Methodological Note of the Climate Security Index

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1 Introduction

***Daniele, could you give a motivation like the one you wrote for the grant proposal?

2 CSI concept

When thinking about the connection between climate-related events and human security, two fundamental dimensions come into mind: (1) how extreme are climate events and (2) how well prepared is a society to deal with them. These are the first two components of modules of the CSI, and they are in line with the relevant literature. On the one hand, extreme events are shocks that test the resilience of a system. On the other, institutional frameworks to manage such shocks (e.g. evacuation plans, reallocation policies, support income programmes, reconstruction strategies, etc.) act as the resilience buffers of societies. While both of these components are important to understand climate security, their interaction is much more nuanced than what one could disentangle from reduced analysis such as regressions. The CSI tries to account for such nuances by borrowing concepts stemming from the literature on complex adaptive systems ***cite. More specifically: connectivity and synchronicity.

2.1 Connectivity

To understand the nuanced relationship between climate events and the resilience provided by institutional buffers, it is important to understand the structural features of a country or system. Often, structure relates to the way different component of a system interconnect. Such interconnections capture how a change in part of the system may reach another part. In the context of the CSI, we can think of a system as a country or region, and of its components as the different development dimensions that society pays attention too. One prominent example of such a multidimensional view is the United Nations Sustainable Development Goals (SDGs), which divides socioeconomic systems into 17 broad dimensions, covering topics such as poverty, food security, public health, clean aquatic environments, the economy, and public governance to mention a few. In the CSI, one could consider any set of dimensions that may be relevant to a particular country or region.

The relevance of connectivity come into play when thinking the potential reach of shock produced by extreme climate events. For example, suppose that most of the food supply of a country is domestically produced. Assuming such a country lacks instruments to diversify its food sources (e.g., international trade agreements), one would expect a more direct impact of climate events such as extended droughts on food scarcity and prices. If much of the society allocates a significant portion of their income to basic products such as food, one would expect poverty-related indicators to be affected by the droughts through the food channel. This type of indirect dependencies between different development dimensions such as food security and poverty are key to understand the breath and depth of climate-event impacts. They create additional pressures to the institutional buffers that a country or region may have, so it is crucial to quantify such structures of conditional dependencies between different development dimensions.

A natural language to formalise the idea of connectivity is networks. Network analysis is a well established field that overlaps across different scientific communities (e.g., sociology, applied mathematics, economics, physics, etc.). In fact, network studies have recently become popular to analyse the structure connecting the SDGs (***cite). Thus, one could exploit some of these methods to quantify the structure that characterises a particular country or region. Here, the idea is to infer the network structure of conditional dependencies between development indicators, and to obtain an index of how interconnected are the different development dimensions of a system. In a country like the one described in our previous example, such measure would quantify strong connectivity between the dimension of food security and poverty. Thus, the aim of the connectivity module is to quantity the easy with which a shock in a specific development dimension may reach other ones. Arguably, a highly connected structure imposes additional burden to the institutional buffers as the government would need to implement coordinated responses across various policy domains.

2.2 Synchronicity

Synchronicity or synchronisation is a phenomenon that has been documented in physical systems since the 17th century, when Dutch physicist Christiaan Huygens observed that two pendulum clocks hanging from a common support would, after some time, exhibit certain degree of coordination (***cite books). Since then, the phenomenon of synchronisation has been documented across numerous physical and biological systems (e.g., birds flocking, circadian rhythms, menstrual cycles, groups of running mammals, predator-prey cycles, neurological activity, etc.). According to (***cite Arkady p.8), we can understand synchronisation as an adjustment of rhythms of oscillating objects due to their weak interaction. In the context of the CSI, the different development dimensions can be understood as the oscillating objects as it is possible to track their dynamic levels through indicators. Furthermore, if such data are subjected to signal-processing techniques (such as the ones introduced in ***), it is possible to transform development indicators into wave data that can be used to measure synchronicity.

Why is synchronisation important in the CSI? With the development of complexity sciences, many studies on physical and biological systems have shown that synchronicity often facilitates what is known as phase transitions. In a nutshell, a phase transition is a qualitative change in the (often aggregate) properties of a system that happens in a non-smooth or gradual fashion.[1] For example, certain types of neural synchronisation relate to brain seizures (***cite), while synchronised stock prices may lead to bubble bursts and crashes (***cite). While the early findings about synchronisation were made in the physical and biological domains, the recent availability of large-scale data and computer simulation has enabled the discovery of various situations in social systems in which synchronicity enable major shifts in the aggregate behaviour of a the system. One of these cases that is particularly relevant to the CSI is conflict.

In a study on worldwide protests and the 'Arab spring', *** show that major historical upraises have followed high a synchronisation between communications technology changes and media openness. In a landmark model on the emergence of civil violence, ***citeEpstein shows that the coordinated perception of hardships (from a repressive authority) in an agent population gives raise to local or even global outbursts of violence. ***show, more formally, that this type of civil violence models exhibit clear phase transitions under which the entire system may switch from a peaceful state to one overtaken by violence. Furthermore, ***cite analyse how these dynamics may be influence by network connectivity, finding that small-world networks facilitate synchronised behaviours. Synchronicity, thus, captures how coordinated would be the responses of different societal sectors should there by a climate event. Thus, societies that exhibit high levels of synchronicity are expected experience fasted and stronger responses, potentially increasing the risk of security threats such as civil violence. Under a synchronised response, the institutional buffers are subjected to further pressures in terms of generating timely responses.

Note that synchronicity if different from connectivity. In fact, in its original conception, synchronisation

[1] In complexity science, synchronisation is often seen as a catalyse for the spontaneous emergence of order in chaotic systems ***cite.

was a way to measure rhythmic similarities between *weakly coupled* objects. Thus, two development dimensions that are not structurally connected (in a network sense), may still exhibit high levels of synchronicity. This also implies that synchronisation is different from correlation, and that the former does not imply the latter, and the other way around.

2.3 Conceptual illustration

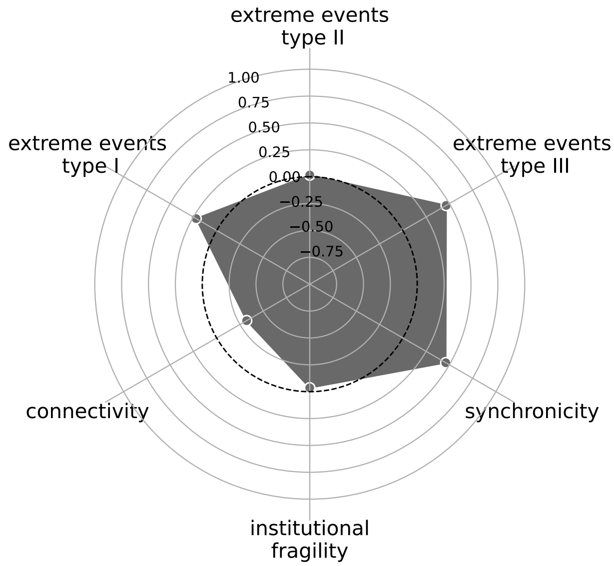
Together, connectivity and synchronicity provide information on the nuanced interaction between climate events and institutional buffers. All the components of the CSI constitute four modules to diagnose climate security risk in a given country or region. In Figure 1, we provide an illustration of the CSI diagnostic tool. Given that the types of climate events are conditional on geography, the CSI allows to introduce any type of events that may be relevant to the geographical unit under study. In this example, we have denoted three types of climate events as I, II, and III. In the lower part of the plot, we have the remaining three modules of the CSI. In this chart, higher values (outer rings) in any module represent a worse outcome. For example, higher levels in extreme events type I mean that it is more likely to observe an extreme event of such type in the near future; in terms of connectivity, it means that shocks to a development dimension are more likely to propagate to other dimensions; and for synchronicity it means that the different parts of this hypothetical society tend to respond with fewer delays from each other's responses. Consequently, the area described by the polygon can be considered a first measure of climate security risk, so the CSI can be constructed using this information. Nevertheless, the disaggregate version of the CSI provides a richer diagnostic tool to understand where are the main weaknesses, strengths, and threats.

In the rest of this methodological note, we explain the type of data that needs to be collected to construct the CSI diagnostic tool and the specific methods used to quantify each of its four modules.

2.4 Data

***Daniele: could you fill this in? Maybe following the structure of the four modules; you could also add a couple of charts showing examples of indicators and time series. *** introduce the idea of development dimensions or policy areas *** also mention the requirements in terms of sample size

Figure 1: Conceptual illustration of the CSI



Notes: Outer rings represent worse levels in each module.

3 Methods

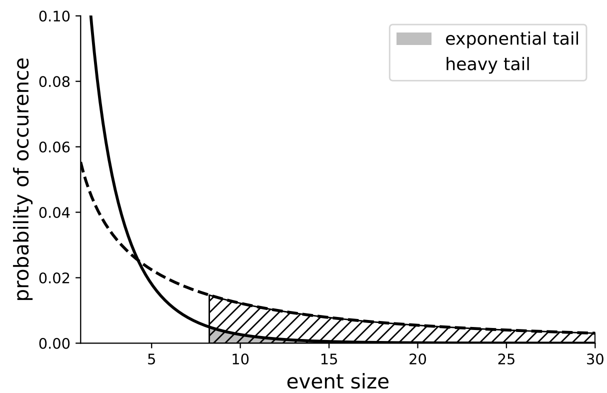
In this section, we provide technical details on the types of analysis and methods used to quantify each of the CSI modules. Something important to keep in mind is that, within each module there exist numerous quantitative methods coming from various disciplines that try to capture conceptually similar phenomena. However, when working with development data, the reality is that most of such methods cannot be used. The reason has to do with the fact that development indicators tend to be coarse grained, so they do not fulfil the data-demanding requirements of frameworks such as machine learning. In fact, the development of the CSI is the result of carefully consider analytic tools that (1) are conceptually meaningful to each module and (2) can be used with small data. Thus, while the reader may be aware of alternative methods for one of more modules, they should consider whether they are empirically viable in this context.

Let us explain the different methods module by module. In each case, we provide the general intuition of the approach and refer to the original publications that developed the respective framework. Once these details have been explained, we proceed to demonstrate the CSI with a real-world application.

3.1 Extreme events likelihood

An ubiquitous feature of complex adaptive systems is the prevalence of extreme events. Statistically speaking, this characteristic is often described through a probability distribution with a heavy tail. That is, a distribution where the likelihood of extremely large events is more likely than under the assumption of exponentially-decaying tails such as those from a normal distribution. If one assumes that the size of a climate event of certain type can be modelled as a random variable, then the presence of heavy tails in its distribution would be a warning of potential shocks to the system.

Figure 2: An illustration of the likelihood of extreme events under heavy tails



When studying empirical data on event sizes, one would like to establish whether this information is generated from a heavy-tailed distribution. In the literature of extreme value theory, various t*tail indices* have been created for this purpose, for example, the Hill ***cite and the Pickand ***cite indices. In essence, these metrics measure the excess of probability mass for observations that lie beyond the starting point of the tail.[2] More excess means that there is more mass accumulated in extreme events, making there more likely to occur. Figure 2 shows an example comparing a heavy-tailed distribution against one with an exponentially decaying tail. Clearly, the stripped region contains much more mass than the grey one, suggesting that extreme events are more likely to occur under the dashed distribution. Tail indices such as Hill's and Pickand's quantify such heavy-tailness.

***citeResnik points out that, while both the Hill and the Pickand (and other similar) indices are useful to compare datasets coming from heavy-tailed distributions, one needs to have ex-ante, other type of evidence suggesting heavy-tails. Thus, if the data comes from a distribution with exponential tails, these diagnostic tools are not expected to perform well. Thus, when one has different types of event-size data, ***citeResnik suggests employing the moment estimator developed by ***cteDeHann. This metric is sensible to both thin and heavy tails and, while it is not bound, negative values suggest exponential-like tails, while positive ones indicate heavy tails. Thus, in terms of assessing climate security risk, one could say that a higher moment estimator denotes larger risk as extreme events are more likely to occur.

[2]The starting point of the tail of a distribution is often determined by choosing an order statistic that lies beyond the 66th percentile.

Next, let us provide the formal definition of the moment estimator as introduced by ***citeDeHaan. Let X denote a random variable on climate even sizes with order statistics $X_{(1)} \geq X_{(2) \geq \cdots \geq X_{(n)}}, \ldots x_n$, where n denotes the sample size. For the kth order statistic defining the beginning of the upper tail, and for $r = 1, 2$, define

$$H^{(r)}_{(k,n)} = \frac{1}{k} \sum_{i=1}^{k} \left(\log \frac{X_{(i)}}{X_{(k+i)}} \right)^r . \tag{1}$$

Then, the moment statistic is defined as

$$\hat{\gamma}_n = H^{(1)}_{(k,n)} + 1 - \frac{1/2}{1 - (H^{(1)}_{(k,n)})^2 / H^{(2)}_{(k,n)}} . \tag{2}$$

Note that $H^{(1)}_{(k,n)}$ corresponds to the Hill index. Effectively, the moment estimator estimates the parameter γ of the extreme value distribution $\Pr(x) = \exp\{-(1+\gamma x)^{-\gamma^{-1}}\}$. Parameter γ determines the heavy-tailness of the distribution. ***citeDeHaan shows that $\hat{\gamma}_n$ converges in probability to γ as $n \to \infty$. As we have mentioned previously, a non-negative $\hat{\gamma}_n$ indicates heavy tails, while negative values suggest thin ones.[3] Thus, the CSI uses this index to assess the extreme-event component in each type of event.

Note that an empirical challenge of estimating heavy-tail indices tends to be the scarce availability of large-scale data, as extreme events usually 'show up' in large datasets. Hence, to address this, we produce a bootstrap sample of size $n_b >> n$ of the event-size dataset, and compute $\hat{\gamma}_{n_b}$. We repeat this procedure several times and report the average value of $\hat{\gamma}_{n_b}$ obtained from the ensemble of bootstrapped samples. While the moment estimator is not bound below nor above, in empirical studies, it typically tends to hover in the range of -1 to 1 (see ***cite for applications using financial data). Therefore, one can use this range as the reference space to assess the likelihood of experiencing extreme events. Furthermore, from a qualitative point of view, the zero value provides an intuitive threshold to know if a particular type of event is governed by a heavy or light tailed distribution.

3.2 Institutional fragility

***Daniele, could you fill this?

3.3 Connectivity

Let us recall that the aim of measuring the connectivity of a system in the context of the CSI is to assess the 'easiness' with which a shock in a particular policy domain or development dimension may reach one or more

[3] In fact, $\gamma = 0$ yields a Gumbel distribution, which is another heavy-tailed one.

different ones. As explained in ***, by dimension or policy domain we mean broad categories that encompass multiple development indicators as their target populations or policy instruments can be considered somehow close or related. In network parlance, these dimensions are known as labels that define communities of nodes. Here, nodes represent indicators, and the links between them capture the potential that a shock starting in one indicator reaches another one. Thus, the end goal of this module is to measure how much node connectivity takes place between communities (development dimensions) in relation to how much happens within them. To achieve this, we need to break down our methodology into three steps: (1) estimating conditional dependencies, (2) constructing a compounded conditional dependency (CCD) network, and (3) estimating the modularity of the CCD network. Let us explain one step at a time.

3.3.1 Conditional dependencies

First, we measure the interdependencies between indicators using the information contained in their time series. While there exists a large number of methods to estimate networks from sets of time series, the vast majority rely on long series, at least of the order of hundreds of observations. ***cite provide a comprehensive overview of different classes of methods and assess the most adequate ones when dealing with short time series such as those from development indicators. From these potential methods, the most adequate one is one of sparse Bayesian networks (`sparsebn`) developed by ***citeArgam.

The method `sparsebn` is part of a larger family of so-called graphical models that construct a directed acyclic graph of conditional dependencies between indicators.[4] Usually, these methods start with a proposed directed graph and, then, perform conditional independence tests across all the indicators to discard edges. This process is repeated until one achieves the acyclical property. What makes `sparsebn` particularly well-suited for development indicators is that it was designed to work with short time series and a large number of variables. It achieves this by sacrificing network density in the underlying graphical model, hence the sparsity.

It is important to mention that, while these models estimate links in terms of conditional dependencies that are often interpreted as causal, in the context of the CSI, these relationships cannot be considered causal; only conditional dependencies. Generally speaking, this is so because development indicators are the result of vertical causal chains. In other words, causal inference methods such as graphical models are design to study system that operate roughly at the same level of aggregation (e.g., clinical studies), but complex adaptive systems such as an economy differs from such configuration as interventions take place at the micro-level wnhile their outcomes are measured at the macro one. This is extensively discusses in ***citePPI2-ppiaccs

[4] In network analysis, directedness means that the network edges point in one direction, while acyclicality means that, if one starts a walk on a network, it is impossible to return to the initial node of the walk (there are no cycles).

in the context of the SDGs. To provide a brief explanation why one should not make causal claims from these estimates, consider an arrow $i \to j$ that represents a change in indicator j conditioned by a change by indicator i, not a causal link. That is, the existence of $i \to j$ means that, if we observe a change in j, a change in i was likely to have taken place. However, a change in i does not necessarily trigger a change in j; otherwise it would be a causal link.[5] In terms of the model, a positive edge $i \to j$ indicates a higher likelihood of j growing, while a negative one translates into a lower likelihood.

The resulting object from this step is an adjacency matrix $\mathbb{A}$ representing the acyclical network structure of conditional dependencies between indicators. This network, however, does not allow us yet to measure the connectivity of the system. The reason for this is that we are interested in indirect dependencies, as these are informative about the connectivity of the system. Thus, in the next step, we explain how to construct a denser network that captures these indirect connections.

3.3.2 Compounded conditional dependency network

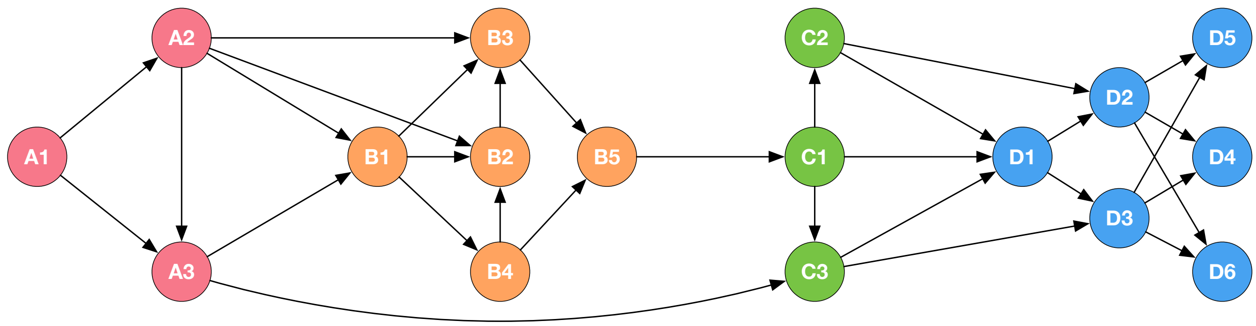
To motivate this step, let us use a theoretical example of a network where each node belongs to a community or development dimension. Recall that the aim of the connectivity module is to quantify how different communities facilitate the reach of shocks. Thus, for this example, let us assume that we are trying to count the links between and within communities using the directed acyclic graph obtained from `sparsebn`. Figure 3 shows a hypothetical example of a network of conditional dependencies. Here, we can see that community A has direct links to communities A and C, but not to D. Nevertheless, it is clear that, should there be a shock any node in A, it is possible that its effects could reach community D through indirect channels. For example, one potential path for a shock in A2 is $A2 \to B3 \to B5 \to C1 \to D1$. Like this, there are many potential paths through which a shock in community A could impact D. It is precisely the implied structure of these indirect impacts what we aim to quantify to capture the connectivity of the system across development dimensions.

If one were to directly assess connectivity using the network presented in Figure 3, the community-level connectivity structure would be the one shown in Figure 4. Clearly, this network leaves our the indirect channels, as community D is only connected to C; not to A nor B. Thus, it is necessary to construct a send network that captures the implied structure of indirect paths. Such a network is denser than the one of conditional dependencies, and provides the information needed to assess how 'contained' would a shock to a particular community be.

We construct a second network by compounding the conditional dependencies across the paths connecting

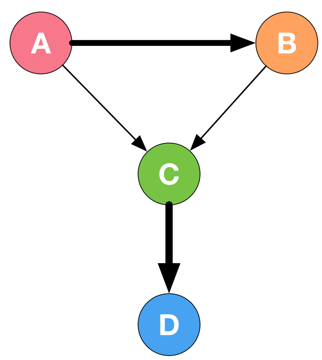
[5] Conditional dependencies are not plain correlations either. A correlation is just a co-movement of two variables, but which could be produced by a third variable, so no conditioning between i and j is necessary.

Figure 3: Example of a network of conditional dependencies



Notes: Nodes represent development indicators. They are coloured according to hypothetical development dimensions or policy areas.

Figure 4: Connectivity between development dimensions implied by the network of conditional dependencies



Notes: Colours represent hypothetical development dimensions or policy areas.

two given nodes i and j. Given the adjacency matrix $\mathbb{A}$ it is possible to find all the possible paths from i to j through common algorithms such as breadth-first search ***cite or depth-first search ***cite.[6] Let the n-tuple $\mathcal{P} = (i, \ldots, j)$ denote a path from i to j, and $\mathbf{P}^{(i,j)}$ the set of all paths from i to j. Then, the compounded conditional dependency from i to j is

$$C_{i,j} = \frac{1}{|\mathbf{P}^{(i,j)}|} \sum_{\mathcal{P} \in \mathbf{P}^{(i,j)}} \prod_{k=1}^{|\mathcal{P}|-1} \mathbb{A}_{\mathcal{P}_{k,k+1}}. \tag{3}$$

Essentially, what Equation 3 does is multiply all the weights along a path from i to j–the compounded conditional dependency (CCD)–and, then, obtaining the average CCD across all the possible paths from i to j. Finally, to construct the CCD network, we need to filter only those values $C_{ij} > 0$. The reason is that, given the normalisation of the development indicators–where higher value denote better outcomes–a negative shock (the relevant one for the CSI) comes in the form of a reduction in the value of an indicator, so the CCD needs to be positive to reflect an indirect negative impact. Thus, by collecting all positive CCDs,

[6]Note that this task is more efficient in the CSI because the network of conditional dependencies is acyclic.

we construct an adjacency matrix $\mathbb{C}$ that encodes the network of compounded conditional dependencies.

3.3.3 Modularity

Once we have constructed the CCD network, we can compute a popular metric known in network science as *modularity*. In a nutshell, modularity measures the structural balance between links within communities and within communities in a network. In the context of the CSI, recall that communities are given by the development dimension. Hence, a high modularity would indicate a tendency to exhibit more within-community edges than between them. Thus, in highly modular systems, a shock to a particular community is more likely to be contained in that community.

There specific modularity measure that we employ is designed for directed weighted network, and was developed by ***cite. First, let $m = \sum_{i,j} \mathbb{C}_{i,j}$ denote the total weights in the CCD network. Then, $s_i^{out} = \sum_j \mathbb{C}_{i,j}$ is the total 'outgoing strength' of node i, while $s_i^{in} = \sum_j \mathbb{C}_{j,j}$ is the 'incoming' one. Finally, modularity is defined as

$$Q = \frac{1}{m} \sum_{i,j} \left[\mathbb{C}_{i,j} - \frac{s_i^{out} s_j^{in}}{m} \right] \delta_{c_i c_j}, \tag{4}$$

where $\delta_{c_i c_j}$ is an indicator function returning 1 if i and j belong to the same community, and 0 otherwise.

In its original form, the modularity score ranges from -1 to 1, with negative values indicating low modular structure and positive ones a high one. To be consistent with the direction of the extreme-events module, let us define the connectivity index as

$$C = -Q. \tag{5}$$

Higher levels of connectivity indicate less modular structure and, hence, higher risk of a shock propagation outside the community that originally experienced it. A value of $C = 0$ indicates that the structure is as modular as a random network would be. Thus, one could interpret that negative values of connectivity would tend to contain shocks to specific development dimensions and genereate less pressures to the institutional buffers.

3.4 Synchronicity

There exist various methods to quantify the synchronisation of two time series. In the CSI, we use an approach that has become a standard in the study of neuroscience, pioneered by ***cite, and that is well suited to work with short time series. This method takes a signal and extracts information on its instantaneous phase (the position of a waveform within its cycle at any given moment in time) of two time series and calculates its angular difference, i.e. the phase locking value (PLV). By computing the PLV over all pairs of signals, we obtain the average PLV of the system, which describes its degree of synchronisation. The original PLV goes from 0 to 1, where 1 is full synchronisation and 0 none. To make this module consistent with the rest of the CSI, we re-normalise the PLV to be between -1 and 1, such that 1 means full synchronisation and -1 none. Thus, the interpretation of the PLV is that larger values mean a higher risk as the various responses to extreme events across a country or region may happen at a similar rhythm, imposing additional pressures to the institutional buffers.

Next, let us provide further details on how to transform development indicators into waveform signals and, then, computing the PLV. Let $X = x_1, x_2, \ldots, x_T$ denote a time series with T observations. To detrend this series, we take its first differences and obtain $X^d = (x_2 - x_1), (x_3 - x_2), \ldots, (x_T - x_{T-1})$. Next, take differences with respect to the mean and normalise by the standard deviation, so we obtain

$$x_t^n = \frac{x_t^d - \hat{\mu}_{X^d}}{\hat{\rho}_{X^d}}, \tag{6}$$

where $\hat{\mu}_{X^d}$ and $\hat{\rho}_{X^d}$ are the sample mean and standard deviation of the detrended time series respectively.

Once the time series has been pre-processed to focus on its wave features, we need to transform the time normalise series into an analytical signal by applying the Hilbert transform.[7] From this transformation, we obtain the phase ϕ_x (which is the imaginary part resulting from the Hilbert transformation), so the PLV between two time time series X and Y as defined by ***cite is

$$PLV_{x,y} = \frac{1}{T-1} \left| \sum_{t=1}^{T-1} e^{j(\phi_x - \phi_y)} \right|, \tag{7}$$

where j reverts the angular difference to an imaginary number.

Finally, averaging over a dataset with N time series and re-normalising the PLV, we obtain our synchronicity module index

$$S = \frac{2}{N} \sum_{i,j} PLV_{i,j} - 1. \tag{8}$$

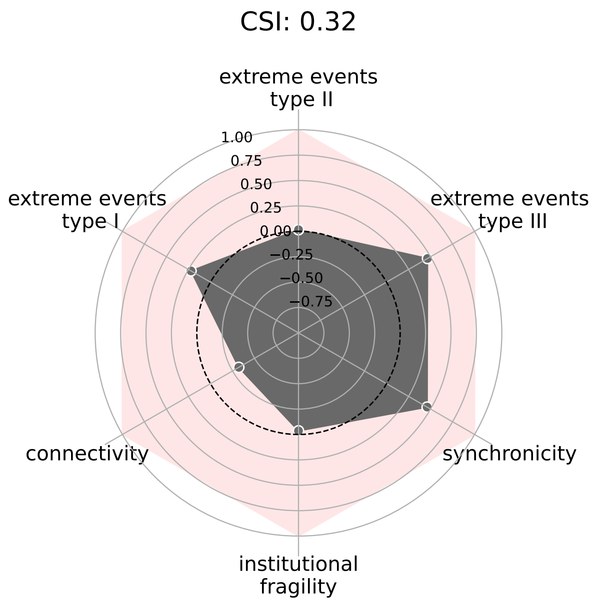
3.5 Computing the CSI

In summary, we have discussed the different methods used to quantify the four modules of the CSI: (1) extreme events likelihood, (2) institutional fragility, (3) connectivity, and (4) synchronicity. Each of these

[7] The Hilbert transform is a signal-processing method with certain technical depth. We refer the reader to more specialised readings in signal processing as this method is very standard in this domain.

modules yields an index that hovers in the -1 to 1 space, where larger values can be interpreted as a higher risk in the corresponding module. Thus, if one considers these values as coordinates in the space of climate security risk, then the area within these points provides a reduced quantification of the degree of such risk. In Figure 5 we show the same polygon from Figure 1 overlaid on the maximum area that could be produced by setting each module to its worst value. The CSI is area of the inner polygon as a fraction of the area defined by the outer one. Thus, higher values for the CSI denote more climate security risk. Since the extreme events modules are not bound by 1, the CSI goes from 0 to infinity, but it is highly unlikely to expect values beyond 1.

Figure 5: Quantification of the CSI



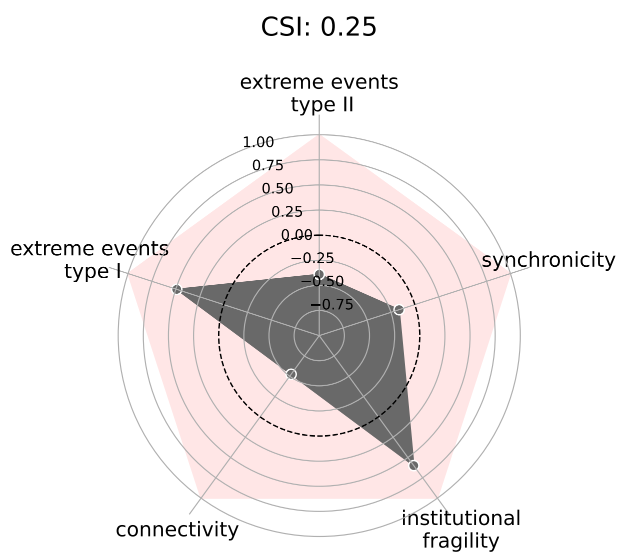
Notes: Outer rings represent worse levels in each module.

The `Python` package accessible in ***url provides all the necessary functions compute the CSI, as well as a tutorial to walk the reader througuh the data preparation. In the next section, we show an application of the CSI to the case of Kenya.

4 An application to Kenya

***Daniele: could you start filling this with the application to Kenya?

Figure 6: An application to Kenya



Notes: Outer rings represent worse levels in each module.