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Performance of a Five-Layer ANN Model for Earthquake Magnitude Prediction and Spatial Risk Mapping in Turkey

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ABSTRACT

Turkey faces significant seismic risks, necessitating accurate earthquake forecasting for effective disaster preparedness. This study employs advanced Artificial Neural Networks (ANN) to predict earthquake magnitudes and assess risks specific to Turkey. Focusing on a distinct segment of the USGS earthquake catalogue from January 2014 to August 2023, the research tailors ANN algorithms with five layers to Turkey's seismic challenges. Rigorous dataset cleaning and processing ensure accuracy, with the ANN model demonstrating exceptional alignment with earthquake data (RMSE: 0.078, R2: 0.89). Comparative evaluations highlight the effectiveness of ANN models in forecasting earthquake magnitudes in Turkey. The study explores the spatial distribution of earthquake risk across Turkey through an ANN-based map, emphasizing the critical window for preventive measures in this seismically active region. The analysis ensures further enhancement of model accuracy in seismic-prone areas globally. This study advances earthquake prediction by showcasing the high accuracy of our five-layer ANN model in forecasting magnitudes and spatial risk, significantly improving disaster preparedness and risk management in regions such as Turkey.

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1. Introduction

Earthquakes stemming from Earth's dynamic geological processes are inescapable (Fig. 1). The perpetual movement and interaction of tectonic plates result in the release of seismic energy, giving rise to earthquakes. Instead of attempting the impossible feat of preventing these events, our focus should pivot toward preparedness and prediction. By leveraging geological knowledge, insights from seismology, and cutting-edge technology, we gain the capacity to foresee earthquakes and mitigate their impact. Acknowledging their inevitability is foundational in safeguarding lives and property.

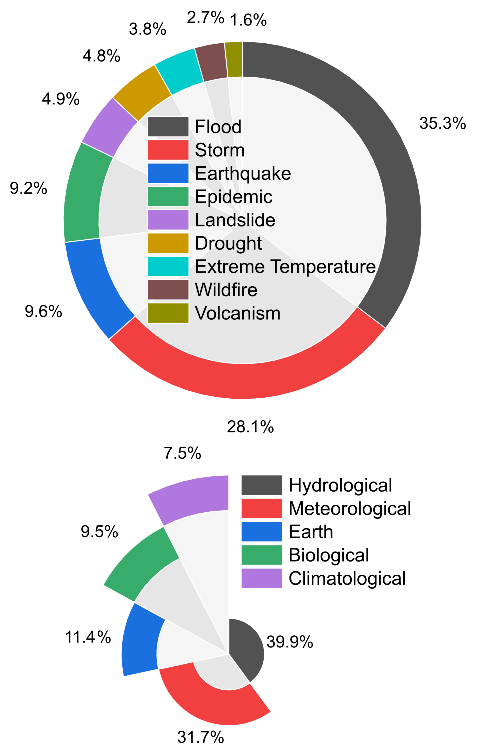


Fig. 1. Global distribution of earthquakes among various types of disasters.

Turkey grapples with the harsh reality of earthquakes, enduring consequences that extend well beyond initial tremors. Loss of life, crumbling infrastructure, and economic setbacks punctuate the aftermath of these events. This harsh reality underscores an urgent need for enhanced understanding, prediction capabilities, and effective mitigation strategies. Situated in a seismically active region, Turkey is particularly vulnerable to earthquakes of varying severity. The historical record accentuates the imperative for robust prediction methods, including events like the 2011 Van earthquake and the catastrophic 2023 Turkey-Syria earthquakes. Analyzing past events provides valuable insights, offering a glimpse into potential risks faced by communities and infrastructure throughout the country. Turkey's geographical location, positioned at the convergence of several active tectonic plates, amplifies its susceptibility to earthquakes, further emphasizing the critical importance of predictive strategies and preparedness measures.

Conventionally, earthquake prediction has leaned on statistical and physical models, serving as the cornerstone of our comprehension of seismic activity. Nevertheless, these traditional approaches encounter growing hurdles in comprehending intricate relationships within seismic data and adjusting to dynamic datasets. The intricacies embedded in seismic information frequently exceed the capacities of conventional models, imposing constraints on precise forecasting. The introduction of artificial intelligence (AI), mainly through machine learning (ML) and specialized algorithms like Artificial Neural Networks (ANNs), presents a transformative solution to the shortcomings of traditional earthquake prediction methods (Wang et al. [1]). ANNs, inspired by the human brain, distinguish themselves through their remarkable capacity to learn and adapt from extensive datasets. This adaptability makes them well-suited to address the dynamic nature of earthquake data, providing a powerful tool for accurate predictions. Comparative evaluations consistently highlight the exceptional performance of ANN models, showcasing their potential to mitigate earthquake risk more effectively than traditional approaches. By harnessing the learning capabilities of ANNs and their adeptness at handling vast datasets, these models usher in a new era of precision in earthquake magnitude forecasts. Numerous studies substantiate the superior performance of ANNs in magnitude estimation and location forecasting, underscoring their significance. This shift towards AI-driven earthquake prediction signifies a paradigm change, promising more accurate risk assessments and developing proactive disaster preparedness strategies.

Current earthquake prediction technologies, such as seismic early warning systems and statistical models, face limitations in terms of accuracy and real-time applicability. These limitations underscore the need for advanced predictive models like the one proposed in this study, which leverages artificial neural networks to improve forecasting precision. This study is dedicated to enhancing earthquake prediction and reinforcing resilience against these inevitable natural events, recognizing the imminent threat posed by earthquakes. At its core, the primary goal is the application of advanced AI and machine learning techniques, specifically focusing on utilizing three distinctive ANN models. ANNs, which are sophisticated machine learning algorithms, are characterized by intricate networks of interconnected neurons designed to execute complex computations collaboratively. In this study, three unique neural network architectures were crafted, each employing one of three optimizers—RMSprop, Adam, and Stochastic Gradient Descent (SGD)—all structured with five layers. In addition to earthquake prediction, a crucial component of our methodology involves the development of an ANN-based map for assessing high-risk regions for earthquake magnitudes in Turkey. This comprehensive approach underscores our commitment to advancing earthquake prediction methodologies, emphasizing the significance of harnessing diverse ANN architectures and optimizers for robust and accurate forecasting while contributing to the spatial understanding of earthquake risk across the region.

2. Literature Review

In recent years, seismic prediction methodologies have significantly transformed by adopting AI-driven approaches that leverage data analysis and pattern recognition [2]. These methods, particularly ML models, stand out for their ability to process diverse datasets, including real-time information from seismic and environmental sensors. This data-driven approach enhances the accuracy and timeliness of earthquake predictions, treating them as regression problems to glean insights into both occurrence and magnitude.

Pioneering work by Asim et al. [3] exemplifies the strides made in earthquake magnitude prediction. Employing four ML techniques, they focused on the Hindukush region, achieving notable progress and underscoring the potential of ML in seismic forecasting. Shifting the focus to Cyprus, Asim et al. [4] conducted seismicity analysis using ML methods, with Random Forests excelling at lower thresholds and Support Vector Machines demonstrating versatility across scenarios. In northern Pakistan, Aslam et al. [5] identified seismic hotspots, achieving a 69% positive predictive value for earthquakes with $M \geq 4$, contributing to the development of advanced predictive models. Expanding on this, Aslam et al. [6] utilized seismic features in an SVR-HNN classification system for improved forecasting in the Hindukush region for higher magnitude earthquakes ($M \geq 5.5$). Khalil et al. [7] extended this progress by developing an earthquake prediction model for Baluchistan, Pakistan, achieving an impressive 81.2% prediction accuracy and offering insights for urban planning and disaster mitigation. Recent research has emphasized spatiotemporal correlations and data-driven approaches to enhance prediction accuracy and early warning capabilities. Berhich et al. [8] introduced an attention-based LSTM network for significant earthquake prediction, surpassing other scenarios. Abebe et al. [9] employed a transformer algorithm in the Horn of Africa, outperforming traditional LSTM models. Zhang et al. [10] proposed EPT, a data-driven transformer model enhancing prediction accuracy by 50%. Additionally, Bhatia et al. [11] introduced an IoT-Edge-centered framework with enhanced performance and reduced computational delay. Together, these diverse methodologies contribute to the ongoing evolution of earthquake prediction, promising more accurate and timely forecasts.

Adopting a comprehensive approach, this study systematically examines the strengths and weaknesses inherent in various earthquake prediction models. By delving into the intricate landscape of seismic data, the research aims to unravel complex patterns, temporal dependencies, and non-linear relationships embedded within. Utilizing a diverse dataset encompassing continuous variables like latitude, longitude, earthquake magnitude, depth, error metrics, and discrete variables such as magnitude types and location sources ensures a thorough investigation into earthquake prediction methodologies. The specific focus on Turkey, a region particularly prone to seismic activity, underscores the targeted nature of the study, providing valuable insights into earthquake prediction methods in high-risk areas. Through a rigorous assessment that employs well-established regression metrics, the study robustly evaluates the performance of various models, enabling meaningful comparisons with baseline methods.

3. Methodology

The methodology implemented in this study is meticulously crafted to establish and enhance a robust earthquake forecasting approach by utilizing ANN algorithms. The foundational step involved the extensive collection and processing of earthquake data spanning a decade, from January 2014 to August 2023, sourced from the United States Geological Survey (USGS) (Fig. 2). The dataset encompasses critical parameters such as earthquake magnitude, magnitude types, magnitude error, magnitude stations, minimum distance, gap, root mean square, depth, depth error, latitude, longitude, and location source. These parameters play a pivotal role in delineating seismicity and predicting earthquake magnitudes. A stringent process of data cleaning and handling missing values was systematically executed to ensure the precision and reliability of the results. The computational aspect of the research was

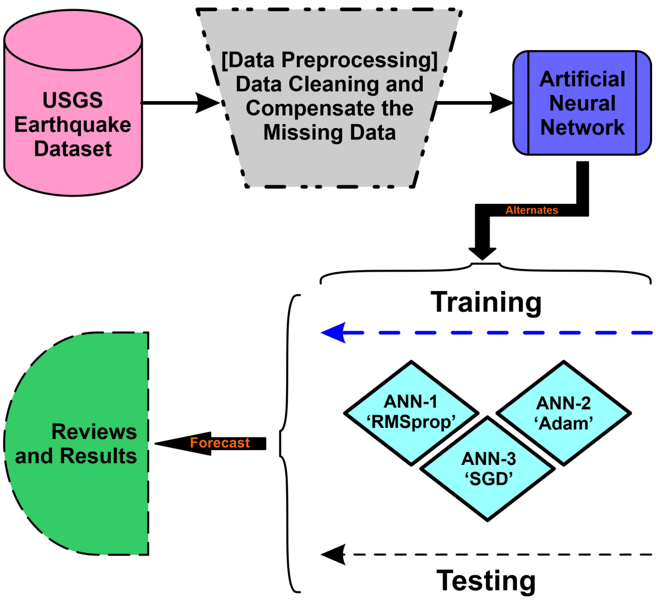


Fig. 2. Flowchart of proposed methodology

conducted on a macOS-operated computer equipped with an Apple M1 chip, 8GB of unified memory, an 8-core CPU, a 7-core GPU, and a 16-core neural engine. The implementation language chosen was Python 3.8.8, in conjunction with the Jupyter Notebook, and the proposed models were developed using Python libraries, namely Scikit-learn (Pedregosa et al. [12]), TensorFlow (Abadi et al. [13]), and Keras (Chollet [14]).

An additional preprocessing step was introduced for the ANN models using the StandardScaler technique (Pedregosa et al. [12]) to scale the data, ensuring it maintains a mean of zero and unit variance. This scaling process is imperative to optimize the data for effective training of ANN models, thereby augmenting their overall robustness and performance. Addressing missing or NaN values involved utilizing the widely adopted median imputation technique. This approach entails substituting missing values with the median values of the elements in close proximity within the dataset. The choice of median imputation proves advantageous due to its robustness as a measure of central tendency, especially when dealing with skewed data distributions or the presence of outliers. This

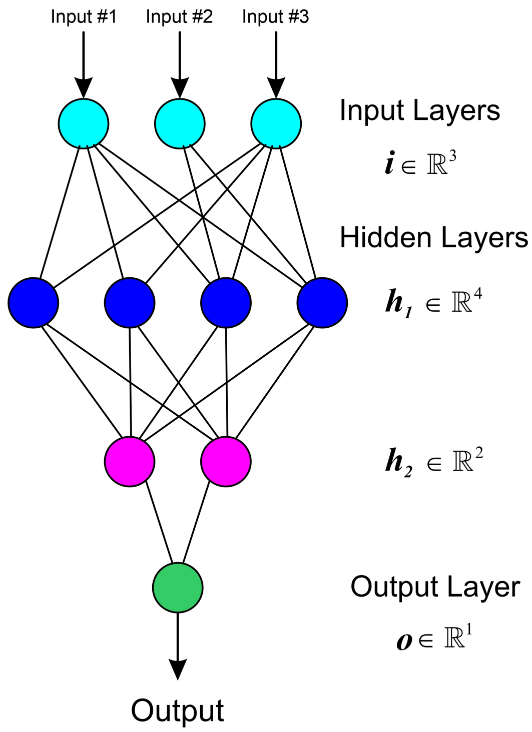


Fig. 3. Architecture of ANN Model

study designed three neural network architectures, each employing one of three optimizers: RMSprop, Adam, and Stochastic Gradient Descent (SGD). These models consist of five layers, following configurations from prior research (Chollet [14]; Abadi et al. [13]). The initial layer comprises 12 neurons dedicated to a unique dataset parameter. Subsequently, layers with 32, 16, 8, and 4 neurons are introduced, each adding non-linearity with the Rectified Linear Unit (ReLU) activation function. The output layer features a single neuron, producing the final result (Fig. 3). Each model employs a distinct optimizer—RMSprop, Adam, or SGD—for training. We chose RMSprop, Adam, and SGD as optimizers for their distinct advantages. RMSprop and Adam are known for their adaptive learning rate capabilities, which enhance convergence speed and stability. SGD provides a baseline for comparison.

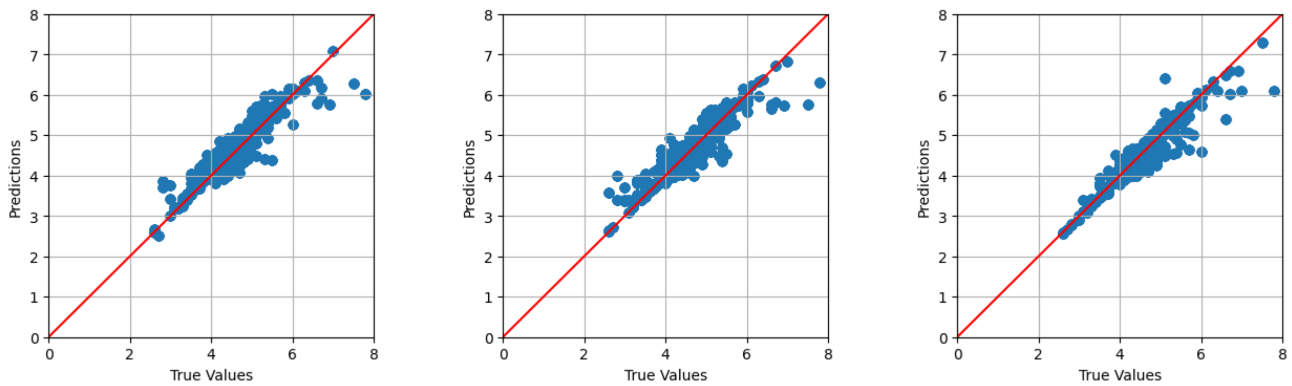
Three ANNs were trained and evaluated using the processed data to identify the most effective approach. The dataset was divided into training and testing sets, with a 75% split for training and a 25% split for testing in the ANN models. This division allowed the models to comprehensively grasp the intricate relationships between input parameters and earthquake risk during training. Conversely, the testing set assessed their performance through various metrics. A noteworthy aspect of the models is their design to accommodate continuous and discrete-valued parameters, enabling them to capture complex interactions among input variables and accurately predict earthquake magnitudes.

4. Results

The training process for the three ANN models, namely ANN-1, ANN-2, and ANN-3, comprised 1000 iterations with continuous monitoring of the loss function (MAE) and the evaluation metric (MSE). After training, ANN-1 exhibited commendable performance metrics, including an MAE of 0.1316, MSE of 0.0897, RMSE of 0.0897, R2 of 0.8753, and NRMSLE of 0.177 (TABLE 1). The close correspondence between MAE and MSE values for the training sets post-1000 iterations suggested that ANN-1 struck a balance, avoiding overfitting and underfitting. Fig. 4a visually represents the accuracy of ANN-1, showcasing the alignment of data points along the x=y line, illustrating the model's learning process and evolution to minimize loss while aligning with actual data.

Table 1
Performance Metrics for ANN Models

ANN Model	ANN-1	ANN-2	ANN-3
Optimizer	RMSprop	Adam	SGD
MSE	0.0211	0.0210	0.0182
R2	0.8753	0.8762	0.8928
RMSE	0.0897	0.0781	0.0785
MAE	0.0897	0.0781	0.0785
NRMSLE	0.0202	0.0177	0.0175



(a) ANN 1 **(b)** ANN 2 **(c)** ANN 3

Fig. 4. Prediction Performance of ANN Models

ANN-2 consistently demonstrated synchronization between loss values (MAE and MSE) during training and validation, indicating adept handling of overfitting and underfitting. Similar to ANN-1, ANN-2 exhibited performance metrics—RMSE, R2, and MAE—closely aligned with those of ANN-1 (TABLE 1). Fig. 4b visually emphasizes the precision of ANN-2, with data points aligning closely with the x=y line, signifying accuracy. For ANN-3, an exhaustive training process of 100 iterations was undertaken, with careful monitoring of the evolution of loss (MAE) and metric (MSE) values. Post-training, ANN-3 achieved a final MAE value of 0.1961 and an MSE value of 0.0785. Additional performance metrics for ANN-3 included an RMSE value of 0.0785, an R2 value of 0.8928, and an NRMSLE of 0.175

(Table 1). These metrics reaffirmed ANN-3's effective balancing of overfitting and underfitting, evident in the alignment between loss and metric values for training and validation data. Fig. 4c illustrates the performance of ANN-3 within the dataset, showcasing data points closely tracing the x=y line, indicating high accuracy.

The comprehensive evaluation of all three ANN models (ANN-1, ANN-2, and ANN-3) incorporated a range of updated performance metrics. ANN-1 displayed good accuracy during testing, with an MAE of 0.1316 and a small prediction error (MSE of 0.0897). Building upon this, ANN-2 demonstrated improved accuracy with an MAE of 0.1254 and a lower MSE of 0.0781. While ANN-3 showed slightly lower accuracy with an MAE of 0.1961 and an MSE of 0.0785, it maintained moderate accuracy. All models exhibited excellent fits to the data, as indicated by high R2 values, showcasing their ability to explain variance in earthquake magnitude data. The precision of our models was further highlighted by NRMSLE, with ANN-1 achieving a value of 0.177, emphasizing its high accuracy. ANN-2 surpassed this with a lower NRMSLE of 0.177, and although ANN-3 had a slightly higher NRMSLE of 0.175, it still indicated relatively accurate forecasts. Collectively, all three ANN models performed well in predicting earthquake magnitudes.

5. Mapping for Turkey Based on ANN-driven Magnitude

In testing the earthquake forecasting capabilities for Turkey, our artificial intelligence models, particularly ANN1 and ANN3, have exhibited compatibility with seismic events occurring along active fault zones. The shared areas highlighted in Fig. 5, where the error margin is minimal, are primarily situated in the Eastern Mediterranean, the northwest part of Marmara, and western Central Anatolia. The performance maps provide insights into the accuracy of AI-oriented earthquake forecasts for Turkey. The regions in Central Anatolia, northwest Marmara, and the Eastern Mediterranean, where the models demonstrate lower error rates, align with areas known for relative tectonic activity.

However, moderate to high error values are observed in some regions, prompting a more in-depth analysis. The moderate to high error values, as depicted in Fig. 5, can be attributed to various factors. One key consideration is the relative tectonic activity of geological structures in these regions. Additionally, areas undergoing aseismic movements or exhibiting seismic gaps can contribute to the observed error rates. Recognizing that the known tectonic activity and the potential existence of unmapped faults or yet-to-be-discovered fault lines impact the forecast accuracy is crucial.

6. Discussion

This study addresses key gaps in the current research on earthquake prediction, specifically the challenge of integrating spatial risk mapping with magnitude prediction. By utilizing a five-layer ANN model, this research provides a novel approach that enhances both prediction accuracy and spatial risk assessment. The results and high-risk area mapping derived from the ANN models for earthquake magnitude prediction in Turkey showcase promising advancements in seismic forecasting. Each ANN model, namely ANN-1, ANN-2, and ANN-3, demonstrated commendable accuracy, effectively balancing overfitting and underfitting. The evaluation metrics, including MAE, MSE, R2, RMSE, and NRMSLE, provided a comprehensive assessment of the models' performance. The spatial analysis through ANN-driven maps revealed areas of low error margins aligning with known tectonically active regions, emphasizing the models' proficiency. This precision holds promise for emergency response agencies, policymakers, and urban planners, offering a valuable tool for informed decision-making and resource allocation. Disaster response managers can utilize the high-risk area maps generated by the ANN models to prioritize and customize their strategies. Regions with consistently low error rates, such as

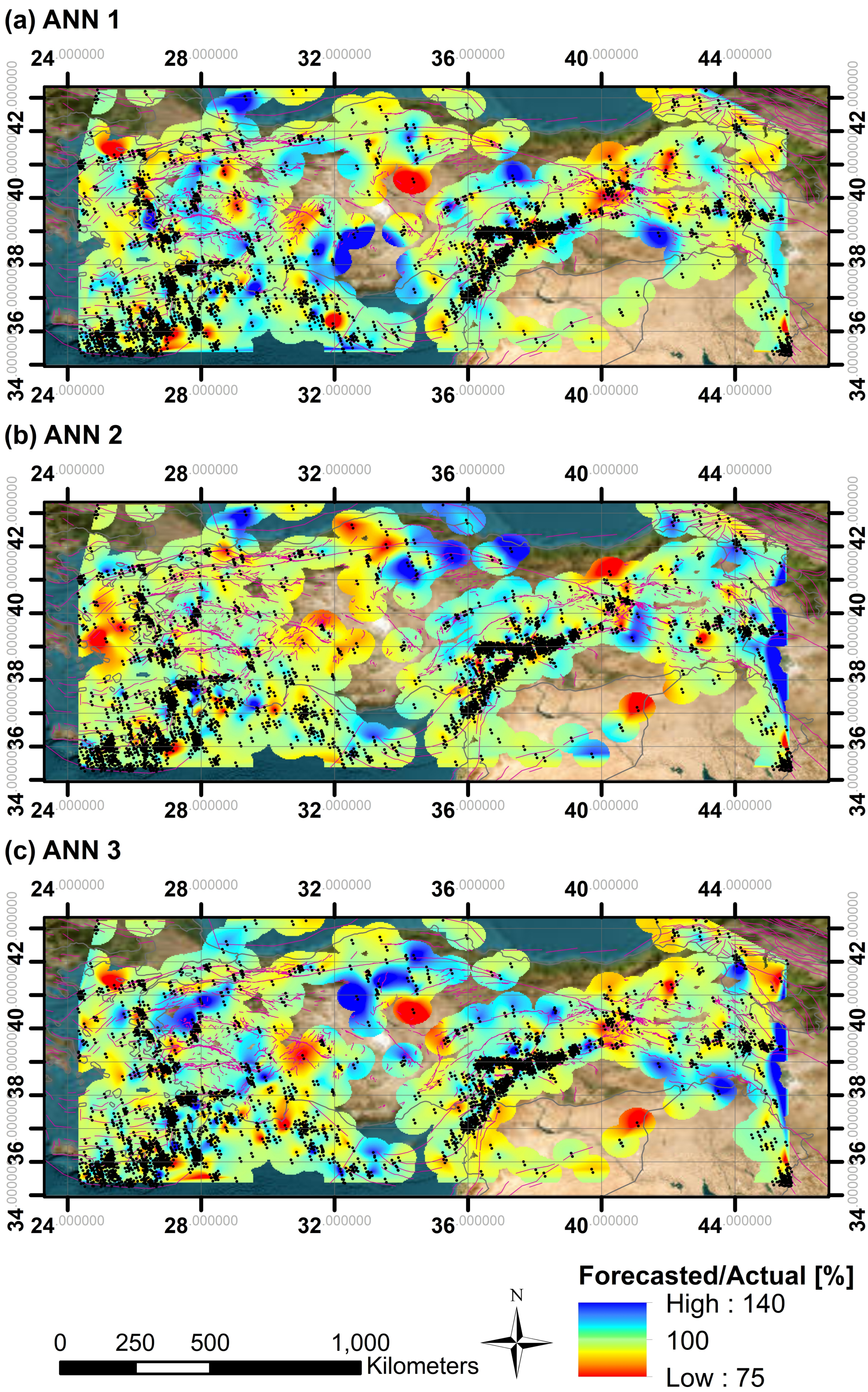


Fig. 5. **ANN-derived maps depicting the performance of earthquake magnitude predictions in Turkey.**

the Eastern Mediterranean, northwest Marmara, and western Central Anatolia, can be earmarked for focused resource allocation, including efforts to enhance infrastructure resilience, implement early warning systems, and bolster community preparedness. However, moderate to high error values in certain areas highlight the complexities of geological structures, seismic data gaps, and aseismic movements. The insights gained from this study offer a foundation for future advancements, calling for continuous model refinement, real-time data integration, and interdisciplinary collaboration to enhance earthquake prediction accuracy and bolster preparedness in seismic-prone regions like Turkey.

7. Conclusion

In conclusion, this study marks a significant advancement in earthquake prediction methodologies, focusing on Turkey's seismic landscape. Utilizing ANNs, our research strives to enhance the accuracy of earthquake magnitude forecasts. The diverse ANN model architectures, incorporating different optimizers (RMSprop, Adam, and Stochastic Gradient Descent), contribute to robust predictions, addressing the intricate nature of seismic data. The rigorous processing of a decade-long dataset from the United States Geological Survey ensures the reliability of ANN models, with crucial parameters forming the basis for seismic risk assessments.

The development of ANN-based maps provides valuable spatial insights into earthquake risk across Turkey, driven by ANN-driven magnitude predictions. These maps highlight high-risk areas, such as western Central Anatolia, northwest Marmara, and the Eastern Mediterranean, showcasing the proficiency of the models. Despite variations in specific performance metrics, the three ANN models—ANN-1, ANN-2, and ANN-3—demonstrate commendable accuracy in earthquake magnitude prediction, validated by aligning model predictions with actual seismic events.

The high-risk area mapping identifies regions prone to seismic events in Turkey based on ANN-driven magnitude predictions. Areas with low error margins underscore the models' proficiency, while factors like geological structures and seismic data gaps provide insights for ongoing research and improvement. Looking ahead, continuous efforts to refine ANN models, update datasets, and address forecasting challenges are crucial for enhancing seismic preparedness. Collaborative endeavours between seismic researchers, geologists, and data scientists will play a pivotal role in fortifying Turkey's resilience against seismic risks. This study advances scientific understanding and provides actionable insights for policymakers, emergency responders, and vulnerable communities. The integration of cutting-edge technology and interdisciplinary collaboration positions Turkey toward a more resilient and prepared future in the face of seismic challenges. Future research could explore the integration of more sophisticated neural network architectures, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), to further enhance prediction accuracy. Additionally, incorporating real-time data streams could improve the model's responsiveness to emerging seismic events.

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Conflicts of Interest

The authors declare no conflicts of interest.

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