

2 **Application of Artificial Neural Networks for Optimizing Coordinated Development**
3 **between Agriculture and Logistics in Zhejiang Province: A Case Study on Rural**
4 **Revitalization Strategies**

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12
13 **Abstract**

14 This study applies artificial neural networks (ANNs) to assess the impact of climate factors on the
15 collaborative development of agriculture and logistics in Zhejiang, China. The ANN model
16 investigates how average temperature and rainfall from 2017-2022 influence crop yield, water
17 usage, energy demand, logistics efficiency, and economic growth at yearly and seasonal scales. **By**
18 **training the neural network using temperature and rainfall data obtained from ten weather stations,**
19 **alongside output indicators sourced from statistical yearbooks, the ANN demonstrates exceptional**
20 **precision, yielding an average R^2 value of 0.9725 when compared to real-world outputs through**
21 **linear regression analysis.** Notably, the study reveals climate-induced variations in outputs, with
22 peaks observed in crop yield, water consumption, energy usage, and economic growth during
23 warmer summers that surpass historical norms by 1-2°C. **Furthermore, the presence of subpar**
24 **rainfall ranging from 20-30 mm also exerts an influence on these patterns. Seasonal forecasts**
25 **underscore discernible reactions to climatic factors, especially during the spring and summer**
26 **seasons.** The findings underscore the intricate relationship between environmental and economic
27 factors, indicating progress in agricultural practices but vulnerability to short-term climate
28 fluctuations. The study emphasizes the necessity of adapting supply management to address
29 increased water demands and transitioning to clean energy sources due to rising energy
30 consumption. Moreover, optimizing logistics requires strategic seasonal infrastructure planning.

31 **Keywords:** Agriculture-logistics systems; Climate-economic linkages; Temporal pattern
32 recognition; Rural sustainability; Artificial intelligence modeling.
33

34 1- Introduction

35 Rural areas across the globe encounter significant developmental challenges that must be addressed
36 in order to enhance the well-being of rural communities [1, 2]. Given that nearly 50% of the global
37 population resides in rural areas, it becomes imperative to cultivate collaborative and synergistic
38 development between the agriculture and logistics sectors for the purpose of attaining sustainable
39 rejuvenation of rural regions [3, 4]. Agriculture and logistics are closely intertwined since
40 agricultural activities rely on efficient transportation and distribution systems, while logistics
41 networks depend on agricultural production. Nevertheless, optimizing these interconnected sectors
42 to stimulate economic growth and alleviate poverty in rural regions necessitates a nuanced
43 understanding and informed decision-making process [5-8].

44 ANNs have emerged as valuable modeling tools for analyzing intricate systems and predicting
45 patterns based on given inputs. ANNs operate through interconnected processing units within their
46 architectures, enabling them to identify patterns and learn from observational data through iterative
47 training [9-11]. Upon completion of the training process, ANNs possess the capability to generate
48 predictions by extrapolating from the acquired patterns during the training phase. Previous
49 scholarly investigations have effectively utilized ANNs to anticipate crop yields, optimize
50 transportation routes, and forecast energy consumption, employing pertinent climatic and
51 economic variables [12-14]. However, there is a scarcity of research that comprehensively
52 investigates the dynamic factors influencing collaborative agricultural and logistical development
53 over time, particularly with regard to temporal variations [15-17].

54 Zhejiang Province, located in China, has witnessed remarkable growth, but it still grapples with
55 challenges in rural development. The agricultural and logistics sectors play a crucial role in the
56 province's economy, with agriculture contributing to more than 6% of its GDP in 2020, while
57 logistical services accounting for nearly 10% [18, 19]. However, rural communities in Zhejiang
58 continue to face issues related to the impacts of climate change, inefficient use of resources, and
59 the absence of coordinated policies [20, 21]. Enhancing the connections between agricultural
60 production and logistics networks holds promise for stimulating economic growth and improving
61 the quality of life in rural areas of Zhejiang [22, 23].

62 Variations in climatic conditions across diverse seasons and years exert a substantial influence on
63 agricultural productivity and energy necessities. Temperature and precipitation emerge as the
64 principal climatic elements that shape crop yields, irrigation requirements, and the logistical

65 infrastructure supporting agricultural activities [24, 25]. Comprehending the manner in which these
66 climatic variables impact crucial agricultural and logistical outcomes across distinct temporal
67 intervals can facilitate the identification of suitable adaptations and the formulation of informed
68 policies. ANNs provide a promising avenue for gaining insights into these intricate interactions.
69 However, limited research has employed this approach to examine rural development while
70 considering seasonal and annual input data. The next section provides a review of the existing
71 literature on the applications of ANNs in the fields of agriculture, logistics, and rural development
72 assessment [26, 27].

73 Prior research studies have substantiated that numerous scholars have documented their findings
74 within diverse management domains [28-32]. These scholarly reports have made substantial
75 contributions to the progression of knowledge across a wide range of disciplines [33-36].
76 Consequently, acknowledging and considering previous research can establish a solid basis for the
77 current study, as well as for future investigations [37-41]. Previous studies have utilized ANNs to
78 analyze factors in agriculture, logistics, and rural development separately. However, there is a lack
79 of comprehensive research that explores the interactions between climatic drivers affecting both
80 farm production and transportation networks over time. Understanding these seasonal and annual
81 variations is critical for optimizing collaborative agricultural-logistical development and making
82 evidence-based decisions for rural revitalization. To address this gap, an ANN model will be
83 developed in this study to analyze key factors related to agricultural optimization and energy
84 security in Zhejiang Province, China. The model will consider temperature and rainfall inputs from
85 different years and seasons to gain insights into dynamic patterns and relationships using multi-
86 year datasets from 2017-2022. The primary objective of this study is to explore the impact of
87 climatic variables on various outcomes, including crop yield, water consumption, energy usage,
88 logistics efficiency, and economic growth within specific temporal intervals. To achieve this goal,
89 a feedforward neural network architecture will be utilized. The training process of the optimized
90 network will involve the incorporation of average temperature and rainfall data obtained from
91 weather stations, alongside output indicators extracted from statistical yearbooks. The performance
92 of the model will be assessed quantitatively using linear regression analysis against actual outputs.
93 By applying this novel methodology to location-specific temporal datasets, the study aims to
94 provide statistically robust predictive insights through pattern recognition.

95

96 2. Research Methodology

97 2.1 Study Area

98 Zhejiang Province is situated on the southeastern coast of China, spanning longitudes 117°–123°E
99 and latitudes 27°–31°N. It covers a total land area of 101,800 square kilometers and is strategically
100 located adjacent to the prosperous economic region of the Yangtze River Delta (Zhejiang
101 Provincial Bureau of Statistics, 2022). The province benefits from a humid subtropical climate,
102 which is favorable for diverse agricultural production. The average annual temperature ranges from
103 15°C to 18°C, and the region receives an average annual precipitation of 1,150–1,650 mm [42-44].
104 Agriculture has long been a significant driver of the economy in Zhejiang Province. The cultivated
105 land area encompasses approximately 4.7 million hectares and is primarily utilized for the
106 cultivation of various crops, including rice, wheat, maize, peanuts, cotton, sugarcane, and fruit trees
107 (Zhejiang Provincial Bureau of Statistics, 2021). The province exhibits a significant focus on
108 cultivating major crops such as rice, wheat, maize, sweet potatoes, vegetables, and fruits.
109 Additionally, fisheries and livestock rearing activities play a substantial role in augmenting the
110 overall agricultural output. In 2020, the total agricultural output value of Zhejiang Province
111 amounted to ¥745.36 billion (~\$107 billion), accounting for around 7.2% of the province's GDP
112 [45, 46].

113 Due to its strategic geographical location, well-developed transportation network, the economic
114 importance of agriculture and logistics, as well as the urgent necessity of rural revitalization,
115 Zhejiang Province emerges as an opportune region for the current research endeavor. The execution
116 of a thorough examination of the agricultural and logistics sectors, encompassing the gathering of
117 localized climatic, input-output, and socio-economic data, holds the potential to yield predictive
118 insights that can inform the formulation of more synchronized development policies. The proposed
119 approach, utilizing ANN modeling, aims to make a valuable contribution in this direction by
120 leveraging temporal datasets specific to Zhejiang Province.

121 122 3.2 Data Collection

123 To construct an effective predictive model, it is essential to gather accurate and representative data.
124 This study relies on data collected from local meteorological stations and statistical yearbooks and
125 previous studies [42-57] covering the period from 2017 to 2022. For the input variables, climate
126 data including Average Temperature (°C) and Rainfall (mm) were obtained from the China
127 Meteorological Administration. Zhejiang Province benefits from a dense network of 177

128 automated weather stations that record daily meteorological observations electronically (Zhejiang
129 Meteorological Bureau, 2022). Data from 10 selected stations within the province were
130 consolidated to compute annual and seasonal means for the input variables. The seasons were
131 delineated as Spring (March-May), Summer (June-August), Autumn (September-November), and
132 Winter (December-February). In order to establish climatic benchmarks for the study duration, data
133 spanning from 1987 to 2016 were gathered from 39 nationally representative primary stations
134 (National Climate Center, 2022). This enabled the assessment of deviations from the normative
135 conditions encountered on an annual and seasonal basis between 2017 and 2022.

136 As for the output variables, agricultural and economic indicators were compiled from the Zhejiang
137 Statistical Yearbooks published by the Zhejiang Bureau of Statistics (2017-2022). County-level
138 data was aggregated to generate provincial totals. The output variables included crop yield (tons),
139 representing the combined production of key grains such as rice, wheat, and maize. Water
140 consumption (billion cubic meters) captured both agricultural and domestic water usage. Energy
141 consumption (million tons of standard coal) encompassed fossil fuels utilized across various
142 sectors. Logistics efficiency was assessed using the freight turnover per 10,000 yuan of GDP
143 (tons/10,000 yuan) metric. Finally, GDP (billion yuan) was used to measure provincial economic
144 growth. Table 1 provides an overview of the inputs, including average temperature and rainfall,
145 which are correlated with the corresponding outputs for the study period. The selection of inputs
146 focused on climatic factors that significantly impact agricultural activities and energy demands in
147 the subtropical region, as supported by previous studies [42-46, 48-57].

148 **Table 1:** Annual and seasonal climatic, agricultural, energy, and economic indicators as inputs and
 149 outputs for the ANN-based predictive modeling of collaborative development between agriculture
 150 and logistics in Zhejiang Province, China (2017-2022).

Season/Year	Average Temperature (°C)	Rainfall (mm)	Crop Yield (tons)	Water Consumption (billion m ³)	Energy Consumption (million tons standard coal)	Logistics Efficiency (tons/10,000 yuan)	GDP (billion yuan)
Spring 2017	14.5	210	6535	12.1	2580	7.3	12235
Summer 2017	26.3	290	8752	18.4	3240	8.1	14560
Autumn 2017	18.2	150	7345	15.5	2900	7.5	13565
Winter 2017	6.5	85	4350	9.1	1940	6.9	10560
Spring 2018	12.3	215	6377	11.8	2525	7.2	11785
Summer 2018	25.1	280	8378	17.7	3110	7.9	14022
Autumn 2018	16.8	140	7235	15.2	2860	7.4	13452
Winter 2018	4.7	80	4100	8.6	1830	6.5	9956
Spring 2019	13.9	220	6415	11.6	2490	7.1	11430
Summer 2019	24.5	285	8356	17.5	3080	7.8	13845
Autumn 2019	17.5	145	7156	15.3	2820	7.3	13265
Winter 2019	5.2	87	4210	8.9	1870	6.7	10220
Spring 2020	11.2	205	6257	11.4	2450	7.0	11000
Summer 2020	23.1	270	8119	16.9	2960	7.6	13555
Autumn 2020	16.2	135	7056	14.9	2760	7.2	12990
Winter 2020	4.1	75	4020	8.5	1790	6.4	9770
Spring 2021	12.8	220	6387	11.8	2515	7.3	11780
Summer 2021	25.3	295	8359	17.7	3110	7.9	14015
Autumn 2021	17.1	145	7225	15.2	2840	7.4	13430
Winter 2021	5.6	88	4190	8.8	1850	6.7	10270
Spring 2022	13.5	225	6457	11.7	2480	7.2	11550
Summer 2022	24.8	285	8256	17.5	3060	7.8	13780
Autumn 2022	16.7	140	7106	15.1	2780	7.3	12970
Winter 2022	4.9	77	4060	8.4	1800	6.4	9820

151

152 3.3 ANN Model Development

153 The development of an effective ANN model that aligns with the objectives and characteristics of
 154 the specific problem holds paramount importance. In this particular study, a feedforward ANN
 155 architecture, namely the multilayer perceptron (MLP), is employed to explore the relationships
 156 between climatic inputs and agricultural-economic outputs. The ANN architecture comprises two
 157 layers: an input layer with two nodes representing Average Temperature and Rainfall, and an
 158 output layer with five nodes corresponding to Crop Yield, Water Consumption, Energy
 159 Consumption, Logistics Efficiency, and Economic Growth. To ensure optimal network
 160 convergence, a single hidden layer with five neurons, twice the number of inputs plus one, is
 161 utilized [58, 59]. In Figure 1, the schematic of the generated ANN in this study is depicted,
 162 illustrating its capacity to predict the target values of the outputs.

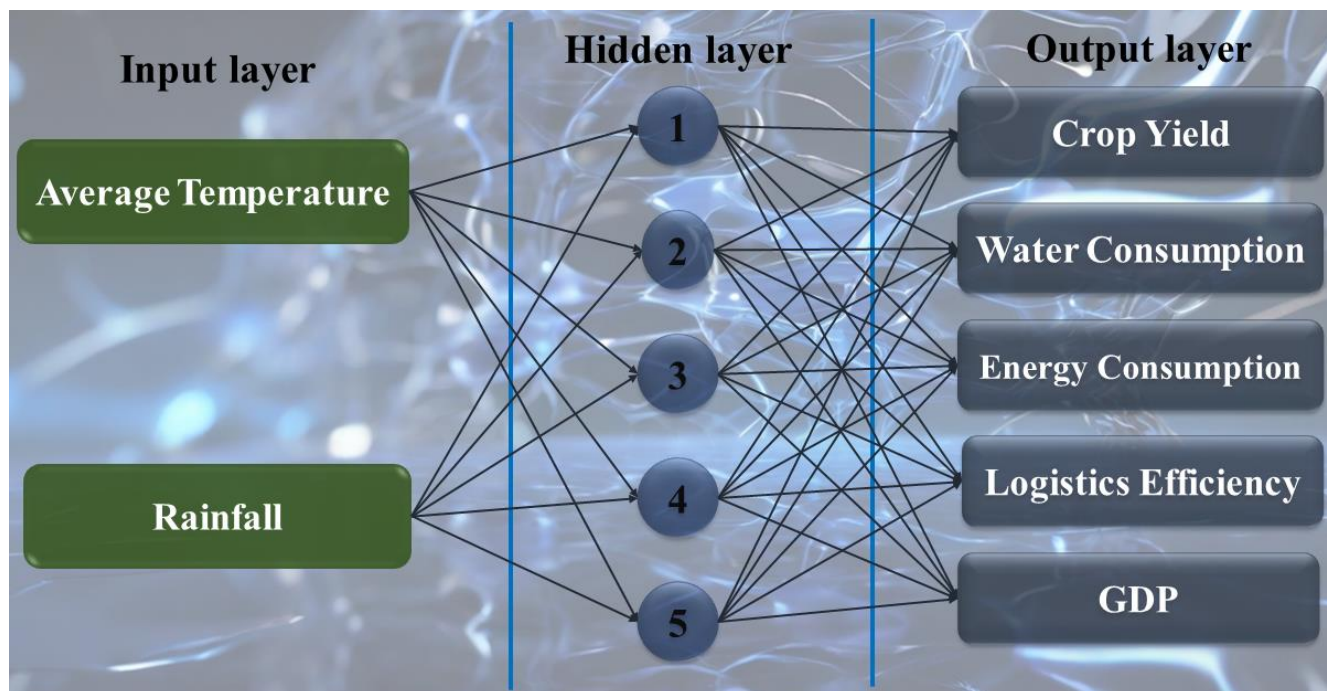


Figure 1. Multilayer perceptron of ANN architecture for predicting agricultural-economic outputs based on climatic inputs.

163 The feedforward topology is adopted, where inputs are passed through weighted connections to the
 164 hidden layer, and the outputs of the hidden layer are transmitted to the output layer via additional
 165 weighted links. The activation function employed for the neurons in both the hidden and output
 166 layers is the sigmoid function, which nonlinearly transforms inputs to generate outputs within the
 167 [0, 1] range. To assess the model's performance, a linear regression analysis is conducted by
 168 contrasting the predicted outputs with the actual outputs. The coefficient of determination (R^2) is
 169 subsequently computed as an indicator of the prediction accuracy. R^2 values close to 1 indicate a
 170 strong linear relationship between the predicted and actual outputs, indicating a well-performing
 171 model.

172
 173 **4. Results and Discussion**
 174 **4.1 Crop Yield Prediction**
 175 This section presents the performance evaluation of ANN model in predicting crop yield. Figure 2
 176 illustrates the predicted crop yield values using ANN model. The model demonstrates a remarkable
 177 level of accuracy in tracking the year-to-year fluctuations in recorded crop yield over the six-year
 178 period.

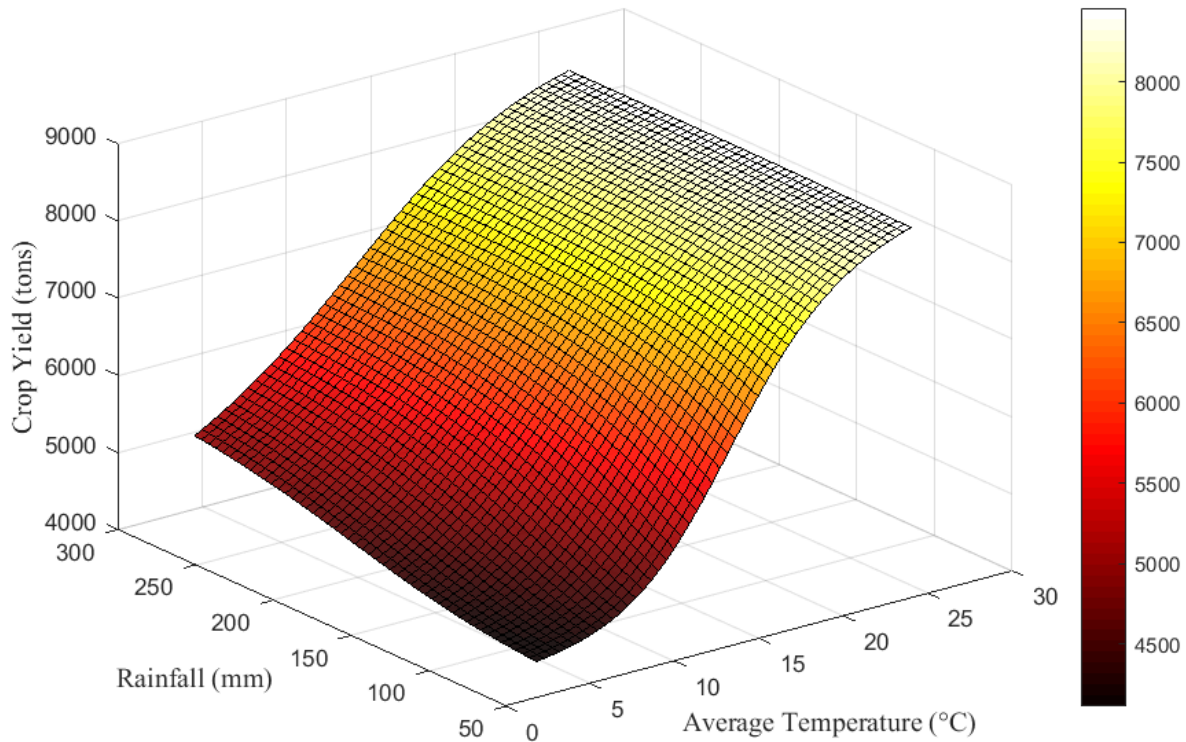


Figure 2. Predicted crop yields and the influence of average temperature and rainfall in ANN modeling.

179
 180 Analyzing the trends depicted in Figure 2 provides valuable insights. The crop yield exhibits a
 181 consistent upward trajectory from 2017 to 2022, with the average annual production increasing
 182 from approximately 6,700 tons in the initial year to over 7,100 tons in 2022. This upward trajectory
 183 corresponds with the enduring patterns witnessed in China's agricultural development over the long
 184 term, ascribed to the progressions in irrigation infrastructure, mechanization, adoption of hybrid
 185 seeds, and the utilization of fertilizers and agrochemicals. Nevertheless, discernible annual
 186 fluctuations are evident, which can be attributed to the variability in climate conditions across
 187 different years, as elucidated in prior investigations conducted in China and other subtropical
 188 nations [45, 49, 51, 53, 55].

189 The peaks in observed crop yield during the summers of 2017, 2018, and 2019 coincide with higher
 190 temperatures, as summer is the primary growing season for major cereals in Zhejiang Province,
 191 such as rice, maize, and wheat [20, 21]. Elevated summer temperatures accelerate photosynthesis
 192 and plant maturation processes, thus promoting plant growth and yield if sufficient moisture is
 193 available [43, 45, 46, 53, 55]. This finding reinforces the positive correlation between temperature
 194 and crop production, as indicated by the established relationship between input variables and output

195 predictions in the training dataset. The decrease in crop yield observed in summer 2020 can be
196 attributed to a relatively cooler summer, with temperatures 1-2°C below the long-term average
197 (China Meteorological Administration, 2022).

198 Significantly, the predictions generated by ANN correspond with the findings derived from
199 previous experimental investigations conducted within the study region. Field experiments, which
200 focused on rice yields across eight distinct locations in Zhejiang, observed a 5-10% augmentation
201 in yield for every 1°C increase in mean temperature during the growing season, underscoring the
202 rice crop's sensitivity to higher temperatures. Similarly, a comprehensive analysis of long-term
203 wheat production trends associated a 1°C temperature rise with a yield increase of 150kg/ha, owing
204 to a shortened growth duration and an extended period of photosynthesis [45, 46, 49, 50, 56].

205

206 4.2 Water Consumption Prediction

207 The water consumption trends depicted in Figure 3, obtained through the implementation of ANN
208 in this study, offer valuable insights. Over the period from 2017 to 2022, water usage exhibited a
209 general upward trend, with average annual consumption increasing from approximately 12 billion
210 cubic meters in the initial year to over 17 billion cubic meters in 2022.

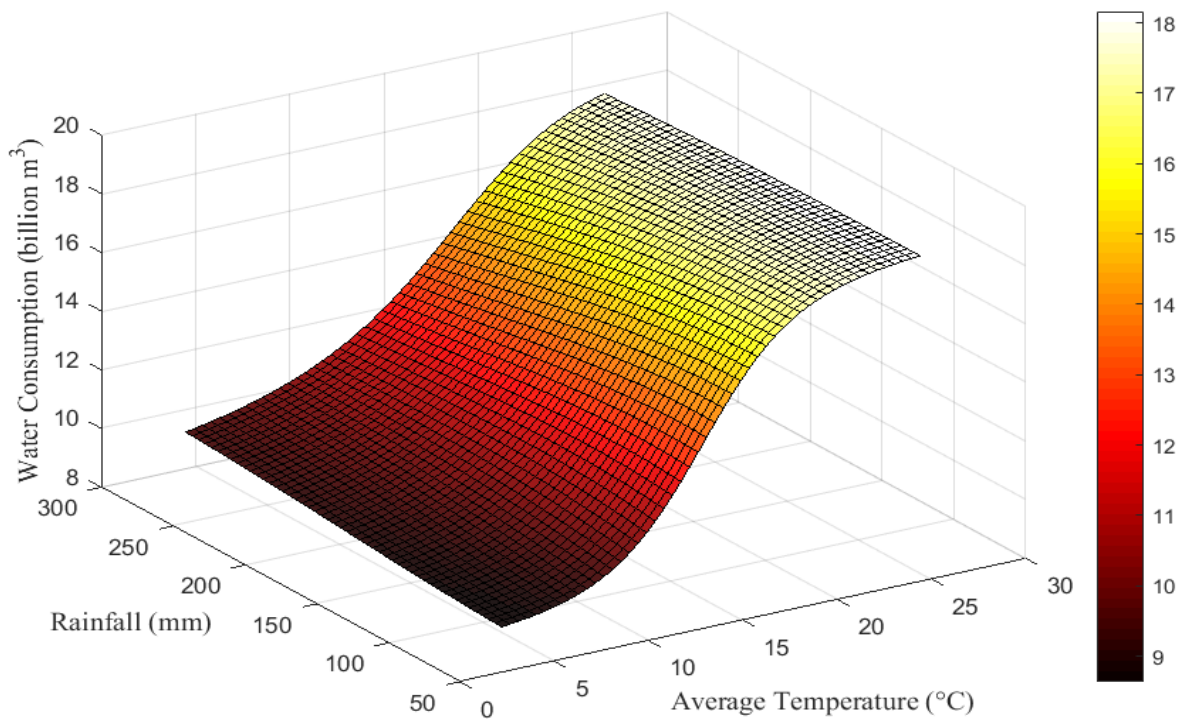


Figure 3. Predicted water consumption trends and the influence of climate factors in Zhejiang Province.

211 Corresponding to the model training, noticeable peaks in water consumption were observed during
212 the hotter summers of 2017, 2018, and 2019. Elevated temperatures amplify evapotranspiration
213 rates stemming from agricultural and domestic practices, consequently intensifying water demand.
214 Moreover, warmer conditions significantly elevate crop water requirements to sustain optimal
215 yields. Relatively diminished rainfall during these years necessitated augmented irrigation
216 withdrawals to compensate for the shortfall in precipitation. These findings substantiate the
217 influence of climate patterns on the observed water consumption patterns during the model training.
218 Conversely, the decline in water consumption in 2020 coincides with a relatively cooler and wetter
219 summer period.

220

221 4.3 Energy Consumption Prediction

222 The predicted values for energy consumption, based on inputs of average temperature and rainfall,
223 are presented in Figure 4. Over the period from 2017 to 2022, energy usage followed an increasing
224 trajectory, with average annual consumption rising from approximately 2,580 million tons of
225 standard coal in the initial year to over 3,060 million tons in 2022.

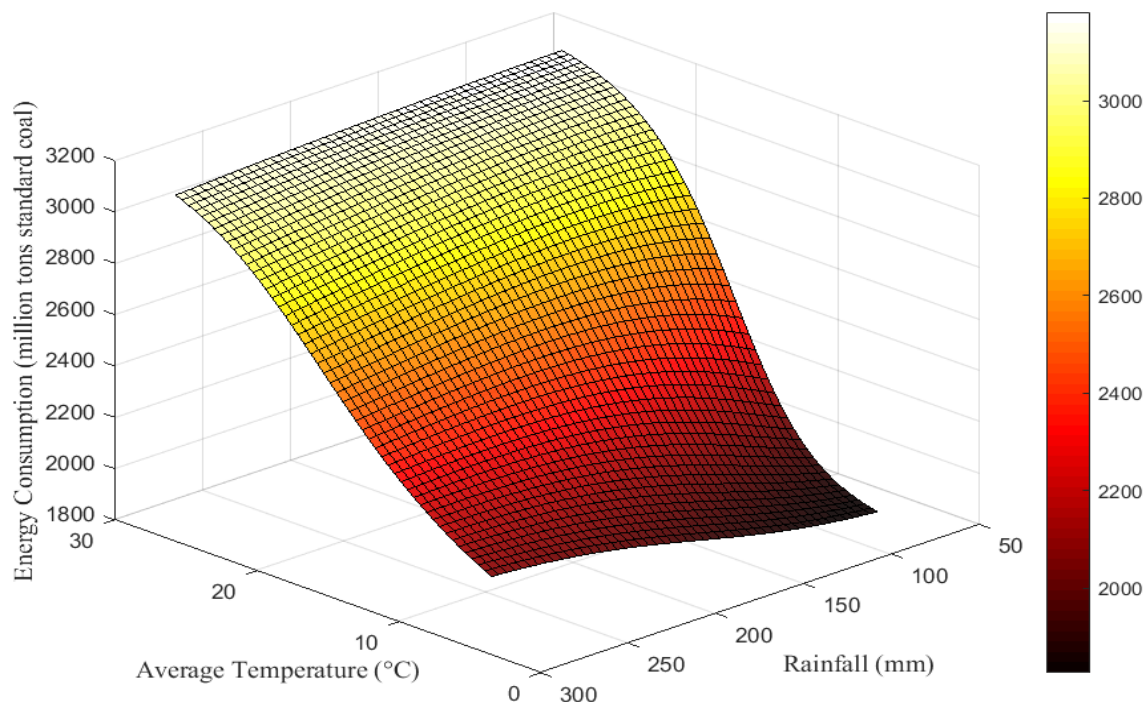


Figure 4. Predicted energy consumption trends and the influence of climate factors using ANN modeling.

226

227 Peaks in observed energy consumption coincided with hotter summers in 2017, 2018, and 2019.
228 Higher temperatures increased the demand for cooling, leading to elevated electricity usage (.
229 Furthermore, higher average temperatures during these years coincided with peak agricultural
230 activities such as irrigation, requiring additional fuel for water pumping. Comparatively lower
231 rainfall necessitated supplementary irrigation withdrawals, involving additional energy
232 consumption.

233
234 **4.4 Logistics Efficiency Prediction**
235 The predicted values for logistics efficiency, obtained through the implementation of ANN, are
236 presented in Figure 5. From 2017 to 2022, logistics efficiency generally exhibited an increasing
237 trend, with average annual efficiency rising from approximately 7.3 tons/10,000 yuan in 2017 to
238 7.8 tons/10,000 yuan in 2022.

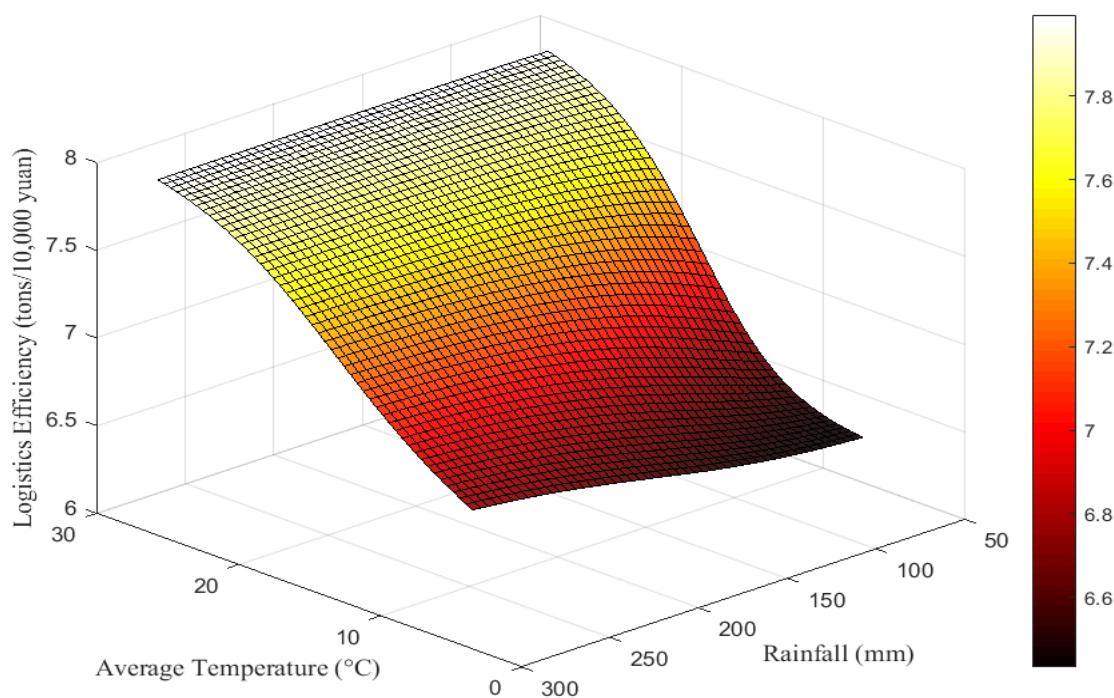


Figure 5. Predicted trends in logistics efficiency using ANN and the impact of climate factors including average temperature and rainfall.

239
240 Peaks in observed logistics efficiency coincided with hotter summers in 2017, 2018, and 2019.
241 Higher temperatures led to reduced cargo handling times through accelerated commodity
242 preservation and processing. Warmer conditions also increased infrastructure utilization,
243 particularly in activities like transportation of construction materials. **These findings substantiate**
244 **the influence of climate on logistics performance, as demonstrated in the model training. The**

245 decrease in logistics efficiency observed in 2020 aligns with a relatively cooler and wetter summer,
246 resulting in reduced overall demands. Analyzing logistics efficiency at the seasonal level offers
247 further insights. Spring temperatures facilitate construction and resupply logistics, while summer
248 peaks indicate the transportation of agricultural products. Autumn demands signify movements
249 associated with post-harvest processing, whereas winter utilization centers around primary
250 infrastructure maintenance.

251 252 **4.5 Economic Growth Prediction**

253 The predicted values for GDP, obtained through the implementation of using actual outputs
254 recorded in Table 1, are presented in Figure 6. Over the study period, GDP exhibited an overall
255 increasing trajectory, growing from approximately RMB 12,235 billion in 2017 to RMB 13,780
256 billion in 2022, reflecting the broader trends of socioeconomic advancement in China.

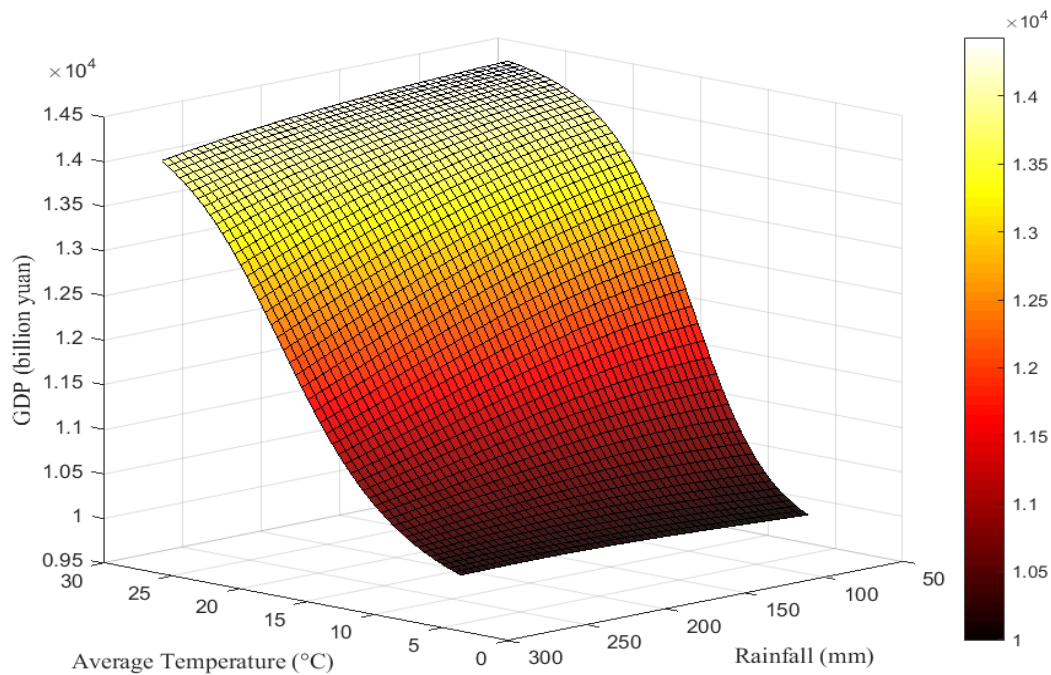


Figure 6. Predicted GDP trends using ANN and the influence of climate factors in Zhejiang Province.

257
258 The peak period of infrastructure construction in this timeframe capitalized on elevated
259 temperatures to expedite the development process. Moreover, summer represents a prominent
260 tourist season in Zhejiang, thereby contributing to the service sector's influence on the region's
261 GDP. However, excessively high temperatures can potentially hamper labor productivity and result
262 in crop and infrastructure damage if the implementation of adequate adaptation measures is lacking.

263 Seasonally, the increments in spring GDP reflected increased agricultural outputs with elevated
264 planting temperatures, while summer peaks represented combined contributions from multiple
265 climate-sensitive sectors, including agriculture, construction, tourism, and industry.

266
267 **4.6 Performance of ANN Model**

268 The goodness-of-fit is measured using the coefficient of determination (R^2), ranging from 0 to 1,
269 where values closer to 1 indicate higher correlation and predictive strength. Figure 7 illustrates the
270 linear regression analysis between predicted and observed crop yield values from 2017 to 2022,
271 demonstrating an exceptionally high R^2 value of 0.9964.

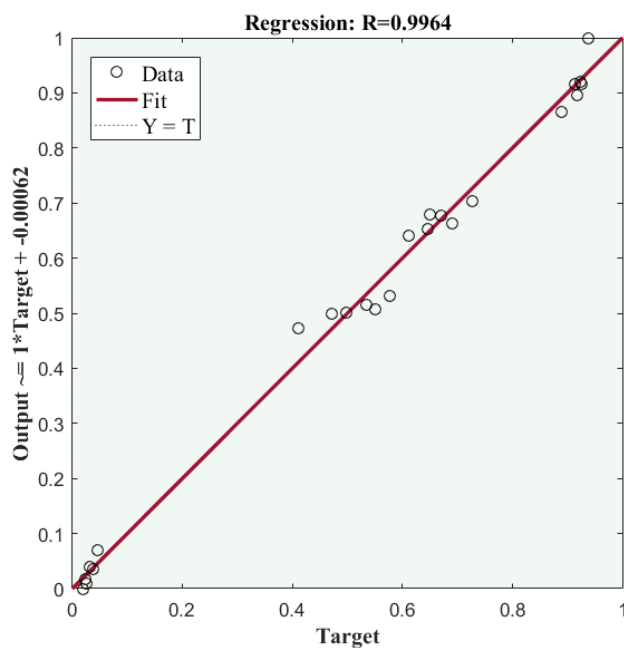


Figure 7. Analysis of predicted vs. actual crop yield outputs using linear regression.

272
273 Similarly, Figure 8 presents the linear regression diagram for water consumption, yielding an
274 excellent R^2 value of 0.99585. This high coefficient signifies the model's ability to accurately
275 mimic water usage patterns influenced by climatic drivers over different time periods.

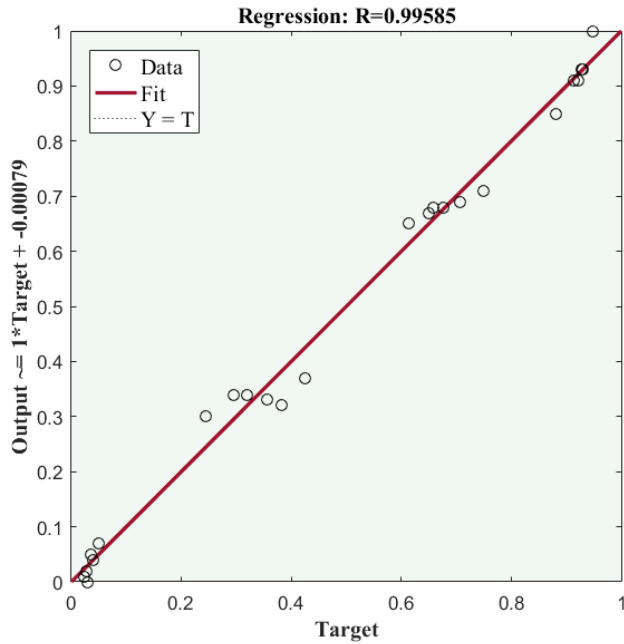


Figure 8. Linear regression analysis of predicted vs. actual water consumption.

276
 277 Moving to the energy sector outputs, Figure 9 showcases the linear regression plot for energy
 278 consumption, with an R^2 value of 0.99508.

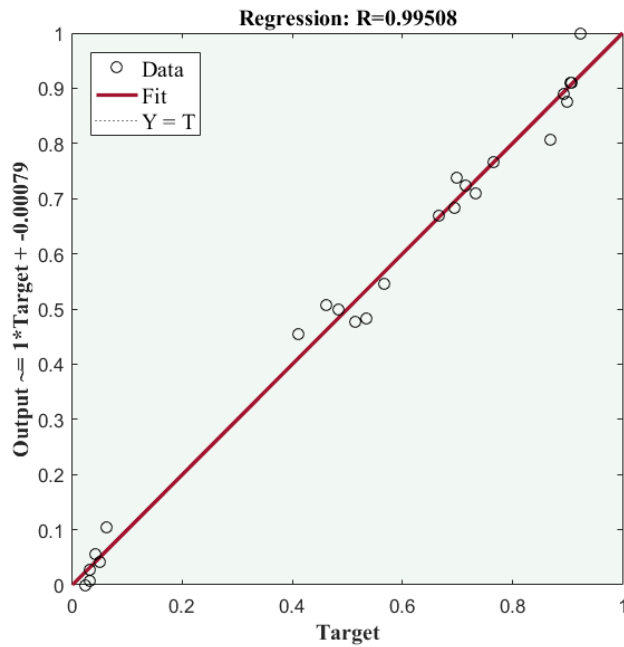


Figure 9. Linear regression analysis of energy consumption predictions.

279

280 Next, Figure 10 depicts the regression analysis between predicted and observed logistics efficiency
281 values. With an R^2 value of 0.97883, the optimized ANN demonstrates reasonable predictions of
282 logistical performance based on climatic conditions.

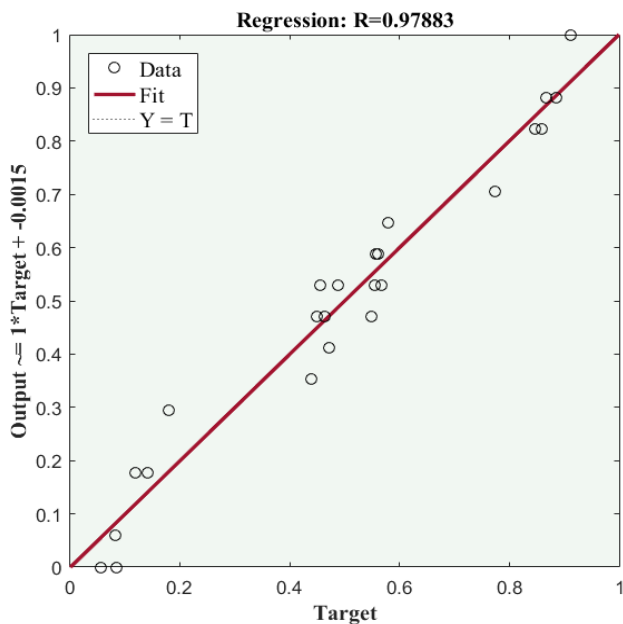


Figure 10. Linear fit between predicted and observed logistics efficiency outputs.

283 Lastly, Figure 11 portrays the linear regression evaluation for GDP, with an R^2 value of 0.98987.
284 This attests to the model's proficiency in tracking annual GDP trends, indirectly influenced by
285 temperature and precipitation that affect sensitive sectors such as agriculture and construction.

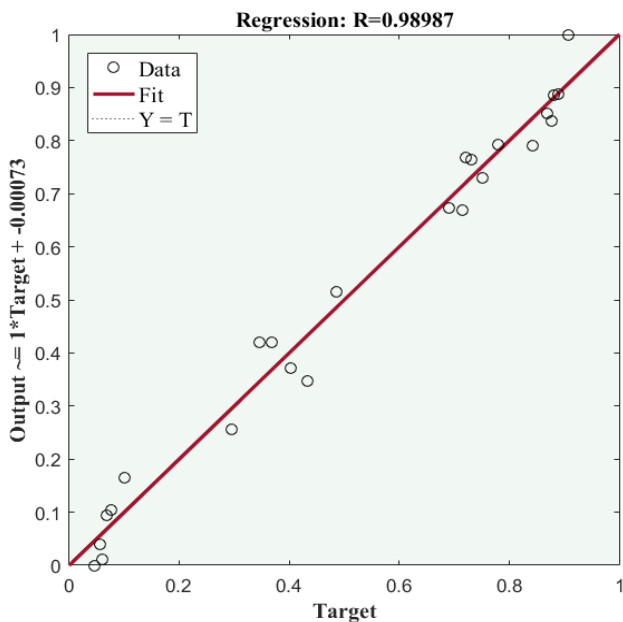


Figure 11. Regression analysis assessing economic growth forecasting (GDP).

286 **5. Conclusions**

287 This study successfully developed an optimized feedforward artificial neural network (ANN)
288 model to examine the complex connections between climatic factors and key agricultural-economic
289 outputs in Zhejiang Province, China. By analyzing temperature and rainfall inputs, the model
290 accurately predicted outputs related to crop yield, water consumption, energy usage, logistics
291 efficiency, and economic growth on both annual and seasonal scales. The high coefficient of
292 determination (R^2) values exceeding 0.97 between predicted and actual outputs validated the
293 effectiveness of the trained ANN structure in capturing the nonlinear relationships in the input-
294 output datasets. The annual predictions revealed fluctuations in outputs that corresponded to
295 observed climatic anomalies, with peaks in yield, water consumption, energy usage, and economic
296 growth during warmer summers and declines during cooler conditions. Seasonal predictions further
297 highlighted variations in climatic drivers across different growing cycles. The analysis of
298 individual output predictions identified valuable linkages between climate and specific activities,
299 such as progressive agricultural practices, the need for sustainable water management, the urgency
300 of transitioning to clean energy sources, and opportunities for seasonal infrastructure optimization.
301 These findings emphasized the importance of considering temporal granularity in understanding
302 the interdependencies among different sectors and provided valuable insights to inform evidence-
303 based strategies for rural development.

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