**Journal of Sciences, Islamic Republic of Iran 36(1): 39 - 49 (2025)** http://jsciences.ut.ac.ir
University of Tehran, ISSN 1016-1104

# Hybrid Prediction Models for Suicide Mortality Levels in Iranian Provinces: Spatial Econometrics vs. Random Forests

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Received: 1 July 2025 / Revised: 25 September 2025 / Accepted: 15 November 2025

## Abstract

With the growing utilization of advanced machine-learning techniques, such as random forests, understanding the significance of spatial factors within these models is increasingly imperative. This study proposes a novel approach to develop spatially explicit classification random forest models by integrating spatially lagged variables, mirroring various spatial panel data econometric specifications. We assess the comparative performance of these models against traditional spatial and non-spatial regression methods to predict suicide mortality rates across 31 provinces in Iran, utilizing data from 2011 to 2021. Results reveal that the spatial random forest model, incorporating spatial lag parameters, achieves a remarkable accuracy of 89.19% in predicting suicide mortality levels, surpassing traditional spatial econometric models (46.51%) and non-spatial random forest models (27.03%). While highlighting the effectiveness of spatial random forest models with spatial lag parameters, this study also recognizes the continued relevance of traditional spatial econometric models in predicting suicide mortality rates. These findings offer valuable insights into the interplay between spatial considerations and predictive modeling, providing essential guidance for researchers in selecting appropriate models for spatial data analysis.

**Keywords:** Spatial Econometrics models; Machine-Learning Techniques; Random Forests; Iran.

## Introduction

Suicide mortality is a pressing public health concern, with devastating implications for individuals, families, and communities. In this profound challenge, accurate predictive models are essential to inform timely interventions and targeted preventive measures. The field of data science has responded to this need with the emergence of new machine-learning techniques, exemplified by the versatile random forest algorithm, capable of handling large and complex datasets (1, 2, 3). These techniques offer promising avenues for predictive modeling and have garnered significant attention in various domains.

However, as the scope of data science expands, so does the recognition of the critical role that spatial considerations play in the accuracy and applicability of predictive models. Spatial data, characterized by geographic and interdependencies, adds layer of complexity to the modeling process. Understanding the spatial context is pivotal for unraveling underlying patterns and relationships that contribute to suicide

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mortality rates, as well as for identifying spatially varying risk factors and vulnerability (4, 5).

Integrating spatial considerations into machine-learning models is crucial for several reasons (6, 7). First, traditional machine-learning techniques, including random forests, have been predominantly developed for predictive applications, often leaving researchers with limited insights into the underlying explanatory relationships between variables. Consequently, these models are often regarded as "black boxes" that limit both the interpretation and the generalization of results, especially in spatial contexts where understanding spatial interactions is essential.

Second, the spatial dimensions of the data demand specialized attention. Spatial econometrics, a well-established branch of spatial statistics, has long been utilized to analyze spatially explicit data, accounting for spatial autocorrelation, spatial heterogeneity, and spatial dependence. Nevertheless, the recent surge of interest in machine-learning techniques has left open questions about the effectiveness of spatial econometrics compared to machine-learning models such as random forests.

Despite the increasing application of machine-learning techniques and spatial econometrics as separate approaches (8, 9, 10), there is still a lack of studies that systematically integrate the two for the prediction of suicide mortality, especially in the context of Iranian provinces. To address this gap, this paper introduces a hybrid framework that incorporates spatially lagged variables into random forest models, enabling a direct comparison with traditional spatial econometric approaches and advancing a novel methodology for spatially explicit predictive modeling. To the best of our knowledge, this is the first study to systematically integrate spatial econometric lags into random forests for predicting suicide mortality in Iranian provinces.

This paper addresses these crucial issues by presenting a novel approach that bridges the gap between spatial econometrics and random forests. We propose constructing spatially explicit classification Random Forest models by thoughtfully incorporating spatially lagged variables. By emulation, we mean that the inclusion of different types of spatial lags—such as lagged dependent variables and lagged explanatory variables—allows the random forest to approximate the relationships captured by spatial panel data econometric models (e.g., SLM, SDM), without formally distinguishing between them in a strict econometric sense. This design enables us to test the comparative performance of these hybrid models against both traditional spatial econometric techniques and non-spatial regression methods. The focus is on predicting suicide mortality rates across 31 provinces in Iran over eleven years (2011–2021), utilizing a comprehensive spatial panel dataset.

This study addresses fundamental questions at the forefront of predictive modeling research. Our focus centers on comparing two distinct approaches: the predictive machine-learning models, exemplified by the random forest algorithm, and the traditional spatial econometric techniques. Moreover, we endeavor to ascertain whether spatially explicit random forest models possess the potential to outperform standard non-spatial random forest models when applied to the crucial task of predicting suicide mortality rates. By unraveling the answers to these pivotal questions, our research aims to provide valuable insights into the interplay between machine-learning techniques and spatial econometrics, opening new avenues for improved predictive modeling in spatially explicit contexts.

By assessing the predictive accuracy and interpretability of these models, we provide findings that shed light on the relationship between spatial considerations and predictive modeling. We aim to provide essential guidance for researchers in selecting appropriate models for spatial data analysis, particularly in the context of suicide mortality prediction. Ultimately, this study advances the expanding literature on spatially explicit machine learning methods while providing direction for future research on their spatial implications and potential applications.

As the importance of spatially aware data analysis grows, our study aims to inform suicide prevention strategies and underscore the significance of embracing spatial considerations in predictive modeling endeavors.

The remainder of this paper proceeds as follows. Section 2 reviews the relevant literature on spatial econometrics and machine learning applications. Section 3 describes the data collection and preparation process. Section 4 presents the estimation methodology, including integrating spatially lagged variables into random forest models. Section 5 reports the results, including model performance comparisons and interpretation of key findings. Finally, Section 6 concludes the paper, highlighting the main contributions, limitations, and directions for future research.

***Literature Review***

In machine learning, which finds diverse applications across various domains, including crime analysis, it is of utmost importance to establish foundational definitions and distinctions. Machine-learning methods, a subset of artificial intelligence (AI), are designed to learn from data and effectively predict outcomes for new, previously unseen data (11). These methods fall into two main categories: supervised and unsupervised techniques.

Supervised algorithms operate by learning the relationship between independent and dependent variables, which they then use to predict outcomes for new instances. This type of prediction enables the algorithm to generalize its learning from the training data to unseen data. Within the realm of supervised learning, we encounter a diverse array of techniques, ranging from conventional statistical methods such as linear and logistic regression to more advanced and sophisticated approaches such as support vector machines (SVM), decision trees, random forests, and neural networks (12).

On the other hand, unsupervised algorithms generate predictions, often in the form of classifications, solely based on the underlying relationships among the provided independent variables. Examples of such techniques include clustering methods such as k-means and dimensionality reduction techniques such as principal component analysis (PCA) (12). These approaches are valuable for tasks where labeled data is absent, as the determining factor for their application is the absence of labeled data rather than clear relationships between variables.

This categorization of machine-learning methods lays a solid foundation for understanding their respective applications and potential advantages in crime analysis and other domains. Combining traditional statistical techniques and cutting-edge machine-learning algorithms allows researchers and practitioners to tackle complex problems and make accurate predictions, thereby contributing to advancements in various fields of study.

While these distinctions are well-suited for predictive applications, they can perplex those accustomed to using these statistical techniques for explanatory purposes. Additionally, some of the newer machine-learning algorithms, such as decision trees, random forests, and neural networks, do not explicitly measure the relationship between independent and dependent variables, leading to criticism and being labeled as "black box" methods. Consequently, the more critical distinction lies between primarily predictive machine-learning techniques, such as random forests, which do not produce coefficients or explicit relationship measures between independent and dependent variables, and the more traditional explanatory machine-learning techniques, such as linear regression, that are familiar with generating such measures. However, it is worth noting that even predictive models such as random forests can still provide insights into explanatory features, as demonstrated in the application within this paper.

Moreover, alongside applying existing predictive machine-learning methods to Spatial Criminology inquiries, scholars have recognized the importance of developing spatially explicit predictive models and methods (7, 13, 14). Singleton and Arribas-Bel (2019) succinctly emphasize that one of the most promising areas for Geographic Data Science to enhance core data science techniques is explicitly incorporating spatial information to improve the performance of predictive machine-learning models. Notably, a limited number of existing studies that have created spatially explicit prediction frameworks reveal that these methods tend to outperform non-spatial methods when applied to spatial datasets (13, 15, 16, 17).

To gain deeper insights into the role of space in predictive machine-learning models, this paper systematically examines various spatial lags in a random forest model, compares random forest models to more conventional spatial econometric models, and evaluates the factors that contribute to enhanced predictive performance for either random forests or spatial econometric models. In the context of our research, we draw from these prior investigations and aim to shed light on the interplay between spatial considerations and predictive modeling. By doing so, our study will offer valuable guidance to researchers seeking to harness the potential of machine learning for spatial data analysis, specifically in predicting suicide mortality rates across provinces in Iran. The outcomes of this investigation will have implications for the development of improved public health policies and interventions in the region, thereby contributing to the broader body of knowledge in spatial data analysis and machine learning.

## Materials and Methods

### *Data Collection and Preparation*

Suicide mortality data in Iran come from reports published by the Iranian Forensic Medicine Organization (IFMO), which operates under the Iranian Judicial Authority (5). The IFMO keeps a comprehensive suicide registry and conducts autopsies for all recorded suicide cases (4). Suicide rates per 100k individuals for each province and socio-demographic and economic data for all 31 provinces were obtained from the Statistical Center of Iran.

The data encompass 2011 to 2021, representing the most recent available data. The variables collected include unemployment rate (X1), labor force participation rate (X2), natural log of population aged 15 and over (X3), consumer price index or CPI (X4), literacy rate among individuals aged six and older (X5), and natural log of gross domestic product or GDP (X6). These variables will be used to identify factors influencing suicide mortality rates per 100k populations

(y) using an econometric model that considers spatial correlations. The explanatory variables X1 to X6 are available for each of the 31 provinces, allowing for a comprehensive, province-specific analysis and modeling.

The study employs panel data covering 31 provinces over 11 years. This panel data structure enables the analysis of individual provinces over time and cross-sectional variations among provinces. It provides a robust framework for examining spatial and temporal dynamics, enhancing the understanding of the factors influencing suicide mortality rates in Iran.

Table 1 provides a descriptive overview of the independent variables used in the study. The dataset used in our experiment comprises a total of 341 instances. To enable prediction, a new attribute called 'suicide category' was added to the dataset. Converting the target (class) attribute to a nominal type was necessary for prediction purposes. As all the original characteristics in the dataset were numeric, the new nominal attribute 'suicide category' was introduced to facilitate prediction.

The 'suicide category' attribute categorizes cases based on the percentage of suicide mortality. Instances with 'suicide rates per 100k individuals' below 33% fall into the 'Low' category in the 'suicide category' attribute.

Those with 'suicide rates per 100k individuals' equal to or greater than 33% but less than 66% were labeled as 'Medium'. Finally, instances with 'suicide rates per 100k individuals' equal to or greater than 66% were categorized as 'High' in the 'suicide category'. The values for the 'suicide category' attribute were meticulously calculated for all 341 instances and cross-checked multiple times by all authors to ensure accuracy and eliminate any potential errors.

Since the analysis is conducted at the provincial level, spatial proximity may induce correlations among the residuals. The incorporation of spatial considerations is crucial to account for potential spatial dependencies and patterns in the data, allowing for a more accurate and comprehensive analysis of suicide mortality across the Iranian provinces. Spatial autocorrelation analysis is a vital aspect of understanding the patterns and dynamics of suicide mortality rates across geographical regions.

To explore spatial dependencies of the 31 Iranian provinces, we employ the queen-contiguity weight matrix (18). This matrix is specifically tailored to the polygonal nature of our data and provides a comprehensive definition of neighborhood relationships. It captures spatial connectivity based on shared vertices between neighboring spatial units. In our dataset, provinces can be considered as polygonal areas with irregular shapes, and the queen-contiguity matrix efficiently captures spatial relationships between these areas. Specifically, for each province, neighboring provinces that share at least one common vertex are considered connected. This definition ensures that spatial interactions are accounted for not only through shared boundaries but also through shared vertices, providing a more complete representation of spatial relationships.

For transparency and reproducibility, we explicitly document the rationale for our methodological decisions. First, the queen-contiguity specification captures spatial interactions among provinces effectively and follows best practices in regional health research (18, 19), ensuring comparability with prior studies. Second, random forest hyperparameters were systematically optimized through repeated cross-validation—rather than arbitrarily selected—focusing on the number of trees, maximum tree depth, and minimum sample size at terminal nodes (2, 20). This process balanced predictive accuracy with the need to mitigate overfitting. Finally, during data preprocessing, spatially lagged variables derived from econometric specifications were generated and incorporated directly into the random forest training process (6, 21). This integration preserved the predictive flexibility of machine learning while explicitly modeling spatial spillover effects. By documenting these methodological choices and their rationale, we enhance the reproducibility of the study and provide a transparent roadmap for future research using similar spatial panel datasets.

In spatial econometrics, selecting the appropriate model specification is crucial, and an empirical specification test is a valuable tool for this purpose. The specificity-to-generality approach is commonly employed, starting with a basic non-spatial model and

**Table 1.** Overview of Descriptive Statistics for Dependent and Independent Variables

| Variable | Minimum | Mean | Maximum | SD | Skewness | Kurtosis |
|---|---|---|---|---|---|---|
| **X1** | 5.80 | 11.20 | 21.70 | 3.07 | 0.90 | 4.16 |
| **X2** | 32.30 | 41.38 | 50.20 | 3.62 | -0.28 | 3.01 |
| **X3** | 12.38 | 14.13 | 16.46 | 0.77 | 0.12 | 2.63 |
| **X4** | 39.20 | 139.40 | 401.00 | 97.43 | 1.18 | 3.26 |
| **X5** | 70.80 | 84.49 | 92.90 | 4.36 | -0.62 | 3.52 |
| **X6** | 10.30 | 11.77 | 14.39 | 0.85 | 0.59 | 3.23 |

testing for misspecifications arising from omitted autocorrelation. To address this issue, Anselin et al. (1996) introduced the Lagrange multiplier (LM) tests, which offer robustness against alternative sources of spatial dependence.

Spatial dependencies refer to the interdependence and interaction of observations in space, where the values of neighboring observations can influence each other. Neglecting this spatial autocorrelation can lead to biased and inefficient parameter estimates in the model. The LM test focuses on spatial autocorrelation in the residuals of a non-spatial econometric model, such as the Ordinary Least Squares (OLS) model. Its fundamental idea is to examine whether the residuals exhibit a systematic spatial pattern. A significant result in the LM test indicates that the model is mis-specified and fails to account for spatial dependencies in the data.

By conducting the LM test, we can identify the presence and extent of spatial autocorrelation. Significant spatial autocorrelation indicates that a spatial econometric model is more appropriate for the data. This implies that neighboring observations interact, so the model explicitly considers their spatial relationships. Including of geographical attributes in the model is one way to address significant and positive spatial autocorrelation.

Table 2 presents Lagrange multiplier diagnostics for spatial dependence. The Lagrange Multiplier test for error spatial dependence (LMerr) examines spatial autocorrelation in the residuals of a non-spatial econometric model. In contrast the Lagrange Multiplier test for lag spatial dependence (LMlag) focuses on spatial autocorrelation in the dependent variable. The Robust Lagrange Multiplier test for error spatial dependence (RLMerr) and the Robust Lagrange Multiplier test for lag spatial dependence (RLMlag) offer robust versions of these diagnostics, enhancing reliability in detecting spatial autocorrelation. Additionally, the Spatial Autoregressive Moving Average (SARMA) model, as discussed in Haining (2003), incorporates spatial autocorrelation, spatial heterogeneity, and spatial dependence in the modeling process. By applying these Lagrange multiplier tests, we can detect and correct spatial autocorrelation in the data, thereby ensuring the validity of our spatial econometric models (22, 23).

The test results reveal that LMerr, LMlag, and RLMerr tests show highly significant P-values (below the 0.05 significance level), indicating strong evidence of spatial autocorrelation in the residuals and the dependent variable. Additionally, RLMlag exhibits a P-value smaller than 0.05, suggesting the presence of spatial autocorrelation in the dependent variable. The SARMA model further supports the significant spatial autocorrelation in the data.

In conclusion, the LM tests are crucial in identifying spatial autocorrelation and supporting the inclusion of spatial lag terms in the econometric model. By explicitly considering spatial relationships among observations, we can ensure a more accurate and robust analysis, which is vital for understanding and addressing spatial patterns in the data.

***Estimation Methodology***

This study aims to compare the predictive accuracy of traditional spatial econometric models with random forest models for predicting suicide mortality levels in the provinces of Iran. To achieve this, we employed eight distinct model specifications: spatial lag (autoregressive) (SAR), spatially lagged **X** (SLX), spatial Durbin (SDM), random forests (RF), random forests with the spatial lag of **y** included (RFSAR), random forests with spatial lags of both **X** and **y** included (RFSDM), and random forests with only the spatial lag of **X** included (RFSLX). Each model provides distinctive insight into the relationship between spatial dependencies and suicide mortality. In the subsequent sections, we delve into the comprehensive estimation details of these models to uncover their strengths and limitations in predicting suicide mortality levels.

***Spatial Econometric Models:*** Spatial econometric models capture spatial dependence in the data-generating process, recognizing that objects in proximity exhibit stronger relationships than those farther apart, a concept known as Tobler's First Law of Geography (24). These models extend the Ordinary Least Squares (OLS) approach by incorporating a spatial weights matrix (**W**) that represents the spatial relationships between observations directly into the model estimation process

**Table 2.** Lagrange Multiplier Diagnostics for Spatial Dependence

| Test | Statistic | P-value |
|---|---|---|
| **LMerr** | 417.06 | < 2.2e-16 |
| **LMlag** | 247.38 | < 2.2e-16 |
| **RLMerr** | 176.3 | < 2.2e-16 |
| **RLMlag** | 6.6259 | 0.01005 |
| **SARMA** | 423.68 | < 2.2e-16 |

(19, 22). The placement of the spatial weights matrix in the standard linear regression equation can vary based on theoretical or data-driven considerations, resulting in different model specifications that account for spatial autocorrelation.

The most basic linear regression (OLS) specification is:

$$\mathbf{y} = \mathbf{X\beta} + \mathbf{u}. \qquad (1)$$

In this study, the dependent variable ($\boldsymbol{y}$) represents the suicide mortality rate recorded from 2011 to 2021. The independent variables ($\mathbf{X}$) encompass $\mathbf{X1}$ to $\mathbf{X6}$. The estimated regression coefficients for these variables take the notation $\boldsymbol{\beta}$, and the error term takes the notation $\mathbf{u}$.

If spatial dependence exists in the underlying data, the OLS regression coefficients will be biased and/or the error term will be enlarged; in either case, this results in an imprecise estimation of the underlying relationships between the variables.

Spatial dependence can be explicitly modeled in a variety of ways. The spatial autoregressive (SAR) or spatial lag model inserts a parameter that captures spatial autocorrelation in the dependent variable, that is,

$$\mathbf{y} = \boldsymbol{\rho}\mathbf{Wy} + \mathbf{X\beta} + \mathbf{u}, \qquad (2)$$

where $\mathbf{W}$ is a spatial weights matrix that captures the spatial neighborhood of each observation. The weight matrix represents the spatial relationships between 31 observations (provinces) over the course of 11 years, considering the proximity of each observation to the other 30 provinces. Additionally, the spatial autoregressive parameter, represented by $\boldsymbol{\rho}$, captures the influence of spatial spillover effects on the dependent variable. By incorporating $\boldsymbol{\rho}$ in the model, we can analyze how the attributes of the neighboring provinces influence the dependent variable's values and gain insights into the spatial patterns and dynamics present in the dataset.

Another approach to modeling spatial dependence is to not to incorporate spatially lagged covariates in the equation. The spatial lag specification (SLX) for $\mathbf{X}$ is defined as follows:

$$\mathbf{y} = \mathbf{X\beta} + \mathbf{WX\theta} + \mathbf{u}. \qquad (3)$$

In this model, $\boldsymbol{\theta}$ represents a vector of spatial spillover parameters. Beyond considering the direct effects of covariates, the model considers the additional influence from neighboring units' covariates, capturing the indirect spillover effects.

A noteworthy aspect of the model is its incorporation of spatial effects for each covariate, which the $\boldsymbol{\theta}$ vector encompasses. This feature enables the exploration of the spatial relationships and dependencies among the covariates, providing a comprehensive understanding of how neighboring units' characteristics contribute to the overall model dynamics.

In contrast, the Spatial Durbin Model (SDM) combines the spatial spillover specification of the covariates with the spatial autoregressive term of the dependent variable, yielding:

$$\mathbf{y} = \boldsymbol{\rho}\mathbf{Wy} + \mathbf{X\beta} + \mathbf{WX\theta} + \mathbf{u}. \qquad (4)$$

In practice, selecting the most appropriate model specification can be difficult, particularly when strong theoretical justifications are absent (25, 26). The primary objective of this paper is to assess the performance of traditional model specifications compared to random forest regressors. We evaluate the models based on prediction accuracy under two distinct testing scenarios and perform the estimation using R version 4.2.2.

***Random Forests:*** Random forests, an ensemble learning technique, stand as a formidable tool in predictive modeling, amalgamating insights from multiple decision trees to refine predictions. At its core lies the Classification and Regression Tree (CART) training algorithm, which orchestrates the intricate dance of data partitioning and criterion optimization (12).

Decision trees, the elemental units of random forests, wield the power to address classification and regression tasks. In this study, we primarily focus on predicting nominal outcomes classified as 'Low', 'Medium', and 'High'. This focus naturally directs our analysis toward classification tree methods.

CART operates as a nonlinear function, sculpting the data landscape through a series of splits aimed to minimize impurity measures such as the Gini index or entropy (27). These criteria are commonly used in classification trees to maximize the purity of the resulting subsets after each split, which is crucial for accurate classification tasks.

Random forest harnesses the wisdom of crowds, leveraging the law of large numbers to refine predictions. By assembling an ensemble of decision trees, typically around 1,000, trained on random subsets of the data with replacement, random forest mitigate overfitting and enhance generalization capacity. The amalgamation of predictions from these individual trees through averaging yields a robust final prediction (28).

To promote diversity and independence among individual predictors, random forests restrict each tree’s access to explanatory variables. By considering only a random subset of variables at each split, the classifier encourages diversity among predictors, which enhances the ensemble’s overall predictive performance (2, 12).

Random forest's versatility extends beyond its robustness to noisy data and resilience to outliers. It offers interpretability through feature importance rankings, allowing users to understand the contribution of each variable to the prediction process. Furthermore, its scalability makes it suitable for large datasets and parallel processing environments, ensuring efficient computation (28).

In our analysis, we embarked on a journey through four distinct random forest (RF) specifications to unravel the nuances of spatial factors in predictive modeling. The baseline model ("RF") mirrored the covariates utilized in the preceding spatial econometric models. Furthermore, we introduced the "RFSAR" model, which was engineered to emulate the spatial autoregressive (SAR) model by integrating the spatially lagged dependent variable. The "RFSDM" model extended its reach to encompass spatial lags of the dependent and independent variables, striving to mirror the spatial Durbin model (SDM). Lastly, the "RFSLX" model focused solely on the spatial lags of independent variables, akin to the spatial lag of the **X** model. By scrutinizing RF models through various spatial lenses, we unravel valuable insights into the intricate dance between spatial dynamics and predictive prowess, enriching our understanding and honing our predictive capabilities (15, 29, 30).

It is essential to clarify the distinction between incorporating spatiality in our random forest models and traditional spatial models. In our approach, spatially lagged variables were engineered as features and included in the RF training process to provide spatial context. This approach enables the model to indirectly capture spatial spillover effects, using the flexibility of machine learning to identify nonlinear relationships between neighboring provinces and suicide mortality rates. However, unlike conventional spatial models—such as spatial regression or spatial survival models—spatial dependence in RF is not intrinsic to the model’s theoretical formulation or computational mechanics (31). In traditional spatial models, the likelihood or covariance structure explicitly incorporates spatial relationships, modeling spatial autocorrelation as an integral part of the estimation process. In contrast, our feature-engineered approach relies on the predictive power of RF to learn from spatially informative inputs, providing a practical but conceptually distinct mechanism for incorporating spatiality into predictive modeling. This distinction highlights the complementary nature of our hybrid framework: it combines the flexibility and nonlinear modeling capabilities of random forests with explicit spatial information, without requiring a fully parametric spatial dependence structure.

Overall, when constructing the hybrid random forest models, we incorporate spatial dependence directly at the data level. Specifically, spatially lagged variables were generated using the queen-contiguity weight matrix and added as input features to the dataset before model training (18). We did not modify the random forest algorithm, and we kept the tree-splitting criteria, such as the Gini index, unchanged (3). As a result, spatial spillover effects are captured indirectly through feature selection, rather than being explicitly included in the objective function. This approach maintains the robustness and reproducibility of the original random Forest framework, while enabling the model to incorporate spatial information effectively. Researchers have successfully applied similar strategies to enrich random forest models with spatially derived features in geoscience, environmental, and climate prediction tasks (15, 16, 30, 32), which further supports the validity of this method.

## Results

In this study, we applied three spatial econometric models—SAR, SLX, and SDM—together with four data mining models—RF, RFSAR, RFSLX, and RFSDM—to classify provinces based on suicide mortality rates. These models classify outcomes into three categories: Low, Medium, and High. We applied these models to predict suicide mortality levels, categorizing each observation as Low, Medium, or High. This rigorous approach ensured a thorough assessment of the models' classification ability.

Table 3 provides a comprehensive evaluation of the models' performance across various metrics, facilitating comparison and identification of superior models in terms of accuracy, precision, sensitivity, F-score, and specificity. Notably, RFSDM emerged as the standout model based on these criteria.

**Table 3.** Performance Metrics Calculated on the Entire Dataset: A Comparative Analysis of Prediction Models for Suicide Mortality Levels

| Model | Accuracy | Precision | Sensitivity | F-score | Specificity |
|---|---|---|---|---|---|
| **SAR** | 0.3659 | 0.3750 | 0.2727 | 0.3158 | 0.4737 |
| **SLX** | 0.4651 | 0.4500 | 0.4286 | 0.4390 | 0.5000 |
| **SDM** | 0.4651 | 0.4211 | 0.4000 | 0.4103 | 0.5217 |
| **RF** | 0.2703 | 0.0769 | 0.4000 | 0.1290 | 0.2500 |
| **RFSAR** | 0.8250 | 0.4615 | 1 | 0.6316 | 0.7941 |
| **RFSLX** | 0.8684 | 0.4444 | 1 | 0.6154 | 0.8529 |
| **RFSDM** | 0.8919 | 0.4286 | 1 | 0.6000 | 0.8824 |

Accuracy measures the overall correctness of the model's predictions, calculated as the ratio of correctly predicted instances to the total number of cases. For example, the RFSLX model achieved an accuracy of 0.8684, indicating it correctly predicted 86.84% of cases.

Precision assesses the proportion of accurate optimistic predictions out of all optimistic predictions made by the model. Higher precision values signify fewer false positives. The RFSDM model demonstrated a precision of 0.4286, indicating 42.86% of predicted positive instances were true positives.

Sensitivity, also known as recall or actual accurate rate, measures the proportion of accurate optimistic predictions from all actual positive instances, indicating how well the model identifies positive instances. The RFSAR model displayed a sensitivity of 1, accurately identifying all positive instances.

The F-score, the harmonic mean of precision and sensitivity, evaluates the balance between these metrics. A higher F-score indicates better performance in handling false positives and false negatives. For instance, the RFSAR model achieved an F-score of 0.6316, indicating balanced performance.

Specificity measures the proportion of accurate pessimistic predictions from all actual negative instances, indicating how well the model identifies negative instances. Higher specificity values suggest fewer false positives. For example, the RFSDM model demonstrated specificity values of 0.8824, correctly identifying 88.24% of negative cases.

In summary, these performance metrics, calculated on the entire dataset, provide valuable insights into the predictive capabilities of each model, aiding in informed decision-making and model selection for predicting suicide mortality levels.

The confusion matrix and the out-of-bag (OOB) error plot are pivotal evaluation tools for assessing the performance of a random forest model in classification tasks. While the confusion matrix provides a detailed breakdown of the model's predictions for each class, aiding in assessing accuracy, precision, sensitivity, specificity, and other metrics, the OOB error plot visualizes the OOB error rate. This rate, estimating the model's prediction error on unseen data, is plotted against the number of trees in the random forests. This allows us to gauge the model's overall performance and identify the optimal number of trees. In Figure 1, the x-axis represents the number of trees, and the y-axis represents the OOB error rate, which exhibits a notable decrease with an increasing number of trees.

However, the OOB error rate eventually stabilizes, around 0.09 or 9% after approximately 30 trees, indicating diminishing returns beyond this point. Thus, the OOB error plot assists in determining the optimal number of trees for our random forest model (RFSDM), striking a balance between capturing patterns and avoiding overfitting.

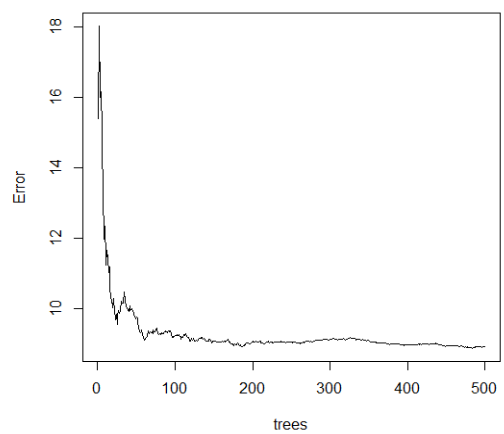

**Figure 1.** Out-of-Bag (OOB) Error Rate Trend for RFSDM.

By selecting an appropriate number of trees, typically around 30 in our case, we ensure that our RFSDM model performs well on unseen data while minimizing computational complexity. In conclusion, analyzing the OOB error rate trend provides useful insights into model performance and supports more informed research decisions.

Table 4 displays the confusion matrices for the six models utilized in this study to forecast suicide mortality levels categorized as Low, Medium, and High. The evaluation of each model’s performance compares its predicted outcomes with the actual observations.

The table delineates the instances classified into each level for the corresponding model's predictions, along with the total counts of correct and incorrect predictions made by each model. The analysis examines the SAR, SLX, SDM, RF, RFSAR, RFSLX, and RFSDM models and carefully documents their correct and incorrect predictions. These confusion matrices provide invaluable insights into the efficacy of each model, facilitating an assessment of their accuracy and error rates.

Upon comparison of these models' performance, it is evident that RFSDM surpasses the others in predicting suicide mortality levels, demonstrating superior accuracy and overall predictive performance. Specifically, the model correctly predicts 92 instances: 30 in the Low category, 29 in the Medium category, and 33 in the High category. However, it erroneously predicts 12 cases across all levels.

Table 5 illustrates the cross-tabulation of the RFSDM Model's predictions with the actual suicide mortality levels within the dataset. The table cells contain various

**Table 4.** Confusion Matrix using the Seven Models

| Model | Level | Low | Medium | High | Correct | Incorrect |
|---|---|---|---|---|---|---|
| **SAR** | Low | 9 | 6 | 13 | 33 | 71 |
| | Medium | 10 | 15 | 12 | | |
| | High | 16 | 14 | 9 | | |
| **SLX** | Low | 11 | 9 | 9 | 36 | 68 |
| | Medium | 11 | 11 | 12 | | |
| | High | 12 | 15 | 14 | | |
| **SDM** | Low | 12 | 8 | 9 | 37 | 67 |
| | Medium | 11 | 11 | 12 | | |
| | High | 12 | 15 | 14 | | |
| **RF** | Low | 8 | 2 | 0 | 56 | 48 |
| | Medium | 24 | 25 | 12 | | |
| | High | 3 | 8 | 23 | | |
| **RFSAR** | Low | 27 | 6 | 0 | 86 | 18 |
| | Medium | 7 | 26 | 2 | | |
| | High | 0 | 3 | 33 | | |
| **RFSLX** | Low | 29 | 4 | 0 | 90 | 14 |
| | Medium | 5 | 28 | 2 | | |
| | High | 0 | 3 | 33 | | |
| **RFSDM** | Low | 30 | 3 | 0 | 92 | 12 |
| | Medium | 4 | 29 | 2 | | |
| | High | 0 | 3 | 33 | | |

**Table 5.** Confusion Matrix: Predicted vs. Suicide Mortality Levels

| Categories | Low | Medium | High | Row Total |
|---|---|---|---|---|
| | 30 | 3 | 0 | |
| | 34.211 | 5.916 | 11.106 | 33 |
| **Low** | 0.909 | 0.091 | 0.000 | |
| | 0.882 | 0.086 | 0.000 | 0.317 |
| | 0.288 | 0.029 | 0.000 | |
| | 4 | 29 | 2 | 35 |
| | 4.841 | 25.178 | 8.118 | |
| **Medium** | 0.114 | 0.829 | 0.057 | 0.337 |
| | 0.118 | 0.829 | 0.057 | |
| | 0.038 | 0.279 | 0.019 | |
| | 0 | 3 | 33 | |
| | 11.769 | 6.858 | 36.001 | 36 |
| **High** | 0.000 | 0.083 | 0.917 | |
| | 0.000 | 0.086 | 0.943 | 0.346 |
| | 0.000 | 0.029 | 0.317 | |
| **Column Total** | 34 | 35 | 35 | 104 |
| | 0.327 | 0.337 | 0.337 | |

information, including the number of observations (N), the Chi-square contribution, the proportion of observations relative to the row total (N / Row Total), the proportion of observations relative to the column total (N / Col Total), and the proportion of observations relative to the overall total (N / Table Total).

The cross table encompasses a total of 104 observations from the dataset. It is important to emphasize that these 104 instances constitute a comprehensive evaluation of the model's performance across all categories and provinces, ensuring a thorough assessment of the predictive accuracy and effectiveness of the random forest models in predicting suicide mortality levels in the Iranian provinces. The cross table is structured with rows representing the predicted suicide mortality levels by the model and columns denoting the actual suicide mortality levels. Additionally, the rightmost column showcases the row totals, indicating the total number of observations for each predicted suicide mortality level. Furthermore, the bottom row provides the column totals, representing the cumulative number of observations for each suicide mortality level.

To interpret the table, we scrutinize the values within each cell. For example, in the first row, the model predicts 30 instances as Low, three as Medium, and none as High. The row total, up to 33, signifies the total number of predictions made for the Low category.

The Chi-square contribution values in Table 5 reflect each cell's impact on the overall Chi-square statistic, a metric assessing the model's goodness of fit. This measure evaluates how well the model fits the data when predicting suicide mortality levels across the categories of Low, Medium, and High.

These values indicate how much each cell contributes to the overall Chi-square statistic, which measures the discrepancy between the observed and expected frequencies in the data.

Similarly, we can interpret the other rows and columns to gauge the model's performance in predicting suicide mortality levels. Overall, the table furnishes invaluable insights into the model's accuracy and predictive prowess, revealing the degree of alignment between the model's predictions and the actual data.

***Conclusion***

In this study, we advanced the predictive modeling of suicide mortality across Iranian provinces by comparing traditional spatial econometric models (SAR, SLX, and SDM) with random forest–based methods. We also introduced a hybrid framework that integrates spatially lagged features into random forests. This framework combines the strengths of both approaches: the predictive accuracy of random forests in capturing complex nonlinear interactions among covariates (2, 12) and the interpretability of spatial econometric models in uncovering structured spatial dependencies and spillover effects (21, 33). The strong performance of the RFSDM model shows that embedding spatial information into machine learning improves prediction accuracy while preserving interpretability that supports evidence-based decision-making (15, 32).

Our findings extend the literature on suicide prediction by demonstrating the value of spatially informed machine learning. While earlier studies focused mainly on socio-demographic and environmental correlates of suicide (34, 35, 36), our hybrid approach uncovers additional spatial patterns and risk structures that remain hidden in purely econometric models (22) or non-spatial machine learning models (28). These findings underscore the importance of incorporating spatial context into predictive modeling, especially when neighboring regions influence outcomes.

The practical implications for public health policy are substantial. By accurately identifying high-risk provinces and anticipating spatial spillovers in suicide risk, policymakers can allocate mental health resources more efficiently and design targeted, region-specific prevention strategies. The hybrid framework serves as a decision-support tool by predicting suicide risk and guiding intervention planning, thereby enhancing the effectiveness of evidence-based prevention programs in Iran and potentially in other regions (World Health Organization, 2021; 37).

Despite these contributions, the study has several limitations. Aggregating data at the provincial level may obscure intra-provincial variability, and the choice and availability of predictor variables may influence model performance. Additionally, temporal dynamics were not explicitly incorporated in the current analysis. Future research should explore richer covariates, test alternative spatial machine learning algorithms, integrate dynamic spatial models, and extend the framework to other health outcomes (7, 30). Addressing these avenues will refine spatially explicit predictive modeling and enhance its applicability for public health decision-making.

In summary, this study makes three key contributions: (i) development of a hybrid RF–spatial econometric framework that balances predictive accuracy and interpretability; (ii) demonstration that incorporating spatial lags into machine learning substantially improves suicide risk prediction; and (iii) provision of actionable insights for public health policy, enabling targeted, data-driven suicide prevention strategies. These contributions highlight the value of combining traditional spatial modeling with modern machine learning approaches for health outcomes research.

***Funding***

No funding sources supported our research.

***Conflicts of Interest***

We declare no potential conflicts of interest or competing interests related to the research.

## References

1. Openshaw S, Openshaw C. Artificial intelligence in geography. New York (NY): John Wiley & Sons Inc; 1997.
2. Breiman L. Random forests. Mach Learn. 2001;45:5-32.
3. Breiman L. Statistical modeling: the two cultures. Stat Sci. 2001;16:199-231.
4. Shojaei A, Moradi S, Alaeddini F, Khodadoost M, Barzegar A, Khademi A. Association between suicide method and gender, age, and education level in Iran over 2006–2010. Asia Pac Psychiatry. 2014;6:18-22.
5. Khademi AMS. Statistical investigation of unnatural deaths in Iran (2001–2010). Tehran: Forensic Medicine Organization; 2012.
6. Rey S. Geographical analysis: reflections of a recovering editor. Geogr Anal. 2019;1-9. doi:10.1111/gean.12193.
7. Singleton A, Arribas-Bel D. Geographic data science. Geogr Anal. 2019;1-15. doi:10.1111/gean.12194.

8. Adin A, Retegui G, Villegas AS, Ugarte MD. Suicide Mortality in Spain (2010-2022): Temporal Trends, Spatial Patterns, and Risk Factors. arXiv preprint arXiv:2509.01342. 2025.
9. Al-Remawi M, Agha ASA, Al-Akayleh F, Aburub F, Abdel-Rahem RA. Artificial intelligence and machine learning techniques for suicide prediction: Integrating dietary patterns and environmental contaminants. Heliyon. 2024;10(24).
10. Ehtemam H, Sadeghi Esfahlani S, Sanaei A, Ghaemi MM, Hajesmaeel-Gohari S, Rahimisadegh R, et al. Role of machine learning algorithms in suicide risk prediction: a systematic review and meta-analysis of clinical studies. BMC Med Inform Decis Mak. 2024;24(1):138.
11. Prateek J. Artificial intelligence with Python: a comprehensive guide to building intelligent apps for Python beginners and developers. Birmingham (UK): Packt Publishing; 2017. p. 49-67.
12. Géron A. Hands-on machine learning with Scikit-Learn & TensorFlow: concepts, tools, and techniques to build intelligent systems. Boston (MA): O'Reilly Media; 2017. p. 3-224.
13. Janowicz K, Gao S, McKenzie G, Hu Y, Bhaduri B. GeoAI: spatially explicit artificial intelligence techniques for geographic knowledge discovery and beyond. Int J Geogr Inf Sci. 2019;34:625-36. doi:10.1080/13658816.2019.1684500.
14. Credit K. Transitive properties: a spatial econometric analysis of new business creation around transit. Spatial Econ Anal. 2019;14:26-52.
15. Hengl T, Nussbaum M, Wright MN, Heuvelink GBM, Gräler B. Random forests as a generic framework for predictive modeling of spatial and spatio-temporal variables. PeerJ. 2018;6:e5518. doi:10.7717/peerj.5518.
16. Georganos S, Grippa T, Gadiaga N, Linard C, Lennert M, Vanhuysse S, et al. Geographical random forests: a spatial extension to the random forests algorithm to address spatial heterogeneity in remote sensing and population modeling. Geocarto Int. 2019. doi:10.1080/10106049.2019.1595177.
17. Yan B, Janowicz K, Mai G, Zhu R. A spatially explicit reinforcement learning model for geographic knowledge graph summarization. Trans GIS. 2019;29:620-40.
18. Farzammehr MA, Moradi S. Classical and spatial cluster analysis of smuggling in Iranian provinces. Reg Sci Policy Pract. 2022;16(2):12609.
19. Anselin L. Spatial econometrics: methods and models. Dordrecht: Kluwer Academic Publishers; 1988. p. 169-79.
20. Probst P, Wright MN, Boulesteix AL. Hyperparameters and tuning strategies for random forest. Wiley Interdisciplinary Reviews: data mining and knowledge discovery. 2019 May;9(3):e1301.
21. Elhorst JP. Spatial econometrics: from cross-sectional data to spatial panels. Heidelberg: Springer; 2014 Jan 16.
22. LeSage JP, Pace RK. Introduction to spatial econometrics. New York (NY): CRC Press; 2009. p. 25-75.
23. Haining RP. Spatial data analysis: theory and practice. Cambridge university press; 2003 Apr 17.
24. Tobler WR. A computer movie simulating urban growth in the Detroit region. Econ Geogr. 1970;46:234-40.
25. Anselin L, Rey S. Modern spatial econometrics in practice. Chicago (IL): GeoDa Press LLC; 2014. p. 1-43.
26. LeSage JP. Spatial econometric panel data model specification: a Bayesian approach. Spatial Stat. 2014;9:122-45.
27. Krzywinski M, Altman N. Classification and regression trees. Nat Methods. 2017;14:757-8.
28. Fox EW, Ver Hoef JM, Ohlen AR. Comparing spatial regression to random forests for large environmental data sets. PLoS One. 2020;15(3):e0229509.
29. Lagomarsino D, Tofani V, Segoni S, Catani F, Casagli N. A tool for classification and regression using random forest methodology: applications to landslide susceptibility mapping and soil thickness modeling. Environ Model Assess. 2017;22:201-14.
30. Talebi H, Peeters LJ, Otto A, Tolosana-Delgado R. A truly spatial random forests algorithm for geoscience data analysis and modelling. Math Geosci. 2022;54(1):1-22.
31. Madadi M, Motarjem K. Survival data analysis using statistical learning methods. J Stat Sci. 2025;18(2).
32. Wang Y, Yin Y, Gao B, Zeng Y, Zhao Y, Chen Z, et al. A novel spatial prediction method integrating Exploratory Spatial Data Analysis into Random Forest for large-scale daily air temperature mapping. IEEE Trans Geosci Remote Sens. 2025.
33. Anselin L, Bera AK, Florax R, Yoon MJ. Simple diagnostic tests for spatial dependence. Reg Sci Urban Econ. 1996;26:77-104. doi:10.1016/0166-0462(95)02111-6.
34. Nock MK, Borges G, Bromet EJ, Cha CB, Kessler RC, Lee S. Suicide and suicidal behavior. Epidemiologic reviews. 2008 Jul 24;30(1):133.
35. Bilsen J. Suicide and youth: risk factors. Frontiers in psychiatry. 2018 Oct 30;9:540.
36. Credit K. Spatial models or random forests? Evaluating spatially explicit machine learning methods to predict employment density around new transit stations in Los Angeles. Geogr Anal. 2022;54:58-83.
37. Stack S. Contributing factors to suicide: Political, social, cultural and economic. Preventive medicine. 2021 Nov 1;152:106498.