Project Outline

By Thomas Schincariol

Introduction

Does climate change cause conflict? In this paper, I aim to provide a novel approach to answer to this question by modelling climate change as a dynamic trajectory, rather than as a static variable. The objective is to uncover the complex dynamics between climate change—temperature, soil moisture and precipitations in particular—and the onset and escalation of civil conflicts.

The existing literature has studied the connection between climate change and conflict extensively. However, results have so far been mixed. While meta-analyses [1] [2] suggest the existence of a causal link between temperatures and precipitations and conflict, the results are typically limited to small subsets of countries and times. [3] Moreover, the underlying mechanisms remain largely unclear. I argue here that these mixed results are due to the limited methodological tools used. In particular, the use of static methods (observations treated as independent from one another) are inadequate because the impact of climate variation on conflict mechanisms is complex and requires methods that can model time flexibly. Without considering global climate dynamics, models only rely on extreme weather events as potential triggers for the escalation of conflict. This does not take into account the ability of local populations to adapt to them. In fact, only the accumulation in time of these extreme conditions leads to higher risk of conflict, so the global dynamic of the variable should be used—not just its spot value.

Instead, novel methods derived from the field of image processing and data mining are used. These methods allow to uncover complex nonlinear dynamics in temperature and precipitations. Consider for example the case of the 2011 civil war in Syria [4]. Water management has been suggested as one of the factors that contributed to the onset of conflict in the beginning of the 2010's. The repeated droughts in the beginning of the 2000's triggered migrations from rural to urban zones and sparked food insecurity. In turn, the deterioration of local livelihood and lowered access to food and resources harmed political stability and contributed to the escalation of tensions into a civil war. In this case, the dynamics of droughts—the complex pattern of repeated droughts over time--was an early warning signal of conflict, whereas the individual drought episodes did not explain the onset of violence. However, using classical regression, dangerousness of repeated events cannot be well evaluated due to the non-perception of its recurrence. Only methods that can handle dynamic recognition would allow to assess the risk generated by these climatic patterns.

In this paper, a nationwide study is conducted on the indirect link between climate time series and civil war onsets using Shapelets classification. The African continent will be studied over the period 1988-2020. The objective is then two-fold : (i) the detection of climate patterns relevant to the study of conflicts and (ii) their classification for forecasting purposes.

Data

Earth Observation Data

ERA-5 [5], a reanalyzed product of the ECMWF Integrated Forecast System (IFS), provided the data for temperature, precipitation, and soil moisture. It is produced by the Copernicus Climate Change Service (C3S) and accessible on the C3S Climate Data Store freely. The monthly data has a 0.1° resolution and is extracted from the 1st January 1989 to the 31st of December 2020.

The ERA-5 product was chosen due to his historical accessibility and a good overall quality. However, the precipitation product is controversial. But better quality products are only available for short periods of time (especially SM2RAIN–ASCAT).

Agronomic data

MIRCA 2000 [6] project provides the agronomic data. Its database inventory of the world's agricultural land. It gives information on the type of crop, the growing season, and the amount of cultivated land (yield), with a 5 arcminutes resolution. This data will be used to weight temporally (growing season of the crops) and spatially (presence/absence of the crop type in the area) the climatic data.

Conflict data

Conflict data is extracted from UCDP Dataset [7],[8]. It covers the period 1946-2020, for the 189 countries of the UCDP dataset. Civil conflict is defined an intrastate armed conflict with more than 25 battle deaths.

Method

This study relies on 3-years temporal sequences to study the link of climate patterns and the onset of conflict. The dependent variable is civil wars onsets over the period 1989-2020. The unit of analysis is the country-month.

Extraction of the TS

First, each country is divided in cells using the MIRCA grid (see Figure 1). One cell is associated with the type of crops exploited in it, its surface and its seasonal growing. To facilitate the extraction, the zone considered is a 0.1° buffer around the centroid of the cell. Temperature, precipitation, and soil moisture TS are extracted following (1) :

$$Val_{t,c} = \frac{\sum_{i=1}^{n} x_{t,n} * S_{n,cro,t}}{\sum_{i=1}^{n} S_{n,cro,t}} \quad (1)$$

With, $Val_{t,c}$ the value of the TS at the date t, for the country c ; $x_{t,n}$ the value of climatic variable for the date t and the cell n ; $S_{n,cro,t}$ the surface of the crop *cro* , in cell n, at the t time (if t ∉ seasonal growing, S=0)

This crop and seasonal weightings allow a better apprehension of the growing season of the crops and a real focus on the climatic variation.

Classification

General model

The identification and classification of potential pre-conflict climatic patterns is based on the Shapelets method. [9] Originally developed for image processing, this method is now being applied to other fields with convincing results [10], especially in the processing of time series.

Shapelets are short sequences. They provide information about the similarity of two sequences based on their distance to this specific subsequence. They can be used to convert time series to features by computing the distance between each time series and the meaningful shapelet (see Figure 2). The degree of belonging of a Shapelet and a time series is defined by (2) :

$$d(TS, sha) = min\|TS_{t\rightarrow t+L} - sha\|_2 \quad (2)$$

With, L the length (number of timestamps) of Shapelet sha and $TS_{t\rightarrow t+L}$ is the subsequence extracted from time series seq that starts at time index t and stops at $t + L$. If the above-defined distance is small enough, then Shapelet sha is supposed to be present in time series TS.

Learning phase : Clustering

During the learning phase, the ‘pre-war’ (TS which precedes an onset) and the ‘pre-peace’ (TS which not) sequences are separated. In each group, unsupervised learning classification is applied to select the accurate number of classes. In other word, a clustering process is implemented to gather the similar sequences around the same Shapelets. Like this, n_w number of ‘pre-war’ classes is determined (same for n_p, the number of ‘pre-peace’ classes). Therefore, this first learning phase has a double objective : (i) highlight and segregate scenarios leading to a conflict. For example, one class could represent the repeated drought (repeated decreasing picks of soil moisture), or long high-temperature season (a constantly high value of temperature for a long time). (ii) create the future classes of the supervised classifier.

Testing phase : Supervised classification

Once the classes and their associated Shapelets well-defined, we apply a supervised classification process :

(i) Preprocess of the data : normalization, then separation of the train/test data (70%/30%)
(ii) Learning phase with gradient descent procedure on the train data
(iii) Testing phase : Classify the test data with their distances to the Shapelets of each class

The overall procedure is described in .

Word count : 1220

(< 5 doubles-space pages ~ 1250 words)

Bibliography

[1] M. Burke, S. M. Hsiang, et E. Miguel, « Climate and Conflict », *Annual Review of Economics*, vol. 7, nᵒ 1, p. 577-617, 2015, doi: 10.1146/annurev-economics-080614-115430.

[2] S. M. Hsiang et M. Burke, « Climate, conflict, and social stability: what does the evidence say? », *Climatic Change*, vol. 123, nᵒ 1, p. 39-55, mars 2014, doi: 10.1007/s10584-013-0868-3.

[3] G. J. Abel, M. Brottrager, J. Crespo Cuaresma, et R. Muttarak, « Climate, conflict and forced migration », *Global Environmental Change*, vol. 54, p. 239-249, janv. 2019, doi: 10.1016/j.gloenvcha.2018.12.003.

[4] P. H. Gleick, « Water, Drought, Climate Change, and Conflict in Syria », *Weather, Climate, and Society*, vol. 6, nᵒ 3, p. 331-340, juill. 2014, doi: 10.1175/WCAS-D-13-00059.1.

[5] « The ERA5 global reanalysis - Hersbach - 2020 - Quarterly Journal of the Royal Meteorological Society - Wiley Online Library ». https://rmets.onlinelibrary.wiley.com/doi/10.1002/qj.3803 (consulté le oct. 13, 2021).

[6] F. T. Portmann, S. Siebert, et P. Döll, « MIRCA2000—Global monthly irrigated and rainfed crop areas around the year 2000: A new high-resolution data set for agricultural and hydrological modeling », *Global Biogeochemical Cycles*, vol. 24, nᵒ 1, 2010, doi: 10.1029/2008GB003435.

[7] « Organized violence, 1989–2018 and peace agreements - Therése Pettersson, Stina Högbladh, Magnus Öberg, 2019 ». https://journals.sagepub.com/doi/full/10.1177/0022343319856046 (consulté le oct. 18, 2021).

[8] N. P. GLEDITSCH, P. WALLENSTEEN, M. ERIKSSON, M. SOLLENBERG, et H. STRAND, « Armed Conflict 1946-2001: A New Dataset », *Journal of Peace Research*, vol. 39, nᵒ 5, p. 615-637, sept. 2002, doi: 10.1177/0022343302039005007.

[9] L. Ye et E. Keogh, « Time series shapelets: a new primitive for data mining », in *Proceedings of the 15th ACM SIGKDD international conference on Knowledge discovery and data mining - KDD '09*, Paris, France, 2009, p. 947. doi: 10.1145/1557019.1557122.

[10] O. Patri, M. Wojnowicz, et M. Wolff, « Discovering Malware with Time Series Shapelets », janv. 2017. doi: 10.24251/HICSS.2017.734.

Appendix

Potential Results/Discussion

Discussion

First, the extraction method might appear surprising. Indeed, the shape files used to get the zonal stats of a pixel grid is not square but circle. In fact, a buffer of half the diagonal of a pixel is drawn around the center of the cell to create the shape. This choice is justified by the too low extraction capacity when using the MIRCA grid squares. As a matter of fact, adding a bit more surface of the pixel facilitates the extraction. We assume that multiplying the surface by $\frac{\pi}{2}$ (~1.57)[1] will not strongly affect the climatic values, as the pixel are relatively small (5x5 arcminutes).

The use of Shapelets method might itself be another limit. By definition, a Shapelet is a characteristic subsequence shared by a specific class. Therefore, some information contained in the entire TS might be missed by focusing only on these Shapelets. On the other hand, Shapelets should capture everything relevant for classification. Then, it is no longer a problem if the learning is properly done (and feasible).

Finally, we chose to study data with a monthly frequency at the country level. Another possibility would have been to work at the MIRCA grid level. However, we assume that climatic variation would not just impact the population of the cell itself. Indeed, climate affects the agriculture and by extension, life of inhabitants at a regional or national level. Furthermore, climatic TS are aggregated monthly. The yearly and daily level are inappropriate due to, respectively, missing information and too much noise. We suppose that the monthly level has a better information/noise ratio than the weekly one. Also, the computing time and amount of data needed is more beneficial.

Potential Results

Once the study completed, I expect to be able to detect at least two or three significant classes of 'Pre-War' sequences. I guess a certain number of sequences would be hardly classifiable, but the study would be successful if some classes have significant Shapelets that implies a civil war onset in the next months. Therefore, I don't expect brilliant results globally. However, for the few relevant classes, we can expect a strong prediction power.

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[1] By taking the surface of a circle which have the diagonal of the square as diameter, we multiply it by $\frac{\pi}{2}$

$S_{square} = a^2 \quad S_{circle} = \pi * \left(\frac{a\sqrt{2}}{2}\right)^2$ with a : side of the square,

$=> S_{circle} = \frac{\pi}{2} * S_{square}$

Figures

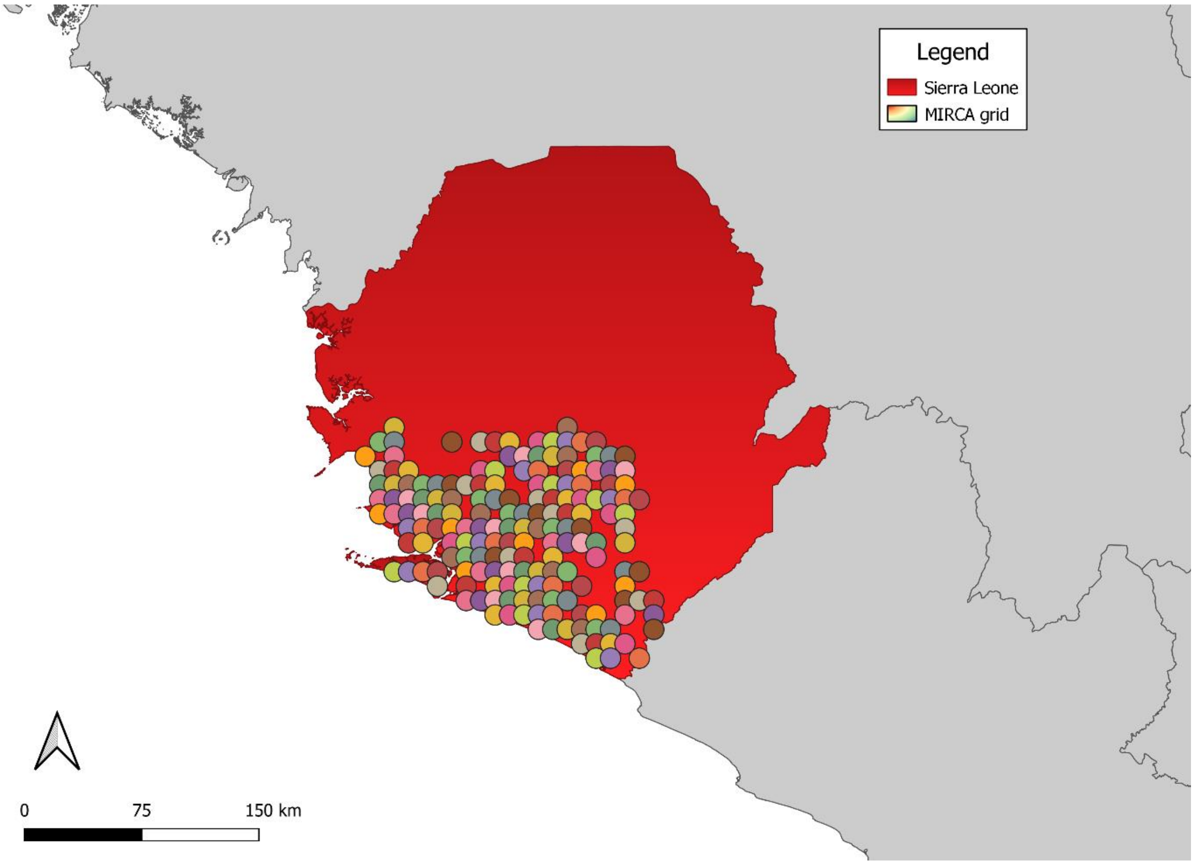

Figure 1 : MIRCA extraction grid of Sierra Leone

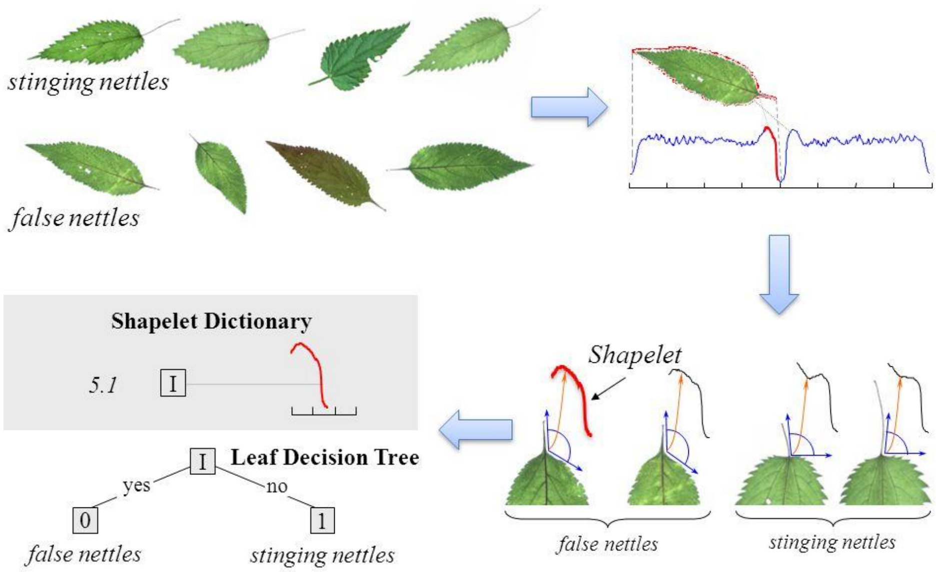

Figure 2 : Shapelets classification process, extracted from [9]

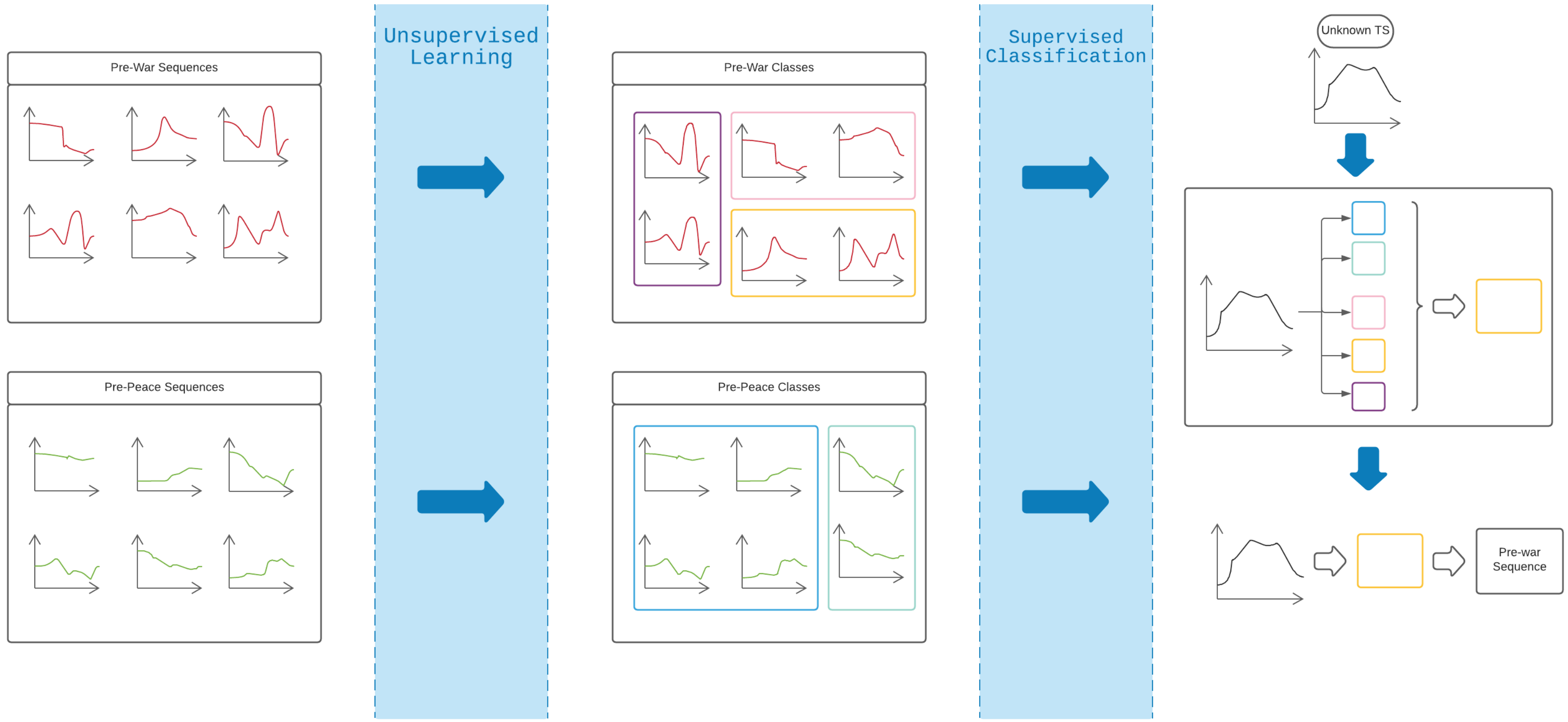

Figure 3 : Layout of the Classification process