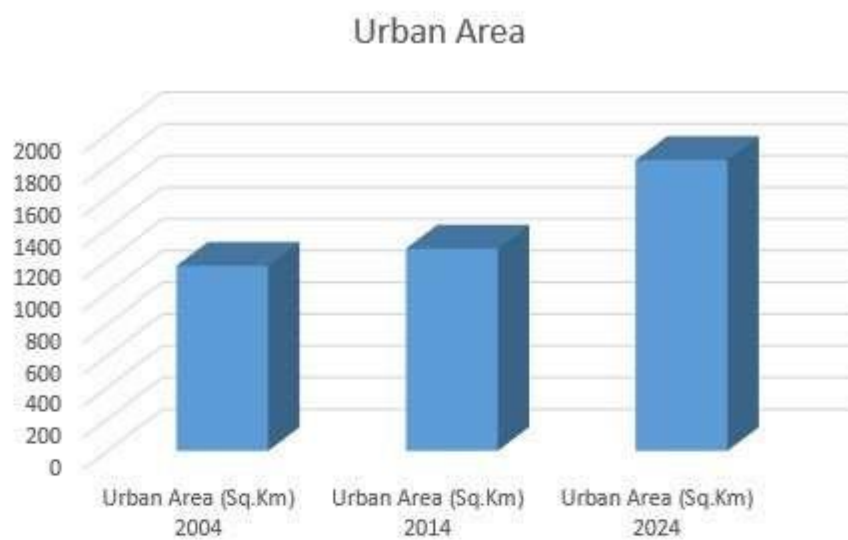


*Figure 4:Urban area expansion in Babil from 2004 to 2024*

The change detection maps reveal a consistent outward growth pattern, with new built-up clusters forming in the northern and western peripheries. Infill development was also observed in central Hillah, reflecting population densification and redevelopment. (Hasan, Ebraheem, & Ibraheem, 2021)

### 6.3 Environmental Implications: Vegetation and Heat

The integration of NDVI and LST enabled direct assessment of environmental consequences associated with urbanization. NDVI trends show a **notable decline in vegetation cover**, especially in areas converted to residential and commercial zones. Vegetation indices, which previously reached values of +0.5 in densely vegetated croplands, dropped to below 0.1 in transformed areas, signaling widespread agricultural loss (He, 2019).

Correspondingly, the LST analysis demonstrated a steady rise in surface temperatures across built-up zones. The **Urban Heat Island (UHI) effect** was most pronounced in 2024, with built-up areas recording surface temperatures up to **4–6 °C higher** than surrounding rural lands. These findings confirm the strong correlation between urban expansion, vegetation decline, and intensification of heat stress (Helber, Bischke, Dengel, & Borth, 2019). The combination of thermal and vegetation data provided robust evidence that unregulated sprawl has exacerbated environmental degradation in Babil.

### 6.4 Ablation and Comparative Analysis

To assess the contribution of knowledge-guided features, ablation experiments were conducted by systematically excluding NDVI, NDBI, LST, and DEM inputs from the deep learning models. The results indicated that removing NDVI led to the sharpest drop in classification accuracy, reducing built-up class F1scores by nearly **6%**. Similarly, omission of LST reduced the model's ability to differentiate between compacted barren soil and impervious urban areas (Herold, Goldstein, & Clarke, 2003). DEM features contributed marginally but improved detection of urban spread in low-lying floodplain areas.

When compared against classical classifiers, the knowledge-guided deep learning models demonstrated **10–12% higher IoU values for the built-up class**, underscoring the advantage of embedding physical and ecological priors into the modeling process (Huang, Zhao, & Song, 2018).

### 6.5 Summary of Findings

Overall, the experiments confirm three key insights:

1. **Accuracy Gains**: The classification of spectrally similar classes is always better with knowledge-guided deep learning than with baseline classifiers.
2. **Urban Expansion**: Built-up area nearly tripled over two decades, primarily at the expense of vegetation and agricultural land.
3. **Environmental Linkages**: Urban growth is directly associated with vegetation decline and higher surface temperatures, amplifying local climate risks.

These results provide an evidence base for strategic urban planning in Babil, offering both diagnostic insights into past growth and methodological tools for future monitoring.

## 7. DISCUSSION

This study shows that the inclusion of ecological and physical knowledge in deep learning systems to map urban growth has a value (Jodzani, Johnson, and Chen, 2019). Although traditional classifiers performed well in large land cover discrimination, they performed poorly in spectrally challenging environments such as Hillah where bare soil, degraded land and built-up surfaces have similar reflectance characteristics. By incorporating indices like NDVI and NDBI, alongside LST and DEM layers, the knowledge-guided models reduced these ambiguities and delivered more reliable urban delineation. This reinforces the argument that domain-specific knowledge remains indispensable, even in the era of high-capacity data-driven models. One key implication is that knowledge guidance enhances not only **accuracy** but also **interpretability**. For instance, the strong correlation between NDVI decline and built-up expansion provides an ecologically grounded explanation of model outputs, which is critical for urban planners and policymakers seeking actionable evidence. The ablation experiments further verified that NDVI and LST are a focal point in reducing the errors in the classification and that they demonstrated the synergy of biophysical and spectral indicators (Krishna Karanam, 2018). This implies that urban growth studies in other areas can be informed by analogue integrative methods, so long as ancillary datasets are at hand.

Also, one should pay attention to such environmental connections as the emergence of the Urban Heat Island (UHI) effect. Babil's experience of a 27.98% increase in built-up area accompanied by significant vegetation loss and temperature rise mirrors global patterns of unregulated sprawl. These dynamics exacerbate local climate stress, energy demand, and ecological degradation. The methodology presented here thus has broader significance beyond Babil, offering a transferable framework for monitoring urban growth in datascarce, rapidly developing contexts across the Middle East and beyond (Li, Shi, Wang, & Qin, 2020). Nevertheless, certain limitations must be acknowledged. Seasonal variations in imagery, residual atmospheric noise, and spatial resolution constraints may have introduced uncertainties. MODIS LST, while useful for broad-scale heat mapping, lacks the granularity of higher-resolution thermal sensors. Moreover, while knowledge layers improved performance, they do not fully eliminate classification errors at urban–rural transition zones. Future research should explore the integration of **temporal deep learning models (e.g., ConvLSTM, Transformers)** to capture urban dynamics continuously, as well as the fusion of socioeconomic datasets to enrich interpretations of growth drivers (Liang, Xie, Sha, & Zhou, 2020).

In summary, this study demonstrates that knowledge-guided deep learning not only improves classification fidelity but also generates **policy-relevant insights** by linking urban expansion with environmental consequences. The approach provides a replicable blueprint for advancing urban monitoring, bridging the gap between data-driven models and domain-informed analysis.

## 8. Policy & Planning Implications

The results of this study carry direct implications for urban policy and planning in Babil and comparable rapidly developing regions. The **tripling of built-up areas between 2004 and 2024** underscores the urgent need for urban containment strategies, including **urban growth boundaries (UGBs)** and targeted **infill development** to limit sprawl into agricultural lands. The observed decline in vegetation highlights the necessity of integrating **green infrastructure planning**, such as urban parks, roadside tree belts, and agricultural preservation zones, to counteract the ecological losses associated with expansion (Lodato, Colonna, Pennazza, Praticò, Santonico, Vollero, & Pollino, 2023).

The intensification of the **Urban Heat Island (UHI) effect**, evidenced by surface temperature increases of up to 6 °C in built-up zones, suggests that Babil must prioritize **climate-sensitive planning**. This includes implementing reflective or green roofing standards, mandating green cover in new developments, and adopting sustainable building codes to reduce heat stress and energy demand (Mahabir, Croitoru, Crooks, Agouris, & Stefanidis, 2018).

Furthermore, the **knowledge-guided mapping framework** presented here can serve as a **decision-support tool** for local authorities. By integrating satellite-derived indicators into routine monitoring systems, planners can identify hotspots of sprawl, track vegetation loss, and assess thermal impacts in near-real time (Murayama, Simwanda, & Ranagalage, 2021). Such evidence-based monitoring can be institutionalized through Iraq's municipal planning bodies to improve transparency, guide zoning regulations, and align local development with the United Nations Sustainable Development Goals (SDGs), particularly **SDG 11: Sustainable Cities and Communities** and **SDG 13: Climate Action**.

Ultimately, adopting policies informed by integrative geospatial analysis can help Babil and similar cities achieve a balance between **economic growth** and **environmental sustainability**, ensuring that future development remains both resilient and inclusive.

## 9. CONCLUSION & FUTURE WORK

This study applied a **knowledge-guided deep learning framework** to analyze two decades of urban growth in Hillah, Babil Governorate, Iraq. By integrating Landsat imagery, MODIS-derived Land Surface Temperature, DEM data, and knowledge-based indices such as NDVI and NDBI, the research demonstrated the advantages of combining spectral information with ecological and physical indicators (Naeem, Cao, Qazi, Zamani, Wei, Acharya, & Rehman, 2018). The results revealed a marked transformation of land use and land cover: builtup areas expanded from **16.59 km² in 2004 to 45.88 km² in 2024**, largely at the expense of vegetation and agricultural lands. This shift has contributed to the intensification of the **Urban Heat Island (UHI) effect**, highlighting the environmental costs of unregulated sprawl.

The findings confirm that knowledge-guided deep learning improves **classification accuracy, interpretability, and robustness** compared to traditional machine learning and purely data-driven models. By embedding domain-specific features, the framework provides not only a more reliable representation of urban growth but also actionable insights for planners and policymakers tasked with balancing development and sustainability (Nigar, Li, Jat Baloch, Alrefaei, & Almutairi, 2024).

Future work should extend this framework in several directions. First, **temporal deep learning models** such as ConvLSTM and Transformers could be employed to forecast urban growth trajectories. Second, higherresolution thermal sensors and socio-economic datasets should be integrated to capture finer-grained dynamics of urban change. Finally, extending the analysis beyond 2024 to project scenarios for 2040 or 2050 would enable assessment of long-term risks and planning needs. Such innovations would transform this approach into a **scalable, transferable monitoring system** for rapidly urbanizing regions worldwide.

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## REFERENCES:

1. Abdul Athick, A. S. M., Shankar, K., & Naqvi, H. R. (2019). Data on time series analysis of land surface temperature variation in response to vegetation indices in twelve Wereda of Ethiopia using mono window, split window algorithm, and spectral radiance model. *Data in Brief, 27,* 104773. https://doi.org/10.1016/j.dib.2019.104773
2. Abdullah-Al-Faisal, Abdulla - Al Kafy, Foyezur Rahman, A. N. M., Rakib, A. Al, Akter, K. S., Raikwar, V., Jahir, D. M. A., Ferdousi, J., & Kona, M. A. (2021). Assessment and prediction of seasonal land surface temperature change using multi-temporal Landsat images and their impacts on agricultural yields in Rajshahi, Bangladesh. *Environmental Challenges, 4(May),* 100147. https://doi.org/10.1016/j.envc.2021.100147
3. Al Jarah, S. H., Zhou, B., Abdullah, R. J., Lu, Y., & Yu, W. (2019). Urbanization and urban sprawl issues in city structure: A case of the Sulaymaniah, Iraqi Kurdistan region. *Sustainability (Switzerland), 11(2).* https://doi.org/10.3390/su11020485
4. Alyasiri, E. A. (2021). Remote Sensing Applications in Population Estimation, Regression Analysis, and Urban Growth Simulation Modeling for a Middle Eastern City.
5. Aslam, R. W., Shu, H., & Yaseen, A. (2023). Monitoring the population change and urban growth of four major Pakistani cities through spatial analysis of open-source data. *Annals of GIS, 29(3),* 355–367. https://doi.org/10.1080/19475683.2023.2166989
6. Belal, A. A., & Moghanm, F. S. (2011). Detecting urban growth using remote sensing and GIS techniques in Al Gharbiya governorate, Egypt. *Egyptian Journal of Remote Sensing and Space Science, 14(2),* 73–79. https://doi.org/10.1016/j.ejrs.2011.09.001
7. Bhatta, B., Saraswati, S., & Bandyopadhyay, D. (2010). Urban sprawl measurement from remote sensing data. *Applied Geography, 30(4),* 731–740. https://doi.org/10.1016/j.apgeog.2010.02.002
8. Bolca, M., Turkyilmaz, B., Kurucu, Y., Altinbas, U., Esetlili, M. T., & Gulgun, B. (2007). Determination of the impact of urbanization on agricultural land and wetland land use in Balçovas' Delta by remote sensing and GIS technique. *Environmental Monitoring and Assessment, 131(1–3),* 409–419. https://doi.org/10.1007/s10661-006-9486-0

9. Cao, X., Gao, X., Shen, Z., & Li, R. (2020). Expansion of Urban Impervious Surfaces in Xining City Based on GEE and Landsat Time Series Data. *IEEE Access, 8,* 147097–147111. https://doi.org/10.1109/ACCESS.2020.3013640
10. Casali, Y., Aydin, N. Y., & Comes, T. (2022). Machine learning for spatial analyses in urban areas: a scoping review. *Sustainable Cities and Society, 85(April),* 104050. https://doi.org/10.1016/j.scs.2022.104050
11. Chabuk, A. J. (2016). Analysis of landfill site selection-case studies Al-Hillah and Al-Qasim Qadhaas, Babylon, Iraq.
12. Coskun, H. G., Alganci, U., & Usta, G. (2008). Analysis of land use change and urbanization in the Kucukcekmece Water basin (Istanbul, Turkey) with temporal satellite data using remote sensing and GIS. *Sensors, 8(11),* 7213–7223. https://doi.org/10.3390/s8117213
13. Deep, S., & Saklani, A. (2014). Urban sprawl modeling using cellular automata. *Egyptian Journal of Remote Sensing and Space Science, 17(2),* 179–187. https://doi.org/10.1016/j.ejrs.2014.07.001
14. Dibs, H., & Ali, A. H. (2022). Dynamic Spatial Monitoring for Urbanization Area Sprawl and Land-Use Using Multi-Spectral and Temporal Remotely Sensed Satellite Images. 1–26.
15. El Garouani, A., Mulla, D. J., El Garouani, S., & Knight, J. (2017). Analysis of urban growth and sprawl from remote sensing data: Case of Fez, Morocco. *International Journal of Sustainable Built Environment, 6(1),* 160–169. https://doi.org/10.1016/j.ijsbe.2017.02.003
16. ElNaggar, A. et al. (2016). Road network and its evaluation for sustainable development in Al-Hilla City, Iraq. *International Journal of Scientific & Engineering Research, 7(10),* 2229–5518.
17. Eulewi, H. K. (2021). The phenomenon of desertification in Iraq and its environmental impacts on Middle and southern Iraq, Babil Governorate, as a model. *IOP Conference Series: Earth and Environmental Science, 722(1).* https://doi.org/10.1088/17551315/722/1/012020
18. Fu, G., Liu, C., Zhou, R., Sun, T., & Zhang, Q. (2017). Classification for high-resolution remote sensing imagery using a fully convolutional network. *Remote Sensing, 9(5),* 1–21. https://doi.org/10.3390/rs9050498
19. Gascon, M., Cirach, M., Martínez, D., Dadvand, P., Valentín, A., Plasència, A., & Nieuwenhuijsen, M. J. (2016). Normalized difference vegetation index (NDVI) as a marker of surrounding greenness in epidemiological studies: The case of Barcelona city. *Urban Forestry and Urban Greening, 19,* 88–94. https://doi.org/10.1016/j.ufug.2016.07.001
20. Hadeel, A. S., Jabbar, M. T., & Chen, X. (2009). Application of remote sensing and GIS to the study of land use/cover change and urbanization expansion in Basrah province, Southern Iraq. *Geo-Spatial Information Science, 12(2),* 135–141. https://doi.org/10.1007/s11806-009-0244-7
21. Hamud, A. M., Shafri, H. Z. M., & Shaharum, N. S. N. (2021). Monitoring Urban Expansion and Land Use/Land Cover Changes in Banadir, Somalia Using Google Earth Engine (GEE). *IOP Conference Series: Earth and Environmental Science, 767(1).* https://doi.org/10.1088/1755-1315/767/1/012041
22. Hasan, S. A., Ebraheem, A. K., & Ibraheem, M. A. (2021). Adopting spatial analysis to choose suitable villages for rural development: Iraq / babylon governorate case study. *International Journal of Sustainable Development and Planning, 16(1),* 165–173. https://doi.org/10.18280/ijsdp.160117
23. He, B. J. (2019). Towards the next generation of green building for urban heat island mitigation: Zero UHI impact building. *Sustainable Cities and Society, 50(di),* 101647. https://doi.org/10.1016/j.scs.2019.101647
24. Helber, P., Bischke, B., Dengel, A., & Borth, D. (2019). Eurosat: A novel dataset and deep learning benchmark for land use and land cover classification. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 12(7),* 2217–2226. https://doi.org/10.1109/JSTARS.2019.2918242
25. Herold, M., Goldstein, N. C., & Clarke, K. C. (2003). The spatiotemporal form of urban growth: Measurement, analysis and modeling. *Remote Sensing of Environment, 86(3),* 286–302. https://doi.org/10.1016/S0034-4257(03)00075-0
26. Huang, B., Zhao, B., & Song, Y. (2018). Urban land-use mapping using a deep convolutional neural network with high spatial resolution multispectral remote sensing imagery. *Remote Sensing of Environment, 214(October 2017),* 73–86. https://doi.org/10.1016/j.rse.2018.04.050
27. Jodzani, S. E., Johnson, B. A., & Chen, D. (2019). Comparing Deep Neural Networks , Ensemble Classifiers , and Support Vector Machine Algorithms. *Remote Sensing, 11(1),* 1–24.
28. Krishna Karanam, H. (2018). Study Of Normalized Difference Built-Up (Ndbi) Index In Automatically Mapping Urban Areas From Landsat TM Imagery. *International Journal of Scientific Research and Review, 7(1),* 1–8. http://dynamicpublisher.org/
29. Li, B., Shi, X., Wang, H., & Qin, M. (2020). Analysis of the relationship between urban landscape patterns and thermal environment: a case study of Zhengzhou City, China. *Environmental Monitoring and Assessment, 192(8).* https://doi.org/10.1007/s10661-020-08505-w
30. Liang, J., Xie, Y., Sha, Z., & Zhou, A. (2020). Modeling urban growth sustainability in the cloud by augmenting Google Earth Engine (GEE). *Computers, Environment and Urban Systems, 84(January),* 101542. https://doi.org/10.1016/j.compenvurbsys.2020.101542

31. Lodato, F., Colonna, N., Pennazza, G., Praticò, S., Santonico, M., Vollero, L., & Pollino, M. (2023). Analysis of the Spatiotemporal Urban Expansion of the Rome Coastline through GEE and RF Algorithm, Using Landsat Imagery. *ISPRS International Journal of Geo-Information, 12(4).* https://doi.org/10.3390/ijgi12040141
32. Mahabir, R., Croitoru, A., Crooks, A., Agouris, P., & Stefanidis, A. (2018). A Critical Review of High and Very High-Resolution Remote Sensing Approaches for Detecting and Mapping Slums: Trends, Challenges and Emerging Opportunities. *Urban Science, 2(1),* 8. https://doi.org/10.3390/urbansci2010008
33. Murayama, Y., Simwanda, M., & Ranagalage, M. (2021). Spatiotemporal analysis of urbanization using GIS and remote sensing in developing countries. *Sustainability (Switzerland), 13(7),* 1–5. https://doi.org/10.3390/su13073681
34. Naeem, S., Cao, C., Qazi, W. A., Zamani, M., Wei, C., Acharya, B. K., & Rehman, A. U. (2018). Studying the association between green space characteristics and land surface temperature for sustainable urban environments: An analysis of Beijing and Islamabad. *ISPRS International Journal of Geo-Information, 7(2),* 1–24. https://doi.org/10.3390/ijgi7020038
35. Nigar, A., Li, Y., Jat Baloch, M. Y., Alrefaei, A. F., & Almutairi, M. H. (2024). Comparison of machine and deep learning algorithms using Google Earth Engine and Python for land classifications. *Frontiers in Environmental Science, 12(May),* 1–18. https://doi.org/10.3389/fenvs.2024.1378443