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Linear and nonlinear influences of climatic changes on migration flows: a case study for the 'Mediterranean bridge'

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LETTER


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Antonello Pasini¹  and Stefano Amendola²¹ Institute of Atmospheric Pollution Research, National Research Council, Rome, Italy² Department of Mathematics and Physics, Roma Tre University, Rome, ItalyE-mail: pasini@iia.cnr.it**Keywords:** climate–migrations relationship, neural network modelling, climatic causes of migration, nonlinear climatic effectsSupplementary material for this article is available [online](#)**Abstract**

The influence of climatic changes on migrations around the world is a topic widely discussed in the scientific literature, but investigations are often limited to particular regions. The possible causes of migration flows from Africa to Europe due to landings in Italy, a peninsula which can be considered as a ‘bridge’ between these two continents, have not been investigated in detail even if, at present, this problem is at the top of the political agenda in Europe. Here a simple linear model and a fully nonlinear one (neural networks—NNs) are applied to the study of possible climatic influences on migration flows from the Sahel to Italy during the period 1995–2009. The results show the ability of the NN model to explain the majority of the variance found in the data and permit the identification of the major climatic drivers affecting the amount of yields in Sahelian countries and the migrations flows from them to Italy. In particular, the use of a NN model fully identifies both linear and nonlinear influences. We can explain much of the variance in the migration data ($R^2 = 0.775$). Agriculture (harvest yields) is shown to link climatic changes and migration, and poor yields can enhance this latter phenomenon. Heat waves (during the cereal growing season) have an important nonlinear role. The annual temperature, however, is most likely the dominant climatic factor influencing migrations in this region.

1. Introduction

At present, forced migration is one of the most critical global challenges ahead of us and a problem at the top of the political agenda in Europe. Among European states, Italy is a favoured landing country due to its role as a ‘bridge’ between the African continent and Europe. Any advance in understanding the causes of these migrations can help substantially the study and implementation of policies at European level, and potentially in other countries where similar phenomena occur.

Many causes can be recognized as drivers for the observed migration flows. Among them, we may cite civil wars, such as the recent Syrian one, other kinds of conflicts, terrorism, difficulties in maintaining subsistence agriculture, loss of yields, etc. Obviously, also many other ‘push and pull’ factors may contribute to the migration decisions of individuals, even in less critical situations, and the classical social science approach to the study of migrations is essentially based on them (Lee 1966). In this sociological framework, environmental challenges only began to be considered relatively recently (see, for instance, Black *et al* 2011, Mallick and Etzold 2015). Evidences for a specific role of climatic changes in triggering or amplifying conflicts and/or migrations has appeared in the scientific literature: see, for instance, Hsiang *et al* 2011, Werrell *et al* 2013, UNCCD 2014, Kelley *et al* 2015, Cai *et al* 2016, Carleton and Hsiang 2016, Schleussner *et al* 2016, Mastrojeni and Pasini 2017, Missirian and Schlenker 2017. Taking climatic changes into consideration leads to a better

understanding of forced migrations (Castles 2003). Recently research into the connection between climate change and migration has increased substantially: see Piguet *et al* 2018 and references therein.

This climatic role can be quite clear, for instance as an initial cause of tension leading to conflict as seen in the Syrian drought that preceded the Syrian crisis (Kelley *et al* 2015). Other cases involve a combination of influences, such as the contribution to land degradation by climatic factors in all the Sahelian belt, and more specifically in the Chad region, where the lake (and its associated ecosystem services) have been strongly affected (UNCCD 2014). Clearly, even within a complex mixture of causes, much evidence leads us to seriously consider climate change as an important factor in triggering or amplifying migrations. See, however, Adams *et al* (2018), who conducted a bibliometric analysis and showed a bias in the investigations on direct links between climate and conflicts, where the latter can be considered the forerunners of migrations.

Furthermore, it is worthwhile to note that the specific phenomenon of migrations towards foreign countries is even more complex, because it represents the last step of the displacement of a population (only after internal migrations), and may also be driven by specific economic factors, such as the availability of enough capital to migrate. At present, however, data on migration flows are almost exclusively available for migrations towards developed countries, due to official registrations at their boundaries or landing sites, so that—in this research field—quantitative studies can be better performed on these specific data.

In this framework, here we analyze data concerning migrations from the Sahelian belt to Italy in the 15 years before the Syrian crisis and the so called Arab Spring (period 1995–2009). In doing so, we try to avoid the major changes in causes which could overwhelm the direct role of climate change. Of course, at least a local crisis was present in the Sahelian countries during these years (the Darfur conflict) and can be a cause of migrations. Thus, in what follows we will explicitly analyze how our results are impacted by the data of migrations from Sudan and adjacent Chad, which were probably affected by this conflict.

Together with simple linear techniques, we apply fully nonlinear neural network (NN) models (specifically developed for the analysis of small data sets) and an ensemble strategy. This allows us to highlight the influence of climatic drivers on harvest yields in the ten countries of the Sahel (Senegal, Gambia, Mauritania, Mali, Burkina Faso, Niger, Nigeria, Chad, Sudan, Eritrea) and on migration flows from these countries to Italy.

Even if some seemingly important explanatory variables (coming from social science studies and needed for more comprehensive results) could not be included due to lack of data, for the first time, to our knowledge, this NN method permits investigation of both the linear and nonlinear influences of climatic drivers, yields and gross domestic product (GDP) on a complex migration phenomenon, such as that from Sahelian countries to Italy. The final results show that the complexity of migrations can be reasonably disentangled, at least in our case study.

2. Data

For bilateral international migration flows, we use a subset of the more general dataset of Cai *et al* (2016). Specifically, data of migrations from the Sahelian countries to Italy in the period 1995–2009 are considered. In some cases, data for the first year are not available, and for Eritrea data for 1995 and 1996 are absent. Nevertheless, this data subset has a lower percentage of missing data compared with the main dataset by Cai *et al* (2016).

Data concerning cereal yields were obtained from the World Bank (<http://databank.worldbank.org>). Yields are measured as kilograms per hectare of harvested land and include wheat, rice, maize, barley, oats, rye, millet, sorghum, buckwheat and mixed grains.

GDP data (the purchasing power parity converted GDP per capita at 2005 constant prices) come from the Penn World Tables 7.0 (Heston *et al* 2011).

Monthly mean temperature and total precipitation data were collected from the NASA Modern Era Retrospective Analysis for Research and Applications (Rienecker *et al* 2011). The original gridded data were aggregated at country level and population-weighted, i.e. the weather conditions for populated regions within a country are given more weight. In addition, we derived the number of hours with temperatures higher than 30 °C during the growing season, 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>) to determine the growing seasons for each grid cell: further details may be found in Cai *et al* (2016).

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

3. Method

Besides simple multilinear regressions, the main analysis technique adopted in this paper is neural network modelling. Since the end of the '90 s, NNs have been used in atmospheric and climate sciences: see Hertz *et al*

Table 1. Data about population, cereal yields and migration rates from Sahel to Italy in the period 1995–2010.

Country	Mean population (millions)	Cereal yield—mean (kg/ha)	Cereal yield—minimum (kg/ha)	Cereal yield—maximum (kg/ha)	Migration rate to Italy—mean ($\times 10^{-5}$)	Migration rate to Italy—minimum ($\times 10^{-5}$)	Migration rate to Italy—maximum ($\times 10^{-5}$)
Mauritania	2.307	788.7	630.9	1011.7	1.824	1.008	2.192
Mali	9.663	1105.2	792.3	1588.2	0.758	0.429	1.335
Burkina F.	10.425	959.8	704.5	1203.8	4.961	2.362	8.409
Niger	9.650	388.1	267.9	488.8	0.546	0.305	0.890
Nigeria	111.020	1323.4	1171.4	1598.4	2.109	0.263	3.158
Chad	7.360	698.8	528.4	862.5	0.145	0.050	0.321
Sudan	30.846	572.3	429.5	729.4	0.448	0.111	1.168
Eritrea	3.473	532.9	158.2	959.6	18.599	6.132	53.099
Senegal	8.726	893.2	651.6	1201.1	34.428	6.194	76.030
Gambia	1.100	1082.0	800.3	1295.8	4.169	2.154	7.469

Table 2. Data about the climatic factors and GDP, considered in this study for the period 1995–2010.

Country	Mean annual cumulated precipitation (mm/year) [min–max]	Mean annual temperature (°C) [min–max]	Growing season exposure above 30 °C (hours) [min–max]	Gross domestic product (2005 Int\$/person) [min–max]
Mauritania	196.2 [128.0–267.2]	29.7 [28.8–30.3]	23.1 [11.4–32.7]	1349 [1195–1717]
Mali	538.5 [403.8–757.6]	29.7 [27.9–31.0]	315.8 [186.2–402.0]	839 [707–980]
Burkina F.	304.9 [153.1–497.7]	29.5 [27.6–31.3]	1048.0 [730.0–1318.5]	819 [671–905]
Niger	25.4 [12.8–41.5]	29.9 [28.2–31.3]	1095.6 [750.0–1355.8]	514 [476–631]
Nigeria	1619.4 [1255.1–2044.7]	26.3 [25.4–26.8]	1233.6 [902.7–1459.4]	1370 [1084–1942]
Chad	428.2 [129.9–864.3]	30.8 [28.5–32.5]	1088.4 [539.7–1546.4]	945 [723–1293]
Sudan	356.3 [155.5–628.3]	31.0 [29.2–32.2]	24.8 [16.9–39.9]	1691 [1311–2130]
Eritrea	660.4 [547.2–803.0]	27.5 [26.4–28.4]	21.3 [4.6–67.6]	796 [597–1154]
Senegal	566.4 [449.5–702.7]	27.7 [27.0–28.3]	659.2 [526.8–757.5]	1320 [1154–1495]
Gambia	782.8 [608.8–927.3]	27.9 [27.3–28.7]	48.0 [16.3–147.8]	930 [750–1427]

(1991) and Bishop (1995) for general texts on NNs, Hsieh (2009), Haupt *et al* (2009) and Krasnopolsky (2013) for review books on NN environmental applications.

Here we adopt a NN tool, specifically developed for modelling relationships among variables in small datasets, first used in Pasini and Modugno (2013), extensively described in Pasini (2015) and recently applied to the important problem of attribution of global temperature behaviour (Pasini *et al* 2017). It is worthwhile to note that a previous version of this tool has been successfully applied also to modelling specific impacts of changes in meteo-climatic variables at local scale (Pasini *et al* 2009) and in other regional studies (Pasini and Langone 2010, 2012).

The NNs of this tool are feedforward ones with one hidden layer and backpropagation training. They are endowed with hyperbolic-tangent transfer functions at the hidden level and a linear function at the output neuron. In general, in a complex system these NNs are able to find reliable nonlinear ‘laws’ linking some predictors—considered as inputs of the networks—to a predictand (the target to be ‘approached’ by the networks’ output) after a standard training-validation-test procedure. Here, however, our dataset is quite small (a total number of slightly more than 140 yearly inputs-target pairs for the ten countries), so that particular generalized leave-one-out and ensemble strategies are adopted (see Pasini 2015 for more details).

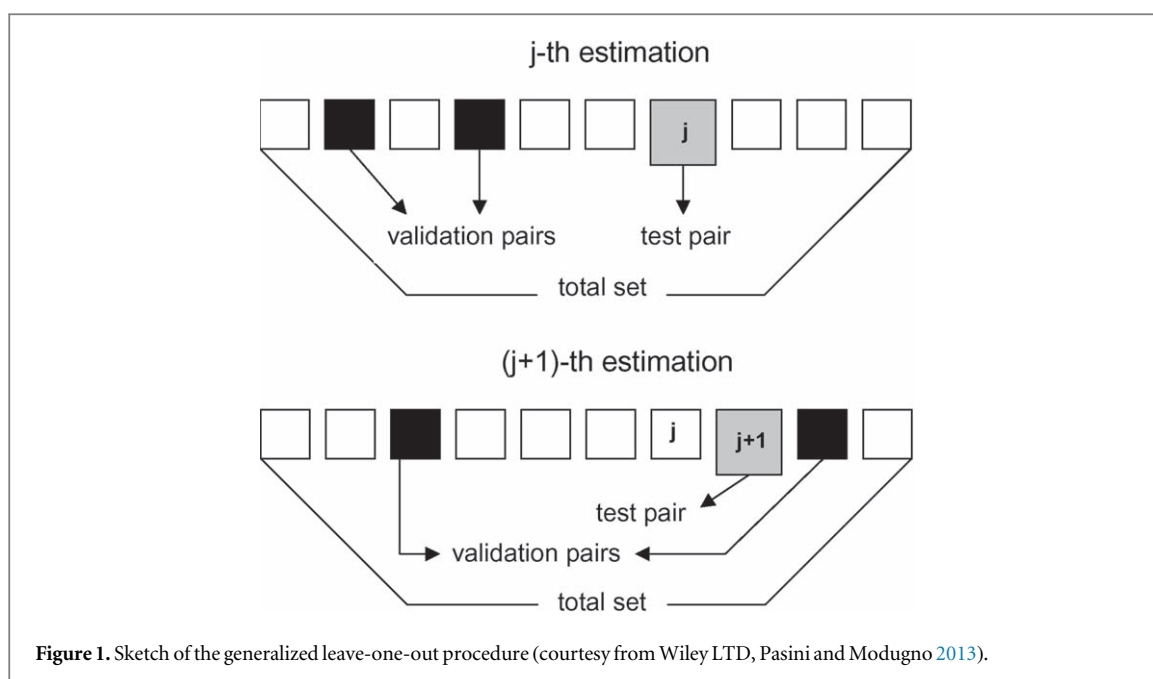
Each inputs-target pair (also called ‘pattern’) refers to a single country for a specific year and is comprised of the data of a certain number of predictors (see the following section for details on the climatic variables used as predictors in our NN runs) and the target (specifically, yields or migration flows for that country and that year). Starting from the first inputs-target pair of the dataset (which includes all years and countries), a single pair is extracted from the total available dataset and considered as a test set on which we measure the performance of the NN model. A validation set is then randomly chosen (it represents the 10% of pairs) and the remaining pairs constitute the training set. At the end of the NN model run, the connection weights are fixed, a transfer function is found from inputs to output and an estimate (the result of our model) for the first value of the predictand is obtained.

After this, we follow the same procedure for the other years and countries (each of them becomes—sequentially—the test set), thus permitting the estimate of all output values at the end of the procedure (see figure 1). In doing so, however, this result can be influenced by the initial (random) choice of the weights and the members of the validation set: in particular, a NN needs to be initialized by randomly choosing the weights associated with the connections which link the different neurons, and this can influence the final result of the NN model. Thus, multiple runs may be performed by choosing different random values for the initial weights and members of the validation set. We performed 20 runs in an ensemble approach and then calculated the average of their output estimates, in order to filter out variability.

In the appendix contained in the supplementary information (it is available online at stacks.iop.org/ERC/1/011005/mmedia) we show how these generalized leave-one-out and ensemble strategies perform better than other classical NN alternatives in the context of the analyzed problem.

This particular training-validation-test procedure is not the only method to avoid overfitting problems. Here, the initial number of inputs and hidden neurons is kept small, so that the free parameters of our NN models are an order of magnitude less than the number of patterns in the training set.

In the multilinear regression model—whose results must be compared with those coming from the NN models in order to identify and distinguish linear and nonlinear influences—the same approach to training is adopted: for each single pair, the regression coefficients are fixed on the other data (the union of the training and validation sets used in the NN method). In doing this, the linear model is obviously given an advantage, thus the generally better performance of the NN model—shown in the following section—is even more notable.



4. Results

In order to test the influence of climatic factors on cereal yields in the Sahelian countries and migration flows to Italy, we consider the fundamental climatic predictors included in the dataset by Cai *et al* (2016)—annual mean temperature, annual total precipitation and the total number of hours during which the plants are exposed to $T > 30^\circ\text{C}$ during the growing season—and compare the results coming from applications of both multiple linear regressions and NN models. Furthermore, a pruning activity—excluding an input in turn from the neural networks—is performed. By doing this, we can test which inputs have a dominant role in achieving a correct estimate of the observed target data and we are able to investigate and identify specific linear and nonlinear influences.

The first scope of this paper is to analyze how much the climatic variables are able to reconstruct the annual harvest yields (our target) in the ten countries of the Sahel. Feedforward NNs with a 3-4-1 topology are fed in input by data for the same year, annual mean temperature, annual total precipitation and the total number of hours during which the plants are exposed to $T > 30^\circ\text{C}$ during the growing season. This low number of hidden neurons has been empirically chosen after several trials: it allows us to achieve a good generalised overview and not to fall into overfitting problems.

The results of the ensemble runs of our NN models are depicted in figure 2, where red lines represent the single NN runs and the blue line is the ensemble mean. Even if some overestimation is visible for Eritrea and Niger, quite good estimates are generally obtained for the other countries, with the best performance achieved for the high yields in Nigeria.

In the first row of table 3 the performance of NNs and multiple linear regressions is compared in terms of R-squared (R^2) between target and output. The nonlinear method (through its ensemble mean outputs) seems to establish better the relationship between predictors and predictand, and the climatic variables included in our analysis, and can explain approximately half of the variance in the yield data ($R^2 = 0.502$). However, the linear and nonlinear importance of the single variables can be more thoroughly investigated using a pruning activity, by building models in which we extract a variable in turn from the input layer and then analyse their performance in reconstructing the harvest yields.

Table 3 shows the results of this pruning. Precipitation and the number of hours with $T > 30^\circ\text{C}$ seem to have a major role in leading to a correct output for harvest yields, because, when these variables are extracted from the input layer, the performance of the NN ensemble mean decreases noticeably. This does not happen when temperature is extracted from the input layer. Furthermore, there is evidence for a clear nonlinear role of the number of hours with $T > 30^\circ\text{C}$, because, when this variable is no longer used as input, the performance of the NN ensemble mean does not differ from that of the multiple linear regression. This indicates the possibility of a nonlinear threshold effect of possible heat waves on cereals during the growing season.

Obviously, our results show that the yields are not driven by climatic variables only (the explained variance is not that high), but probably other external drivers, such as the availability of fertilizers or the phenomenon of land abandonment for external reasons, e.g. conflicts, are influential.

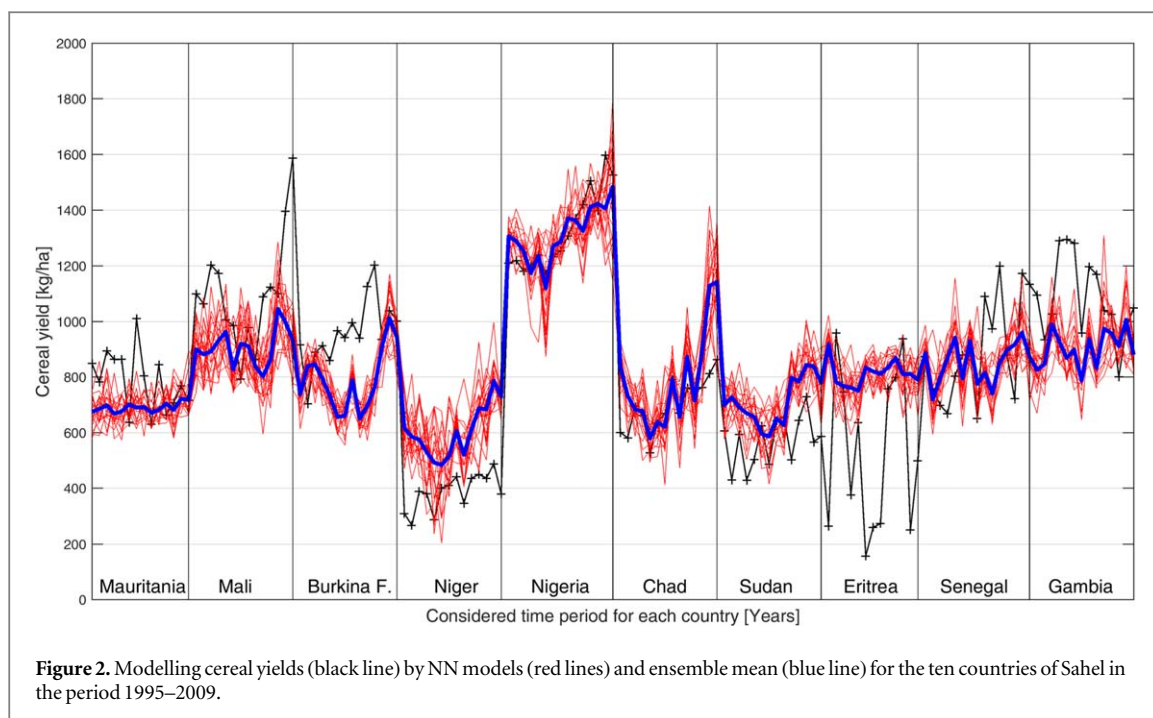


Table 3. Performances (in terms of R^2) of yield estimation by NNs and multilinear regressions for the complete runs and for pruned models.

Inputs	Target	NN (R^2)	Multilinear (R^2)
Prec.—temp.—# hours $T > 30$ °C	Yield	0.502	0.405
Prec.—temp.	Yield	0.406	0.406
Prec.—# hours $T > 30$ °C	Yield	0.516	0.407
Temp.—# hours $T > 30$ °C	Yield	0.386	0.216

Nonetheless, variations in yields can themselves be drivers for migrations. Thus, moving to the investigation of the climate-migration link in our dataset, we build NN models with a 4-4-1 topology, where the previous climatic variables and observational yield data are considered as inputs. As target/predictand we choose a variable often considered in migration studies, that is the natural logarithm of the migration rate (from the Sahelian countries to Italy). Here, migration rate is defined as the annual migration flow from the origin country to Italy divided by the population of the country of origin in the same year. Note that one is added to all migration flows before calculating migration rates, in order to deal with the zero-flows issue.

The results of this NN investigation are shown in figure 3. If we exclude the quite evident overestimation for the migration rates from Chad, the model estimate of migrations seems very good. This is confirmed by the first row of table 2, which shows a high level of explained variance in the migration data ($R^2 = 0.775$). Considering the hypothesized strong influence of other non-climatic and non-agricultural drivers on migration flows, this finding seems very impressive.

Of course, also different measures of performance may be considered. Hence, we calculate the ROC diagram, a method used in studies on model performance assessment (see, for instance, Wilks 2001). In its simplest form it is a parametric plot of the hit rate (or probability of detection) versus the false alarm rate, as a decision threshold is varied across the full range of a continuous estimated quantity. The diagonal line corresponds to random estimations and the amount of concavity is taken to be a measure of performance. In particular, the area under the ROC curve can be taken as a scalar measure of performance. An area of 0.5 reflects random estimations, while a ROC area = 1 implies perfect estimations. In figure 4 the ROC method is applied to the estimations of migration rates coming from our NN tool and multilinear regression. The results clearly show a better performance in the case of NN estimations.

Furthermore, as before, the results of a pruning activity, shown in table 4, give information on linear and nonlinear influences of the input variables on the predictand. In this case, temperature is clearly the most

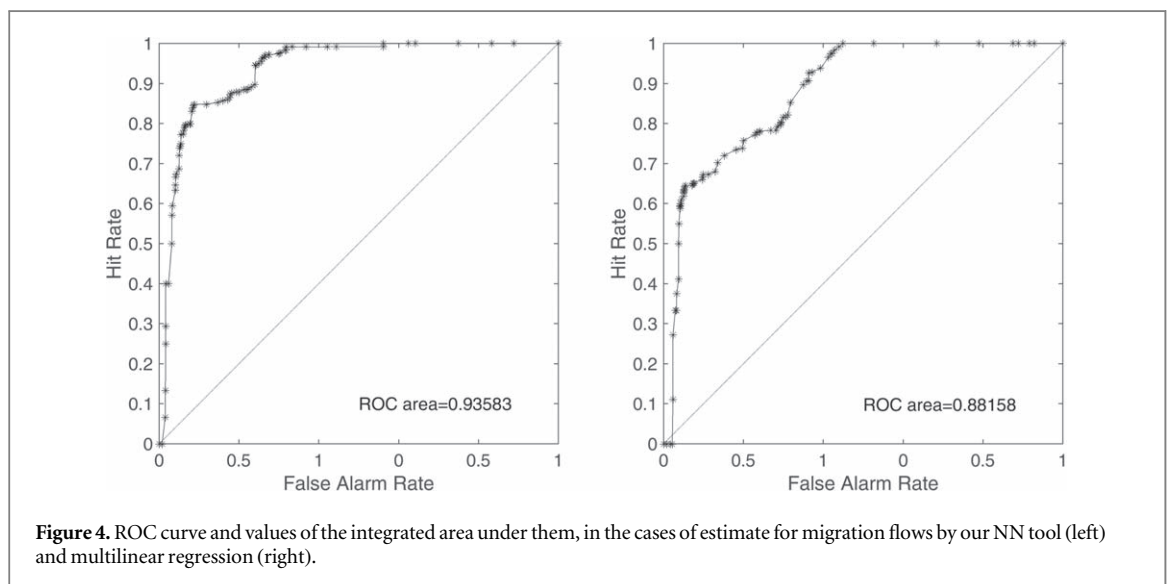
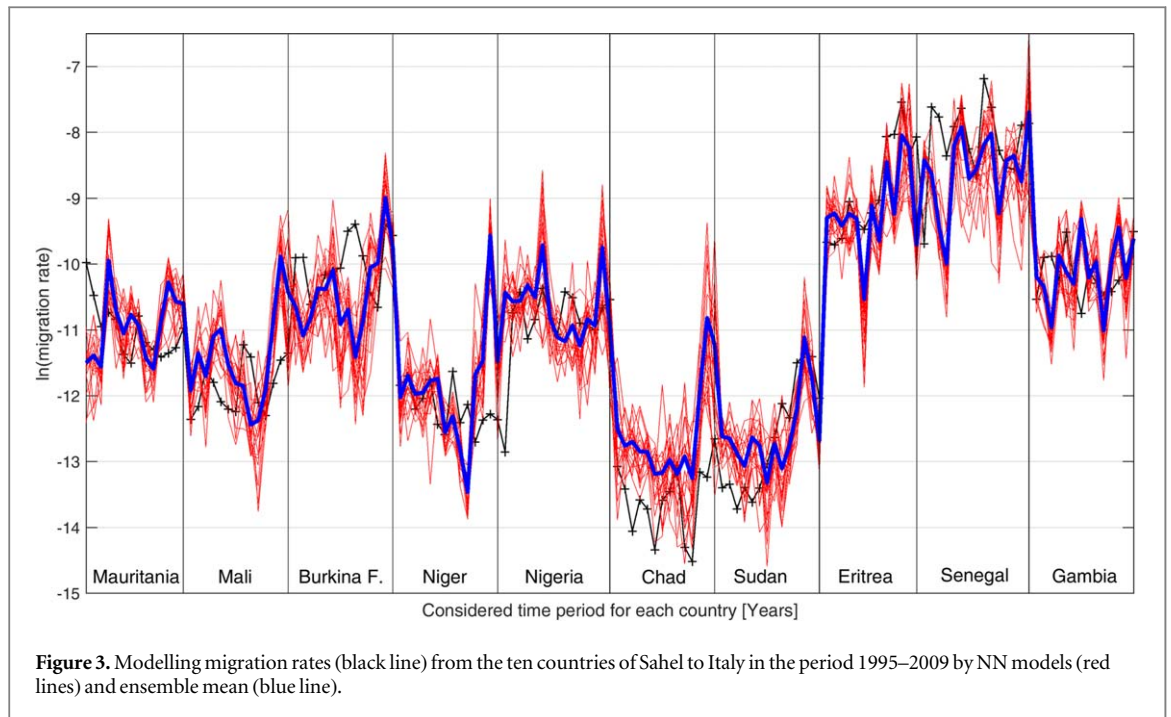


Table 4. Performances (in terms of R^2) of migration rates estimation by NNs and multilinear regressions for the complete runs and for pruned models (data about yields are observed ones: they are not coming from the previous NN estimations in table 3).

Inputs	Target	NN (R^2)	Multilinear (R^2)
Prec.—temp.—# hours $T > 30\text{ }^\circ\text{C}$ —yield	$\ln(\text{MigRate})$	0.775	0.626
Prec.—temp.—# hours $T > 30\text{ }^\circ\text{C}$	$\ln(\text{MigRate})$	0.671	0.611
Prec.—temp.—yield	$\ln(\text{MigRate})$	0.683	0.632
Prec.—# hours $T > 30\text{ }^\circ\text{C}$ —yield	$\ln(\text{MigRate})$	0.361	0.085
Temp.—# hours $T > 30\text{ }^\circ\text{C}$ —yield	$\ln(\text{MigRate})$	0.715	0.447

influential variable on migration rate, due to a strong decrease in performance of both NN and linear models when it is excluded from the input layer. This decrease in performance is less marked when other variables are extracted from the input layer. However, it is worthwhile to note that harvest yields and the number of hours with $T > 30\text{ }^\circ\text{C}$ have a clear nonlinear role. In the case of their exclusion from the predictors, in fact, the performance of the multilinear model changes very little and the performance of the NN model is very close to that of the linear one.

These results support the idea that nonlinear changes in yields and heat waves could enhance migrations, due to threshold effects. However, the dominant role on migration flows appears to be due to the effect of annual mean temperature, indirectly on the yields, but also directly on the population. As previously discussed, mean temperature does not influence yields very much. Thus, just as a hint, this could confirm previous studies which show how the large observed increase in mean temperatures and heat waves directly influence humans and animals, by exceeding their threshold of thermal tolerance, especially in low-income countries such as those of the Sahel (Herold *et al* 2017, Mora *et al* 2017). Clearly, further investigation is necessary on more detailed datasets, which can bridge our present gap of knowledge about more specific social drivers and other indirect influences of temperature.

As cited in the Introduction, the Darfur conflict could have influenced migrations from Sudan and the related migration pressure may have influenced migration patterns from Chad, too. Unfortunately, we do not possess the quantitative data necessary to consider this influence in our model, thus we have performed a sensitivity analysis by eliminating from our dataset the data of migrations from Sudan and Chad after 2002 (the Darfur conflict began in 2003), when the migrations increased effectively, even if they are quite well described by our climatic drivers (see figure 3). Doing this, we note only slight changes in the estimation performance of migration rates for other countries and for Sudan and Chad before 2003. It therefore seems that the Darfur conflict does not corrupt our main results concerning the importance of climatic factors in our case study.

Of course, migrations to foreign countries are influenced also by availability of enough money to finance long and sometimes dangerous journeys. Data regarding wealth distribution in the Sahelian countries should be considered, but unfortunately we do not possess this information. A rough proxy for this, GDP, however is available in our dataset.

GDP was added as an input to our NN models, by considering 5-4-1 networks with the natural logarithm of migration rate as the target. The results show that the performance of the models are substantially unchanged: $R^2(\text{NN}) = 0.762$, $R^2(\text{multilinear}) = 0.632$ (compare with the first row of table 4). This is quite understandable if one considers that in the Sahelian countries the GDP is primarily due to agricultural activities and the two variables show similar temporal evolution. In other words, no new substantial information has been given to the NN models.

Further information may be gained however by substituting GDP for harvest yields in a 4-4-1 network topology: the results become $R^2(\text{NN}) = 0.721$, $R^2(\text{multilinear}) = 0.619$. Thus, it appears that the migrations flows are more closely linked to agricultural yields than to the general GDP of the countries. It seems that migrants are more closely associated to agricultural activities and therefore more affected by the increase or decrease of yields.

Lastly, delayed influences of climatic variables on migrations are explored in our models. The results show a general (quite slight) decrease of performance in migration estimate when data of one and two years previously are considered. This confirms the importance of recent climate conditions and annual yields on this phenomenon. Obviously, due to the limited dataset available and the statistical method adopted here, we are not able to study the influence of other phenomena, e.g. prolonged multi-year droughts, which can have important delayed impacts.

5. Conclusions

The results obtained in this investigation permit the assessment of climatic influences on harvest yields in Sahelian countries and on migration flows from these countries to Italy, considered as a 'bridge' between Africa and Europe.

In particular, we achieve a high explained variance by climatic factors and yields in the migration data ($R^2 = 0.775$). Considering the hypothesized strong influence of other non-climatic drivers on migration flows, this finding is very impressive.

Furthermore, the comparison between the performance of a simple linear model and a fully nonlinear NN one, together with the adoption of a pruning strategy, allows us to achieve quite distinct results.

In short, as already shown elsewhere (Cai *et al* 2016), agriculture (harvest yields) represents a link between climatic changes and migrations, which can enhance this latter phenomenon. Heat waves (during the growing season) also have an important nonlinear role. The annual temperature, however, is probably the dominant factor that influences migrations. This leads us to suppose that also exceeding the threshold of thermal tolerance can have a role. Of course, we could envisage also some indirect pathways through which this direct temperature driver could actually work, but, unfortunately, these are not investigable in our limited and mainly climatic dataset.

Finally, the influences of GDP and delayed climatic factors and yields appear not to be important in our study, but more complete datasets are needed to consider wealth distribution in Sahelian countries and to include delayed driving factors.

Obviously, our results corroborate other studies (cited in the Introduction) which showed the importance of climatic factors for inducing migrations. However this paper represents the first attempt to apply a novel method to the analysis of possible climate-induced migrations. At the present stage of development of our study, a comparison with the many studies on this topic from social sciences, which consider the influence of other factors (more linked to socio-economic and personal/familiar attitudes) is not possible. More complete datasets are needed, in which these factors can be included in a quantitative manner. We hope that this work can stimulate collaboration for more comprehensive interdisciplinary studies to be performed by natural and social scientists together.

Finally, we would like to stress that this study shows how indirect climatic impacts in a developed country such as Italy arise not only from climatic changes within its borders, but also from changes in the climate of other countries where migration flows originate. From the point of view of decision makers of a developed country, this leads to the requirement of consideration of—besides internal mitigation and adaptation—also action in these poor countries, to aid recovery of degraded lands and to build a more resilient agriculture for sustenance and development of their inhabitants. This has the benefit of preventing the phenomenon of forced migrations, and allowing individuals to reach decisions unforced by external phenomena about his/her own possible migration. It is worthwhile to note that these actions represent win-win strategies which help to solve together climatic problems (these actions have a mitigation value) and other challenges which affect a large part of the world, such as food security and hunger (Mastrojeni and Pasini 2017, Pasini *et al* 2018). In the framework of the UN 2030 Agenda for Sustainable Development, which requires a systemic view on integrated solutions, these actions should be seriously considered by policy makers.

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