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TEMPERATURE AND PRECIPITATION FORECAST FOR WESTERN TRANSYLVANIAN PLAINS USING ARTIFICIAL INTELLIGENCE

Felicia CHEȚAN[1], Eva-Henrietta DULF[2], Teodor RUSU[3], Cornel CHEȚAN[1], Alina ȘIMON[1]

[1]Agricultural Research and Development Station Turda, 27 Agriculturii Street, 401100, Turda, Romania
[2]Technical University of Cluj-Napoca, Faculty of Automation and Computer Science, 28 Memorandumului Street, 400114, Cluj-Napoca, Romania
[3]University of Agricultural Sciences and Veterinary Medicine Cluj-Napoca, Faculty of Agriculture, Department of Technical and Soil Sciences, 3-5 Mănăstur Street, 400372, Cluj-Napoca, Romania

Corresponding author emails: eva.dulf@aut.utcluj.ro; trusu@usamvcluj.ro

Abstract

Climate change represents a growing risk factor for agriculture, climate predictions being very important for adaptation measures. The ecological frame from the Transylvanian Plain is given by the existence of interaction among a great number of factors, of which two are very important for the agro-ecosystem: the first is the thermal background with high temperature variations and low rainfall, characteristics which impose significant restrictions for crop plants and secondly it is the hill orography, with slope land. The present paper analyze the weather evolution of the farm from Agricultural Research and Development Station Turda located on Western Transylvanian Plains, using artificial intelligence. Study developed mathematical models based on data measured in the last 63 years (1957-2019). The average annual temperature for the period 1957-2019 is 9.2°C and multiannual average precipitation is 531.4 mm. From the simulation of the evolution of the main climatic factors, temperature and precipitation, in the next decade it can be observed the sharp increase of the average annual temperature and a lower fluctuation of the precipitation regime. It could be noticed that the predicted average temperature values for the summer of the next 10 years are: 17.3°C for June, 23.8°C for July and 25.9°C for August, resulting an average of 22.33°C for summer. Agriculture must adapt to the new conditions, taking some measures, the modification or improvement of current plant cultivation technologies, the use of varieties/hybrids that are more resistant or at least tolerant to prolonged drought and during periods with high temperatures, the adoption of new technologies to accumulate/preserve water in the soil for a longer period.

Key words: *agriculture, artificial intelligence, prediction, weather evolution.*

INTRODUCTION

Climate change represents one of the biggest threats to the environment, the social and economic framework. Extreme climate events, including heat waves, droughts and floods, are expected to become more frequent and more intense (Kivinen et al., 2017; Drumond et al., 2020; Santos et al., 2022) the use of temperature and precipitation records being, in this context, very useful in predicting these phenomena. Governments and companies invest billions of dollars into weather forecasting every year for good reason (Lin et al., 2021; Schuldt et al., 2021). There is effectively no sector of the economy which is not directly or indirectly impacted by the weather (Abraham et al., 2020; Vicente-Serrano et al., 2021; Ferreira et al., 2023; Nemukula et al., 2023). The benefits of improved weather forecasting for agriculture are obvious, making farms a major customer of private forecasting companies (Zuma-Netshiukwi et al., 2013; Shen et al., 2022). Weather determines the best time to sowing, fertilized, sprayed, irrigated and harvest crops (Butts-Wilmsmeyer et al., 2019; Chețan et al., 2019; Haș et al., 2022; Șimon et al., 2022). Having accurate weather information about every part of a field can allow farmers to maximize their yield (Wilcox et al., 2014; Shang et al., 2016; Spinoni et al., 2016; Kujawa et al., 2021). We can say that 90 percent of crop losses are due to weather events and 25 percent of weather-related crop losses could be prevented by using predictive weather modeling (Epure et al., 2017; Elias et al., 2019).

The trends of the drought was studied in Romania by Angearu et al. (2020) during 2001-2019, and was based on a multi-temporal analysis and trends of the Drought Severity Index (DSI), and its validation based on meteorological data, soil moisture content, agricultural yield, etc. The measurements were precise and accurately determined the agricultural areas most affected by the drought, during the April-September period (Angearu et al., 2020). In recent years, operational Numerical Weather Prediction (NWP) models have significantly in-creased in resolution) (Du & Deng, 2022; Quin et al., 2023; Zhao et al., 2023). Applying Artificial Intelligence (AI) techniques in conjunction with a physical understanding of the environment can substantially improve prediction skill for multiple types of high-impact weather (Cojocaru, 2020; Haupt et al., 2020; Dewitte et al., 2021). In recent years, forecasters and researchers have begun to adopt AI techniques much more widely, as they demonstrate their power in a wide variety of applications (Mukhamediev et al., 2022). Artificial Neural Networks (ANN) are interconnected networks of weighted nonlinear functions (Abdolrasol et al., 2021). When connected and trained in multiple layers, ANNs can represent any nonlinear function (Maarif et al., 2022). They also provide the foundation for deep learning methods. ANNs have been used in a wide variety of meteorology applications since the late 1980 (Key et al., 1989) including cloud classification (Bankert, 1994), tornado prediction and detection (Marzban & Stumpf, 1996), hail size (Manzato, 2013) and precipitation classification (Lukshmanan et al., 2014). Reduced rainfall related to high temperatures leads to hydrological drought, reducing river flow, fact mentioned in the research conducted by Anghel and Ilinca (Anghel & Ilinca, 2023), which used the mathematical model for the anaBanlysis of the frequency of hydrological drought in Romania.

Artificial Neural Networks (ANNs) are computing systems inspired by biological neural networks, which are part of every living organism (Dulf et al., 2022). ANNs are used for prediction, pattern recognition and clustering. A neural network consists of a number of elements called neurons. Each neuron receives a number of signals which are called inputs. Each neuron is internally defined by certain states which determine whether the received signal will be transmitted to another neuron or not (threshold value). In addition, when the signal is transmitted, it is coupled with an internal weight coefficient, which essentially determines how closely the specified neuron is to the receiving one.

The training of a neural network refers to the adjustment of the weight and bias values until the desired, optimal performance is reached. This is achieved through solving the optimization problem: minimizing the cost function. In regression problems, usually this cost function is the mean squared error, minimized using gradient descent method. There are several optimization algorithms for neural networks, such as Levenberg-Marquardt, Scaled Conjugate Gradient, Bayesian Regularization, Gradient Descent with Momentum (Lorenzovici et al., 2021). The Levenberg-Marquardt is considered to be the fastest optimization algorithm for feed forward networks (Mukhamediev et al., 2022). Another alternative for time-efficient training is the quasi-Newton algorithm, but the Levenberg-Marquardt optimization method is more reliable and ensures better performance on nonlinear regression (also called as function fitting) compared to pattern recognition tasks.

Regarding the architecture of the neural network, there are several rules to consider to prevent over fitting, which is a common problem that occurs during the training process. Explained in a simplified manner, the over fitting means that the model learns also the noise from the training data, not only the useful information. In this way, the ability of the network generalization decreases. When constructing neural networks, a network should be large enough to build complex functions and achieve good performance, but small enough to prevent over fitting. In order to prevent it, the network should have considerably less parameters than the amount of data samples in the training set (Rajendra et al., 2019; Lorenzovici et al., 2021).

Transylvanian Plain is considered as an area with a low capacity to adapt to climate changes (Haggard, 2012), monitoring the climate and implementing the adaption measures being essential for the development of certain durable agricultural technologies (Rusu et al., 2017). Data recorded in the Transylvanian Plain confirms that the condition of land degradation and its effects, being the result of local extreme physical-geographical conditions (Moraru et al., 2014), is susceptible to degradation (evidenced by the erodibility index), which overlaps the extreme climatic conditions (Rusu et al., 2019). Considering these conditions, the hypothesis of our research is that by making a temperature and precipitation forecast we can recommend technological adaptation measures in agriculture.

The present paper analyze the weather evolution of the farm from Agricultural Research and Development Station Turda (ARDS Turda), using artificial intelligence. The main goal of the paper is to develop mathematical models based on data measured in the last 63 years. The models are useful in temperature and rainfall prediction and assist in the planning of agricultural activities in order to increase productivity and benefits.

MATERIALS AND METHODS

Transylvanian Plain is a 395,000 ha region located in north-central Romania and is an area of agronomic importance in the region (Lorenzovici et al., 2021). Transylvanian Plain is characterized by hilly terrain, dissected by the Someş and Mureş Rivers. The terrain creates a unique situation when assessing pedology and soil temperature (Haggard, 2012; Rusu et al., 2017). Soils can change quickly across the landscape in the Transylvanian Plain due to the terrain. ARDS Turda is located in the Western Transylvanian Plains, the physiographic section: Aiton - Viișoara Hills and almost all the agricultural lands of the unit are located at 405 m elevation.

The weather conditions during the 1957-2019 measured at Meteorological Station Turda (23°47'longitude; 46°35'latitude; 427 m altitude) can be seen in Tables 1 and 2. Meteorological Station Turda is part of the administrative structure of the Northern Transylvania Regional Meteorological Center under the Romanian National Meteorological Administration. This Center manages part of the surface meteorological network, the meteorological network representing the basic structure in which meteorological measurements and observations are carried out and the main sources of meteorological data for forecasting activity, climate research studies, diagnosis and international exchange of meteorological data (www.meteoromania.ro; accessed on 23.04.2023).

Table 1. The thermal regime during 1957-2019 at ARDS Turda

Year/	Temperature (°C)												I-XII
month	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII	
1957	-3.5	2.1	6.6	9.8	13.2	18.5	20.5	18.8	16.3	10.8	5.7	-2.9	9.7
1958	-1.9	3.9	0.7	7	17	17.1	19.7	19.2	15.3	9.8	4.6	0.8	9.4
1959	-3.3	-4.4	5.9	9	13.8	16.6	20.4	18.2	12.5	7.8	3.2	1.8	8.5
1960	-2.3	-3.8	4.8	9.5	13.7	7.3	18.6	18	12.9	11.4	6.8	4	9.2
1961	-5	-0.2	5.2	11.2	11.3	19.2	19	19.1	16.2	11.2	6.1	-1	9.4
1962	-2.1	-1.7	0.6	10.8	14.6	16.4	17.8	20.8	14.6	10.7	6.6	-4.5	8.7
1963	-9.1	-3.2	0.8	10.7	16	18.5	21.6	21.3	17.2	9.8	7	-4.1	8.9
1964	-9.8	-4.6	3	9.7	12.8	21.3	19.4	17.6	14.8	10.8	4.6	-0.6	8.3
1965	-5	-6	3.8	7.5	13	17.6	19.1	16.8	16.3	9.2	2.1	-0.2	7.9
1966	-5.2	3.7	4.2	11.2	14.4	16.5	19.3	18.8	14.2	13.3	4.9	-1	9.5
1967	-6.5	-2.2	4.7	9.3	15	17.1	20.9	19.4	16.6	11.8	4.4	-1.7	9.1
1968	-4.6	1.3	4.2	12.7	16.6	19.5	18.6	17.4	14.9	9.1	6.8	-2.7	9.5
1969	-8	-1.2	2.2	8.4	16.8	16.5	18.2	18.6	15.1	9.4	6.5	-0.5	8.5
1970	-2.4	-1.2	3.4	9.8	12.3	17	19.8	18.6	14	7.9	5.1	0	8.7
1971	0.3	0.2	2.6	9.8	16	16.5	18.8	20	12.7	7.7	3.1	0.4	9
1972	-2.9	2.2	6	11.7	14.5	18.7	20.4	18.4	12.2	7.1	3.5	-1.1	9.2
1973	-2.9	0.6	2.7	9.5	15	17	18.8	18.8	16.6	8.9	0.3	-4.2	8.4
1974	-3.8	3	6.6	7.5	12.6	15.6	17.8	19.8	15.8	8.2	2.3	0.2	8.8
1975	-1.4	-1.8	7.2	9.4	16	18	19	18.4	16.9	9	0.6	-2.1	9.1
1976	-3.4	-4.4	0.9	10.2	13.9	16.4	19.6	15.8	14.1	10.3	4.7	-1	8.1
1977	-2.2	3.6	7.1	8.1	14.8	17	18.6	17.8	12.7	9.8	4.3	-4.7	8.9
1978	-4.2	-1.3	5	8.4	12	16.6	17.1	16.7	12.3	8.3	0.3	-1	7.5
1979	-4.6	-0.1	5.8	8.2	15.4	20.1	16.4	17.6	15.7	7.8	5.2	0.9	9
1980	-6.8	-0.8	3.5	7.5	12.1	16.4	17.6	17.7	13.6	9.9	2.9	-1.7	7.7
1981	-4.6	-2.1	6.2	8.2	14	19.1	18.2	17.8	15.4	10.5	1.5	-1.9	8.5

1982	-7.2	-4.8	2.9	6.7	15.9	17.9	18.6	19.6	18	10.2	1.5	1.9	8.4
1983	0.3	-1.9	5.5	11.4	16.4	17.2	20.2	18.8	15.4	8.1	0.3	-2.1	9.1
1984	-1.8	-2.9	1.9	8.8	14.7	15.7	16.8	17.5	15.3	10.6	3.5	-8.7	7.6
1985	-8.4	-9.1	3.1	10	15.8	15.1	18.9	19.3	13.9	7.8	3	-0.3	7.4
1986	-1	-3	4.3	11.9	16.9	17.8	18.1	20.3	15.8	8.6	2.4	-4.1	9
1987	-5	-1.1	-0.8	8.7	13.2	18.2	22	16.8	17.4	8.9	4.6	-0.4	8.5
1988	0.4	1	2.3	8.2	15.2	16.8	21.4	19.9	15.2	8.7	-1.3	-0.7	8.9
1989	-6.6	1.4	6.5	12.3	14	16.4	19.7	19.2	14.7	9.6	2.4	-1.3	9
1990	-3.4	2.6	8.5	10.1	15	17.5	19.6	20	12.9	10.1	5.6	-1.1	9.8
1991	-1.9	-2.5	6.6	9	11.7	17	20.5	18.3	15.1	9	4.1	-4.6	8.5
1992	-4.7	-1.8	4	10.8	14.3	18	19.9	23.3	14.4	9.5	4.4	-3.5	9.1
1993	-3.2	-4.9	3.9	8.8	17.3	18.5	18.7	19.9	13.5	11.3	-0.3	1.2	8.7
1994	-0.5	1.8	6.7	11.1	14.7	18.1	21.4	20.6	19.1	8.5	3.9	-0.7	10.4
1995	-3.5	3.4	4.9	9	14.3	18.2	22.3	19	13.9	10.9	-0.3	-1.8	9.2
1996	-2.4	-2.7	-0.8	10	17.1	19.7	18	18.8	11.8	9.9	5.7	-1.4	8.6
1997	-1.9	-0.6	2.8	5.4	15.4	18.1	18.3	18.5	13.5	6.7	4.5	0.5	8.4
1998	-0.9	2	1.5	11.3	14	18.5	19.7	19.4	13.8	10.4	1.8	-5.6	8.8
1999	-2.2	-1.8	4.8	10.2	14.3	19.7	21.2	19.4	16.8	9.4	2.1	-2	9.3
2000	-6.4	-0.6	3.5	12.9	16.9	19.2	19.7	21.2	14.3	11.1	7.4	0.1	9.9
2001	-0.4	0.8	7.3	10.1	15.6	17	20.4	21	14	11.4	5.7	-7.2	9.6
2002	-3.1	3.2	7.1	10.7	18.3	19	21.6	19.1	14.6	9.7	5.7	-3.1	10.2
2003	-3.3	-5.9	2.4	8.4	19.5	21.1	20.3	21.9	15	7.5	4.5	-2.2	9.1
2004	-4.6	-1.2	4.7	10.7	14	17.7	19.9	19.3	14.1	10.7	4.9	0	9.2
2005	-2.1	-4.2	1.5	9.8	15.7	17.2	19.7	19	16.1	10.1	3.5	-0.9	8.8
2006	-5.1	-2.4	3.4	10.8	14.3	17.6	21.2	18.5	15.8	10.5	3.5	-0.1	9
2007	2.4	2.5	7.3	10.8	17	20.3	22	20.1	13.7	9.3	1.9	-3.2	10.3
2008	-2.8	3.8	5.4	10.5	15	19.4	19.5	21	14	10.7	4.1	1.1	10.1
2009	-2.3	-0.5	3.7	13.2	16.2	18.7	21	20.7	17.4	10	5.2	0.1	10.3
2010	-3.1	1	4.3	10.5	15.4	18.9	20.7	21	14.2	7.4	7.6	-1.6	9.7
2011	-3.8	-3.2	5.3	10.7	15.6	19.2	20.1	20.8	18.2	8.8	0.7	0.8	9.4
2012	-2.3	-6.1	4.7	11.8	16.2	21	24	22.3	19.1	11.4	5.2	-2.6	10.4
2013	-2.4	2	3.5	12.3	16.8	19.4	20.9	22.1	13.8	11.2	7.1	-1.7	10.4
2014	0.5	3.8	8.8	11.4	15.1	18.5	20.4	19.9	16.6	10.8	5.7	1.3	11.1
2015	-0.7	0.6	5.5	9.6	15.8	19.4	22.3	21.9	17.3	9.7	6.1	0.7	10.7
2016	-2.8	4.6	5.9	12.4	14.3	19.8	20.5	19.6	17.1	8.3	2.9	-2.7	10
2017	-6.7	1.5	8.4	9.9	15.7	20.7	20.3	22.3	15.8	11.6	4.9	1	10.5
2018	0.2	-0.3	3.3	15.3	18.7	19.4	20.4	22.3	16.7	12.7	6	-0.9	11.2
2019	-2.2	1.7	7.3	11.3	13.6	21.8	20.4	22.1	17.1	13.5	8.9	0.8	11.4

Table 2. The precipitation regime during 1957-2019, at ARDS Turda

Year/	Precipitation (mm) - monthly amount												Sum
month	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII	
1957	9	33.9	2.5	82.7	102.5	53.3	36	35.9	4.4	25.1	23	14	422.3
1958	6.5	36.5	21.9	62.6	18	92.3	3.8	65.2	19.4	25.4	26.3	16	393.9
1959	17	6.6	54.7	23.5	46.8	105.3	156.2	73.8	48	2.5	28.2	27.4	590
1960	36.1	21.3	35	29.9	95.8	43.1	117.7	29.9	20.3	44.1	55.7	25.7	554.6
1961	7.1	10.6	3.6	26.3	65.3	53.8	44.4	37.4	1.2	11.6	39.7	23.7	324.7
1962	14	19.2	74.9	37.8	49.1	49.8	45.8	10.8	27.6	1.7	28.3	21.4	380.4
1963	96.7	15.6	37.2	18.8	40.2	35.5	52.8	51.6	37.7	39.5	8.3	68.5	502.4
1964	12.7	17.2	43.9	40.4	76.4	61.6	76.2	67.8	21.2	68.5	34.1	43.1	563.1
1965	37.3	15.6	24.4	39.2	87.2	78.2	52.1	57	18.4	4.4	37.1	26.3	477.2
1966	43.7	28.7	35.3	76.2	55.1	46.3	112.4	63.9	30.5	47.6	53.6	21.2	614.5
1967	28.4	21.2	14.6	36.4	84.1	49.3	111.3	60.1	41.6	13.1	22.3	34.3	516.7
1968	24.5	25.2	9.1	39.5	76	39.7	122.5	94.9	82.9	36.9	59.5	42.5	653.2
1969	4.4	58.7	18.7	24.9	80.6	132.1	75.9	90.4	84.7	12.7	23	40.5	646.6
1970	16.9	34.7	37.2	40	105.7	106.2	75.8	82.1	35	49.5	23.9	10.8	617.8
1971	31	14.5	8	21.6	91.1	70	53.6	39.6	47.3	19	30.2	38.7	464.6
1972	13.5	16.4	9.9	60.2	78.3	72.5	31	110.1	37.8	81.7	43.4	0	554.8
1973	14.1	22.9	12.3	53	73.2	103.8	73.9	35.3	28.9	30.1	10.2	15.6	473.3
1974	14.7	5.4	10	52.5	76.3	140.5	85.8	67.6	36.8	60.6	23.7	32.3	606.2
1975	2.6	4.1	3.6	52	68.1	123.1	162.5	44.1	24	42.6	10.6	6.2	543.5
1976	50.4	0	12.7	58.6	42.4	77.8	59.3	52.4	34.3	21.5	51.7	22.5	483.6
1977	27.4	21.1	39.1	73	70.9	57.7	32.2	33.2	44.3	7	69.7	19.1	494.7
1978	11.8	65.1	10.8	71.3	64.7	53	95	49.2	91	5	22.6	17.9	557.4
1979	22.5	10.4	20.3	24.9	38.2	86.8	83.2	61.1	55.2	17.3	20.1	17.5	457.5
1980	29.5	5.9	23.9	72.8	97	36.5	175.5	47.8	29.3	70.7	38.6	46.2	673.7
1981	20.6	9.7	42.5	56.8	38	53	77.1	29.4	25.7	60.4	25.7	73.5	512.4
1982	13.2	19.3	19.6	43	26.4	79.9	64	46.5	7.6	33	5.7	33.8	392
1983	15.3	11.5	9.9	63.7	72.8	124.5	47.9	29.6	48	7.4	17.6	11.8	460

1984	43.2	38.5	28.1	21.8	130.7	61.9	92.9	61.9	62.6	24.6	18.1	27.9	612.2
1985	25.1	31.2	12.8	49.9	106.1	90.5	36.1	70.6	9.5	17.8	66.2	22.1	537.9
1986	13.8	28	14.2	55.4	40.5	57.7	72.7	34.7	4.8	22.5	5.1	6.7	356.6
1987	25	7.1	25.3	53.2	126.6	65.8	15.8	72.5	9.6	34.8	53.5	38.5	527.7
1988	44.5	15.7	69.4	40.1	63.2	80.5	61.8	21.5	33.6	11.1	6.4	34.2	482
1989	10.2	15.4	15.4	90.4	67.7	117.6	20.8	105.6	36.4	18	13.9	8.7	520.1
1990	6.2	6	3.4	41.7	35.8	65.6	77.1	32.4	24.8	20.2	20.1	47.7	381
1991	11.9	4.1	7.1	30.6	94.1	59.5	82.7	57.8	35.1	55.4	34.8	25.9	499
1992	17.3	6.7	3.1	19.4	31.2	134.6	69	11.7	32.8	35.5	17.6	16.4	395.3
1993	6.4	10.2	41.7	52.5	111.5	49.3	57.6	42.4	70.1	17.9	62	35.6	557.2
1994	4.4	5.2	13.7	48.8	67	111.7	62.7	60.3	41.2	57.7	11	10.9	494.6
1995	20.5	15.5	2.9	16.6	65.9	114.4	8	63	38	0.1	26.8	35.6	407.3
1996	28.6	16.4	21.9	20.4	84.4	73.9	43.8	40.5	90.5	36.4	12.7	40.1	509.5
1997	4.1	8.6	13.8	58.4	41.8	91.7	91.4	65	34.2	34.9	21.3	39.8	505
1998	22.5	7.8	11	40.7	57.5	181.5	57.6	26.7	61.9	78.1	30.5	4.9	580.7
1999	10.5	35.5	10.7	73.6	109.7	134.8	68.4	61.2	31.4	31.7	20.8	40	628.3
2000	11.4	8.4	17.8	14.6	32.5	37.4	66.9	3.1	38.8	2.3	1.1	25.4	259.7
2001	30.8	12.5	35.7	55.5	64.1	82.7	103.1	35.6	109.5	27.6	44.8	7.7	609.6
2002	5.5	5.5	24.9	21.6	43.9	75	61.6	73.9	51.3	28.4	38.9	22.5	453
2003	44.3	11.6	13.9	17.9	26.6	21.9	151.4	1.3	28.3	66	35.4	7.5	426.1
2004	24.4	25.8	28.8	49.4	15.2	85	160.1	111.9	76.6	21	67.4	18.2	683.8
2005	24.3	27.7	33.3	81.5	54.9	95.4	131.6	180.8	62.4	6	7	37.6	742.5
2006	11.4	17.1	45.3	70.8	77.9	118.2	16.5	148.6	32.6	18.6	6.1	17.7	580.8
2007	12.8	30.7	24.4	10.1	103.8	77.1	54.4	118.1	84.7	93	25.4	20.8	655.3
2008	17.3	11.2	30.3	58.4	89	136.8	125.2	9	41	45.4	21.1	45.9	630.6
2009	9.5	22.4	53.5	8.4	31.4	113.4	52.5	38.1	3.4	77.8	48	35	493.4
2010	39.2	30.6	17.6	52	87.6	172.6	121	49.2	67.2	31.6	30.8	40.4	739.8
2011	26.8	19.9	15.3	22.6	41.4	116.8	130.4	12.8	22.8	8.8	0.2	15.2	433
2012	26.2	30.7	5.3	78.4	89.2	67.4	52.4	28	30.2	42	9.6	45	504.4
2013	19.8	10.3	57.9	53.3	79.3	86.2	37.6	44	57.8	67.8	5.9	3.3	523.2
2014	51.6	15.5	23.1	72	66.2	48.4	144.4	83.8	48.4	67.4	34.2	86.8	741.5
2015	12.3	20.9	12.8	32.2	66	115.7	52.2	72.2	172.6	45.4	32	6.9	641.2
2016	25	23.8	47	62.2	90.4	123.2	124.9	91	24.6	152.2	45.3	7.2	816.8
2017	2.6	19.2	46.1	65.2	65.4	30.6	110.2	36.1	56.2	49.2	30.8	20.7	532.3
2018	16.7	33.4	40.9	26.2	56.8	98.3	85.7	38.2	29.8	26.8	29.6	58.3	540.7
2019	46	14.7	12.3	62.6	152.4	68.8	35	63.8	19.4	25.6	28.4	14.2	543.2

The weather station of the ARDS Turda is located in the West of Transylvania Plain, in Turda town, Cluj County, Romania. The used data are recorded for 63 years (1957-2019) and contains the average values of temperature and rainfall for each month. Using these data are developed mathematical models based on artificial intelligence. The dataset is divided into two parts: 70% for training and 30% for validation. This data division strategy is used for model and performance evaluation. In order to obtain the highest possible accuracy for the developed models, different network architectures were analyzed, comparing their performance measures. The type of networks was feed forward with back propagation in all experiments, but the number of layers and neurons were varying. Both the number of layers and the number of neurons were taking three types of values: low, medium, large. The final architecture was chosen using the conclusions drawn from the results. The performance function was Mean Squared Error (MSE) (Tang et al., 2019):

$$\mathrm{MSE} = \sum_{i=1}^{N} \left(y_i - \hat{y}_i \right)^2,$$

where N denotes the number of samples and MSE represents the square of difference between target value y_i and predicted value (obtained from a trained model). The networks were trained on a computer with i7 9700K, 4.7 GHz Turbo Boost CPU and a ddr4 memory of 16 GB. It is important to mention that the resulting performance measures of the networks presented below may vary depending on the hardware on which the training is performed.

The training and simulation were made in Matlab® software environment, Machine Learning and Neural Network toolboxes.

RESULTS AND DISCUSSIONS

For the final results it was chosen a system architecture with one input layer, one hidden and one output layer, as it presented in Figure 1. Using 10 neurons and the Levenberg - Marquardt optimization method, it was obtained the mean squared error of 3.9982,

Figure 2, and a correlation coefficient of 0.9757, as it is presented in Figure 3.

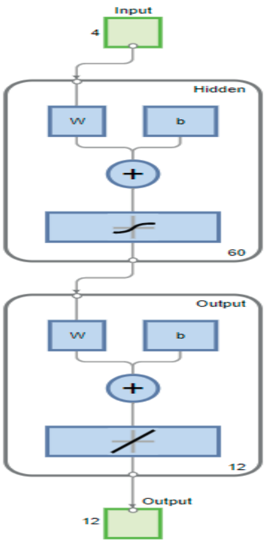


Figure 1. System architecture

It can be seen that the minimum of the cost function was reached after 8 epochs. The correlation coefficient between the experimental data and the predicted data of mean air temperature are between 0.967 and 0.978, demonstrating a high relation between the estimated and observed data. Compared with other similar results in literature, this is a very good performance (Gao et al., 2022; Lokoshchenko et al., 2023). The best reported regression value for similar datasets are between 0.92 and 0.93 (Moraru et al., 2014).

The comparison with real data is presented in Figure 4a, with a zoom in 4b, high-lighting the same good performances for both low and high temperature levels and for both instantaneous and cumulative measures. The model ability to estimate uncertainty and capture variation is undubitable.

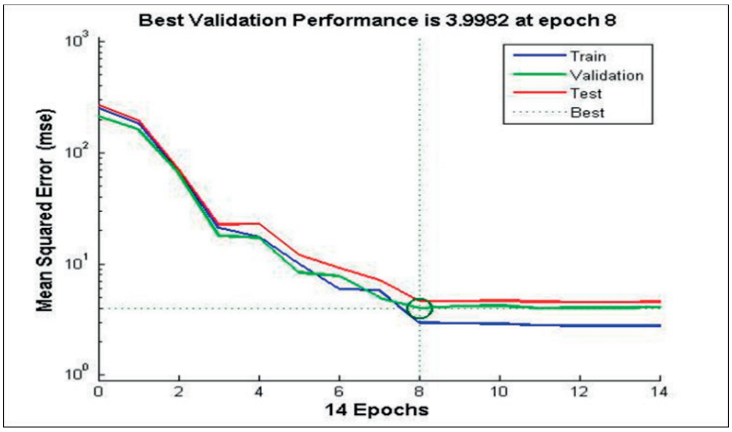


Figure 2. Evolution of mean squared error

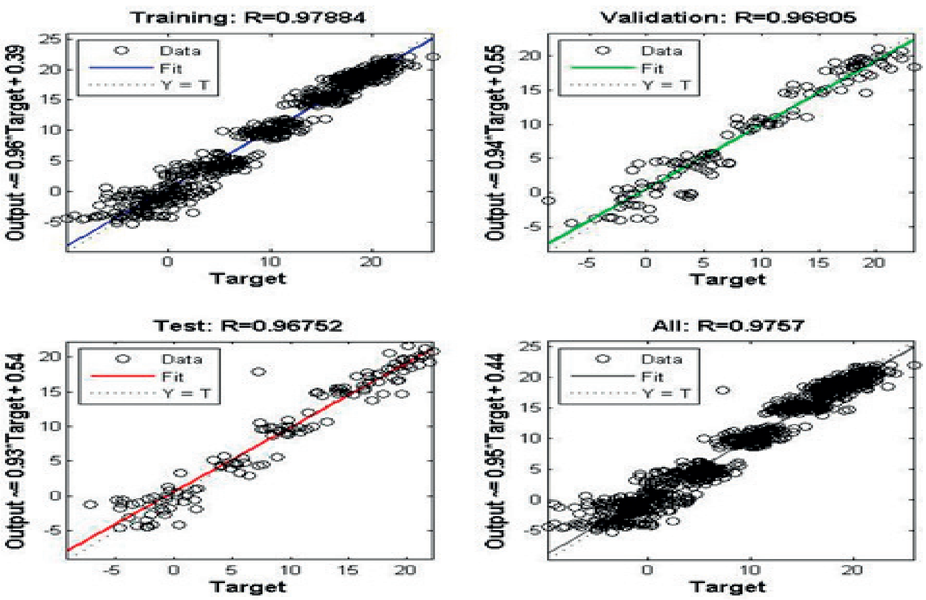
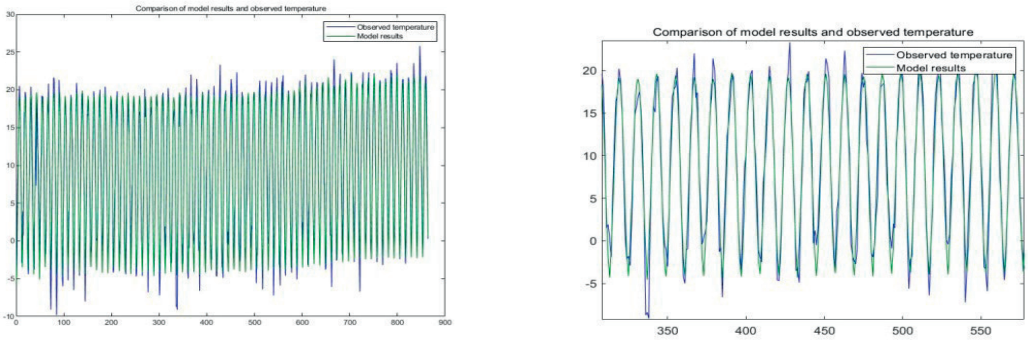


Figure 3. Regression analysis



a b

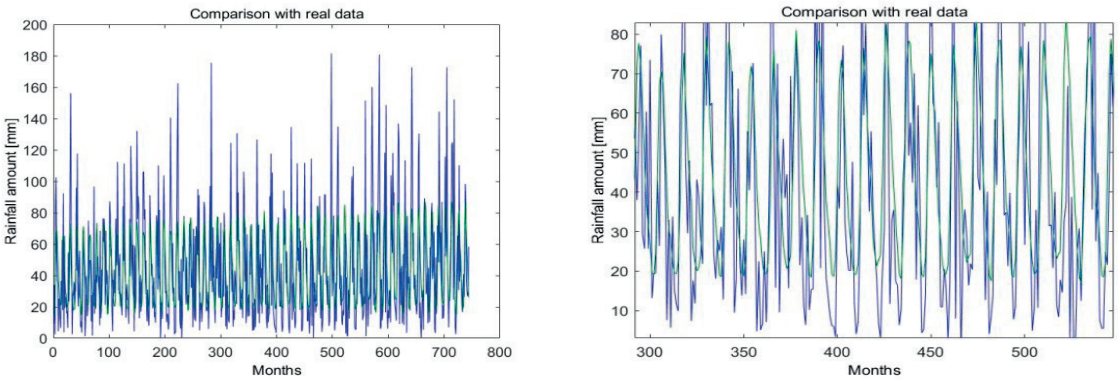
Figure 4 (a, b). Comparison of temperature simulation results with observed data

The performance measures of the resulted models are summarized in Table 3. As demonstrated in Table 3, the precision of temperature forecast is very good. The mean squared error varies between 1.57 and 1.77 for different seasons. It can be observed that no significant differences are obtained for different seasons in any of performance measures, although the temperature values varies pretty much. The results are comparable with other published results in the field (Rajendra et al., 2019). However, the largest temperature deviations in some points are obtained for the winter season data, being involved the largest temperature variations.

A similar ANN model, with the same parameter settings is established for the precipitation evolution in the same time period and zone. Precipitation forecast is more challenging, being a fast-changing weather variable. The obtained model has a correlation coefficient of 0.9468. The simulation results obtained (with the model) are presented in Figure 5a with a zoom in Figure 5b.

Table 3. Performance analysis of the created neural network for temperature in different seasons

Evaluated season / Performance measures	Spring	Summer	Autumn	Winter
Epoch	10	7	7	7
Elapsed Time	00:00:03	00:00:02	00:00:03	00:00:03
Mean squared error	1.58	1.7	1.57	1.77
Gradient of the square of the error function	0.361	0.278	0.0571	0.25
Momentum update	0.0001	0.001	0.001	0.001
Validation Checks	6	6	6	6



a b

Figure 5 (a, b). Comparison of rainfall amount simulation results with observed data

The performance measures of the resulted models are summarized in Table 4. As demonstrated in Table 4, the precision of precipitation forecast is also very good. The mean squared error varies between 283 and 301 for different seasons, which is comparable with results reported for other regions in the literature (Rajendra et al., 2019).

From the analysis of the climate data presented in Tables 1 and 2 pronounced fluctuations of the two climate factors are highlighted, especially after the year 2000, the warmest month of the year is July and the rainiest is June. In different phases of crop vegetation, sudden changes in temperature can occur (very different values between day and night, strong heat), with negatively affect the development of the culture (Wagas et al., 2021), shortening the vegetation period with direct repercussions on the quantitative and qualitative yield (Čimo et al., 2022; Siomos et al., 2022). The specialized literature mentions some estimated values of temperature and precipitation depending on the crop plant (Wegrzyn et al., 2022; Soares et al., 2023), the main crops in the Transylvanian Plain area being wheat, maize and soybean.

Table 4. Performance analysis of the created neural network for precipitation in different seasons

Performance measures \ Evaluated season	Spring	Summer	Autumn	Winter
Epoch	7	7	9	9
Elapsed Time	00:00:04	00:00:03	00:00:03	00:00:03
Mean squared error	288	301	287	283
Gradient of the square of the error function	246	65.6	13.1	17.8
Momentum update	0.01	0.1	0.1	0.1
Validation Checks	6	6	6	6

For example, the winter wheat requires lower temperatures at the beginning of the vegetation (withstand up to 18-20°C at the twinning node level), moderate during the intensive vegetative growth phase and high during the grain ripening period (Wegrzyn et al., 2022; Soares et al., 2023; Skendžić et al., 2023). Maize belongs to the category of plants with high temperature requirements, (Khaeim et al., 2022). Soybean also belongs to the group of heat-demanding plants, the minimum temperature for germination is above 7 °C (Staniak et al., 2021; Szczerba et al., 2021). Low temperatures after sowing have an obvious negative influence on the growth of maize and soybean plants (Staniak et al., 2023). Each culture has a specific water consumption, of major importance being the distribution of precipitation on each phase of the vegetation (Qu et al., 2023). For example at maize the critical phases for water are: germination - ripening, flowering, grain formation and grain filling (El-Sanatawy et al., 2021; Wang et al., 2023). Soybean yield is conditioned by the humidity in the flowering - seed formation - grain filling phases (Mandić et al., 2020; El-Sanatawy et al., 2021; Qu et al., 2023; Staniak et al., 2023; Wang et al., 2023). Winter wheat have maximum requirements for water at germination, grain formation and grain filling phases (Hlaváčová et al., 2022).

From the simulation of the evolution of the main climatic factors, temperature and precipitation, in the experimental area in the next decade it can be observed the sharp increase of the average annual temperature and a lower fluctuation of the precipitation regime. The climatic factors studied did not have constant values, but varied in time and space, within minimum-maximum limits, with a certain frequency and a certain magnitude. The average annual temperature for the period 1957-2019 is 9.2 °C with amplitudes from 7.4 °C in 1985 to 11.4 °C in 2019. The coldest month of the year is January (multiannual average 3.3 °C) and the warmest is July (multiannual average 19.8 °C). Analyzing the average temperatures recorded in all 63 years, compared to the multiannual average, we can see an obvious warming in the Western Transylvanian Plains area taken into account. Nagavciuc et al. (2022), from studies conducted in the summer months of 1950-2020, reveals that in Romania there is a strong variability of temperatures at monthly and decadal level, higher values notified in the last 30 years. The multiannual average precipitation is 531.4 mm, the driest month is February (multiannual average 18.97 mm) and the rainiest is June (multiannual average 83.93 mm). Specific to the last years, was the uneven distribution of rainfall, there were dry periods of time, followed by torrential rains.

Based on the established model presented above, a prediction of temperature evolution is performed for the next 10 years. The simulation results are presented in Figure 6a, with a zoom in Figure 6b. This can help researchers gain new insight about the climate changes and evolution trends. For example for the next 10 years, a continuous average temperature increase is stated.

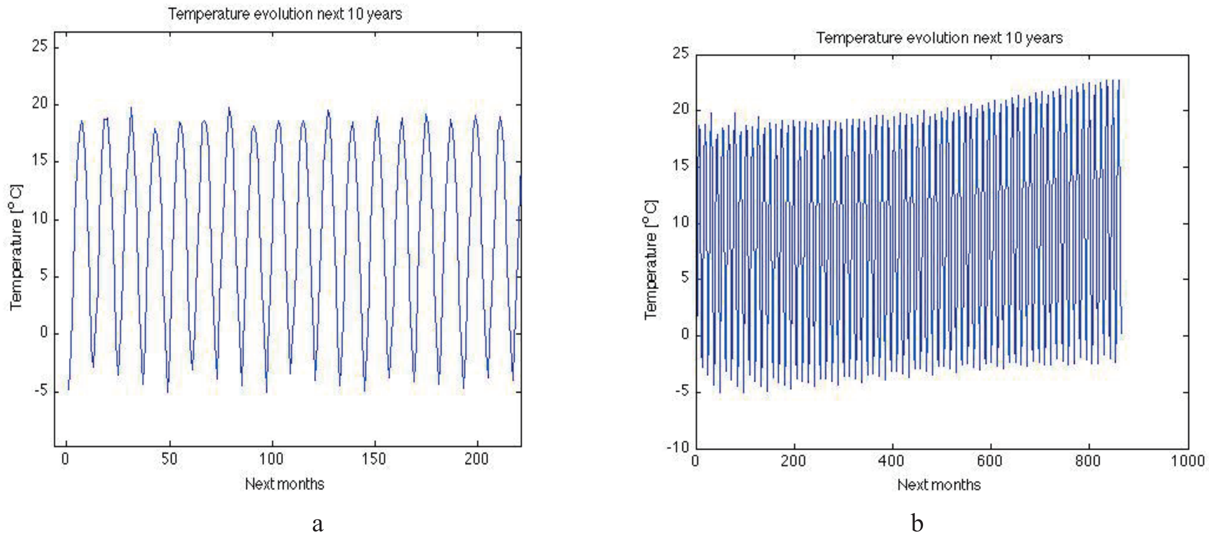


Figure 6 (a, b). Temperature prediction for the next 10 years

It could be noticed that the predicted average temperature values for the summer of the next 10 years are: 17.3°C for June, 23.8°C for July and 25.9°C for August, resulting an average of 22.33°C for summer. This predict an ascending trends, while the measured values were much lower, e.g. 18.6°C for summer of 2019.

The predicted values of precipitation using the developed model are plotted in Figure 7a, with a zoom in Figure 7b. It can be observed that some very high picks are present (e.g. months 52, 198, 288), with a continuous increasing average.

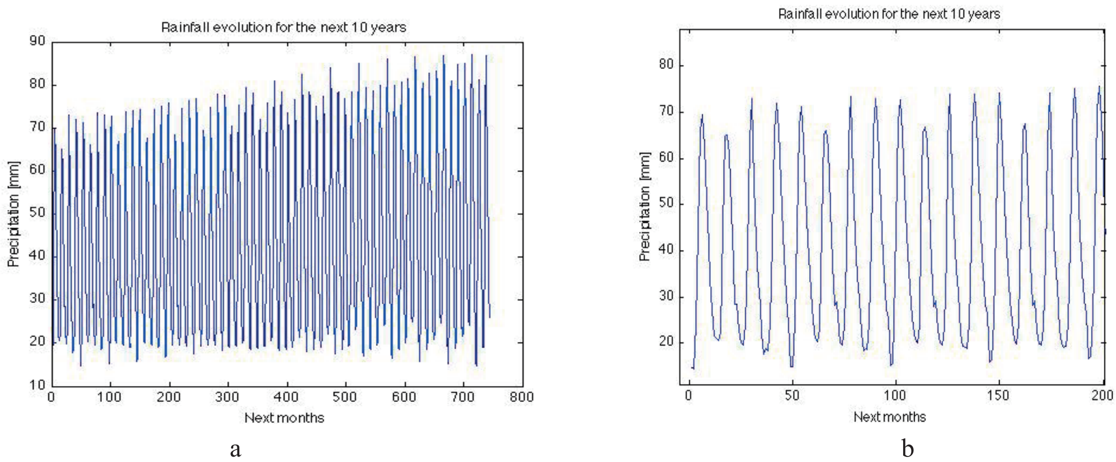


Figure 7 (a, b). Precipitation prediction for the next 10 years

Currently, purely physics-based models dominate short-term weather forecasting. But these models have a limited forecast horizon. The availability of meteorological data offers an opportunity to improve sub-seasonal forecasts by blending physics-based forecasts with machine learning. Sub-seasonal forecasts for weather and rainfall for a wide range of time would help agriculture and industries adapt to the challenges brought on by climate change (Ma et al., 2012).There is an increase in extreme climate phenomena, represented by prolonged periods of drought correlated with reduced amounts of precipitation, phenomena that lead to the reduction of the soil's ability to constantly ensure optimal moisture for plants (Gentilucci & Burt, 2018). Particular attention must be paid in the situation where the soil water deficit is associated with periods of drought in critical periods with maximum requirements for humidity and temperature that negatively influence physiological processes in plants leading to decreases in their productivity (Ma et al., 2012; Gentilucci & Burt, 2018; Diao et al., 2021). In this sense, it is necessary to apply some agricultural technologies that lead to the maintenance of water in the soil, as well as the irrigation of crops, in critical phases, to ensure an optimal production potential of crops.

CONCLUSIONS

In order to successfully manage the agricultural activities, temperature and precipitation forecast must take into account. In the present study, future temperature and precipitation evolution patterns for the catchment under study were revealed. As the climate change, such types of analysis are extremely important in order to minimize the uncertainty and risks related to the agriculture. With the used ANN models, the obtained correlation coefficient between the experimental data and the predicted data are between 0.967 and 0.978, indicating a close relationship between the input and output values. Future work will focus on model update with new data values and extension to daily data instead of monthly average values. A graphical interface of the models will be also designed to be easy to use by any user.

The increase in average annual temperature as well as the uneven distribution of precipitation inevitably leads to changes in the environment. The predicted average temperature values for the summer of the next 10 years are: 17.3°C for June, 23.8°C for July and 25.9°C for August, resulting an average of 22.33°C for summer. Agriculture must adapt to the new conditions, taking some measures, among which we mention, the modification or improvement of current plant cultivation technologies, for example new sowing times, sowing depth, the use of varieties/hybrids that are more resistant or at least tolerant to prolonged drought and during periods with high temperatures), the adoption of new technologies to accumulate/preserve water in the soil for a longer period.

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