Exploring Potential Causal Models for Climate-Society-Conflict Interaction

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Abstract: Climate change affects human liveability and may increase the likelihood of armed violence. However, the precise repercussions on social cohesion and conflict are difficult to model, and several socio-economic mechanisms exist between local climate changes and conflict, and are often hidden to us. Nonetheless, we offer an exploratory data analysis in this paper at a global scale, on the relationship between diverse climate indicators and conflict. Here we investigate potential basic causal models between climate change and conflict, including the causal direction, causal lag, and causal strength. We use historical climate and extreme environmental event data from the past 50 years across the world to identify geographic region-specific causal indicators. The initial broad findings are: (1) rainfall is a reasonably general indicator of conflict, (2) there are fragile regions which exhibit a strong causal link between extreme climate variations and conflict (predominantly in Africa and South Asia), and 3. there exists a common time lag of the causality between the climate variations and the conflict in many regions, which is worth further study.

1 INTRODUCTION

Among the most worrying of the mooted impacts of climate change is an increased risk in armed conflict. As people compete for diminishing resources, such as arable land and water (Homer-Dixon, 2010), forced migration and labour changes can introduce political tensions and create conflict in fragile states. Research over the past decade has established that climate variability and extreme change may influence the risk of violent conflict (including political violence, terrorism, civil and inter-state wars) (Burke et al., 2009; Hsiang et al., 2011). Authors in (Hsiang and Burke, 2014) examined 50 quantitative empirical studies and found a remarkable convergence in findings and strong support for a causal association between climatological changes and conflict at all scales and across all major regions of the world. However, under various hypothesis, different methodologies and datasets applied, the results in different regions are divergent or even contradictory (Mach et al., 2019; Buhaug, 2010; Slettebak, 2012). Although the relationship between climate and conflict has been empirically tested in a wide variety of studies, the literature has yet to converge on a commonly accepted set of causal mechanisms (Salehyan, 2014). For example, some states may experience an irreversible labour transformation from agricultural economy to urban organised crime, whereas others may see migratory sources of violence.

1.1 Review of Causal Analysis in Complex Systems

Causal analysis in complex systems with no existing explicit mathematical models is challenging. On the one hand, an end-to-end data analysis between climate change and conflict might exhibit certain results, but one cannot be certain they are reasonable and relate to known socioeconomic mechanisms. We offer a brief review of existing data-driven causal inference approaches and then go on to explain our dual approach of verifying data analysis with a toy causal model.

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1.1.1 Stationary to Nonlinear State Space Approaches

Granger causality test is the first proposed stationary approach to detect causality based on statistical hypothesis test. Two time series are given and under Granger's theory, the causality (the alternative hypothesis) is defined as that time series $[..., X(t-1), X(t)]$ provide significant information about $[Y(t), Y(t+1), ...]$ (Granger, 1969). It is valid in stationary linear systems rather than dynamic systems. The predictability improvement (PI) causality test is proposed in response to this issue, where (Krakovska, 2017; Krakovska and Hanzely, 2016; Krakovska et al., 2018) reconstruct the time series in multi-dimensional state spaces, which try to convert the non-linear dynamic system into a linear manifold, where the Granger causality test can then be applied.

Conditional mutual information (CMI) (Hlavackova-Schindler et al., 2007) is based on transfer entropy. Discrete random variables (X, Y, Z) with support sets $(\mathbb{X}, \mathbb{Y}, \mathbb{Z})$ are given, and the CMI $I(X, Y|Z)$ estimates the directed information flow from a variable X to another variable Y under the condition of Z. Different from PI hypothesis test, the CMI approach can yield the value of predictability improvement. CMI does not depend on any assumptions in its formulation compared to other directed information flow measures like Granger causality, which makes this method capable of assessing both linear and non-linear interactions. In time series causality detection application, with a causation lag τ, $I(X(n), Y(n+\tau)|Y(n))$ is normally used to evaluate the causality with directionality (Li and Ouyang, 2010; Wen et al., 2019).

In (Sugihara et al., 2012; Tsonis et al., 2018), Convergent Cross Map (CCM) is proposed to detect the causal relationships in nonlinear dynamical systems. The key idea of CCM lies on the fundamental principle of Takens's theorem, which states that in a time series dynamical system with multi-variables, any single series of one variable of the system can be recovered by the historical series of another variable by high dimensional state space reconstruction. In practical terms of CCM, two time series X, Y is given, and the causality is defined as the extent to which the time series $[X(t-E\tau), ..., X(t-2\tau), X(t-\tau)]$ can be encoded into time series $Y(t)$. The parameter τ here is the time step for the reconstruction while E is the dimension of the reconstruction. CCM has been successfully applied in various climate change fields, such as the soil moisture-precipitation interaction in environment (Wang et al., 2018), the sensitivity of the carbon cycle to tropical temperature variations (Wang et al., 2014) and the relationship between temperature and green-house gases (Nes et al., 2015) in climate research.

1.1.2 Neural Approaches

Long Short-Term Memory (LSTM) is an artificial recurrent neural network (RNN) architecture, which is capable of learning order dependence in series. The training process in LSTM can be considered as an adaptive non-linear regression from the input series to the output series. Owing to the non-linear expressive power of the neurons and the characteristics of RNN, LSTM has the following advantages (Krakovska and Jakubik, 2020): (a) able to store information for an arbitrary duration; (b) resistant to noise (i.e., fluctuations of the inputs that are random or irrelevant for regression); (c) trainable in a reasonable time. In our practice, two time series X, Y is given, we set $X(t)$ and $Y(t)$ as the inputs while $Y(t+1)$ as the output. Then, we can evaluate the causality of $X(t)$ by validating the regression error in LSTM. Other variations of this include the Neural Point Process (NPP), where a given time-series process is established (e.g., point process), and the neural network models a non-linear function that maps diverse variables to the intensity of the PP. This has been quite successful in our recent modeling of climate conflict interactions (Sun et al., 2022).

1.1.3 Summary & Innovation

In summary, methods such as PI gives the non-linear Granger causality between two series through hypothesis testing at the most basic binary level, whereas CMI model the causality strength using the mutual information between two series, and CCM reconstructs one series into another and evaluates the causality using the correlation between reconstructed series and raw series. Neural method such as LSTM and neural point process (NPP) does an adaptive nonlinear regression from one series to another and assess the causality by prediction error. These methods increasingly contribute towards AI algorithms in understanding complex climate social interactions and predicting conflict (Guo et al., 2018). However, without an underlying multi-staged causal model, we have no way of knowing how reasonable these approaches are. Climate change can cause multi-staged social transformations (e.g., agricultural, supply chain, labour markets, migration....etc.) with different dynamical processes and lag times.

As such, this paper first introduces a basic causal toy model to verify first that these approaches can or cannot evaluate artificial data successfully. We then evaluate the real end-to-end data to draw disaggre-

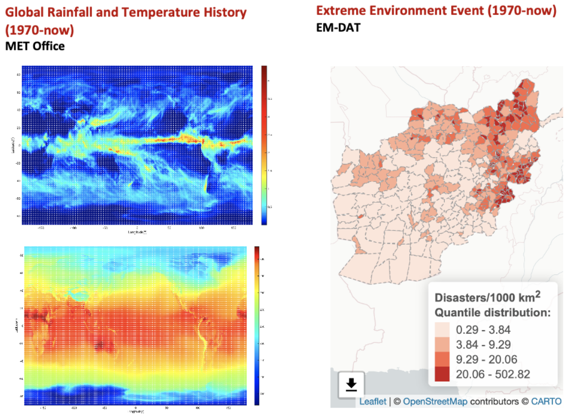

Figure 1: Example data of weather and natural disasters.

gated and general conclusions.

2 DATA & CAUSAL MODEL

2.1 Data

In this paper, temperature and rainfall data are used to represent the general climate conditions. We used the ERA5 dataset (https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5), which records the global temperature and rainfall gridded in 0.5 degree resolution (grid size is 56-79 sqkm depending on latitude), and monthly in scope, spanning 1970-present. For natural disaster events (including tsunami, drought, tornado and etc.) we use the Emergency Events Database (EM-DAT, https://www.emdat.be), which records these events around the world with the dates and locations, spans 1900-present. In this paper, data from Global Terrorism Database (GTD) are selected as the indicator of conflict, which dominate the majority of violent events. GTD is the most comprehensive database of terrorist attacks in the world, which contains over 200k terrorist attacks with the dates and locations, spans 1970-2018.

In our experiments, in order to keep data's attributes consistency in causality tests, the data are preprocessed as follow:

- Data series spans 1970-2018 are selected,
- Data series are unified into monthly resolution,
- For natural disasters and terrorist attacks, we quantify it in terms of its counting times per month
- Data series for the following 12 regions are selected: (i) Northern Africa (AfricaN), (ii) Southern Africa (AfricaS), (iii) Central America (AmericaC), (iv) Northern America (AmericaN), (v) Southern America (AmericaS), (vi) Central Asia (AsiaC), (vii) Eastern Asia (AsiaE), (viii) Southern Asia (AsiaS), (ix) Southeastern Asia (AsiaSE), (x) Eastern Europe (EuropeE), (xi) Western Europe (EuropeW) and (xii) Oceania.

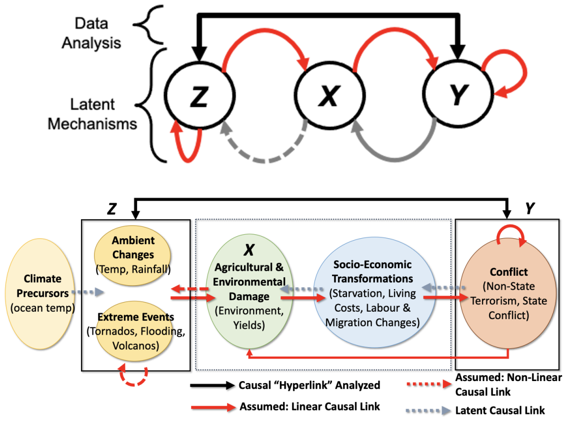

Figure 2: Our assumptions of the overall causal mechanisms between climate change, social transformation, and conflict. End-to-end causal data analysis (top) between Z and Y will be validated by artificial data generated by a causal toy model (bottom).

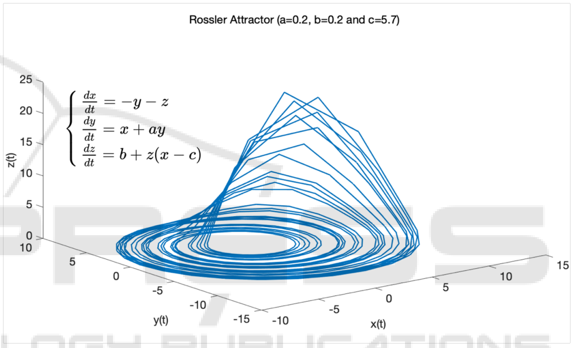

Figure 3: Rossler toy model and underlying equations and parameters.

Example of data is shown in Fig.1.

2.2 Toy Causal Model

We develop a toy causal model as the simplest step one can take to test if causal detection would work. Fig.2 shows the assumptions we used. We assume the climate system (i.e. RainFall (x_1), Temperature (x_2) and Natural Disaster (x_3)) is an autonomous system which has linear and nonlinear internal causality to each other, while there is a unidirectional linear causal link from climate system to the agriculture (y_1). The agriculture has a bidirectional linear causal link with the socio-economic (y_2) while also a unidirectional linear causal link from conflict (y_3) to it.

$X_3 \rightarrow Y_3$	PI	CMI	CCM	LSTM
C = 0	○	0.455	-0.025	45.7%
C = 0.01	○	0.479	0.050	50.8%
C = 0.02	○	0.502	0.183	54.5%
C = 0.03	○	0.564	0.123	48.3%
C = 0.04	○	0.671	0.071	38.4%
C = 0.05	√	0.714	-0.003	27.7%
C = 0.06	√	0.732	-0.010	17.6%
C = 0.07	√	0.778	0.065	25.1%
C = 0.08	√	0.790	0.147	16.4%
C = 0.09	√	0.803	0.420	12.6%
C = 0.10	√	0.805	0.517	9.80%
C = 0.11	√	0.819	0.626	6.41%
C = 0.12	√	0.820	0.759	2.96%
C = 0.13	√	0.826	0.849	7.42%
C = 0.14	√	0.837	0.907	2.3%

Figure 4: Causal analysis verification in the toy model: green is acceptance, blue is borderline, and red is rejection of null hypothesis.

Then, our key assumption is that the agriculture has a nonlinear causal link to the conflict. Based on our assumptions, we establish a toy model using two unidirectional coupled Rossler systems (Fig.3) with an adjustable coupling strength parameter C. The initial conditions can be arbitrary, in our experiments, we set the initial conditions of $\omega_1 = 1.015, \omega_2 = 0.985$ and $x_0 = y_0 = [1,1,0]$. With our initial conditions, two systems would be synchronized when the coupling strength C is about 0.14. An example of the Rossler model is in Fig.3.

2.3 Validation Using Toy Model

Firstly, we test classical causal methods (i.e., PI, CCM and CMI) on the aforementioned theoretical toy model, in order to verify the validity of these methods in detecting our assumed causality mechanism between climate and conflict. Fig.4. gives the causality results in our theoretical toy model with the coupling strength from 0 to 0.14 before the synchronization. The values in PI give the hypothesis test results on whether X_3 cause the Y_3; The outcome in the CMI model give the amount of mutual information given by X_3 to Y_3; The values in CCM give the correlation between the reconstructed Y_3 using X_3 and Y_3 itself;

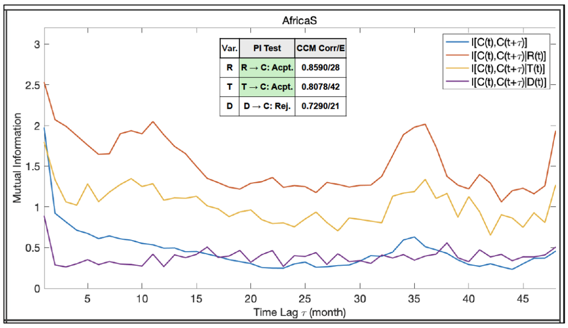

Figure 5: Sub-Sahara causal results of PI, CCM, and CMI by region. The abbreviations are: Var = variable, Acpt. = Acceptance, Rej. = Rejection, Corr = Correlation, RTS = Reconstruction Time Steps, C = Conflict, R = Rainfall, T = Temperature, D = Natural Disaster, R ⇒ C = R cause C.

The values in LSTM give the regression error in percentage.

The result shows that all methods can detect the causality link before the synchronization of two systems. However, it can be observed that PI method has the most sensitivity to the causality among all our proposed methods, while CCM and LSTM require the longest lags to reliably detect causality. Another notable thing is that LSTM is not consistent in performance. PI, CMI and CCM always give better result when the coupling strength goes up while LSTM does not. Due to it is unexplainable, the result come from LSTM is more blackbox than the others and we will analyze the LSTM result separately.

3 GLOBAL RESULTS

3.1 Overall Causality Results by Region

The raw quantitative overall causality results of PI, CCM and CMI by region are shown in Fig.6, with a specific highlighted example of Sub-Sahara in Fig.5. In each sub-figure, we show the CMI results for different cause in different time lags with the coloured lines, and the PI and CCM results in the table attached on. For CCM, we have two values in the grid, the first value is the correlation value between the reconstructed conflict data and raw conflict data, while the second one is the corresponding reconstruction dimension.

In order to have more intuitive interpretation and analysis, we convert these results into qualitative representations with the following rules:

(1) For PI hypothesis test, we use $\surd$ (coloured in green) to represent the accepted positive causality from the variables series towards terrorism series, $\circ$ (coloured in blue) to represent no causality, and

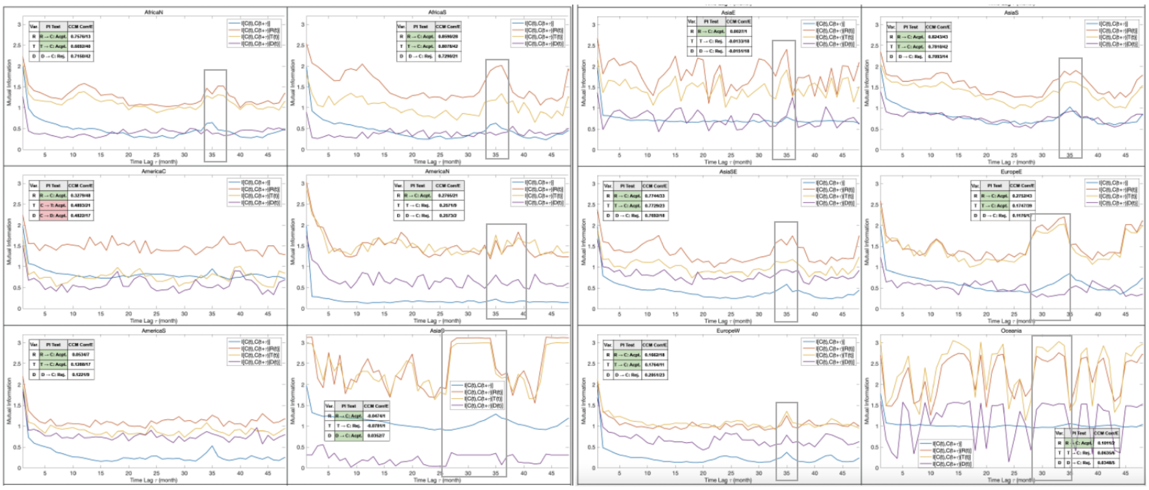

Figure 6: Overall causal results of PI, CCM, and CMI by region. The abbreviations are: Var = variable, Acpt. = Acceptance, Rej. = Rejection, Corr = Correlation, RTS = Reconstruction Time Steps, C = Conflict, R = Rainfall, T = Temperature, D = Natural Disaster, R $\Rightarrow$ C = R cause C.

$\times$ (coloured in red) to represent reversed anti-nature causality from terrorism series towards climate series (2) For correlation degree in CCM, we define $\rho > 0.7$ as strong correlated (coloured in green), $0.4 < \rho \leq 0.7$ as moderate correlated (coloured in blue), and $0.2 < \rho \leq 0.4$ as weak correlated (coloured in red), $\rho \leq 0.2$ as none correlated (3) For causality mechanism complexity degree in CCM, we define $E < 13$ as low complexity, $13 < E \leq 24$ as moderate complexity, $E > 24$ as high complexity (4) There are no absolute standards for CMI which makes the inter-comparison of CMI between different regions' datasets meaningless, thus we use the CMI mean difference over MI of terrorism series:

$$\mathrm{E}(\mathrm{CMI}-\mathrm{MI}) =$$
$$\mathrm{E}\Big(I[C(t),C(t+\tau)-\mathrm{MI}|\mathrm{Var}(t)]-I[C(t),C(t+\tau)]\Big), \quad (1)$$

to demonstrate the assistance of climate series causality in one region and internally compare this causality. The larger the difference between CMI and MI appears, the more causality effect the corresponding condition has. We set the self-mutual information as the baseline and calculate the addition mutual information given by the condition. We coloured the value larger than 0.5 in green, 0-0.5 in blue and negative value in red for clearer demonstrating results.

Fig.7 shows the processed qualitative interpretation of the causality results both in region domain and methods domain according to our rules. We are going to analyse these results in both domains:

3.1.1 Region Domain

It can be observed that the regions of AfricaN, AfricaS, AsiaS and AsiaSE give the strongest causality evidence of climate series affects terrorism series from the results of all these three methods. However, although the result for other regions is ambiguous, it does not necessarily mean that the causality does not exist in these regions, it is also possible that our methods cannot detect the causality completely.

Another notable issue is the inconsistency in results from different methods. The representative examples are AmericaC and AsiaC, causality of natural disaster series results given from PI, CCM and CMI are conflicting with each other. The reason for this would be that the real mechanism in these regions is beyond our assumptions.

3.1.2 Method Domain

PI: With PI hypothesis test, terrorism series in each region shows the predictability improvement from the corresponding rainfall series. However, temperature series act as a cause to terrorism series in just some specific regions, while natural disaster series affect only one region (i.e., AsiaC). Based on this PI method, the rainfall series can be concluded as a universal causation factor to the terrorism series.

CCM: The correlation offered by CCM is always contiguous with climate series in each region, there is no case where one variable series has strong CCM correlation while others have it weak. This result indicates that the climate variables in our experiments can be considered as an autonomous system which the terrorism system is coupled on.

(a)

AfricaN				
Var.	PI Test	CCM Corr.	CCM E	CMI
R	√	strong	moderate	0.78
T	√	moderate	high	0.64
D	○	strong	high	-0.06

AfricaS				
Var.	PI Test	CCM Corr.	CCM E	CMI
R	√	strong	high	1.07
T	√	strong	high	0.56
D	○	strong	moderate	-0.08

AmericaC				
Var.	PI Test	CCM Corr.	CCM E	CMI
R	√	weak	high	0.66
T	×	moderate	moderate	-0.06
D	×	moderate	moderate	-0.24

AmericaN				
Var.	PI Test	CCM Corr.	CCM E	CMI
R	√	weak	moderate	1.29
T	○	weak	low	1.31
D	○	weak	low	0.48

AmericaS				
Var.	PI Test	CCM Corr.	CCM E	CMI
R	√	None	low	0.81
T	√	None	moderate	0.59
D	○	None	low	0.47

AsiaC				
Var.	PI Test	CCM Corr.	CCM E	CMI
R	√	None	low	1.35
T	○	None	low	1.29
D	√	None	low	-0.81

AsiaE				
Var.	PI Test	CCM Corr.	CCM E	CMI
R	√	None	low	1.10
T	○	None	moderate	0.75
D	○	None	moderate	0.02

AsiaS				
Var.	PI Test	CCM Corr.	CCM E	CMI
R	√	strong	high	0.76
T	√	strong	high	0.57
D	○	strong	moderate	-0.03

AsiaSE				
Var.	PI Test	CCM Corr.	CCM E	CMI
R	√	strong	high	0.93
T	√	strong	moderate	0.58
D	○	strong	moderate	0.38

EuropeE				
Var.	PI Test	CCM Corr.	CCM E	CMI
R	√	weak	high	0.93
T	√	None	high	0.84
D	○	None	low	-0.10

EuropeW				
Var.	PI Test	CCM Corr.	CCM E	CMI
R	√	None	moderate	0.79
T	√	None	low	0.85
D	○	weak	moderate	0.44

Oceania				
Var.	PI Test	CCM Corr.	CCM E	CMI
R	√	None	moderate	1.20
T	○	None	high	1.32
D	○	None	moderate	0.14

(b.1)

PI Test												
Var. \Region	AfricaN	AfricaS	AmericaC	AmericaN	AmericaS	AsiaC	AsiaE	AsiaS	AsiaSE	EuropeE	EuropeW	Oceania
R	√	√	√	√	√	√	√	√	√	√	√	√
T	√	√	×	○	√	○	○	√	√	√	√	○
D	○	○	×	○	○	√	○	○	○	○	○	○

(b.2)

Correlation between CCM Reconstruction Estimated Conflict Series and Original Conflict Series												
Var. \Region	AfricaN	AfricaS	AmericaC	AmericaN	AmericaS	AsiaC	AsiaE	AsiaS	AsiaSE	EuropeE	EuropeW	Oceania
R	strong	strong	weak	weak	None	None	None	strong	strong	weak	None	None
T	moderate	strong	moderate	weak	None	None	None	strong	strong	None	None	None
D	strong	strong	moderate	weak	None	None	None	strong	strong	None	weak	None

(b.3)

mean(CMI - MI) = mean(I(C(t),C(t+τ)|Var(t)) - I(C(t),C(t+τ)))												
Var. \Region	AfricaN	AfricaS	AmericaC	AmericaN	AmericaS	AsiaC	AsiaE	AsiaS	AsiaSE	EuropeE	EuropeW	Oceania
R	0.78	1.07	0.66	1.29	0.81	1.35	1.10	0.76	0.93	0.93	0.79	1.20
T	0.64	0.56	-0.06	1.31	0.59	1.29	0.75	0.57	0.58	0.84	0.85	1.32
D	-0.06	-0.08	-0.24	0.48	0.47	-0.81	0.02	-0.03	0.38	-0.10	0.44	0.14

Figure 7: (a) Qualitative interpretation of PI, CCM, and CMI in each region (region domain), (b) Parallel comparison of qualitative interpretations in each region (method domain).

CMI: In CMI method, the condition of rainfall and temperature series offers the positive mutual information between the terrorism series $C(t)$ and $C(t+\tau)$ in all of the regions except for AmericaC. However, the mutual information given by the condition of natural disaster series is ambiguous over these regions, which match the results in (Slettebak, 2012) - natural disasters are not the factors to be blamed for conflict.

3.2 LSTM Causality Result

We analyze the LSTM result separately since it is unexplainable, which makes its result not guaranteed to be true. In our experiments, we establish a LSTM network with two LSTM layers with 128 hidden nodes and three full connect layers with 64,128,16 hidden nodes respectively. There maybe other architectures featuring attention and mixed with graph neural networks we have not considered yet and is left for future work.

We applied one-step prediction along the last ten years (1998-2018), which means for each month in each region, an independent LSTM is applied, while the average prediction percentage error is considered as the causality indicator. Fig.8 shows the results from LSTM. In AmericaC, AmericaS, AsiaE and Oceania, the causality between climate and conflict is ambiguous from a LSTM regression sight, while others shows climate series may help in the conflict prediction which indicates the causality between climate and conflict. However, we can also observe the instability of the algorithm from the results, e.g. in AfricaN, AsiaC, EuropeE and Oceania, the prediction with inputs of C&D is worse than that with only C. This means LSTM has learned some odd mechanisms which actually does not exist and cause an overfitting.

LSTM												
Var. \Erorr	AfricaN	AfricaS	AmericaC	AmericaN	AmericaS	AsiaC	AsiaE	AsiaS	AsiaSE	EuropeE	EuropeW	Oceania
C	29.9%	26.1%	25.9%	34.8%	31.7%	16.7%	34.4%	19.1%	34.3%	29.3%	22.2%	38.2%
C & R	9.8%	16.6%	33.4%	7.5%	25.9%	18.6%	30.4%	5.6%	12.7%	13.2%	12.7%	68.1%
C & T	14.7%	19.7%	67.9%	19.5%	33.8%	4.3%	20.6%	7.9%	19.9%	15.8%	14.1%	35.6%
C & D	31.4%	22.8%	42.1%	14.4%	42.6%	32.1%	17.5%	11.6%	13.9%	44.5%	16.8%	87.5%
ALL	12.4%	14.2%	54.4%	11.3%	37.0%	5.3%	21.2%	6.3%	9.4%	18.4%	13.5%	52.1%

Figure 8: LSTM results.

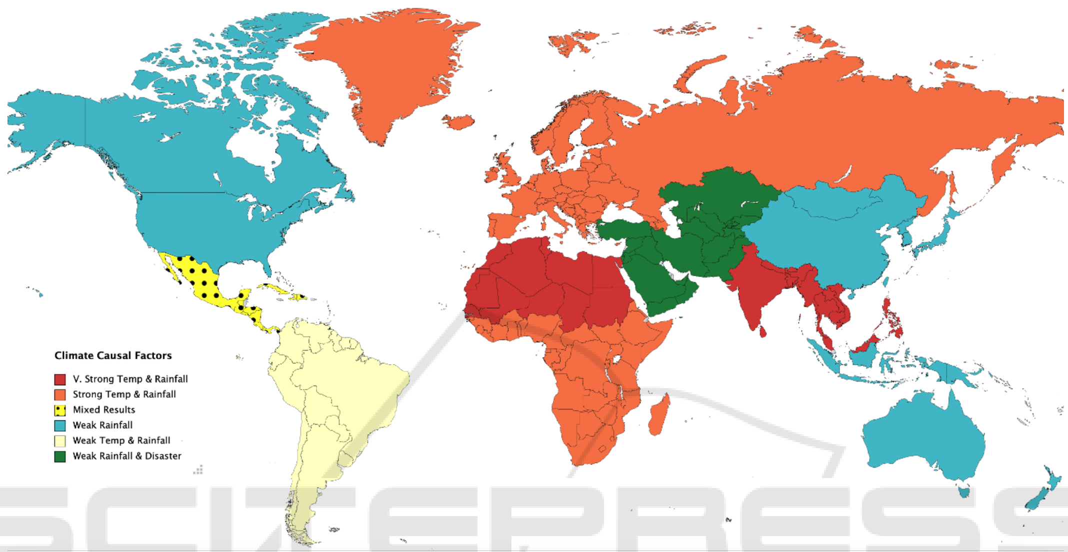

Figure 9: Global result summary by region.

In this report, we will only take the LSTM results as a reference, not as a decisive factor.

3.3 Temporal Lag

Back to Fig.8, we find an interesting phenomenon in CMI(τ) results. Obviously, when temporal lag $\tau = 0$, the mutual information between terrorism series $C(t)$ and $C(t+\tau)$ reaches the maximum. Nevertheless, the rainfall and temperature series CMI(τ) reaches another peek when the temporal lag τ is around 10-14 months (1 year) and around 34-38 months (3 years) in the regions of AfricaN, AfricaS, AsiaE, AsiaS, AsiaSE and EuropeE. This indicates that in these regions, the climate series may have the same causation mechanism in climate $\Rightarrow$ agriculture $\Rightarrow$ socioeconomic $\Rightarrow$ conflict under our assumptions. A possible preliminary answer would be that, in low socioeconomic development and low capabilities regions, or regions dominated by agriculture, the climate has a distinct causation to the region conflict/terrorism with the time lag of one year and three year (Mach et al., 2019). However, the mechanism lay in this phenomenon is still an open question and becomes a further issue for us.

4 CONCLUSIONS AND NEXT STEPS

Climate change affects human liveability and may increase the likelihood of armed violence. However, the precise repercussions on social cohesion and conflict are difficult to model, and several socio-economic mechanisms exist between local climate changes and conflict, and are often hidden to us. Nonetheless, we offer an exploratory data analysis in this paper at a global scale, on the relationship between diverse climate indicators and conflict. Here we investigate potential basic causal models between climate change and conflict, including the causal direction, causal lag, and causal strength. We use historical climate and extreme environmental event data from the past 50 years across the world to identify geographic region-specific causal indicators. The initial broad findings shown in Fig.9 are: (1) rainfall is a reasonably general indicator of conflict, (2) there are fragile regions which exhibit a strong causal link between extreme climate variations and conflict (predominantly in Africa and South Asia), and 3. there exists a common time lag of the causality between the climate variations and the conflict in many regions, which is worth further study. In order to identify the spurious causality in our results from pure data analysis perspective, we proposed to embed the knowledge from social science into our initial assumptions about the mechanisms within climate and conflict.

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