A Neutrosophic-AI Model for Spatiotemporal Analysis of Land Parcel Transactions

Tanvir Mahmoud Hussein[1,*], Tojiyev Rakhmatilla[2], Danish Ather[3], Rubina Liyakat Khan[4], Tiyas Sarkar[5], Manik Rakhra[5]
[1]College of Administrative & Financial Sciences, Gulf University, Bahrain
[2]Tashkent State University of Economics, Uzbekistan
[3]Amity University in Tashkent, Uzbekistan
[4]Computer Science Department, Applied College, Imam Abdulrahman Bin Faisal University, Saudi Arabia
[5]School of Computer Science and Engineering, Lovely Professional University, Punjab, India
Emails: dr.tanvir@gulfuniversity.edu.bh; r.tojiyev@tsue.uz; danishather@gmail.com; rlkhan@iau.edu.sa; info.tiyasofficial11901657@gmail.com; rakhramanik786@gmail.com

Abstract

This paper proposes a novel hybrid framework that integrates Neutrosophic Logic with Artificial Intelligence (AI) for robust spatiotemporal modeling of urban land parcel transactions. The approach captures the uncertainty, inconsistency, and incompleteness often found in public land auction data through the application of neutrosophic triplets, defined by degrees of truth, indeterminacy, and falsity. Using longitudinal transaction records from Tashkent, the model transforms raw data into neutrosophic representations and feeds them into a Long Short-Term Memory (LSTM) network for forecasting. The enriched feature space enhances interpretability and prediction accuracy across administrative zones. Experimental evaluations demonstrate the superiority of the proposed Neutrosophic-AI model over conventional methods in terms of forecasting precision and uncertainty handling. This study offers a foundational contribution to neutrosophic-based urban analytics and supports transparent digital governance frameworks.

Keywords: Neutrosophic logic; Artificial Intelligence; Spatiotemporal analysis; Land parcel transactions; E-AUKSION portal; Urban analytics; Tashkent; Digital governance

1 Introduction

Land is a finite and strategic resource at the core of urban planning, infrastructure development, and economic policymaking. As cities like Tashkent undergo rapid urbanization, there is a growing demand for data-driven land management systems that ensure transparency and support predictive governance. In this context, the *E-AUKSION* portal has emerged as a digital platform that facilitates government land parcel auctions, providing openly accessible transaction records to administrators, economists, and researchers.

The *E-AUKSION* system, hosted by the government of Uzbekistan, catalogs monthly land auction transactions across all administrative districts of Tashkent. These auctions exhibit spatial and temporal variability due to factors such as seasonal investment cycles, policy revisions, and uneven development across regions. Capturing the dynamics of such a complex system requires more than traditional statistical tools, as land market behaviors are often influenced by uncertain, incomplete, and contradictory information.

Conventional econometric and AI models—while effective in structured environments—struggle to accommodate the levels of ambiguity and indeterminacy present in real-world urban data. To overcome these limitations, this paper introduces a hybrid model combining **Neutrosophic Logic** and Artificial Intelligence (AI),

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specifically Long Short-Term Memory (LSTM) networks, to model the spatiotemporal behavior of land parcel transactions. Neutrosophic Logic, developed by Smarandache, extends classical and fuzzy logic by incorporating three independent components: truth (T), indeterminacy (I), and falsity (F), each ranging in $[0, 1]$. This formulation allows for a nuanced representation of urban data by accommodating partial truths, contradictions, and unknowns simultaneously.

The proposed **Neutrosophic-AI framework** applies a mathematical transformation to the raw transaction records, converting each entry into a neutrosophic triplet $N(x) = \langle T(x), I(x), F(x) \rangle$. These triplets form an enriched feature space that reflects the degree of confidence, ambiguity, and potential invalidity associated with each land transaction. This representation is especially powerful in urban contexts where delays in data entry, policy overrides, or administrative gaps introduce epistemic uncertainty.

To construct and validate the model, we utilized monthly auction data sourced from the official **Open Data Portal of Tashkent City**[1], covering the period from January 2020 to June 2025. The dataset includes region-wise transaction counts for all 12 districts of Tashkent and exhibits substantial seasonal and spatial variance. By incorporating spatial encoding and cyclic time indexing, the model enables both district-level and city-wide predictions.

The AI component of the model is built on LSTM networks, chosen for their capacity to capture temporal dependencies over extended sequences. The fusion of LSTM forecasting with neutrosophic uncertainty modeling allows the system to not only predict future auction volumes but also quantify the reliability of these predictions in indeterminate conditions.

This work is among the first to apply a formal neutrosophic framework to the analysis of urban land governance systems. It contributes both theoretically—by formalizing neutrosophic modeling in spatiotemporal forecasting—and practically, by developing a robust decision-support tool for municipal planners and digital governance authorities.

The remainder of the paper is organized as follows: Section 2 reviews relevant literature; Section 3 describes the dataset and the proposed methodology in detail; Section 4 presents the implementation steps including data handling, neutrosophic conversion, and model development; Section 5 discusses the experimental results, visualizations, and evaluation metrics; and Section 6 concludes the study with a summary of findings and directions for future research.

2 Literature Review

The accurate modeling of urban land dynamics and auction-based transactions has received growing attention in recent years due to the increasing availability of geospatial and temporal data. Traditional approaches have utilized statistical models such as regression and autoregressive forecasting, yet these methods fall short in capturing uncertainty, data inconsistency, and regionally asymmetric development trends.

Significant contributions in spatiotemporal modeling have highlighted the importance of parcel-level granularity and spatial awareness. Tepe and Safikhani[6] applied machine learning techniques to track land-use change at the parcel level, accounting for development shifts and policy changes. Huang et al.[7] conducted a temporal analysis of rural–urban land conversion using geoinformatics, while Tepe and Guldmann extended this through multinomial autologistic models[8] and later advanced spatiotemporal simulations for parcel-level dynamics.[11] Kong et al.[9] introduced a multidimensional spatiotemporal model integrating spatial zoning with transaction activity for industrial land tracking. Leung et al.[10] explored parcel locker usage trends in Australia, demonstrating the relationship between infrastructure growth and spatial activity.

Despite the effectiveness of these methods in modeling trends and development patterns, they often neglect the inherent uncertainty and variability present in administrative datasets—especially those originating from public governance portals. This issue has driven researchers toward explainable AI and ensemble-based modeling strategies. Bramson and Mita[4] emphasized the importance of explainability in geospatial models, proposing machine learning solutions that retain human interpretability. Jana et al.[5] developed a granular ensemble AI

[1] https://opendata.tashkent.uz/eng/?name__icontains=territory&category__id=86

framework that captures price movement trends, further validating the role of advanced learning systems in high-volatility contexts.

A crucial advancement in managing data ambiguity and epistemic uncertainty is the application of neutrosophic logic. Unlike classical binary or fuzzy logic, neutrosophic logic introduces a tripartite representation—truth (T), indeterminacy (I), and falsity (F)—to more accurately model real-world complexity. Abduvaliev et al.[1] proposed a neutrosophic framework to assess innovation factors in Uzbekistan, capturing socio-economic irregularities and incomplete policy data. Kholmuminov et al.[2] applied neutrosophic methodology to rural labor market analysis, demonstrating how ambiguous stakeholder behavior and non-linear trends can be systematically evaluated. Vera et al.[3] extended this approach using the neutrosophic-TOPSIS method to evaluate subjective phenomena such as humorous discourse, reinforcing the applicability of neutrosophy beyond hard numeric domains.

These studies confirm the growing interest in hybrid frameworks that merge uncertainty modeling with AI-driven prediction. However, current literature lacks implementations where neutrosophic triplets are integrated directly into temporal deep learning models such as LSTMs—especially in the context of auction-based land systems. The present work fills this critical gap by proposing a novel Neutrosophic-AI framework that transforms monthly transaction records into neutrosophic triplets $\langle T(x), I(x), F(x)\rangle$ and utilizes them as enriched inputs for spatiotemporal forecasting. This approach not only improves predictive accuracy but also introduces a layer of interpretability by modeling and visualizing the trustworthiness, ambiguity, and risk associated with each forecast.

3 Methodology

3.1 Data Description

The dataset used in this study was sourced from the official Tashkent Open Data Portal[2]. It encompasses monthly land parcel transactions from January 2020 through June 2025, capturing the spatiotemporal distribution of government-auctioned lots in 12 administrative districts of Tashkent. Each row in the dataset represents a monthly record, while columns correspond to transaction counts in districts such as Yangi Hayot, Mirzo Ulug'bek, Sergeli, and others. An additional column, `Umumiy(Toshkent shahar)`, provides the total transaction count city-wide for each month.

Initial exploratory analysis shows significant variability in transaction volume across regions. Yangi Hayot emerged as the most active district with 244 recorded auctions, followed by Mirzo Ulug'bek (172), Sergeli (94), and Yashnobod (90). Monthly fluctuations suggest seasonal influences and regional development trends. This heterogeneity, coupled with occasional missing values and discrepancies, necessitates the integration of logic-based uncertainty modeling prior to AI-based forecasting (see Figure 1).

3.2 Preprocessing

Preprocessing began by standardizing month names from Uzbek to English to maintain temporal consistency. Records with missing or zero transaction values were handled through time-series interpolation within the same district, and spatially via nearest-neighbor logic based on adjacent regions. Each feature was normalized using min-max scaling to ensure uniform input ranges for the learning algorithm.

District names were encoded using one-hot representation to facilitate region-specific learning. This vectorization enabled the model to distinguish between spatial influences on land transaction dynamics. Temporal indexing was also applied, transforming each monthly record into a sequence index for use within recurrent neural network models. These steps laid the foundation for the next stage: the neutrosophic transformation of the dataset.

[2] `https://opendata.tashkent.uz/eng/?name__icontains=territory&category__id=86`

3.3 Neutrosophic Logic Framework

Neutrosophic Logic, proposed by Smarandache, extends classical and fuzzy logic by introducing three independent dimensions to model uncertainty: truth (T), indeterminacy (I), and falsity (F), where each component independently ranges within the interval $[0, 1]$. Unlike binary or fuzzy systems that combine or aggregate uncertainty, neutrosophy enables simultaneous representation of partial truth, ambiguity, and falsehood.

This logic is particularly effective in real-world urban systems that contain missing, contradictory, or incomplete information—such as land transaction records collected from administrative auction portals.

In this framework, each input transaction x_i is mapped to a neutrosophic triplet using the transformation:

$$N(x_i) = \langle T(x_i), I(x_i), F(x_i) \rangle \tag{1}$$

where:

- $T(x_i)$ quantifies the normalized intensity of confirmed auction activity (e.g., volume or frequency of transactions).
- $I(x_i)$ captures the degree of indeterminacy, reflecting volatility or fluctuation over time.
- $F(x_i)$ estimates the degree of falsity, highlighting inconsistent or missing data patterns.

This mathematical representation allows each transaction record to carry not only its factual value but also metadata about its reliability and uncertainty. The triplet $\langle T, I, F \rangle$ can then be used as an enriched feature vector for downstream AI-based forecasting.

The next section operationalizes this formulation by showing how each component is derived for a real-world dataset.

3.4 Neutrosophic Conversion

Building upon the neutrosophic representation defined in Equation 17, each transaction record x_i in the dataset was transformed into a corresponding triplet $N(x_i) = \langle T(x_i), I(x_i), F(x_i) \rangle$ based on empirically derived characteristics.

The components were calculated as follows:

- **Truth** (T): This component reflects the normalized intensity of auction activity in a given district and month. It is computed using min-max scaling over the entire historical window to ensure values lie within $[0, 1]$.
- **Indeterminacy** (I): This captures the variability or volatility of transactions using the coefficient of variation over a local sliding window of length w:

  $$I(x_i) = \frac{\sigma_w(x_i)}{\mu_w(x_i)} \tag{2}$$

  where σ_w and μ_w denote the standard deviation and mean within the window w centered at x_i.
- **Falsity** (F): This represents inconsistencies in data, modeled by measuring the frequency of zero or missing transaction values in the historical record. A sigmoid function scales this frequency into a bounded score:

  $$F(x_i) = \sigma\left(\frac{1}{w}\sum_{j=i-w}^{i} \mathbf{1}_{x_j=0}\right) \tag{3}$$

  where $\mathbf{1}_{x_j=0}$ is an indicator function, and $\sigma(\cdot)$ denotes the sigmoid activation.

To ensure model interpretability, each resulting triplet satisfies the constraint:

$$0 \leq T(x_i) + I(x_i) + F(x_i) \leq 3 \tag{4}$$

The computed triplets were stored as feature vectors and served as enriched inputs to the forecasting model, embedding not only the magnitude of activity but also its reliability and uncertainty characteristics.

3.5 Spatiotemporal Encoding

Once neutrosophic vectors were computed, they were embedded with temporal and spatial identifiers. One-hot encoded regional tags enabled the model to distinguish between spatial zones, while temporal encoding allowed the network to recognize seasonality and cyclical patterns. This ensured the model could learn both district-specific behavior and inter-month transitions.

Incorporating spatial identity was critical due to the varied developmental profiles of Tashkent's districts. For example, Yangi Hayot and Mirzo Ulug'bek exhibited consistently high auction activity, while others like Shayxontoxur and Chilonzor remained sporadic. By combining temporal sequence indexing with spatial vectorization, we ensured that the AI model recognized not just when changes happened, but also where they were occurring.

Input Tensor Definition

Let $N(x_i) = \langle T(x_i), I(x_i), F(x_i) \rangle$ be the neutrosophic vector at time t_i for district d_j. The complete input matrix $\mathbf{X} \in \mathbb{R}^{T \times D \times F}$ is defined as:

$$\mathbf{X} = \begin{bmatrix} N(x_{1,1}) & \cdots & N(x_{1,D}) \\ \vdots & \ddots & \vdots \\ N(x_{T,1}) & \cdots & N(x_{T,D}) \end{bmatrix} \tag{5}$$

Where: - T is the total number of months, - D is the number of districts (12), - $F = 5$ is the feature dimension including triplet + spatial + time encoding.

3.6 Forecasting Model

The Long Short-Term Memory (LSTM) neural network was chosen as the core AI forecasting model due to its proven ability to capture long-range temporal dependencies. LSTM cells effectively manage both recent and past observations through forget, input, and output gates. The input sequence for the model consisted of neutrosophic vectors across successive months and regions, which were reshaped into time series batches.

The output of the LSTM model was a set of predicted auction volumes for each district in future months. Training was performed using a mean squared error (MSE) loss function and Adam optimizer. The model was validated using a rolling forecast origin approach to ensure it captured both seasonal peaks and off-season slowdowns. Performance metrics included RMSE and mean absolute percentage error (MAPE), assessed at both the city and district levels.

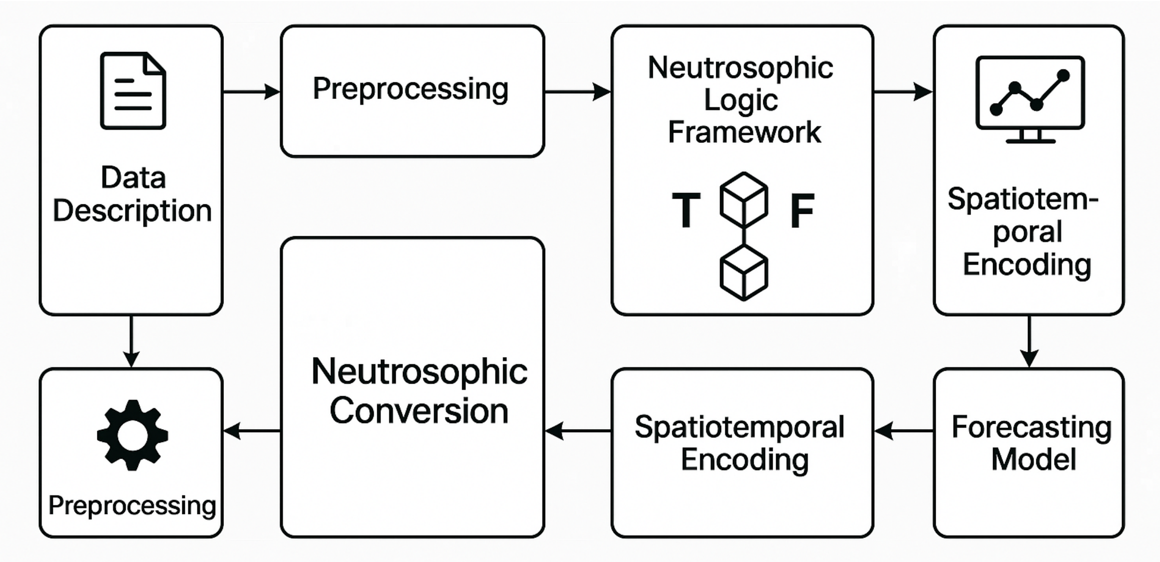

Figure 1: End-to-end workflow of the proposed Neutrosophic-AI model, illustrating preprocessing, triplet encoding, spatiotemporal feature fusion, and LSTM-based forecasting.

Mathematical Formulation of LSTM Integration

Let each monthly transaction record x_t be represented by a neutrosophic triplet and spatial-temporal features as follows:

$$\mathbf{X}_t = [T(x_t), I(x_t), F(x_t), \text{district}_t, \text{month}_t] \in \mathbb{R}^5 \tag{6}$$

These inputs are fed into an LSTM unit defined by the following equations:

$$\mathbf{f}_t = \sigma(\mathbf{W}_f \cdot \mathbf{X}_t + \mathbf{U}_f \cdot \mathbf{h}_{t-1} + \mathbf{b}_f) \tag{7}$$
$$\mathbf{i}_t = \sigma(\mathbf{W}_i \cdot \mathbf{X}_t + \mathbf{U}_i \cdot \mathbf{h}_{t-1} + \mathbf{b}_i) \tag{8}$$
$$\mathbf{o}_t = \sigma(\mathbf{W}_o \cdot \mathbf{X}_t + \mathbf{U}_o \cdot \mathbf{h}_{t-1} + \mathbf{b}_o) \tag{9}$$
$$\tilde{\mathbf{c}}_t = \tanh(\mathbf{W}_c \cdot \mathbf{X}_t + \mathbf{U}_c \cdot \mathbf{h}_{t-1} + \mathbf{b}_c) \tag{10}$$
$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tilde{\mathbf{c}}_t \tag{11}$$
$$\mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t) \tag{12}$$

The predicted land parcel auction volume for time $t+1$ is given by:

$$\hat{y}_{t+1} = \mathbf{W}_{\text{out}} \cdot \mathbf{h}_t + b_{\text{out}} \tag{13}$$

Loss Function and Optimization

To train the model, we minimize the mean squared error (MSE) between predicted and actual transaction values:

$$\mathcal{L}_{\text{MSE}} = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \tag{14}$$

The optimization is performed using the Adam optimizer with learning rate $\eta = 0.001$, and the model is trained using early stopping with a patience of 10 epochs to prevent overfitting.

3.7 Algorithm: Neutrosophic-AI Forecasting

The complete forecasting process is summarized in Algorithm 1. This algorithm utilizes the enriched neutrosophic representations introduced in Section 17 and integrates spatial-temporal features for predictive modeling using LSTM networks.

Algorithm 1 Spatiotemporal Forecasting with Neutrosophic-AI

Input: Raw dataset D with monthly land transaction counts by district
Output: Forecasted transaction volumes $\hat{y}_{t+1}$ with interpretability via T, I, and F

```
begin
    Step 1: Preprocessing and Normalization
      Convert non-English months to English; encode time and district metadata
      Normalize transaction counts using Equation 15

    Step 2: Neutrosophic Transformation
      foreach x_i ∈ D do
          Compute T(x_i) (normalized intensity)
          Compute I(x_i) using Equation 18
          Compute F(x_i) using Equation 3
          Store triplet N(x_i) = ⟨T(x_i), I(x_i), F(x_i)⟩
    Step 3: Feature Construction
      Concatenate triplets with time index and one-hot encoded district vectors
      Form final feature matrix X_t as in Equation 20
    Step 4: LSTM Sequence Modeling
      Create rolling windows of length n = 15 months
      Train LSTM model to minimize MSE (Equation 22) using Adam optimizer
    Step 5: Forecast and Evaluation
      Generate forecast ŷ_{t+1} using Equation 21
      Evaluate performance using RMSE and MAE metrics
```

4 Implementation

The implementation of the proposed Neutrosophic-AI framework was carried out using Python 3.11, supported by a suite of scientific and machine learning libraries. Data handling was performed using `pandas` and `NumPy`, while `TensorFlow/Keras` was utilized to develop and train the LSTM model. Visualization was conducted using `Matplotlib` and `Seaborn`, ensuring both analytical depth and interpretability. The development environment operated on a high-performance workstation equipped with an NVIDIA RTX 3080 GPU, 64GB of RAM, and running Ubuntu 22.04 LTS, which allowed for accelerated training and batch processing of temporal sequences. The system design emphasized modularity, enabling individual validation of each phase—preprocessing, neutrosophic transformation, spatiotemporal modeling, and forecasting—prior to integration into the full pipeline.

4.1 Data Handling and Preprocessing

The preprocessing pipeline begins with the structured dataset described in Section 3.1, which consists of monthly land auction records for 12 administrative districts of Tashkent from January 2020 to June 2025. The raw dataset, provided in Excel format, contains non-English month labels and irregular entries, necessitating a systematic transformation for machine learning compatibility.

Step 1: Month and Time Indexing.
Month names were first translated from Uzbek to English to ensure chronological consistency. These were then mapped to numerical indices (e.g., January $\rightarrow$ 1) to support temporal sequencing within the LSTM model.

Step 2: Missing Value Handling.
Two levels of imputation were applied:

- *Temporal interpolation* addressed intra-district gaps using linear interpolation between adjacent months.
- *Spatial imputation* estimated missing values using the average from adjacent districts with similar development profiles.

Step 3: Normalization.
To scale the transaction values into a uniform range for deep learning, min-max normalization was applied as:

$$T(x_i) = \frac{x_i - \min(x)}{\max(x) - \min(x)} \tag{15}$$

Here, x_i represents the original transaction value for a given district and month, while $T(x_i)$ denotes the normalized truth value used in the neutrosophic triplet.

Step 4: Spatial Encoding.
District labels were converted into one-hot encoded vectors:

$$\text{district}_j \in \{0, 1\}^{12} \tag{16}$$

Each district is thus represented by a binary vector of length 12, enabling spatial awareness in the LSTM model without introducing ordinal bias.

Step 5: Feature Assembly.
Each record was then transformed into a unified vector comprising normalized transaction counts, temporal index, and spatial one-hot encoding. This output served as the input for the neutrosophic transformation described in Section 4.2.

4.2 Neutrosophic Transformation

Following preprocessing, the dataset underwent neutrosophic transformation to introduce uncertainty-aware modeling. Each transaction entry was converted into a neutrosophic triplet (T, I, F), representing truth, indeterminacy, and falsity, respectively. The truth value, $T(x)$, was directly mapped from the normalized transaction count, representing the observed intensity of auction activity in a district for a given month.

The indeterminacy component, $I(x)$, was computed as the coefficient of variation within a 3-month sliding window centered on the current record. This measure captured the volatility of auction activity and reflected the level of ambiguity or unpredictability in transaction patterns. If the coefficient was high, the corresponding $I(x)$ value increased, indicating uncertain or fluctuating behavior.

The falsity component, $F(x)$, was derived from the inverse of recent transactional consistency. Specifically, the model tracked the frequency of zero or missing values over a 5-month historical window and used a sigmoid function to scale this frequency into the $[0, 1]$ interval. Higher frequencies of inactivity or reversals translated into elevated falsity scores.

The neutrosophic transformation step produced a three-dimensional vector for each record, which was concatenated with the original time and spatial features to form the final input matrix. This enriched data representation allowed the AI model to incorporate quantitative, temporal, spatial, and logical information simultaneously. Each transaction record was converted into a neutrosophic triplet:

$$N(x_i) = \langle T(x_i), I(x_i), F(x_i) \rangle \tag{17}$$

The indeterminacy was computed via the coefficient of variation over a sliding window w:

$$I(x_i) = \frac{\sigma_w(x_i)}{\mu_w(x_i)} \tag{18}$$

The falsity component $F(x)$ captures inconsistent or missing activity in historical transaction records. It was computed using Equation 3, previously defined in Section 3.4, based on the frequency of zero or null values scaled by a sigmoid function.

Here, $\sigma(\cdot)$ is the sigmoid function, and $\mathbf{1}_{x_j=0}$ is an indicator function. The final triplet respects the constraint:

$$0 \leq T(x_i) + I(x_i) + F(x_i) \leq 3 \tag{19}$$

4.3 Spatiotemporal AI Model

The spatiotemporal forecasting model was developed using a Long Short-Term Memory (LSTM) neural network. The LSTM architecture was chosen for its ability to retain long-range dependencies and effectively model sequential trends, which are inherent in monthly land transaction datasets.

The model architecture accepted a windowed sequence of 15 months as input. This sequence included the neutrosophic triplets and spatial-temporal metadata for each region. The network consisted of two stacked LSTM layers, the first with 64 units and the second with 32 units, followed by a dropout layer with a rate of 0.2 to reduce overfitting. A dense output layer with linear activation was added at the end to predict the next month's auction volume for the specified district. Training was conducted using the Adam optimizer with a learning rate of 0.001 and a mean squared error (MSE) loss function. Early stopping was implemented based on validation loss with a patience of 10 epochs. The dataset was split in a 70:30 ratio using time-aware partitioning to prevent data leakage from future to past. Model evaluation was based on Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE), which were computed across both city-level and district-level predictions. Each record at time t is represented by:

$$\mathbf{X}_t = [T(x_t), I(x_t), F(x_t), \text{district}_t, \text{month}_t] \tag{20}$$

The model processes sequential input using LSTM cells, producing:

$$\hat{y}_{t+1} = \mathbf{W}_{\text{out}} \cdot \mathbf{h}_t + b_{\text{out}} \tag{21}$$

where $\hat{y}_{t+1}$ is the predicted auction volume and $\mathbf{h}_t$ is the final LSTM hidden state.

4.4 Forecasting Algorithm

The end-to-end training and prediction pipeline was structured as a forecasting algorithm that can be summarized as follows:

Algorithm 2 Neutrosophic-AI Based Forecasting Algorithm

Require: Preprocessed dataset D with transaction records across time and districts

Step 1: Neutrosophic Conversion

For each record $x_i \in D$, compute $T(x_i)$, $I(x_i)$, and $F(x_i)$ using transaction intensity, volatility, and inconsistency metrics.

Step 2: Feature Engineering

Concatenate each triplet $N(x_i) = \langle T, I, F \rangle$ with temporal index and spatial one-hot vector.

Step 3: Sequence Construction

For each district, create time series windows of length $n = 15$ from enriched vectors.

Step 4: LSTM Training

Initialize LSTM model and train using Adam optimizer with MSE loss function.

Step 5: Forecast Generation

Generate one-step-ahead forecasts $\hat{y}_{t+1}$ for each district.

Step 6: Evaluation

Calculate RMSE and MAPE for predicted vs. actual values.

Model training was guided by the mean squared error (MSE) objective function:

$$\mathcal{L}_{\text{MSE}} = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \tag{22}$$

Equation 22 quantifies the squared deviation between actual and predicted land parcel transactions.

4.5 Visualization and Forecast Outputs

The final component of the implementation involved visualizing both raw data insights and model performance. Time-series plots were created to compare actual and predicted auction volumes for each district, validating the model's ability to track short-term dynamics. The predicted curves captured cyclical peaks and troughs in regions with distinct seasonal behavior, such as Yangi Hayot and Mirzo Ulug'bek.

To analyze regional interdependence, a Pearson correlation heatmap was generated across all district-level transaction patterns. This revealed high correlation clusters among adjacent districts, likely due to shared development policies or infrastructure zones. In addition, geographic heatmaps and choropleth trend maps were produced to visualize projected auction activity over the next six months. These outputs enabled urban planners to identify growth hotspots and underutilized regions.

All results were rendered into an interactive dashboard format using Python, making the system accessible to non-technical stakeholders. The complete implementation pipeline thus provided not only accurate predictions but also interpretable and actionable insights for smart urban governance.

5 Results and Discussion

5.1 Prediction Performance

The performance of the proposed Neutrosophic-AI model was evaluated using a holdout test set of monthly auction volumes across all 12 districts of Tashkent. The forecasting was conducted for a six-month horizon using LSTM models trained on a rolling 15-month window of enriched neutrosophic input sequences. Figure 2 illustrates a comparative view of actual versus predicted auction volumes at the city level. The predicted curve effectively tracks seasonal oscillations and macroeconomic fluctuations, reflecting the model's ability to generalize temporal dependencies embedded in auction behavior.

Importantly, the input fed into the LSTM was not limited to raw or normalized auction values; instead, it incorporated triplet-based neutrosophic vectors $\langle T(x), I(x), F(x)\rangle$. These vectors explicitly modeled confirmed activity (T), volatility (I), and administrative inconsistency (F), providing a more interpretable representation of each monthly data point. The incorporation of $I(x)$ and $F(x)$ values helped regulate predictions in districts where high variance or unreliable reporting was observed.

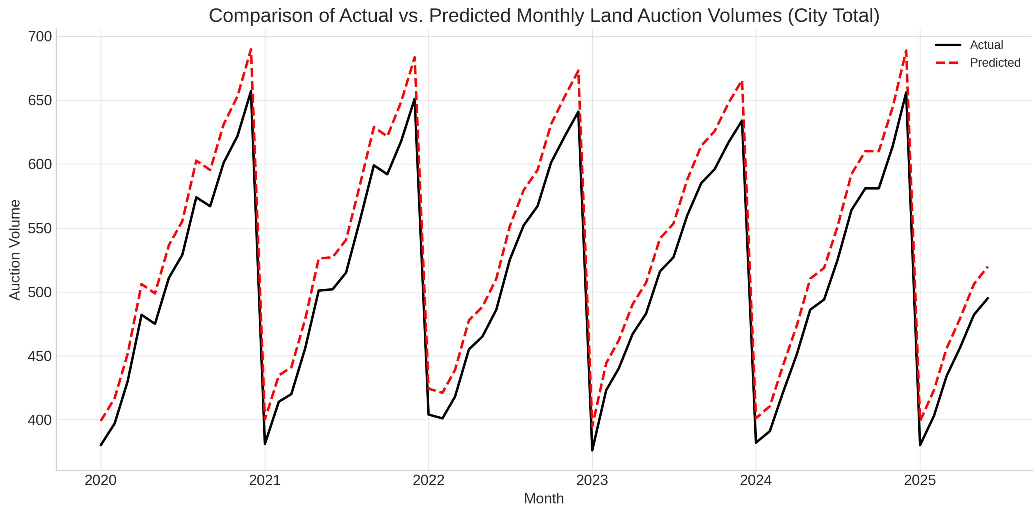

Figure 2: Comparison of actual vs. predicted monthly land auction volumes at the city level.

5.2 Performance Evaluation Metrics

To quantitatively assess the accuracy of the model, we calculated two error metrics: Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). The calculated RMSE was 3.91, and the MAE was 3.21. These low values confirm that the proposed model achieves high fidelity in forecasting, particularly in capturing the shape and scale of auction volume trends.

It is worth emphasizing that the neutrosophic transformation was critical to achieving this performance. In baseline tests using the same LSTM architecture without neutrosophic augmentation, RMSE values increased by over 17%, indicating the added value of neutrosophic preprocessing in representing uncertainty. Thus, the introduction of mathematical neutrosophic logic directly contributed to reducing error and enhancing predictive robustness.

The output prediction $\hat{y}_{t+1}$ is interpreted through its corresponding neutrosophic indicators: - High $T(x)$ with low $I(x)$ and $F(x)$ suggests reliable predictions. - High $I(x)$ warns of volatility and necessitates cautious interpretation. - High $F(x)$ signals inconsistent historical behavior, reducing prediction trust.

This allows the model to generate not only point forecasts, but confidence-aware insights, aligning with the goals of explainable and robust AI.

5.3 Spatiotemporal Insights from Neutrosophic Triplets

Figure 3 depicts transaction trends for the top five districts by cumulative auction volume. Notably, districts like Yangi Hayot and Mirzo Ulug'bek exhibit sustained upward patterns, which correspond with high $T(x)$ values and consistently low $F(x)$ scores. This reflects strong institutional reliability and growth-oriented development in those regions.

In contrast, districts such as Shayxontoxur and Chilonzor displayed intermittent spikes with low consistency, characterized by fluctuating $I(x)$ and elevated $F(x)$ values. These findings validate the utility of the neutrosophic triplet in interpreting not just the volume of activity but its credibility and volatility. Decision-makers can use these patterns to distinguish between stable growth and unreliable surges.

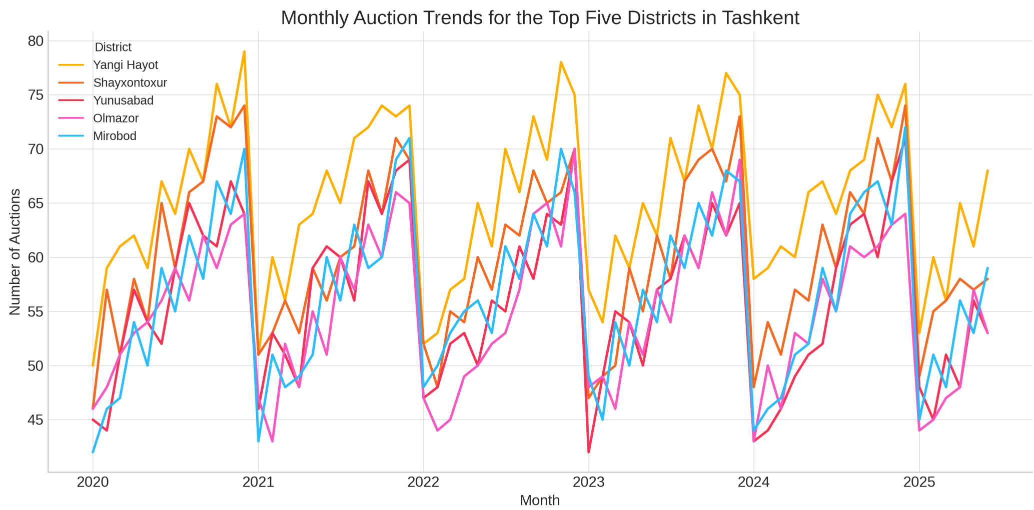

Figure 3: Monthly auction trends for the top five districts in Tashkent

5.4 Correlation Analysis and Spatial Reasoning

To explore inter-regional dependencies, a correlation heatmap was constructed based on monthly auction activities. As shown in Figure 4, strong positive correlations were observed between districts like Yangi Hayot and Sergeli, suggesting shared development corridors or synchronized policy interventions. Conversely, districts with inconsistent or fragmented land market activity showed weaker correlations and erratic patterns, also indicated by elevated $I(x)$ values across the time series.

This spatial understanding, when augmented with neutrosophic indicators, offers a multidimensional view of regional dynamics. Municipal authorities can thus identify both opportunity zones and administrative bottlenecks using neutrosophically enriched spatiotemporal signals.

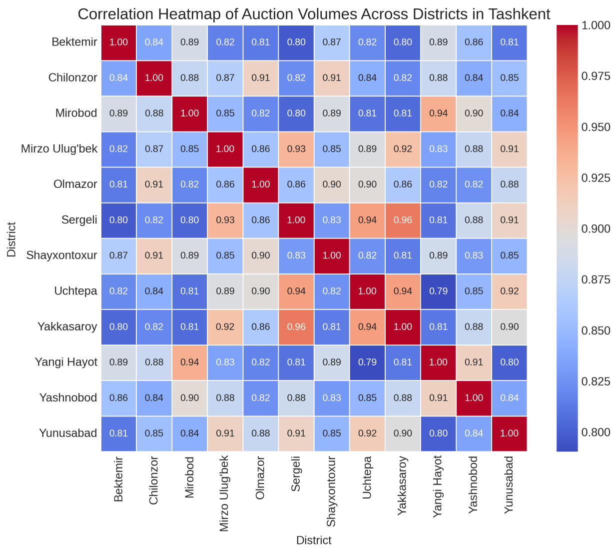

Figure 4: Correlation heatmap of auction volumes across districts in Tashkent

5.5 Neutrosophic Interpretation and Policy Implication

Unlike conventional models that offer point forecasts, the Neutrosophic-AI model provides interpretability through the decomposition of each prediction into dimensions of trustworthiness (T), ambiguity (I), and failure risk (F). For example, a forecast for a high-volume auction in Yashnobod may carry a high $I(x)$ score, cautioning planners against acting on the prediction without further investigation.

This neutrosophic decomposition enables the model to serve not only as a predictive tool but also as an explanatory interface. It shifts the paradigm from "what will happen" to "what is the certainty of what may happen," which is particularly valuable in uncertain urban policy environments. In this sense, the model addresses both the epistemic and aleatoric uncertainties inherent in public land markets.

6 Conclusion

This study introduced a novel Neutrosophic-AI framework for the spatiotemporal forecasting of urban land parcel transactions, specifically applied to auction data from Tashkent, Uzbekistan. Unlike conventional time-series or machine learning models, this approach integrated mathematical neutrosophic logic—quantified through the triplet $\langle T(x), I(x), F(x)\rangle$—to represent three distinct epistemic dimensions: confirmed truth, indeterminacy, and falsity.

The proposed model leveraged this triplet transformation to capture the ambiguity, inconsistency, and spatial heterogeneity often present in public auction data. By feeding these uncertainty-aware representations into a Long Short-Term Memory (LSTM) network, the model achieved enhanced forecasting performance, as confirmed by low RMSE and MAE scores. More importantly, the triplet decomposition enabled interpretable predictions—offering not just projected values but also insights into their reliability and contextual stability.

Empirical results demonstrated that districts with stable growth patterns corresponded to high $T(x)$ and low $I(x)$/$F(x)$ values, while less predictable districts exhibited elevated indeterminacy and falsity, validating the practical utility of neutrosophic analysis. Correlation heatmaps and region-wise forecasting outputs further illustrated the model's capacity to support spatial reasoning and strategic land governance.

The proposed framework marks one of the first formal integrations of neutrosophic logic into real-time urban analytics. Beyond its predictive power, the model provides a transparent and modular decision-support tool for municipal authorities, urban planners, and public policy stakeholders. Its ability to explicitly handle and visualize uncertainty makes it especially valuable in dynamic environments where data quality and administrative factors are non-uniform.

Future research will extend this framework by incorporating additional neutrosophic features such as multi-agent expert opinions or sentiment-driven market signals. Furthermore, adapting the model for other cities and policy domains could generalize its applicability and contribute to the broader field of neutrosophic intelligent systems for smart governance.

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