PREDICTING COUNTRIES' VULNERABILITY TO CLIMATE CHANGE

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B.S., Physics, Boğaziçi University, 2016

Submitted to the Institute for Graduate Studies in
Science and Engineering in partial fulfillment of
the requirements for the degree of
Master of Science

Graduate Program in Computational Science and Engineering
Boğaziçi University
2023

ACKNOWLEDGEMENTS

I would like to thank my thesis supervisor Prof. Levent Kurnaz, for helping me with this research. I am also extremely grateful to Dr. Nazan An and Dr. Tufan Turp for their time and their enlightening questions and comments on my thesis. Their motivation, enthusiasm, and immense knowledge motivated and provided an objective for me to pursue this degree.

ABSTRACT

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Many countries are subject to the consequences of global climate change at varying degrees, and their vulnerability varies according to socioeconomic and environmental factors. Individuals, societies, and countries must be aware of the effects of climate change. Knowledge and understanding of how exposed they are to hazards, their level of vulnerability, and what must be done are critical for the continuation of basic vital activities. Accurately predicting how much a country will be affected by climate change in the future or which life-supporting sectors will suffer is crucial for countries to take precautions. Therefore, in this study, The Notre Dame Global Adaptation Initiative (ND-GAIN) Country Index's data is used for predicting countries' vulnerability to climate change. It's an open-source index that displays how vulnerable a nation is to climate disruptions. The data for this index includes scores for vulnerability and six areas that support life, including food, water, health, ecosystem services, human habitat, and infrastructure, for 182 nations during a 26-year period from 1995 to 2020. Long short-term memory (LSTM) network-based model is built to predict seven countries' six years of data from 2021 to 2026. These countries are Turkey, Australia, Germany, Portugal, Sudan, Georgia, and Kyrgyzstan. The results showed that the model predicts an increase in the vulnerability scores of all countries except Sudan for 2021, a slight decrease in Germany and Australia, and a decrease in Turkey, Portugal, and Kyrgyzstan after 2021. The model predicts a decrease in Sudan and an increase in Georgia for all years. The model's successes are tested using data from 2010 to 2020. Although time series forecasting is challenging, forecasted values are close to actual values. This study is novel since no other studies have predicted countries' future years' vulnerability to climate change.

ÖZET

ÜLKELERİN İKLİM DEĞİŞİKLİĞİNE KARŞI ETKİLENEBİLİRLİKLERİNİN TAHMİN EDİLMESİ

Birçok ülke küresel iklim değişikliğinin sonuçlarına farklı derecelerde maruz kalmaktadır ve bu ülkelerin etkilenebilirlikleri sosyoekonomik ve çevresel faktörlere göre değişmektedir. Bireyler, toplumlar ve ülkeler iklim değişikliğinin etkilerinin farkında olmalıdır. Tehlikelere ne kadar maruz kaldıklarının, etkilenebilirlik düzeylerinin ve ne yapılması gerektiğinin bilinmesi ve anlaşılması, temel yaşamsal faaliyetlerin devamı için kritik önem taşımaktadır. Gelecekte bir ülkenin iklim değişikliğinden ne kadar etkileneceğinin veya hangi yaşamı destekleyen sektörlerinin ne kadar zarar göreceğinin doğru tahmin edilmesi, ülkelerin önlem alabilmesi açısından büyük önem taşımaktadır. Bu nedenle bu çalışmada, ülkelerin iklim değişikliğine karşı etkilenebilirliklerini tahmin etmek için Notre Dame Küresel Uyum İnisiyatifi (ND-KUİ) Ülke İndisi verileri kullanılmıştır. ND-KUİ ülkelerin iklim bozulmalarından ne kadar etkilenebilir olduğunu gösteren açık kaynaklı bir indistir. Bu indisin verileri, 1995'ten 2020'ye kadar 26 yıllık bir dönemde 182 ülke için etkilenebilirlik puanlarını ve gıda, su, sağlık, ekosistem hizmetleri, insan yaşam alanı ve altyapı olmak üzere yaşamı destekleyen altı alanı içermektedir. Uzun kısa süreli bellek (LSTM) ağ tabanlı model yedi ülkenin 2021'den 2026'ya kadar olan altı yıllık verilerini tahmin etmek için oluşturulmuştur. Bu ülkeler Türkiye, Avustralya, Almanya, Portekiz, Sudan, Gürcistan ve Kırgistan'dır. Sonuçlar, modelin 2021 yılı için Sudan hariç tüm ülkelerin etkilenebilirlik puanlarında artış, 2021 sonrasında ise Almanya ve Avustralya'da hafif bir düşüş, Türkiye, Portekiz ve Kırgızistan'da düşüş öngördüğünü göstermiştir. Model tüm yıllar için Sudan'da düşüş, Gürcistan'da ise artış öngörmüştür. Modelin başarısı 2010'dan 2020'ye kadar olan veriler kullanılarak test edilmiştir. Zaman serisi tahmini zor olsa da tahmin edilen değerler gerçek değerlere yakındır. Başka hiçbir çalışma ülkelerin gelecek yıllardaki iklim değişikliğine karşı etkilenebilirliklerini tahmin etmediği için bu çalışma yenidir.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF SYMBOLS

b	Bias
c_t	Memory cell
f	Forget gate
h_t	Hidden state at timestep t
i	Input gate
o	Output gate
sigm	Sigmoid activation function
tanh	Tanh activation function
W	Weight matrix
x	Input at timestep t
$\odot$	Element-wise multiplication

LIST OF ACRONYMS/ABBREVIATIONS

ANN	Artificial Neural Networks
ARIMA	Autoregressive integrated moving average
BiLSTM	Bidirectional Long-Short Term Memory
BPTT	Backward Propagation Through Time
GRU	Gated Recurrent Unit
GWR	Groundwater Recharge
IPCC	Intergovernmental Panel on Climate Change
LSTM	Long short-term memory
LTS	Length of Transmission Season
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MSE	Mean Squared Error
MSM	Meso Scale Model
ND-GAIN	The Notre Dame Global Adaptation Initiative
ND-KUİ	Notre Dame Küresel Uyum İnisiyatifi
PERSIANN	Precipitation Estimation From Remotely Sensed Information Using Artificial Neural Networks
RMSE	Root Mean Squared Error
RNN	Recurrent Neural Networks
SARIMA	Seasonal Autoregressive Integrated Moving Average
SimpleRNN	Simple Recurrent Network
UN	United Nations
WRI	World Resource Institute
WRI	World Risk Index

1. INTRODUCTION

Since the industrial revolution, human-caused greenhouse gas emissions have been the primary cause of climate change. It is predicted that risks posed by extreme weather events, which have risen in recent years as a result of human-caused climate change, to life health, property loss, environment, natural resources, business, and service continuity may gradually increase in the coming years [1]. It has become critical for countries to determine their exposure to the risks that climate change may cause, their vulnerability to these impacts and risks, and to develop accurate and feasible adaptation strategies to mitigate climate change impacts [2]. In the Intergovernmental Panel on Climate Change (IPCC) 2019 special report on climate change, the risks that will be caused by rising temperatures are listed as increased forest fires, rising water levels in coastal areas, reduced yields in agricultural regions located at low latitudes, reduced access to food, reduced freshwater resources, increased morbidity and mortality due to extreme heat or cold, significant loss of vegetation cover, increased soil erosion and continued rapid melting of glaciers [3]. These risks affect different regions of the world differently in terms of physical, geographical, socioeconomic, and demographic aspects [1]. Therefore, adaptation efforts are of great importance in managing the impacts and risks of climate change. Climate change adaptation efforts should be adopted and implemented with the right strategic approach at the regional and country scales as well as at the global scale. Different indices are used to determine the exposure, vulnerability, resilience, and adaptive capacity of regions and countries to climate change [4, 5]. There is a strong correlation between countries' vulnerability, exposure, adaptive capacity, resilience values, and mortality rates due to climate change-related disasters [6]. The index results used to determine these indicators are very important in terms of measures to reduce potential future mortality rates [6]. Developed countries utilize the results of these indices and related indicators when determining the flow of financial resources that developing countries will need to adapt to climate change [7].

There are two indices used to determine countries' vulnerability to climate change. These are *"Notre Dame Global Adaptation Initiative (ND-GAIN) Country Index"* [8] and World Risk Index (WRI). These indices measure vulnerability, exposure, resilience, and adaptive capacity using similar variables, using different calculation methods. This may lead to differences in the evaluation results, and the difference exists because the indices define the concepts differently, and the calculations in the indices are made according to these definitions. For example, in both indices, resilience is not directly given under this heading; in WRI, it is considered as coping capacity, and in ND-GAIN, it is considered as readiness for the climate risks of countries. For this reason, coping capacity and readiness are not considered in this study as they are not general terms for these two indices. This study's motivation is to correctly predict countries' future vulnerability to climate change using a machine learning model. There is a direct correlation between the success of machine learning models and the amount of data used to train them. In this study, both because ND-GAIN Country Index is more widely used and, more importantly, because it has more data than WRI therefore, the vulnerability data of the ND-GAIN Country Index is used. Data insecurity is higher in countries with poor vulnerability scores, so the scores are not very reliable in these countries. But in countries with good vulnerability scores, the scores are reliable. Generally, the scores are better and more reliable in developed and upper-income group countries. Although Turkey and Georgia have different vulnerability scores, in both cases, the habitat sector is the most determinant on the vulnerability score. Although Turkey and Kyrgyzstan have the same vulnerability scores, different sectors have been the most determinant in forming these scores. Turkey and Kyrgyzstan have different income groups. Based on the fact that Turkey and Georgia are in the same income group, the income group is important in determining the sector that will affect the vulnerability the most. The sector that affects the vulnerability score of developed countries the most is health. In these countries, *"the Projected change of deaths from climate change-induced diseases"* [8] is the most determinant indicator in the health sector. For Sudan, health is also a determinant of the vulnerability score. However, in Sudan, *"the Projected change of length of transmission season of vector-borne diseases"* [8] indicator was effective in determining the health sector score.

The main goal of this thesis is to correctly predict countries' vulnerability to climate change. Countries' vulnerability scores are announced every year by ND-GAIN. Time series forecasting can be used to predict next year's vulnerability scores. There are many machine learning algorithms for time series forecasting. In time series forecasting, Artificial Neural Networks (ANN), which use the human brain and nervous system as an example for modeling, is the most widely used machine learning technique. ANN's idea and basic structure is a method that dates back to earlier years but has become widespread, especially in recent years, as computers have become more powerful in terms of hardware. LSTM, which is a machine learning-based deep learning method, is frequently used in this field due to its multi-layer structure, the ability to deepen learning, and the high controllability of variable diversity [9, 10]. LSTM is a recurrent neural network used in time series estimates. Since LSTM offers a solution to the exploding and vanishing gradient problem, which was a longstanding problem for recurrent neural networks by carrying the temporal information, it is often preferred in time series problems. Hence, LSTM training data is preferred to be not shuffled. Besides that, LSTM cells are enabled to solve complex, artificial long-time lag problems that could not be solved with recurrent networks earlier [9]. It has been observed that LSTM models are more successful than deep feed-forward neural networks and many machine learning algorithms in short and long-term forecasts [11]. This is important to note that there are also some disadvantages of LSTM networks. LSTM networks are a bit of a black box, but that is true for all neural networks because studying their structure will not reveal the structure of the function they approximate. Training LSTMs with backward propagation through time (BPTT) is slow and requires much competitive power. However, because our data size is not big, these are not problems for us. For these reasons, the time series forecasting model is developed and tuned using only the LSTM network in this study.

2. LITERATURE REVIEW

Deep learning methods, such as LSTM, use many layers of computational algorithms to find underlying data patterns. LSTM, which is developed to handle long-term dependencies, can predict various time series data such as price, temperature, solar radiation, precipitation, and so on. In both short and long-term forecasting, LSTM models outperform deep feed-forward neural networks and numerous machine learning methods [11]

Salman et al. [12] used single-layer and multilayer LSTM models to forecast humidity, dew point temperature, and air pressure. As a result of the study, they achieved 0.0885 Root Mean Squared Error (RMSE) in 100 epochs trials in the model where the variable was used as pressure as the best result.

Akbari Asanjan et al. [13] compared short-term quantitative precipitation forecasting using LSTM models combined with *"Precipitation Estimation From Remotely Sensed Information Using Artificial Neural Networks (PERSIANN)"* [13] using 0-6 hour data. In the study using precipitation data from Oklahoma, Florida, and Oregon states of the USA, the correlation coefficients of LSTM and LSTM-PERSIANN models were 0.51 in Oregon, 0.45 in Oklahoma, and 0.48 in Florida.

Poornima and Pushpalatha [14] compared the performance of the condensed LSTM-based artificial neural networks method with *"Autoregressive Integrated Moving Average (ARIMA) and Holt-Winters methods"* [14] using rainfall data measured between 1980 and 2014 in Hyderabad, India. As a result of the study, they obtained RMSE results of 3.08 for the Holt-Winters method, 2.84 for the ARIMA method, and 0.33 for the condensed LSTM method.

Kaneko et al. [15] used a two-layer model with LSTM and stack normalization layers to predict precipitation against different global warming challenges, such as floods in Japan, where significant rainfall events occur every year. They compared the Meso Scale Model (MSM) technique to the LSTM method and found successful outcomes in both models but determined that models with LSTM are more effective than models with MSM.

Samad et al. [16] used data from Australia collected between 2007 and 2016 to predict rainfall using LSTM and ANN techniques. The data included rainfall, wind speed, temperature, pressure, humidity, and wind direction. The LSTM method was found to produce results with lower error than the ANN method in all investigated regions, despite the fact that successful outcomes were produced using both methods.

De Saa and Ranathunga [17] compared the performance of ARIMA and LSTM methods for temperature data of Szeged, Hungary, measured between 2006 and 2016. As a result of the study, they reached a 2.42 value for Mean Squared Error (MSE) in the ARIMA method and 1.90 in the LSTM method and concluded that LSTM layers perform better than the ARIMA method.

Dubey et al. [18] studied energy consumption estimation using meteorological parameters such as humidity, temperature, cloudiness, and wind speed. They concluded that humidity is positively correlated with energy consumption and temperature is negatively correlated with energy consumption. Comparisons in LSTM, ARIMA, and *"Seasonal Autoregressive Integrated Moving Average (SARIMA)"* [18] are included in the results. SARIMA and LSTM models were used in accordance with the data, and the RMSE value reached 0.55 in the SARIMA model and 0.23 in the LSTM model.

As we have seen in the paragraphs above, LSTM network-based models are widely used on climate-related data such as temperature, precipitation, and humidity. It has been observed that LSTM network-based models are generally more successful than any other methods in time series prediction.

3. BACKGROUND INFORMATION

In this chapter, some topics required for the rest of the thesis are summarized as background information. There are explanations related to ND-GAIN Country Index and LSTM network.

3.1. Notre Dame Global Adaptation Initiative (ND-GAIN) Country Index

University of Notre Dame's ND-GAIN Country Index measures a country's vulnerability to climate change and its readiness for its impacts. [19]. It also evaluates a country's capacity to utilize private and public sector investments for adaptive measures. [20–22]. Since 1995, the ND-GAIN Country Index has combined over 70 variables into 45 key indicators used to assess the vulnerability of 182 United Nations (UN) countries in terms of public and private investments [8]. In this index, a country's readiness for impacts and risks is measured by its potential to implement actions that contribute to mitigating climate change effects after public and private investments. Political stability in terms of governance and the education level of the society or the country in terms of social aspects are some of the indicators that determine the level of readiness for impacts and risks [8]. The ND-GAIN Country Index divides the level of readiness within the scope of vulnerability to impact, sensitivity, and adaptive capacity, which are measures of vulnerability, into governance, social, and economic components [8]. The framework for the ND-GAIN Country Index is founded on the construction of published peer-reviewed materials, the IPCC review process, and feedback from institutional stakeholders, practitioners, and developing users [8], and its scientific foundation is quite strong. The ND-GAIN Country Index assesses vulnerability across *"six life-supporting sectors: food, water, health, ecosystem services, human habitat, and infrastructure. Each sector is represented by six indicators representing three cross-cutting components: i. the sector's exposure to climate-related or climate-*

exacerbated risks, ii. that sector's sensitivity to risk impacts, and iii. the sector's capacity to cope with or adapt to these impacts" [8, 22]. In order to differentiate the sources of vulnerability, the ND-GAIN country index based its vulnerability measure on projected biophysical climate sensitivity, and current social vulnerability [22, 23].

Chen et al. define vulnerability as *"the propensity or predisposition of human societies to be negatively impacted by climate hazards"* [8]. Climate change exposure refers to the stress that it will put on human society and the industries that support it in the future [8]. The physical elements outside the system that affect vulnerability are characterized by exposure on ND-GAIN Country Index. Sensitivity is the amount to which climate-related changes have an impact on people and the sectors on which they depend [8]. The degree to which certain industries are dependent on climate change, as well as the percentage of people who are particularly vulnerable to its hazards because of topography and demography, are among the factors increasing sensitivity. Adaptive capacity is society and its supporting sectors' capacity to change to lessen possible harm and react to the negative effects of climatic disasters [8]. The adaptive capacity indicators used in ND-GAIN Country Index aim to identify a range of quickly deployable tools for addressing the outcomes of climate change on particular industries.

In order to find indicators that reflect climate vulnerability, the ND-GAIN team studied the most recent research and interviewed researchers, adaption practitioners, and global development specialists. [8]. Vulnerability and sector scores are scaled between ND-GAIN Country Index assesses vulnerability and sector scores. There are 36 indicators that make up vulnerability. For each component, 12 indicators are linked with 6 sectors. Each sector's score is computed by taking the arithmetic mean of its six constituent indicators, and the overall vulnerability score is generated by taking the arithmetic mean of the six sector values. ND-GAIN Vulnerability Indicators can be seen in Table 3.1. The following sections explain each sector's exposure, sensitivity, and adaptive capacity components.

Table 3.1. ND-GAIN vulnerability indicators.

Sector	Exposure component	Sensitivity component	Adaptive Capacity component
Food	Projected change of cereal yields	Food import dependency	Agriculture capacity (Fertilizer, Irrigation, Pesticide, Tractor use)
	Projected population change	Rural population	Child malnutrition
Water	Projected change of annual runoff	Fresh water withdrawal rate	Access to reliable drinking water
	Projected change of annual GWR	Water dependency ratio	Dam capacity
Health	Projected change of deaths from climate change induced diseases	Slum population	Medical staffs (physicians, nurses and midwives)
	Projected change of LTS season of vector-borne diseases	Dependency on external resource for health services	Access to improved sanitation facilities
Ecosystem	Projected change of biome distribution	Dependency on natural capital	Protected biomes
	Projected change of marine biodiversity	Ecological footprint	Engagement in International environmental conventions
Habitat	Projected change of warm period	Urban concentration	Quality of trade and transport-related infrastructure
	Projected change of flood hazard	Age dependency ratio	Paved roads
Infrastructure	Projected change of hydropower generation capacity	Dependency on imported energy	Electricity access
	Projection of Sea Level Rise impacts	Population living under 5m above sea level	Disaster preparedness

3.1.1. Food

The first exposure indicator is *"the projected change in agricultural cereal yield. It is projected that climate change will change the food supply by mid-century for rice, wheat, and maize"* [8]. Two-thirds of human food intake is supplied by these three crops [24]. The second exposure indicator is projected population change. Changes in population and consumption patterns are important factors in food demand [25].

The first sensitivity indicator is *"food import dependency, it is the proportion of cereal consumption obtained from imports"* [8]. Cereal consumption equals production plus imports subtracted exports [8]. Countries that rely heavily on food imports are vulnerable to fluctuations in global food costs. The consequences of climate change on agriculture may exacerbate price volatility [26]. The second indicator is the rural population. It is the total number of people living in a country's rural areas [8]. In the census for Turkey, places outside provincial and district centers are considered rural areas. The great majority of the world's poor reside in rural regions, and agriculture is the primary source of income and near-term development for the rural poor [27]. As a result, a substantial share of the rural population reflects a heavy reliance on subsistence, or near-subsistence, farming. Climate change makes subsistence farmers more vulnerable [28].

The first adaptive capacity indicator is agriculture capacity. Agriculture capacity may help discern between technical phases, which is especially beneficial in developing nations [8]. This indicator is connected to agricultural technology as an indicator of climate adaptation capacity [29]. The second adaptive capacity indicator is child malnutrition. A malnutrition indicator based on the presence of under-5-year-olds with a poor weight-for-height ratio; commonly used to predict chronic malnutrition [8]. This is thought to be a sign of a lack of capacity to meet the most vulnerable members of society's nutritional demands [8].

3.1.2. Water

The first exposure indicator is *"the projected change in annual runoff"* [8]. This illustrates how climate change will affect yearly surface water resources by mid-century [8]. World Resource Institute (WRI) offers data on precipitation minus evapotranspiration and changes in soil moisture storage [8]. The second exposure indicator is *"the projected change in annual groundwater recharge (GWR)"* [8]. This shows how climate change will affect yearly groundwater resources by the mid-century [8]. Groundwater, along with surface water, is an important source of fresh water for drinking water and other water needs [30].

The first sensitivity indicator is the freshwater withdrawal rate. It is the percentage of total real renewable water resources withdrawn in a given year [8]. Annual freshwater extraction from total renewable water resources is a proxy for water stress in nations [31]. Water-stressed countries are less resilient to water scarcity worsened by climate change [8]. The second sensitivity indicator is *"the water dependency ratio"* [8]. It is the percentage of total renewable water resources that originated outside the country, including surface and ground water entering the country or obtained through treaties [8]. A country's reliance on foreign water supplies puts it vulnerable to water insecurity [32,33] because climate change raises the demand for shared, transboundary water supplies [33].

The first adaptive capacity indicator is the dam capacity. It reflects the ability to adapt to changes in the temporal and geographical distribution of freshwater supplies, especially those caused by climate change [8]. The construction of dams and reservoirs is an example of a country's ability to undertake structural works that may mitigate the effects of climate change [34]. The second adaptive capacity indicator is *"access to reliable drinking water"* [8]. If a drinking water supply has a domestic connection, a public standpipe, a borehole, a protected well, or spring or rainfall collecting, it is deemed reliable [8]. The ability of a country to sustain high-level access to better drinking water demonstrates its ability to adapt to water scarcity in general [35].

3.1.3. Health

The first exposure indicator is *"the projected change in deaths from climate change-induced diseases"* [8]. The indicator is a model-based estimate of the number of quality-adjusted life years lost under various climatic scenarios [8]. The second exposure indicator is *"the projected change in vector-borne diseases due to changes in the Length of Transmission Season (LTS)"* [8]. This indicator uses malaria LTS projections to assess the effects of climate change on vector-borne diseases [8].

The first sensitivity indicator is *"the dependency on external resources for health services"* [8]. It represents the proportion of foreign resources in overall national health spending [8]. A strong reliance, mainly on foreign help, indicates a lack of internal capability and vulnerability to climate-related health shocks [8]. The second indicator is the Slum population. Slum-dwelling urban populations are prone to climate change and ill health [36,37] due to high population density and limited access to basic infrastructure, such as sanitation and clean drinking water [8].

The first adaptive capacity indicator is the medical staff. It is the total number of physicians, nurses, and midwives in the country per 1000 people. In many poor nations, a lack of medical personnel is a key hurdle to attaining decent health outcomes [8]. The second adaptive capacity indicator is *"access to improved sanitation facilities"* [8]. The indicator is the percentage of the population who has access to excrete disposal facilities capable of effectively preventing human, animal, and insect contact with excreta [8]. Infectious disease incidence is influenced by sanitation [38].

3.1.4. Ecosystem Services

The first exposure indicator is *"the projected change in biome distribution"* [8]. It shows how climate change will affect the biodiversity of terrestrial biomes within a country by the end of the century [8]. The second exposure indicator is the projected change in marine biodiversity. The indicator works in tandem with the terrestrial biome diversity indicator to assess the risk of changes in the provision of fishery or non-fishery marine resources [8].

The first sensitivity indicator is natural capital dependency. Crops, pasture, forest (timber), forest (non-timber), and protected areas are examples of natural capital related to ecosystem services [8]. The indicator measures a country's reliance on ecosystem services, which are threatened by climate change [8]. The second sensitivity indicator is *"the ecological footprint"* [8]. The ecological footprint calculates the number of hectares of land and water, both within and outside the country, required to meet the population's average demand for ecosystem services [8].

The first adaptive capacity indicator is the protected biomes. It measures the level of protection for biomes according to how much of a country's land area that biome takes up [8]. Countries that effectively protect their primary ecosystem types are likely to be able to carry out a larger variety of actions to maintain and manage ecosystem services in the face of climate change [8]. The second adaptive capacity indicator is *"engagement in international environmental conventions"* [8]. An indicator based on a country's participation in international forums reflects its ability to engage in multilateral discussions and achieve internal consensus on appropriate actions [8].

3.1.5. Human Habitat

The first exposure indicator is *"the projected change of warm periods"* [8]. Extreme heat is a possibility as a result of climate change [8]. Climate change's increased intensity and/or frequency of extreme weather events, such as storms, flooding, landslides, and heat waves, endangers human living conditions [39]. The second exposure indicator is the projected change in flood hazard. It is a measure of precipitation extremes as a result of climate change, and it is a risk factor for flood hazard [40]. An indicator that works in conjunction with the warm period projection to capture one of the most serious threats to human living conditions [8].

The first sensitivity indicator is *"the urban concentration"* [8]. The concentration of a country's population within cities is measured by urban concentration [41]. Countries with concentrated urban populations in a single or small number of urban areas are thought to be more vulnerable to climate change [42]. The second sensitivity indicator is the age dependency ratio. This indicator identifies the vulnerable population as those under 14 or above 65. [8]. The elderly and children may be disproportionately affected by the direct effects of extreme weather [43]. Climate change impacts may also have an indirect impact on them via sociopolitical structures or the economy.

The first adaptive capacity indicator is *"the quality of trade and transport infrastructure"* [8]. Transportation infrastructure has been demonstrated to be critical for migration and development [44, 45]. Migration away from harsh climates is critical for long-term human health improvement [46]. The second adaptive capacity indicator is the paved roads. It is the percentage of total road length that is paved [8]. This is a measure of the road system's strength and the social and economic activity that depends on it [8].

3.1.6. Infrastructure

The first exposure indicator is *"the projected change in hydropower generation capacity"* [8]. A measure of the potential risk associated with hydropower generation capacity, weighted by the importance of hydropower to a single country [8]. Due to the hydrological impact of climate change in the mid-to-long term, climate change is also expected to have a direct impact on hydropower generation capacity [47]. The second exposure indicator is *"the projected change of sea level rise impacts"* [8]. It shows how the combined effects of sea level rise and potential storm surge will affect coastal infrastructure by the end of the century [8]. Climate change threatens coastal infrastructure, necessitating resilient infrastructure that protects coastal areas [48–50].

The first sensitivity indicator is the dependency on imported energy. In a crisis, imported energy prices could rise or be cut off [8]. A greater reliance on imported energy implies a greater vulnerability to price volatility and supply crises. Energy-vulnerable countries are those that rely heavily on imported energy [51]. The second sensitivity indicator is *"the population living under 5m above sea level"* [8]. A population estimate is sensitive to the risks posed by sea-level rise, storm surge, and other similar effects, which are exacerbated by climate change [8].

The first adaptive capacity indicator is electricity access. Access to electricity allows the poor to gain access to the most basic services and economic opportunities, allowing them to improve their standard of living [8]. Given the potential for climate change, access to electricity facilitates health care, disaster relief, food storage, and social services such as education [8]. The second adaptive capacity indicator is disaster preparedness. Infrastructure resilience is determined by its ability to respond to natural disasters [52]. As a result, disaster preparedness, as an indicator of such social capacity, serves as a proxy for measuring infrastructure resilience.

3.2. Long Short Term Memory

Terms such as machine learning and deep learning are becoming more and more popular every day. In time series forecasting, artificial neural networks, which use the human brain and nervous system as an example for modeling, are the most widely used machine learning technique. Recurrent Neural Networks (RNN) are artificial neural networks that were created to analyze sequential data, such as time series data. RNNs have been widely used in a variety of activities, from sequence prediction to sequence labeling. A traditional RNN has three layers: an input layer, a hidden layer, and an output layer. RNNs, in theory, connect historical information to current information by taking both the current input and the previous hidden state vectors as input. The vanishing and exploding gradient problem [53] arises as a result of RNNs' inability to learn long-term dependencies in practice. Long-Short Term Term Memory (LSTM), Bidirectional Long-Short Term Memory (BiLSTM), and Gated Recurrent Unit (GRU) are

RNN sub-methods. LSTM is the most common and well-known model among these methods. The learning of data, the ability to generalize, and the freedom to work with an unlimited amount of variables are the biggest factors in the popularity of the models. LSTM was designed by Sepp Hochreiter and Jürgen Schmidhuber [9].

Ordinary RNNs can only access a small amount of contextual data in practice. The issue is that when an input cycles through the network's recurrent connections, its impact on the hidden layer and, consequently, the output of the network either decays or explodes exponentially. The vanishing and exploding gradient problem is the name given to this issue in the literature. An RNN architecture called LSTM was created especially to deal with the issue [9]. LSTMs differ from RNNs in that they compute the hidden state and output vectors using specific units. A memory cell, an input gate, a forget gate, and an output gate comprise an LSTM architecture. The LSTM structure's gates regulate what is remembered and what is forgotten. If the incoming input is insignificant, it is ignored; if it is significant, it is forwarded to the next stage. The LSTM has complex dynamics that allow it to easily memorize information over a long period of time. Long-term memory is stored in a vector of *memory cells* $c_t^l \in \mathbb{R}^n$. The LSTM equations used in our experiments can be written as

$$h_t^{l-1}, h_{t-1}^l, c_{t-1}^l \rightarrow h_t^l, c_t^l \tag{3.1}$$

$$c_t^l = f \odot c_{t-1}^l + i \odot g \tag{3.2}$$

$$h_t^l = o \odot \tanh(c_t^l). \tag{3.3}$$

All states in these equations are n-dimensional. $h_t^l \in \mathbb{R}^n$ is a hidden state in a layer l in timestep t. $T_{n,m} : \mathbb{R}^n \rightarrow \mathbb{R}^m$ is a transform ($Wx+b$ for some W and b). $\odot$ is an element-wise multiplication and h_t^0 is an input word vector at timestep k. The activations h_t^L are used to forecast y_t, since L is the number of layers in our deep LSTM. Sigmoid activation function (sigm) takes any real value and outputs a value in the range 0 and 1. Tanh activation function (tanh) is similar to sigm but the differences are that its output varies from -1 to +1, and tanh is centered at zero. sigm is used as the gating function, and tanh is used as the output activation function.

4. METHODOLOGY

This chapter explains preparing data, fitting the LSTM network, and evaluating results steps for predicting countries' vulnerability to climate change.

4.1. Data Preparation

ND-GAIN Country Index's Vulnerability data consist of CSV files for each life-supporting sector and vulnerability score. These files include all countries' 26 years scores. These files are combined together and then filtered by country to make graphs consisting of six life-supporting sectors and vulnerability scores for each country. As mentioned earlier, the LSTM network is used to create machine learning modeling. The LSTM network has the advantage of being able to learn to construct a one-shot multi-step forecast, which is beneficial for time series forecasting as well as learning extended sequences. However, one disadvantage of the LSTM network is that it can be difficult to install and requires a significant amount of preparation in order to collect the data in a suitable format for learning.

Before training an LSTM network, the data must be prepared. Firstly, Because the testing data points represent real-world data, the data must be divided into training and testing sets. Data standardization is a technique for centering and normalizing data by subtracting the mean and dividing it by the variance. It is essential not to apply data standardization to the whole data but first to separate it into training and testing data sets and then apply it to the training and testing data sets separately. Because the testing data set represents future values, if we apply it to the whole data, the mean and variance information of the future values will be leaked to the training data. Therefore, standardization is performed over the training data. It is then applied to testing data, utilizing the mean and variance of training variables. This allows us to test and assess if our model can generalize successfully to additional, previously unseen data points. Normally, 30 percent or one-third of data is used for testing and the rest for training. However, we wanted to keep testing data as much as possible because it also affects how many years ahead will be predicted. Therefore, we used 14 years of data from 1995 to 2008 for training and 12 years of data from 2009 to 2020 for testing. After that, we need to transform training and testing data sets into two-dimensional matrices. Some parts of matrices represent a predictor variable, and others represent a predicted variable. It may seem logical to use more than one predictor variable or to use running mean, but in our case, since we have very little data, this would significantly reduce the available data and make it impossible to make a successful prediction. Therefore, we used one predictor variable. Finally, we need to determine how many years ahead it is better to predict. There are different optimization techniques to find out this. However, in this case, there is no need to use these techniques because our data size is not big. We used 12 years of data for testing, and testing data size should be the upper limit to the years' number ahead to be predicted. Therefore, 6 years ahead is predicted because we need to transform one dimensional 12 elements matrix into a two-dimensional matrix, and this makes our testing size six. Training and testing data is visualized in Table 4.1 and Table 4.2 for better understanding. In these Tables, we can think of each cell as having the value of the year written in that cell.

Table 4.1. Training data template.

1995	1996	1997	1998	1999	2000	2001
1996	1997	1998	1999	2000	2001	2002
1997	1998	1995	2000	2001	2002	2003
1998	1999	2000	2001	2002	2003	2004
1999	2000	2001	2002	2003	2004	2005
2000	2001	2002	2003	2004	2005	2006
2001	2002	2003	2004	2005	2006	2007
2002	2003	2004	2005	2006	2007	2008

Table 4.2. Testing data template.

2009	2010	2011	2012	2013	2014	2015
2010	2011	2012	2013	2014	2015	2016
2011	2012	2013	2014	2015	2016	2017
2012	2013	2014	2015	2016	2017	2018
2013	2014	2015	2016	2017	2018	2019
2014	2015	2016	2017	2018	2019	2020

Secondly, if data shows an increasing or a decreasing trend which is true in all six life-supporting sectors and vulnerability for all countries, this trend must be removed by using some methods. Because most time series models, such as LSTM networks, assume that each point is independent of the others in order to predict the future, this means the mean, variance, and covariance do not change over time. But, nonstationary data, by definition, do not have a fixed mean or a fixed variance, so the data must be stationary. In other words, if everything is different in the future, then it is very hard to forecast because everything will be different. Therefore, the key to forecasting is to find something that will be the same in the future and generalize or extend that to the future. The most common method to make data stationary is differencing, which is subtracting a timestep value from the next timestep value and doing this to all timestep values. For some countries, some data the differencing method didn't help to make the data stationary. For this situation, a logarithm or square root is taken to convert the data to stationary.

Thirdly, we can scale data to values between -1 and 1 which are the outputs of the activation function of the LSTM units because we have already split the data into training and testing data sets. The process of standardizing a data set entails rescaling the value distribution so that the mean of observed values is 0 and the standard deviation is 1. The following figures show an example of training data before and after transformations. Germany's original infrastructure training data can be seen in Figure 4.1. The data exhibits an upward tendency that must be corrected using differencing. And after making this data stationary by using the differencing method and scaling data between -1 and 1 can be seen in Figure 4.2.

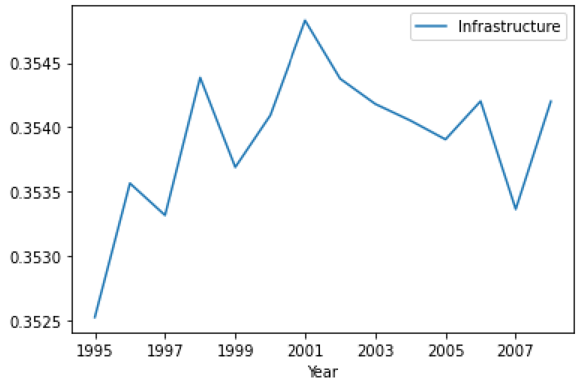

Figure 4.1. Germany's original infrastructure training data.

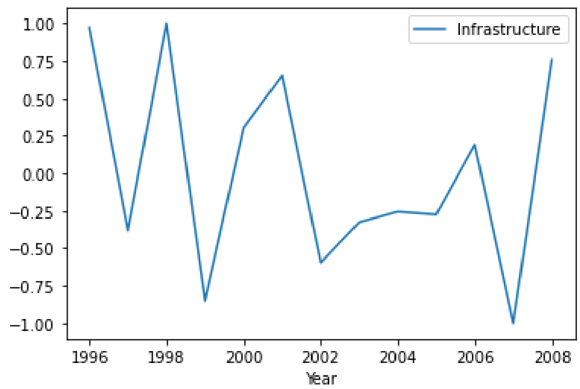

Figure 4.2. Germany's infrastructure training data after taking the difference and scaling.

4.2. Modelling

Now, we can use the training data to fit an LSTM network model. Firstly, The input of every LSTM layer must be three-dimensional. We already had two-dimensional data, and we need to add one dimension for timesteps that size as one. For designing the LSTM network, we can use 1 LSTM unit: an input layer, one hidden layer, and one output layer with linear activation and 6 output values. The mean squared error function and ADAM optimization algorithm, which is a method for stochastic optimization, are used in the network. We generally trained the model with a batch size of 1 and neuron number of 2 over 100 epochs. A batch size of 1 means the size of each update is 1 sample, and this would be stochastic gradient descent. In practice, it has been observed that using a larger batch causes significant degradation in the model's quality, as indicated by its ability for generalization. [54]. Model parameters such as the number of epochs, neurons, and layers are optimized for different countries for different predictions to increase model performance. We monitored the loss function during the training for validation; if we see the loss function start increasing, this means the model would be overfitting. Then, we stopped the training and tried to train fewer number epochs to prevent overfitting. The model was trained more than once in order to show the model's results are not coincidental. Since the training results are very close to each other, we took one of the training results, not the average. After training the model, we can make forecasts using the trained model. After forecasting, we must reverse the transforms to return the data to its original scale. This is required in order for us to compute error scores. We first inverted the scale using a built-in function and then inverted the differences to restore forecasts to their original scale. By adding the value of the most recent observation with the first forecasted value and then propagating the value down the forecast, we reversed the differencing. We additionally flipped the transformations on the testing dataset so that the RMSE scores could be calculated correctly. We calculated the RMSE for each time step of the multi-step forecast, yielding 6 RMSE scores in this example because we are projecting for the next 6 years. t+1 RMSE is the error in predicting the next year with the value of a year. t+6 RMSE is the error in predicting the year six years ahead with the value of a year.

4.3. Evaluation Metrics

There are different evaluation metrics for testing the outputs of a model. They are all based on the concept of error for the single prediction and on some distance between the target value and the predicted value. Some of them are R2-Score, Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). Some of these are not very suitable for time series forecasting and as well as our use case. R2-Score should not be used in time series forecasting. Because time series are generally nonstationary. The statistical properties of a nonstationary time series change over time. That means that the average and variance values are not constant over time. The R2-Score includes this ratio between the sum of squared errors and the estimated variance for the sample set. The larger the sum of squared errors, the further from explaining the dataset. This leads to an R2-Score close to zero. On the opposite, the smaller the sum of squared errors, the closer to the dataset. This leads to an R2-Score close to one. In practice, another factor that can push R2-Score up to one is a growing variance. For non-stationary time series, the value of R2-Score can quickly grow close to one, because of a larger variance, not necessarily because of a lower total error. And this can be deceiving when trying to get a reliable evaluation of the model. MAE is also not a very good metric for evaluating the time series model because it protects outliers. For model optimization and evaluating multiple models, if the error distribution is predicted to be Gaussian, Chai and Drexler prefer RMSE over MAE [55]. MAPE is also not a very good metric for evaluating the time series model. Because, for zero or close-to-zero actual values, it generates infinite or undefined values. [56]. MAPE also penalizes negative errors more severely than positive errors, resulting in an asymmetry. [57]. MSE and RMSE can be good metrics for evaluating our model because they assure us of getting an unbiased forecast. To avoid the MSE losing a unit, we can take its square root, which yields RMSE in the same units as the forecast data. RSME also punishes large errors. For these reasons, we used RMSE for our evaluation metric.

5. EXPERIMENTS AND RESULTS

ND-GAIN Country Index's data is used for training and testing the models. It's a free and open-source index that displays how vulnerable a nation is to climate disruptions. In this index's data, 182 countries' 26 years of values from 1995 to 2020 exist for vulnerability, and food, water, health, ecological services, human habitat, and infrastructure. Since a country's vulnerability is the mean of six life-supporting sectors, it is not fair to use six life-supporting sectors' data while predicting the vulnerability of countries. For this reason, six life-supporting sectors and future vulnerability values are predicted independently; that is to say, for a country, seven predictions are made by training and testing seven models. This is also beneficial for double-checking results because the mean of six life-supporting sectors' prediction and vulnerability predictions can be compared for a country. The initial model was created, trained, and tested using Turkey's data to predict six years of data from 2021 to 2026. Data from 1995 to 2008 is used for training the model, and data from 2010 to 2020 is used for testing the model. To show the models' results are not random, the models are trained and tested more than once. Six more countries are chosen in addition to Turkey from this dataset to show a model created using the LSTM algorithm capable of predicting any country's future years' vulnerability to climate change. These countries are Australia, Germany, Portugal, Sudan, Georgia, and Kyrgyzstan. The reason for choosing these countries is their vulnerability scores for 2020 and geographical locations. Although the same LSTM model is used to predict six countries' six life-supporting sectors and vulnerability values, model parameters are optimized for different countries for different predictions to increase model performance. In the following figures, countries' vulnerability and six life-supporting sectors' scores are shown together then the model results are discussed for seven countries separately.

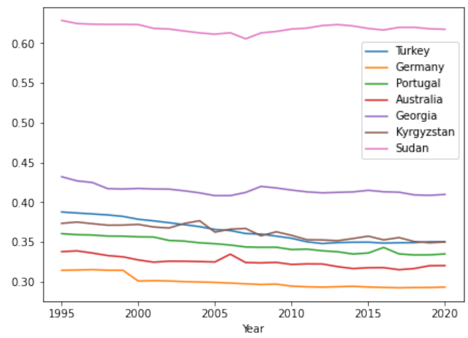

Figure 5.1. Vulnerability scores of countries from 1995 to 2020.

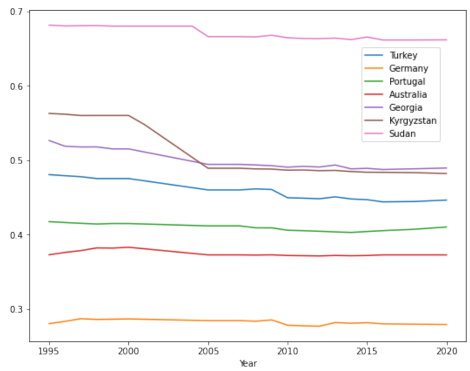

Figure 5.2. Ecosystem scores of countries from 1995 to 2020.

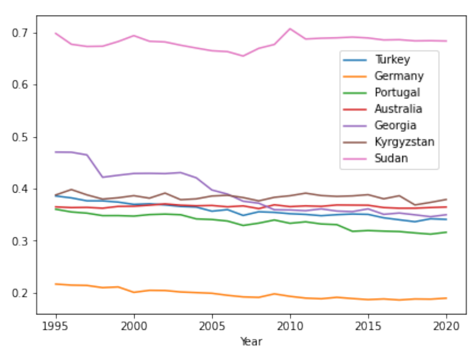

Figure 5.3. Food scores of countries from 1995 to 2020.

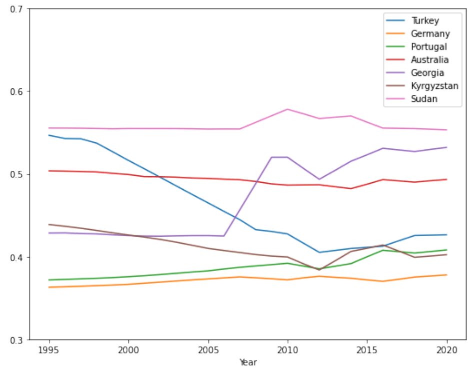

Figure 5.4. Habitat scores of countries scores from 1995 to 2020.

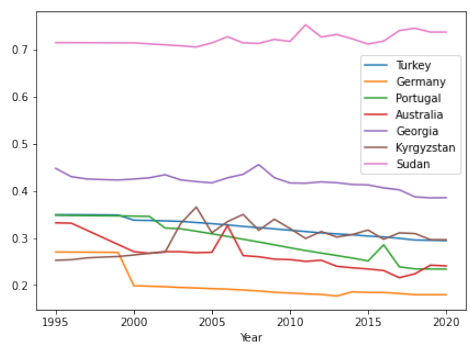

Figure 5.5. Health scores of countries from 1995 to 2020.

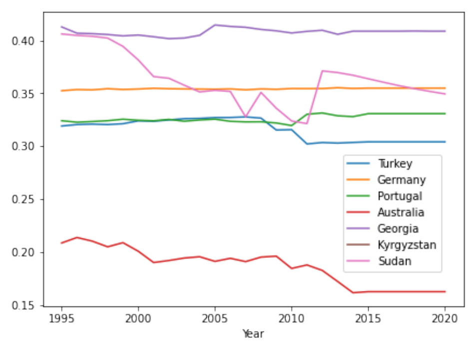

Figure 5.6. Infrastructure scores of countries from 1995 to 2020.

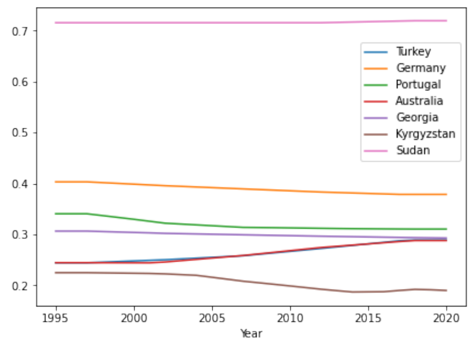

Figure 5.7. Water scores of countries from 1995 to 2020.

5.1. Turkey

Turkey's 2020 vulnerability score is 0.350 [21]. Turkey ranks 28th out of 182 countries with the vulnerability score for 2020 [21]. The mean of 26 years vulnerability values is 0.363. The minimum value was in 2012 as 0.348, and the maximum was in 1995 as 0.387 for vulnerability scores [21]. Turkey's income group is upper middle [21]. The following figures show Turkey's vulnerability and six life-supporting sectors for 26 years values from 1995 to 2020. As seen in Figure 5.8 and Figure 5.9, while Turkey's vulnerability score decreased from 1995 to 2012, it started to increase from 2012 onwards slightly. The main reason for the vulnerability score's increase is the increase in the human habitat sector. Projected change of warm periods and projected change of flood hazard might be the reason for the increase in the human habitat sector. Urban concentration can be another reason for this increase because migration from neighboring countries has increased since 2012.

As expected and seen in Table 5.1, RMSE often worsened as the prediction horizon lengthened. Although t+5 is slightly worse than t+6, this difference is very small and thus can be negligible.

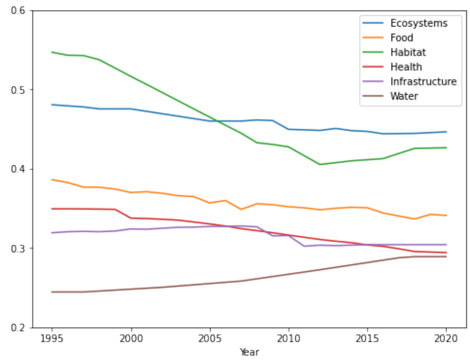

Figure 5.8. Six life-supporting sectors scores of Turkey from 1995 to 2020.

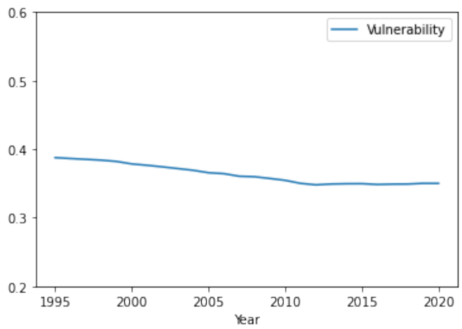

Figure 5.9. Vulnerability scores of Turkey from 1995 to 2020.

Table 5.1. RMSE of Turkey's vulnerability predictions.

t	**RMSE**
t+1	0.002436
t+2	0.003570
t+3	0.006279
t+4	0.008684
t+5	0.009264
t+6	0.009243

The model's forecasts on the testing dataset can be seen in Table 5.2 and Figure 5.10. The results are as expected. Because data for 2009 is used to predict data for

2010. Similarly, data for 2010 is used to predict data for 2011. Until 2015, data from 1 year ago is used; that is why until 2015, the model performance is good. Data for 2014 is used to predict data for 2016, 2017, 2018, 2019, and 2020 in addition to 2015. Therefore, from 2016 model performance started to degrade a little bit.

Table 5.2. Forecasts and actuals of Turkey's vulnerability scores from 2010 to 2020.

Year	**Forecasts**	**Actuals**
2010	0.355701	0.354570
2011	0.352966	0.350163
2012	0.351067	0.347999
2013	0.345863	0.349175
2014	0.347701	0.349608
2015	0.348128	0.349696
2016	0.345791	0.348536
2017	0.341880	0.349014
2018	0.338912	0.349163
2019	0.339117	0.350229
2020	0.339528	0.350170

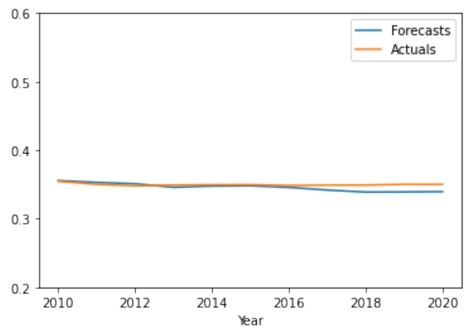

Figure 5.10. Forecasts and actuals of Turkey's vulnerability scores from 2010 to 2020.

Values from 2021 to 2026 are predicted using the trained and tested model. The results predicted a decrease from 2021 to 2024 and a slight increase from 2024 to 2026 in Vulnerability scores. As mentioned before, vulnerability is the mean of six life-supporting sectors so vulnerability can also be calculated using the mean of six life-supporting sectors' predictions as seen in Table 5.3.

Table 5.3. Vulnerability and mean of six sectors predictions for Turkey.

Year	**Vulnerability**	**Mean of six sectors**
2021	0.355774	0.354157
2022	0.353460	0.350798
2023	0.349489	0.347021
2024	0.346548	0.344921
2025	0.346845	0.342394
2026	0.347264	0.340138

In Figure 5.11, two prediction results are compared. Although these are two independent forecasts using the same model, the outcomes are similar, showing the model's success and consistency. The widening gap from 2024 onwards may have been caused by parameter optimization to decrease the RMSE in some life-supporting sectors. The RMSE of 2 different ways of Vulnerability predictions is 0.004.

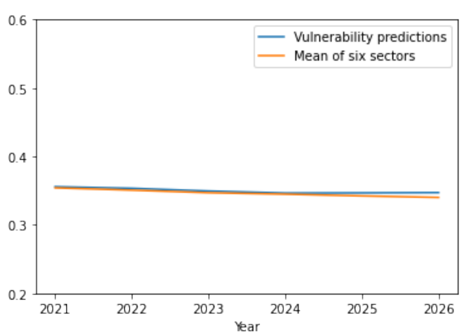

Figure 5.11. Vulnerability and mean of six sectors predictions for Turkey.

5.2. Germany

Germany has one of the best vulnerability scores among countries. It is at the top of the vulnerability ranking in terms of population and land area size. Its 2020 vulnerability score is 0.293 [21]. Germany ranks 4th out of 182 countries with the vulnerability score for 2020 [21]. The mean of 26 years vulnerability values is 0.299. The minimum value was in 2017 as 0.292, and the maximum was in 1997 as 0.315 for vulnerability scores [21]. Germany's income group is upper [21]. The following figures show Germany's vulnerability and six life-supporting sectors for 26 years values from 1995 to 2020. As seen in Figure 5.12 and Figure 5.13, Germany's vulnerability has a decreasing trend, but it has had a very small zig-zag style shape in the last ten years or so. The main reason for the vulnerability score's decrease in 2000 is the decrease in the health sector in the same year. Projected change in deaths from climate change-induced diseases might be the reason for the decrease in the health sector.

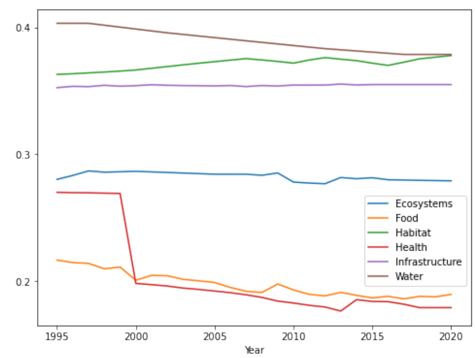

Figure 5.12. Six life-supporting sectors scores of Germany from 1995 to 2020.

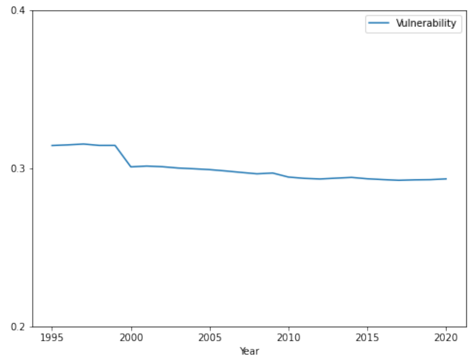

Figure 5.13. Vulnerability scores of Germany from 1995 to 2020.

As expected and seen in Table 5.4, RMSE often worsened as the prediction horizon lengthened.

Table 5.4. RMSE of Germany's vulnerability predictions.

t	**RMSE**
t+1	0.004908
t+2	0.006009
t+3	0.006744
t+4	0.007736
t+5	0.008037
t+6	0.008257

The model's forecasts on the testing dataset can be seen in Table 5.5 and Figure 5.14. As a general expectation, from 2016 the gap between forecasts and actuals started to widen. Because there is a decrease from 2010 to 2012, the model tried to predict a similar decrease but more sharply.

Table 5.5. Forecasts and actuals of Germany's vulnerability scores from 2010 to 2020.

Year	Forecasts	Actuals
2010	0.296730	0.294351
2011	0.288746	0.293543
2012	0.282659	0.293146
2013	0.294512	0.293655
2014	0.292408	0.294143
2015	0.291812	0.293271
2016	0.291037	0.292753
2017	0.290705	0.292301
2018	0.290550	0.292587
2019	0.289793	0.292707
2020	0.289201	0.293204

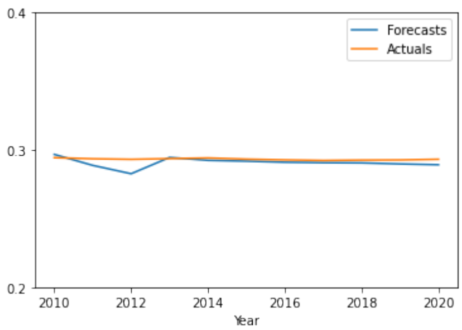

Figure 5.14. Forecasts and actuals of Germany's vulnerability scores from 2010 to 2020.

Values from 2021 to 2026 are predicted using the trained and tested model. Vulnerability predictions forecasted a decline from 2021 onwards. Six life-supporting predictions also forecasted a decline from 2021 onwards, except 2025 as seen in Table 5.6.

Table 5.6. Vulnerability and mean of six sectors predictions for Germany.

Year	Vulnerability	Mean of six sectors
2021	0.296218	0.299429
2022	0.295536	0.296863
2023	0.294830	0.294965
2024	0.294043	0.294591
2025	0.293398	0.295467
2026	0.292881	0.294651

In Figure 5.15, two prediction results are compared. Although these are two independent forecasts using the same model, the outcomes are similar, showing the model's success and consistency. The RMSE of 2 different ways of Vulnerability predictions is 0.002.

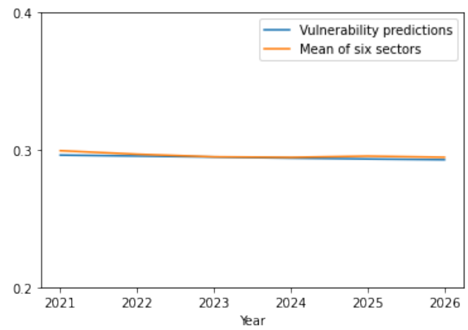

Figure 5.15. Vulnerability and mean of six sectors predictions for Germany.

5.3. Georgia

Georgia's 2020 vulnerability score is 0.410 [21]. Although Georgia and Turkey are in the same income group [21] and geographically close, their vulnerability scores are not close to each other. Therefore, using Georgia's data for training and testing the model is beneficial for validating that the model does not have a bias to any vulnerability score interval. Georgia ranks 78th out of 182 countries with the vulnerability score for 2020 [21]. The mean of 26 years vulnerability values is 0.415. The minimum value was in 2005 as 0.408, and the maximum was in 1995 as 0.432 for vulnerability scores [21]. The main reason for the vulnerability score's increase from 2005 to 2008 is the increase in the human habitat sector. One of the human habitat sector indicators might be the reason for this increase. The following figures show Georgia's vulnerability and six life-supporting sectors for 26 years values from 1995 to 2020. As seen in Figure 5.16 and Figure 5.17, Georgia's vulnerability score decreased from 1995 to 2005. There is no up or down trend after 2005.

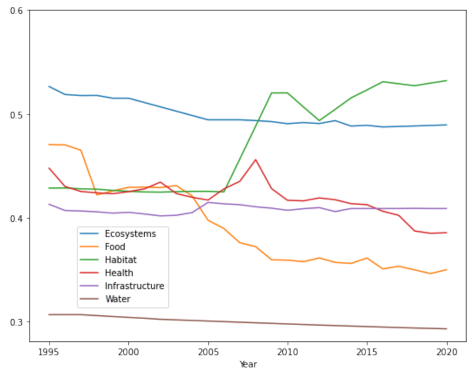

Figure 5.16. Six life-supporting sectors scores of Georgia from 1995 to 2020.

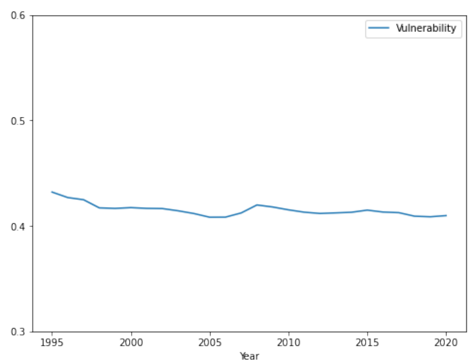

Figure 5.17. Vulnerability scores of Georgia from 1995 to 2020.

As expected and seen in Table 5.7, RMSE often worsened as the prediction horizon lengthened.

Table 5.7. RMSE of Georgia's vulnerability predictions.

t	**RMSE**
t+1	0.002968
t+2	0.004291
t+3	0.006148
t+4	0.007046
t+5	0.007334
t+6	0.007548

The model's forecasts on the testing dataset can be seen in Table 5.8 and Figure 5.18. The forecasts look slightly different from the actual values but show similar trends.

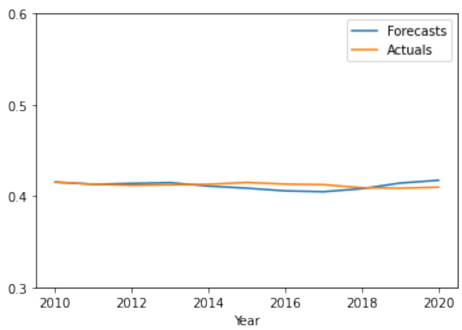

Figure 5.18. Forecasts and actuals of Georgia's vulnerability scores from 2010 to 2020.

Table 5.8. Forecasts and actuals of Georgia's vulnerability scores from 2010 to 2020.

Year	Forecasts	Actuals
2010	0.415362	0.415223
2011	0.412947	0.412992
2012	0.413880	0.411785
2013	0.414697	0.412335
2014	0.410959	0.412919
2015	0.408697	0.414943
2016	0.405729	0.413126
2017	0.404809	0.412552
2018	0.408104	0.409190
2019	0.414268	0.408640
2020	0.417315	0.409754

Values from 2021 to 2026 are predicted using the trained and tested model. Both vulnerability predictions and six life-supporting predictions forecasted an increase until 2025 and a decrease for 2026 as seen in Table 5.9.

Table 5.9. Vulnerability and mean of six sectors predictions for Georgia.

Year	Vulnerability	Mean of six sectors
2021	0.414668	0.417883
2022	0.418795	0.421018
2023	0.423273	0.421663
2024	0.427758	0.422952
2025	0.430964	0.423462
2026	0.429259	0.422744

In Figure 5.19, two prediction results are compared. Although these are two independent forecasts using the same model, the results are similar to each other, showing the model's success and consistency. The RMSE of 2 different ways of Vulnerability predictions is 0.005.

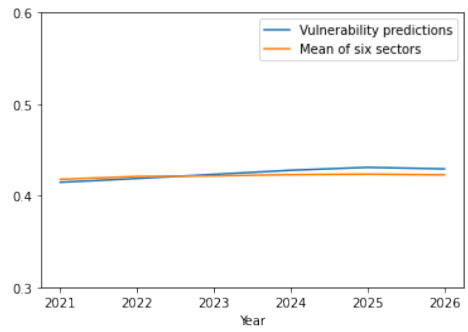

Figure 5.19. Vulnerability and mean of six sectors predictions for Georgia.

5.4. Portugal

Portugal and Turkey have very similar vulnerability scores and as well as climate conditions but they are in different income groups. Portugal's income group is Upper [21]. Portugal ranks 24th out of 182 countries with a vulnerability score of 0.335 for 2020 [21]. The mean of 26 years vulnerability values is 0.346. The minimum value was in 2018 as 0.334, and the maximum was in 1995 as 0.360 for vulnerability scores [21]. The main reason for the vulnerability score's increase in 2016 is the increase in the health sector in the same year. Projected change in deaths from climate change-induced diseases might be the reason for the increase in the health sector. The following figures show Portugal's vulnerability and six life-supporting sectors for 26 years values from 1995 to 2020. As seen in Figure 5.20 and Figure 5.21, Portugal's vulnerability has a decreasing trend except for 2015, 2016, and 2020 years.

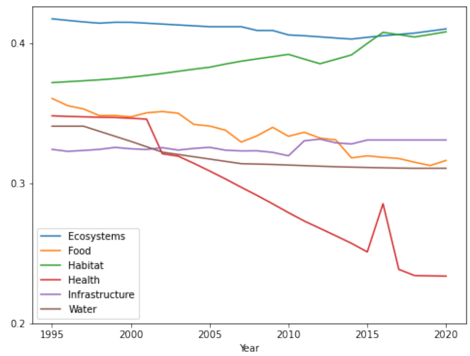

Figure 5.20. Six life-supporting sectors scores of Portugal from 1995 to 2020.

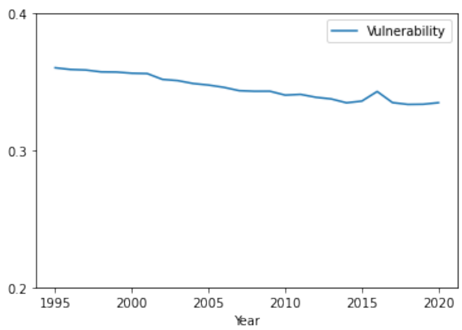

Figure 5.21. Vulnerability scores of Portugal from 1995 to 2020.

Table 5.10. RMSE of Portugal's vulnerability predictions.

t	**RMSE**
t+1	0.001991
t+2	0.005834
t+3	0.006199
t+4	0.006547
t+5	0.007117
t+6	0.007337

As expected and seen in Table 5.10, RMSE often worsened as the prediction horizon lengthened.

The model's forecasts on the testing dataset can be seen in Table 5.11 and Figure 5.22. Forecasts and actuals are very similar until 2016 as expected.

Table 5.11. Forecasts and actuals of Portugal's vulnerability scores from 2010 to 2020.

Year	**Forecasts**	**Actuals**
2010	0.341029	0.340424
2011	0.339244	0.340962
2012	0.338059	0.338840
2013	0.336426	0.337629
2014	0.335098	0.334807
2015	0.331771	0.336051
2016	0.329365	0.343062
2017	0.327016	0.334956
2018	0.325861	0.333629
2019	0.324544	0.333756
2020	0.324324	0.334893

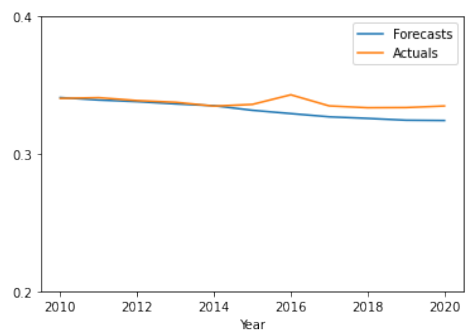

Figure 5.22. Forecasts and actuals of Portugal's vulnerability scores from 2010 to 2020.

Values from 2021 to 2026 are predicted using the trained and tested model. Although, there is little difference between numbers both vulnerability predictions and six life-supporting predictions forecasted a decline in vulnerability scores as seen in Table 5.12.

Table 5.12. Vulnerability and mean of six sectors predictions for Portugal.

Year	Vulnerability	Mean of six sectors
2021	0.338208	0.341600
2022	0.337562	0.339186
2023	0.331425	0.336177
2024	0.332261	0.334951
2025	0.327941	0.333791
2026	0.328482	0.331678

In Figure 5.23, two prediction results are compared and the results are similar to each other showing the model's success and consistency. The RMSE of 2 different ways of Vulnerability predictions is 0.004.

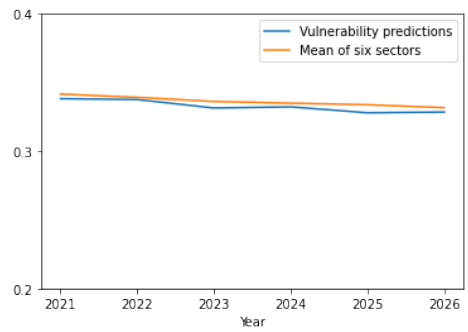

Figure 5.23. Vulnerability and mean of six sectors predictions for Portugal.

5.5. Australia

Australia ranks 16th out of 182 countries with a vulnerability score of 0.320 for 2020 [21]. The mean of 26 years vulnerability values is 0.325. The minimum value was in 2017 as 0.315, and the maximum was in 1996 as 0.339 for vulnerability scores [21]. Australia's income group is Upper [21]. Although Australia and the other countries on our list are too far from each other in terms of location, Australia's data is beneficial for validating that the model does not have a bias toward any specific region in the world. The main reason for the vulnerability score's increase in 2006, 2019, and 2020 is the increase in the health sector in the same years. Projected change in deaths from climate change-induced diseases might be the reason for the increase in the health sector. The following figures show Australia's vulnerability and six life-supporting sectors for 26 years values from 1995 to 2020. As seen in Figure 5.24 and Figure 5.25, Australia's vulnerability has a decreasing trend except for the 2016, 2019, and 2020 years.

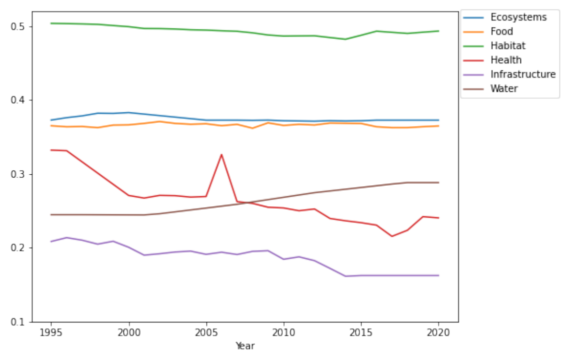

Figure 5.24. Six life-supporting sectors scores of Australia from 1995 to 2020.

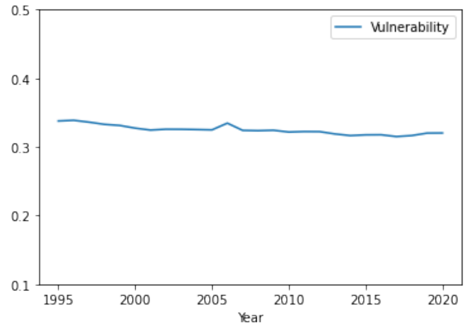

Figure 5.25. Vulnerability scores of Australia from 1995 to 2020.

As expected and seen in Table 5.13, RMSE often worsened as the prediction horizon lengthened, although t+2 is slightly worse than t+3.

Table 5.13. RMSE of Australia's vulnerability predictions.

t	**RMSE**
t+1	0.002013
t+2	0.002640
t+3	0.002205
t+4	0.002830
t+5	0.004371
t+6	0.005522

The model's forecasts on the testing dataset can be seen in Table 5.14 and Figure 5.26. From 2010 to 2020, in the beginning, forecasts are very close to actual values, while towards 2020 the gap between forecasts and actual values widens slightly.

Table 5.14. Forecasts and actuals of Australia's vulnerability scores from 2010 to 2020.

Year	Forecasts	Actuals
2010	0.321489	0.321690
2011	0.319891	0.322366
2012	0.319164	0.322250
2013	0.318295	0.318903
2014	0.316544	0.316506
2015	0.314659	0.317531
2016	0.313454	0.317674
2017	0.312623	0.315073
2018	0.311601	0.316535
2019	0.310947	0.320095
2020	0.310367	0.320237

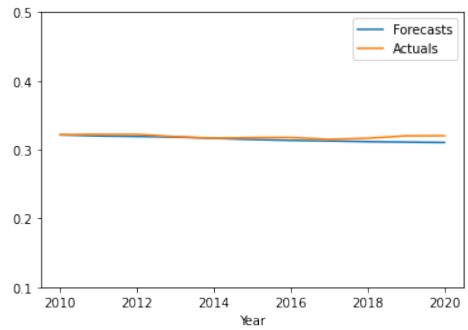

Figure 5.26. Forecasts and actuals of Australia's vulnerability scores from 2010 to 2020.

Values from 2021 to 2026 are predicted using the trained and tested model. Both vulnerability predictions and six life-supporting predictions forecasted a decline in vulnerability scores as seen in Table 5.15.

Table 5.15. Vulnerability and mean of six sectors predictions for Australia.

Year	Vulnerability	Mean of six sectors
2021	0.321438	0.322736
2022	0.320102	0.321302
2023	0.319242	0.318988
2024	0.317800	0.318462
2025	0.317142	0.316911
2026	0.316619	0.315465

In Figure 5.27, two prediction results are compared and the results are similar to each other showing the model's success and consistency. The RMSE of 2 different ways of Vulnerability predictions is 0.001.

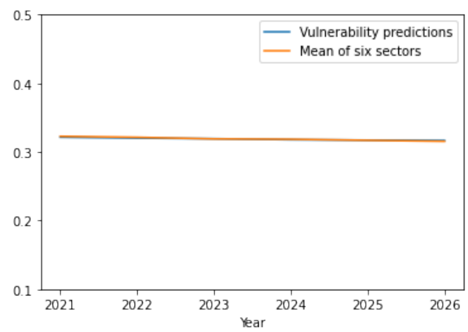

Figure 5.27. Vulnerability and mean of six sectors predictions for Australia.

5.6. Sudan

Sudan has one of the worst vulnerability scores among countries. There are countries with worse vulnerability scores than Sudan, but their data is incomplete. Sudan is the country with complete data and has the worst vulnerability score. Its 2020 vulnerability score is 0.618 [21]. Sudan ranks 178th out of 182 countries with the vulnerability score for 2020 [21]. The mean of 26 years vulnerability values is 0.619. The minimum value was in 2007 as 0.605, and the maximum was in 1995 as 0.628 for vulnerability scores [21]. Sudan's income group is Low [21]. The reasons for the vulnerability score's increase from 2007 are the increases in the food and health sectors. Child malnutrition, the projected change in vector-borne diseases, and the projected change in deaths from climate change-induced diseases might be the reason for the increase in the food and health sectors. The following figures show Sudan's vulnerability and six life-supporting sectors for 26 years values from 1995 to 2020. As seen in Figure 5.28 and Figure 5.29, Sudan's vulnerability has a decreasing trend until 2007 and an increasing trend after 2007.

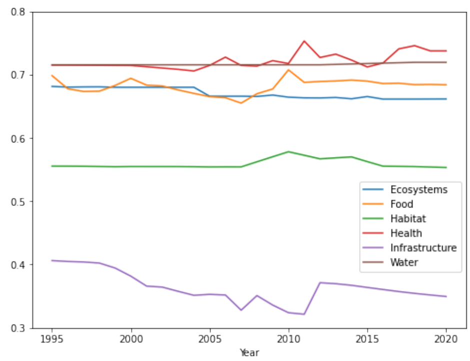

Figure 5.28. Six life-supporting sectors scores of Sudan from 1995 to 2020.

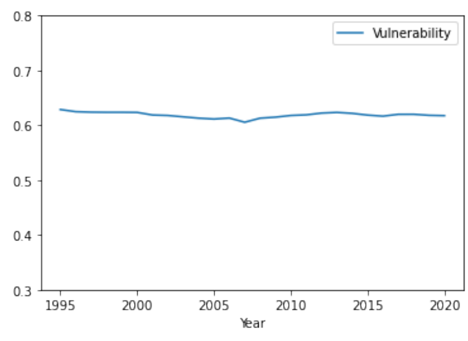

Figure 5.29. Vulnerability scores of Sudan from 1995 to 2020.

As expected and seen in Table 5.16, RMSE often worsened as the prediction horizon lengthened, although t+5 is slightly worse than t+6.

Table 5.16. RMSE of Sudan's vulnerability predictions.

t	**RMSE**
t+1	0.005296
t+2	0.007507
t+3	0.011171
t+4	0.012871
t+5	0.014820
t+6	0.014069

The model's forecasts on the testing dataset can be seen in Table 5.17 and Figure 5.30. Forecasts and actuals show an overall similar pattern, although there are some differences.

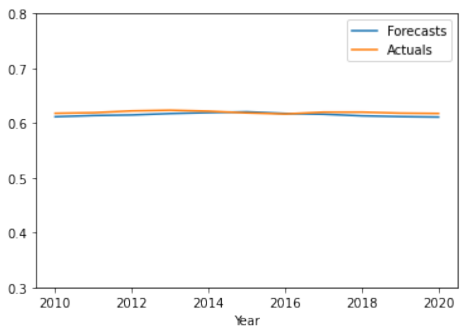

Figure 5.30. Forecasts and actuals of Sudan's vulnerability scores from 2010 to 2020.

Table 5.17. Forecasts and actuals of Sudan's vulnerability scores from 2010 to 2020.

Year	**Forecasts**	**Actuals**
2010	0.611573	0.617844
2011	0.613783	0.618970
2012	0.614835	0.622198
2013	0.617372	0.623445
2014	0.619055	0.621709
2015	0.620505	0.618526
2016	0.617488	0.616615
2017	0.616143	0.619948
2018	0.613221	0.619994
2019	0.611795	0.618131
2020	0.610986	0.617532

Values from 2021 to 2026 are predicted using the model. Both vulnerability predictions and six life-supporting sectors predictions forecasted a decline in vulnerability scores until 2024 but from 2024 vulnerability predictions still forecasted a decline although six life-supporting predictions forecasted an increase. Sudan's water scores stayed the exact same for 18 years. This may cause water predictions and thus the mean of six life-supporting sectors' predictions diverge from vulnerability predictions.

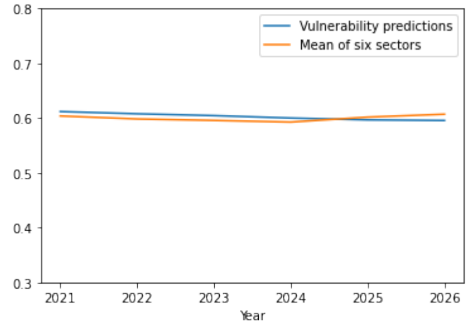

Figure 5.31. Vulnerability and mean of six sectors predictions for Sudan.

Table 5.18. Vulnerability and mean of six sectors predictions for Sudan.

Year	Vulnerability	Mean of six sectors
2021	0.611923	0.603824
2022	0.607839	0.598397
2023	0.604534	0.595713
2024	0.600081	0.592703
2025	0.596713	0.601802
2026	0.595606	0.607056

In Figure 5.31 and Table 5.18, two prediction results are compared and values in the table are close to each other showing the model's consistency. The RMSE of 2 different ways of Vulnerability predictions is 0.008.

5.7. Kyrgyzstan

Kyrgyzstan and Turkey have the same vulnerability scores, but they are in different income groups. Kyrgyzstan's income group is Lower middle [21]. Kyrgyzstan ranks 28th out of 182 countries with a vulnerability score of 0.350 for 2020 [21]. The mean of 26 years of vulnerability values is 0.362. The minimum value was in 2019 as 0.349, and the maximum was in 2004 as 0.377 for vulnerability scores [21]. The main reason for the vulnerability score's increase in 2004 is the increase in the health sector in the same year. Projected change in deaths from climate change-induced diseases might be the reason for the increase in the health sector. The following figures show Kyrgyzstan's vulnerability and six life-supporting sectors for 26 years values from 1995 to 2020. As seen in Figure 5.32 and Figure 5.33, Kyrgyzstan's vulnerability has a decreasing trend even if there are occasional increases.

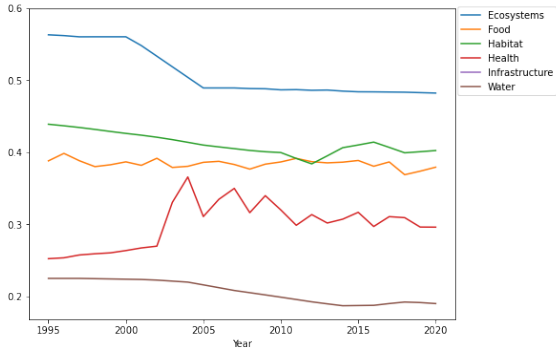

Figure 5.32. Six life-supporting sectors scores of Kyrgyzstan from 1995 to 2020.

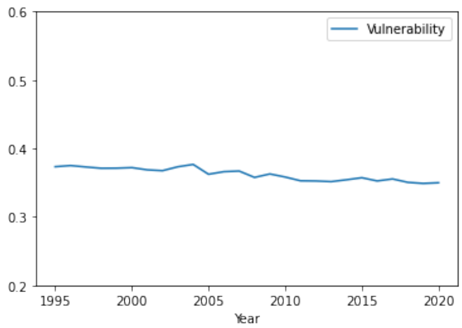

Figure 5.33. Vulnerability scores of Kyrgyzstan from 1995 to 2020.

As seen in Table 5.19, RMSE often worsened as the prediction horizon lengthened.

Table 5.19. RMSE of Kyrgyzstan's vulnerability predictions.

t	**RMSE**
t+1	0.002842
t+2	0.004234
t+3	0.005078
t+4	0.006102
t+5	0.006274
t+6	0.006846

The model's forecasts on the testing dataset can be seen in Table 5.20 and Figure 5.34. Forecasts and actuals show an overall similar pattern, although there are some differences. Forecasts correctly predict increases and decreases in the actuals, but forecasts are not as complex as actuals because forecasts should be a more general model.

Table 5.20. Forecasts and actuals of Kyrgyzstan's vulnerability scores from 2010 to 2020.

Year	Forecasts	Actuals
2010	0.360191	0.358279
2011	0.356783	0.352780
2012	0.352036	0.352488
2013	0.351803	0.351560
2014	0.350837	0.354266
2015	0.353158	0.357254
2016	0.351767	0.352557
2017	0.350089	0.355466
2018	0.348379	0.350512
2019	0.346618	0.348927
2020	0.345201	0.349929

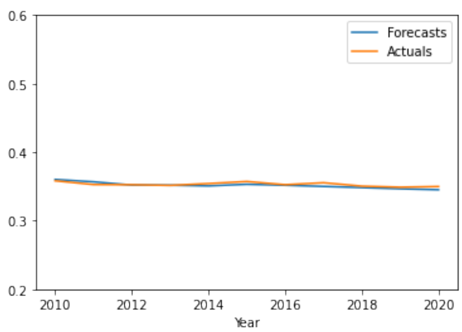

Figure 5.34. Forecasts and actuals of Kyrgyzstan's vulnerabilities from 2010 to 2020.

Values from 2021 to 2026 are predicted using the trained and tested model. Both vulnerability predictions and six life-supporting sectors predictions forecasted a decline in vulnerability scores from 2021 onwards.

Table 5.21. Vulnerability and mean of six sectors predictions for Kyrgyzstan.

Year	**Vulnerability**	**Mean of six sectors**
2021	0.361517	0.359487
2022	0.360052	0.357520
2023	0.358321	0.355479
2024	0.356626	0.354367
2025	0.354720	0.351772
2026	0.353271	0.348993

In Figure 5.35 and Table 5.21, two prediction results are compared and values in the table are close to each other showing the model's success and consistency. The RMSE of 2 different ways of Vulnerability predictions is 0.003.

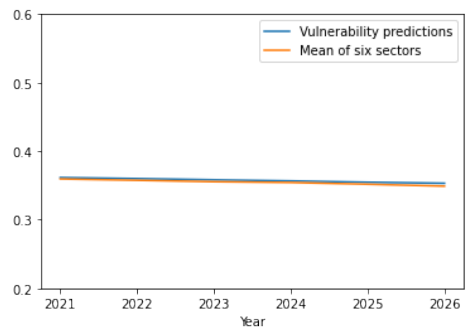

Figure 5.35. Vulnerability and mean of six sectors predictions for Kyrgyzstan.

6. CONCLUSION

This study predicted seven countries' six years of vulnerability and six life-supporting sectors' scores by using the LSTM network-based model from 2021 to 2026. Our model predicted scores close to the actual scores on the testing data. In time series prediction, it is very important to be able to predict the trend correctly. The model correctly predicted the upward or downward trend in almost all data for all countries. Results showed that a model created using the LSTM network capable of predicting any country's future years' vulnerability to climate change. However, if there is war, war-related or unrelated human migration, epidemic, and pandemic in the future, some scores can astronomically change for some countries. This can cause enormous differences between our future years' predictions and real scores. We used data from 1995 to 2020, and we could not see the effects of the Covid-19 pandemic much in the 2020 data. But we think we can see this effect more in the 2021 data. And this may cause our 2021 prediction to differ from the actual score. The intensive use of resources in the country due to the change in the demographic structure of Turkey, which is both a transit region due to migration to the west and a permanent migration region for the Middle East, Africa, and South Asia, has led to an increase in the country's vulnerability to climate change since 2012. The continuation of this situation may cause Turkey to be affected by climate change more than expected in the future. Also, it is important to note that if data for one or more countries from the past few years is lacking, linear interpolation is applied to fill in the gaps. This has led to uncertainty in the real values of some data we use to make predictions. And this may affect the success of some predictions. This study may help countries realize that they need to increase their precautions to mitigate climate change's effects. Developed countries usually take such precautions. Our model was most successful in developed countries. Developed countries have long-term strategies for climate action. But they have targets set for each year to achieve these long-term goals. For example, Germany has permitted annual emission volumes for different sectors set for each year until 2030. This study provides a forecast of whether such countries can meet these annual targets. As this study predicts several years in advance how countries will be affected by climate change, countries can anticipate situations where they will not be able to meet their yearly targets, and thus countries can increase the actions they take to meet their targets. Considering that even Germany has not reached its target for 2021, countries should increase the intensity of the actions they take to reach their targets, taking into account the results of all kinds of short- or long-term forecasting studies to reduce the effects of climate change.

The six life-supporting sectors that make up the vulnerability score are interrelated. Increasing temperatures, drought, and water stress due to climate change reduce agricultural yields, leading to food security problems, which in turn lead to health-related problems. Therefore, it is reasonable and very important to predict future vulnerability and life-supporting sectors' scores for countries to take precautions.

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