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Influence of Meteo-Climatic Variables and Fertilizer Use on Crop Yields in the Sahel: A Nonlinear Neural-Network Analysis

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Abstract: The Sahel is one of the regions with the highest rates of food insecurity in the world. Understanding the driving factors of agricultural productivity is, therefore, essential for increasing crop yields whilst adapting to a future that will be increasingly dominated by climate change. This paper shows how meteo-climatic variables, combined with fertilizers' application rates, have affected the productivity of two important crops in the Sahel region, i.e. maize and millet, over the last three decades. To this end, we have applied a specifically designed neural network tool (optimised for analysis of small datasets), endowed with feed-forward networks and backpropagation training rules and characterised by generalised leave-one-out training and multiple runs of neural network models in an ensemble strategy. This tool allowed us to identify and quantify the impacts of single drivers and their linear and nonlinear role. The variables analysed included temperature, precipitation, atmospheric CO_2 concentration, chemical and organic fertilizer input. They explained most of the variance in the crop data ($R^2 = 0.594$ for maize and $R^2 = 0.789$ for millet). Our analysis further allowed us to identify critical threshold effects affecting yields in the region, such as the number of hours with temperature higher than 30 °C during the growing season. The results identified heat waves and fertilizer application rates playing a critical role in affecting maize and millet yields in this region, while the role of increasing CO_2 was less important. Our findings help identify the modalities of ongoing and future climate change impacts on maize and millet production in the Sahel.

Keywords: Sahel; maize; millet; neural networks; nonlinear influences; meteo-climatic drivers

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1. Introduction

Models predict significant negative impacts on crop yields in many regions of the world due to climate change across a range of global warming scenarios [1,2]. Such predictions are based on experimental evidence largely established in the laboratory and other controlled conditions [3]. Conversely, studies of the impacts of observed climate changes on reported crop yields and trends at the regional scale are almost lacking (see, for instance, in [4,5]), especially for the Sahel Region (Ch. 5 of [2]).

Such analyses, including on the interactions between observed climate trends and agricultural management, would critically complement current modelling studies and thus help to better understand current and expected impacts, with the aim of identifying useful adaptation strategies based on real-world behaviour. This paper, therefore, focuses on illustrating the links between historical meteo-climatic variables observed over the last three decades, the use of fertilizer, and the productivity of two important crops in the Sahel, using officially reported production statistics to FAO over the same period.

We chose the Sahel because agriculture is critically at risk in this region, today, already leading to high levels of food insecurity. Placed between the Sahara Desert to the north and tropical rainforests to the south, the Sahelian belt suffers from heat waves and drought, overlapping and interacting with ongoing desertification trends [6–8]. These trends contribute to make the Sahel region among those with the highest rate of food insecurity in the world, with prevalence of undernourishment around 24% in 2020 [9].

We focus our analysis on yields of maize and millet–two of the most important crops in the Sahel region in terms of production volumes and food security value–between 1980 and 2010. We developed methods to identify and quantify their dependence on a set of drivers, i.e., meteo-climatic variables such as temperature and precipitation and management practices such as application rates of organic and chemical fertilizers. We also examined the observed increases in atmospheric carbon dioxide concentration over the same time range.

In order to distinguish between linear and nonlinear–eventually threshold–effects of meteo-climatic drivers [4,5] and fertilizers [10], we applied a machine learning technique based on neural networks (NNs), using a model capable of establishing complex relationships and highlighting the linear and nonlinear roles of the several variables considered for the yield analysis.

2. Data

Annual data on the yields of maize and millet were taken from FAOSTAT [11], measured as hectograms of grain dry biomass per hectare of harvested land.

Monthly mean temperature (T) and total precipitation (p) data were collected from the NASA Modern Era Retrospective Analysis for Research and Applications [12]. The original gridded data were averaged yearly and aggregated at country level by Cai et al. [13], who applied the population-weighted method (i.e., the weather conditions for populated regions within a country are given more weight). In addition, the number of hours with temperatures higher than 30 °C during the growing season (#hT > 30) was derived, starting from gridded hourly temperature data and using the Crop Calendar Dataset (https://nelson.wisc.edu/sage/data-and-models/crop-calendar-dataset/index.php, accessed on 11 July 2022) to determine the growing seasons for each grid cell: further details may be found in [13].

Annual data of nitrogen fertilizers N and manure (in kilograms per hectare of harvested land) were sourced from FAOSTAT [11]. Annual data of atmospheric CO_2 concentration were downloaded from the Mauna Loa observatory (https://gml.noaa.gov/webdata/ccgg/trends/co2/co2_annmean_mlo.txt, accessed on 11 July 2022).

The choice of the study period, 1980–2010, was due to the availability of meteo-climatic data aggregated at country level for all the 10 states of Sahel.

Chad and Mauritania were nonetheless excluded from the analysis, since they lacked data on nitrogen fertilizers. We also excluded Sudan and South Sudan, for which crop statistics were available only since 2011, namely the date of formation of these two new states, too short a period to meet our analysis needs. In addition, the record of nitrogen fertilizers in Eritrea began in 1993, so that, for this country, the period of study was limited to 1993–2010.

Tables 1 and 2 show the annual data by country, with means and maximum and minimum values.

Table 1. Data about maize and millet yields for the seven countries of Sahel between 1980 and 2010 (1993–2010 for Eritrea).

Country	Maize Yield–Mean (hg/ha) (min–max)	Millet Yield–Mean (hg/ha) (min–max)
Burkina Faso	13,207.9 (5647–19,444)	6688.3 (4215–9603)
Eritrea	5528.5 (2076–9755)	3399.2 (1072–6932)
Gambia	13,284.8 (8687–18,085)	10,403.1 (7983–12,696)
Mali	14,751.1 (8836–33,349)	7604.5 (5105–10,925)

Table 1. *Cont.*

Country	Maize Yield–Mean (hg/ha) (min–max)	Millet Yield–Mean (hg/ha) (min–max)
Niger	7141.3 (2612–15,173)	4102.7 (2548–5291)
Nigeria	14,307 (9707–21,961)	12,502.2 (8336–18,483)
Senegal	13,048.7 (7274–27,961)	6280.1 (4048–7872)

Table 2. Data about meteo-climatic drivers and fertilizers considered in this paper for the seven countries of Sahel between 1980 and 2010 (1993–2010 for Eritrea). CO_2 concentration detected at Mauna Loa station is added in the last column.

Country	*p*–Mean (mm/Month) (min–max)	T–Mean (°C) (min–max)	#hT > 30–Mean (h) (min–max)	N + Manure-Mean (kg/ha) (min–max)	CO_2–Mean (ppm) (min–max)
Burkina Faso	49.7 (28.2–92.3)	29 (25.9–31)	987.4 (514.6–1318.5)	9.8 (3.7–16.2)	362.6 (338.8–390.1)
Eritrea	56.2 (45.6–66.9)	27.4 (26.4–28.4)	20.4 (4.6–67.6)	12.2 (6.5–21.5)	372.4 (357.2–390.1)
Gambia	62.9 (51.1–77.3)	27.9 (27.4–28.7)	56.1 (16.3–147.8)	7.8 (4.5–21.1)	362.2 (338.8–390.1)
Mali	51.5 (33.6–83.9)	29.2 (27–31)	491.6 (186.2–942.5)	10 (5.5–15.5)	362.6 (338.8–390.1)
Niger	30.8 (12.8–62.3)	29.2 (26.4–31.3)	1001.6 (631.7–1355.8)	1.3 (1–1.8)	362.6 (338.8–390.1)
Nigeria	132.7 (104.6–180.4)	25.9 (24.7–26.8)	1124.5 (624.5–1459.5)	7 (4.8–10.9)	362.6 (338.8–390.1)
Senegal	45.3 (33.8–58.6)	27.7 (27–28.3)	671.7 (526.8–778.3)	6.4 (3.3–11.4)	362.6 (338.8–390.1)

3. Methods and Analyses

We adopted a machine learning tool based on NNs. Previous studies showed that even simple NNs are able to find general (nonlinear) relationships between forcing factors and effects, including in geophysical or environmental datasets [14,15]. These methods are particularly useful when no clear bivariate linear correlations between forcing factors and their presumed effects exist. This is the case of our dataset: preliminary bivariate analysis of linear correlation, in fact, displays quite small values for the Pearson coefficient R between any driver and yields.

Recently, one of us (A.P.) developed a NN tool for analyses of small datasets [16,17]. Here, we briefly outline the main features of the tool, referring to the original publications on the subject matter for further details.

The NNs considered in this tool are feed-forward with one hidden layer and characterised by hyperbolic-tangent transfer functions at the hidden level and a linear function at the output neuron. In the present investigation, the training technique of this tool is modified by considering a quasi-Newton backpropagation method—the so-called Broyden–Fletcher–Golfarb–Shanno (BFGS) algorithm [18]—which is more suitable for handling small datasets with respect to the standard backpropagation adopted previously.

With the aim of obtaining a nonlinear relationship between inputs and targets (to be approximated by outputs) which can be generally valid, a training–validation–test procedure must be applied. Usually, the free parameters of the NNs (i.e., the connection weights) are fixed on the training set by stopping the training phase when the error on the validation set begins to increase; then, the generalization performance is measured on a third set, unknown to the NNs, i.e., the so-called test set. In our tool, developed for analysing small datasets, a generalised leave-one-out procedure is adopted for training, validation, and test, which works as follows.

In a dataset formed by annual inputs–target patterns, starting from the first year, we extract a single input–target pattern from the total available dataset and consider it as a test set. Then, a validation set is randomly chosen, and the remaining patterns form the training set. At the end of a NN run, the connection weights are fixed, and we obtain a transfer function from inputs to output. However, this result can be influenced by the specific random choice of the initial weights and of the members of the validation set. Thus, multiple runs are performed in an ensemble approach by choosing different random values for weights and members of the validation set. This makes it possible to calculate the ensemble mean of the outputs and "average away" the intrinsic variability of NN results.

After this reconstruction of the first (annual) value of the target, the procedure must be repeated for the other years; each of their patterns becomes, sequentially, the test set. In this way, one achieves the estimation of all output values on the test set, and their ensemble means at the end of this generalised leave-one-out procedure.

This NN tool has been recently applied to the analysis of several environmental problems, leading to interesting results about meteo-climatic linear and nonlinear influences on them [19–22], and its code has been frequently requested and used by other researchers, as shown by the many citations of [17].

In this study, we also used standard multilinear regressions to understand the specific value added by the implementation of NNs in our analysis. We adopted the same approach to training: for each single pattern, the coefficients of the linear regression are fixed on the other data (the union of the training and validation sets used in the NN method). Obviously, in doing so, an advantage is given to the linear model, so that, as we will show in the following section, the better performance of the NN model is even more notable. Of course, in the linear model no ensemble strategy is required.

Here, adopting this NN tool, the main goal of this investigation is to analyse whether models exclusively endowed with data about meteo-climatic behaviour, manure, and nitrogen fertilizers can reconstruct the patterns of annual yields of maize and millet in the countries of Sahel. In the case of millet, although it is a C4 plant and unlike maize, effects of elevated CO_2 on yield and other characteristic features have been documented [23]; thus, we decided to include annual CO_2 concentrations in the set of the model inputs.

In the case of maize, feed-forward NNs (endowed with a 4–5–1 architecture and annual yields as target) are fed in input by these data for the same year: annual mean temperature (T); annual total precipitation (p); total number of hours with plant exposure to $T > 30\ ^\circ C$ during the growing season (#hT > 30); annual sum of nitrogen (N) in manure and nitrogen fertilizers applied to agricultural soils (N + manure). In the case of millet, our NNs have a topology 5–5–1, and the annual concentration of CO_2 is added to the inputs.

We ran the NN models on the complete dataset of 7 countries, considering 20 models with different initial weights and validation sets in an ensemble approach and measuring the performance of yield reconstruction on the ensemble mean. Even if the generalized leave-one-out procedure, per se, helps avoid overfitting problems, we also keep the number of hidden neurons small, so that the free parameters of NNs are an order of magnitude less than the number of patterns in the training set.

Furthermore, we investigated the relative (linear and nonlinear) importance of single variables, using a pruning activity, i.e., by building models in which we extracted a variable in turn from the input layer and then analysing their performance in reconstructing maize and millet yields.

4. Results and Discussion

The results of our analysis are illustrated in Figures 1 and 2, for maize and millet, respectively. In general, the NN performance of their ensemble mean outputs explains the majority of variance ($R^2 = 0.594$ for maize and $R^2 = 0.789$ for millet). These values were in both cases higher than those obtained with a multilinear model (see Tables 1 and 2). There is a clear overestimation of yields for Eritrea and a less marked underestimation of millet yields for Gambia. Furthermore, some extreme peaks are not well reconstructed in both cases, so that the interannual variability was underestimated in some countries, especially for maize. This is a characteristic feature already found in similar studies [20], due to the aggregate treatment of several countries in the NN model. In most countries, this leads to better performance in terms of average values compared to annual fluctuations. Unfortunately, the dataset available for each country was too limited, preventing single countries estimations.

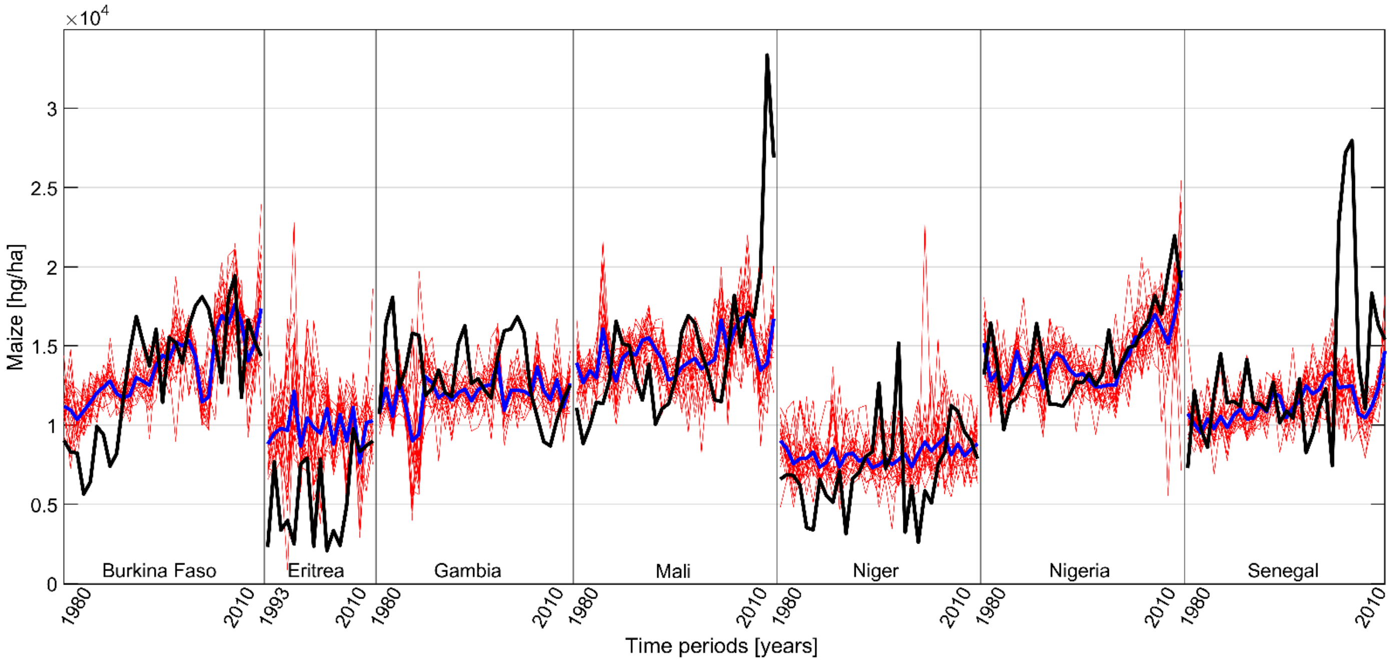

Figure 1. Observed (black line) versus predicted maize yields for seven countries of Sahel between 1980 and 2010. Predictions are the results of 20 runs of NNs endowed with 4 inputs (red lines), and the ensemble mean is shown (blue line).

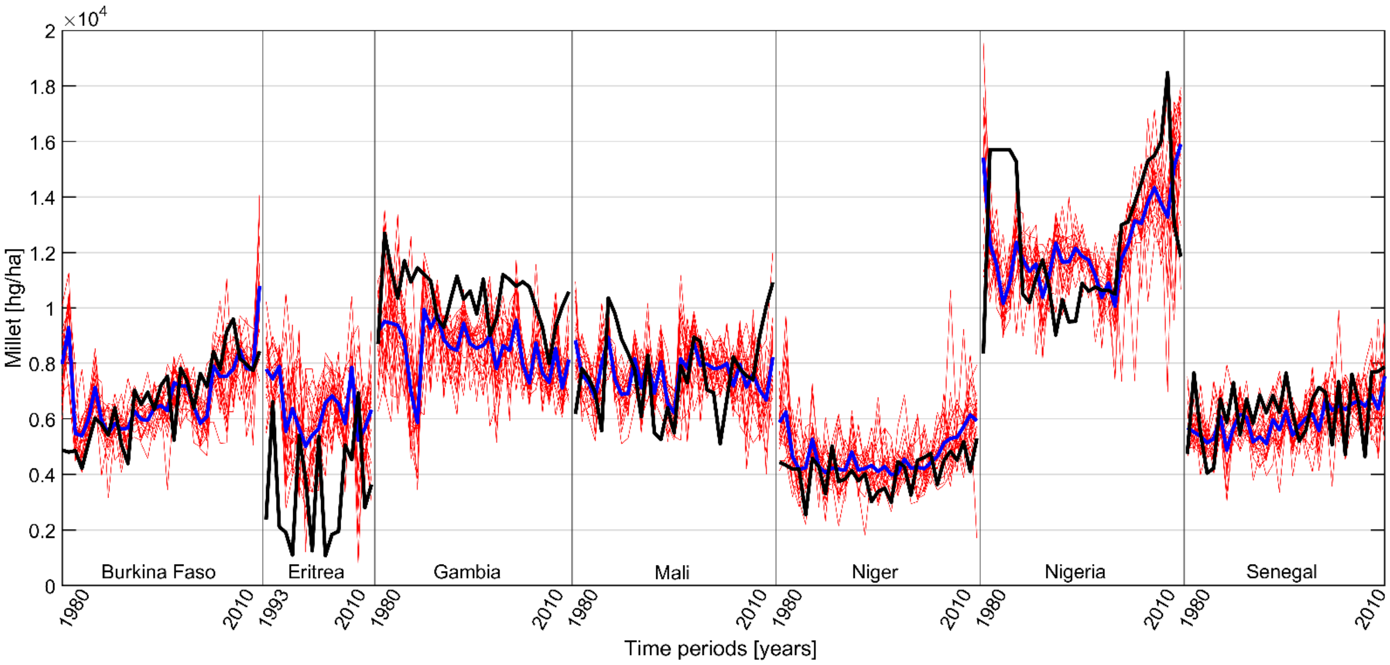

Figure 2. Observed (black line) versus predicted millet yields for seven countries of Sahel between 1980 and 2010. Predictions are the results of 20 runs of NNs endowed with 5 inputs including CO_2 (red lines), and the ensemble mean is shown (blue line).

Despite the fact that important socio-economic factors driving yields over and above climate and fertilizers management were not considered in this study—for instance economic and social instability, availability of labour, and trade dynamics—the NN model developed herein was able to reproduce most of variance in the data. Within the limits of our approach, we thus delved deeper into the relative (linear and nonlinear) importance of single variables, using a pruning activity, i.e., by building models in which, each time, we extracted a variable from the input layer and then analysed its performance in reconstructing maize and millet yields (Tables 3 and 4).

Table 3. Performance of maize yield estimations by NNs and multilinear regressions for the complete runs and for pruned models on the test set.

NN	Inputs	R^2 (NN)	RMSE (NN)	R^2 (Linear)	RMSE (Linear)
4-5-1	p, T, #hT > 30, N + manure	0.594	3884.90	0.457	4287.33
3-5-1	T, #hT > 30, N + manure	0.558	4006.88	0.290	4618.01
3-5-1	p, #hT > 30, N + manure	0.589	3906.97	0.368	4483.21
3-5-1	p, T, N + manure	0.514	4133.76	0.463	4271.62
3-5-1	p, T, #hT > 30	0.507	4162.38	0.419	4376.25

Table 4. Performance of millet yield estimations by NNs and multilinear regressions for the complete runs and for pruned models on the test set.

NN	Inputs	R^2 (NN)	RMSE (NN)	R^2 (Linear)	RMSE (Linear)
5-5-1	p, T, #hT > 30, N + manure, CO_2	0.789	2040.29	0.742	2223.94
4-5-1	p, T, #hT > 30, N + manure	0.782	2068.31	0.743	2219.52
4-5-1	T, #hT > 30, N + manure, CO_2	0.779	2092.79	0.466	2937.33
4-5-1	p, #hT > 30, N + manure, CO_2	0.778	2087.50	0.708	2344.47
4-5-1	p, T, N + manure, CO_2	0.761	2154.80	0.730	2265.67
4-5-1	p, T, #hT > 30, CO_2	0.781	2073.84	0.747	2203.92
3-5-1	T, #hT > 30, N + manure	0.758	2170.96	0.463	2942.41
3-5-1	p, #hT > 30, N + manure	0.769	2119.05	0.711	2331.71
3-5-1	p, T, N + manure	0.753	2184.58	0.733	2256.44
3-5-1	p, T, #hT > 30	0.767	2128.63	0.748	2200.28

For maize, results indicate significant decreases in performance in the complete runs when shifting from NN results to multilinear ones and, in specific cases, from the complete runs to pruned ones (see Table 3). Fertilizers and the number of hours with T > 30 °C were the most important predictors of maize yields: when these variables were extracted from the input layer, the performance of the NN ensemble mean significantly decreased. Conversely, this did not happen when temperature or precipitation was excluded from the input layer. Furthermore, there is evidence for a clear nonlinear role of the number of hours with T > 30 °C, because, when this variable is no longer used as an input, the performance of the NN ensemble mean does not differ very much from that of the multiple linear regression. Highlighting the role of heatwaves, our results complement and provide support—by means of a pure observational data analysis approach—to previous modelling studies on nonlinear high-temperature threshold effects on the physiology of maize during the growing season (see, for instance, [24]). They also enrich and validate established knowledge on climatic drivers in Sahel, with specific reference to the impact of heat waves and extreme temperatures on maize yields in this region (see [2], Ch. 5, and [25]).

Similarly, the results of the R^2s and RMSEs values in Table 3 also suggest a nonlinear role of the use of fertilizers, even if less clear than what was found for #hT > 30. This result, as well, is in line with basic agronomic understanding of the role of increased fertilizer applications, especially combined with the adoption of modern maize cultivars—which tend to exhibit a linear trend up to an application rate threshold, beyond which the impact of increased fertilizers rates decreases (see, for instance, [26]). Finally, it is worth noting that only the use of a nonlinear model can show the fundamental importance of fertilizers and especially of the number of hours with T > 30 °C during the growing season.

For millet, the differences in performance were less marked, although the results of the pruning analysis were similar to the case of maize. In the case of millet, we also considered CO_2 as an input in the full run of the NN model. To this end, Table 4 shows that its contribution permits us to obtain the best results (only in the NN model, not in the linear one). However, the results of networks with topology 4–5–1 show that the CO_2 contribution is quite limited: the decrease in reconstruction performance when we extract CO_2 from the inputs is even smaller than when other variables are extracted. This suggests that, in line with recent findings [27], the observed increases in atmospheric CO_2 were not a dominant driver of millet yield trends in the Sahel.

In the pruning experiments performed (with 4–5–1 networks, but also with 3–5–1 ones in which CO_2 is not used at all), #hT > 30 plays a major (nonlinear) role in leading to a correct output for millet yields. In fact, even in this case the ensemble mean performance (of the NNs in which we have extracted #hT > 30 from the inputs) reduces and appears very similar to that of the multilinear regression. The extractions of the other variables lead to similar small decreases of performance in the nonlinear model. This holds for precipitation, as well, which instead plays a pivotal role in the multilinear regression. Therefore, even for millet yields, the present study underscores a nonlinear threshold effect of the number of hours with T > 30 °C during the growing season. As mentioned above with regard to maize, these results—obtained without relying on counterfactual modelling—corroborate previous findings on the highly negative impact of heat waves on this region in the time range: see [27].

5. Conclusions

We investigated the impacts of meteo-climatic and management factors on maize and millet yields in the Sahel, using a fully nonlinear method (NN modelling). The application of a NN model—specifically developed for handling small datasets—led us to obtain good results, representing an improvement over a multilinear regression approach.

The comparison with the linear model and a dedicated pruning activity allowed us to clarify the specific roles of single drivers. In particular, the identified strong (nonlinear) role of the number of hours with temperatures higher than 30 °C during the growing season points to a nonlinear threshold effect of heat waves on crop yields. Furthermore, our analysis indicates that natural and synthetic nitrogen fertilizers management also play an important role in determining yields. Finally, for millet, the analysis indicated that CO_2 concentration favours an increase in yields, albeit its role is not decisive.

In conclusion, this research aims to emphasise the importance of the application of a machine-learning method for the analysis of yields in poor or developing countries. Our results help to identify critical variables which affect regional maize and millet production in the Sahel and are thus relevant for climate change studies.

Author Contributions: A.P. and F.N.T. conceived this study. A.P. and G.D.F.P. designed the specific neural-network analysis. G.D.F.P. made computations. All authors analysed and discussed the results. A.P. wrote the paper with many contributions by F.N.T. The findings and conclusions provided in this paper are the authors' only and do not reflect necessarily the policies and positions of FAO on the subject matter. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The datasets analysed during the current study are available at web sites and papers indicated herein. The datasets generated and the neural-network model are available from the corresponding author on request.

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