European Commission

JRC TECHNICAL REPORT

INFORM Covid-19 Warning Tool

Concept and Methodology

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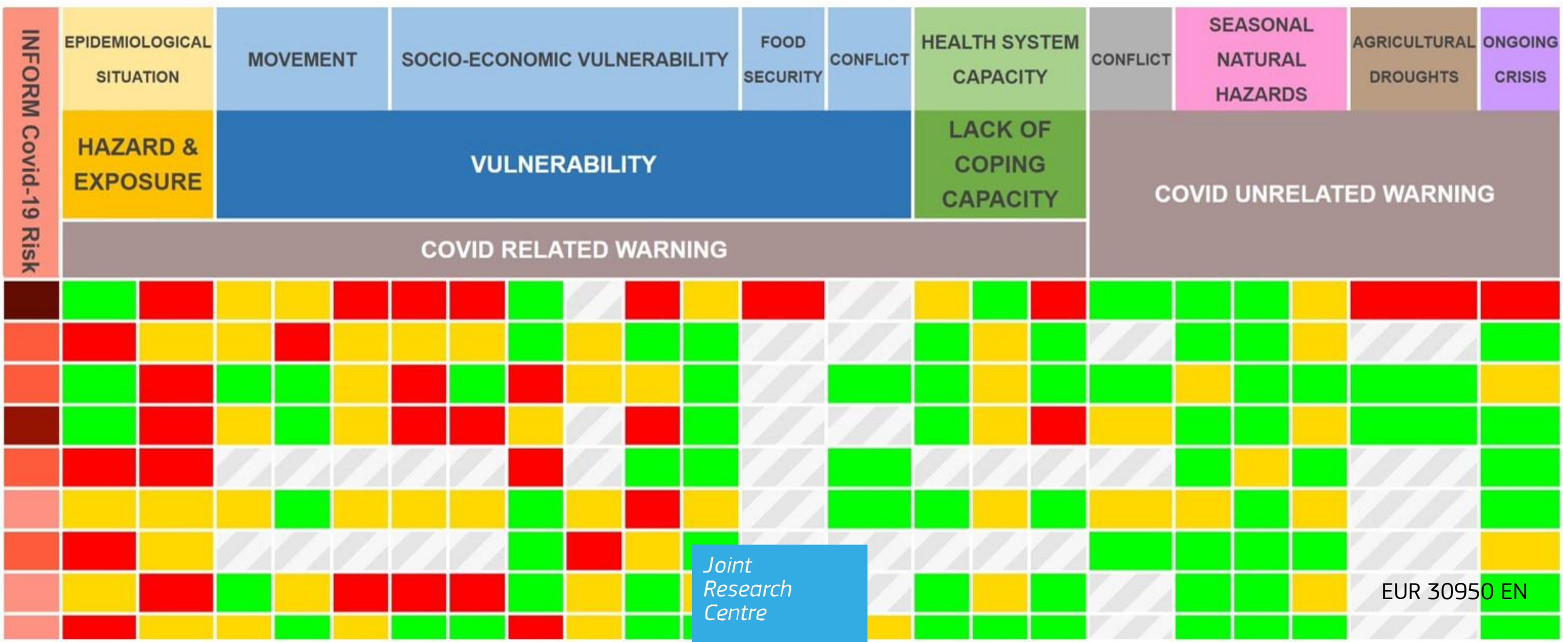

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Role of Authors

Karmen Poljanšek was following the whole process, was responsible for the design and preparation of the report and wrote part of the report.

Luca Vernaccini, as an external consultant and the front-end IT developer (Application Architect), adopted scientific and technical solution, computed and presented the results, coordinated the methodology, data implementation into the system and website and wrote part of the report.

Daniele Dalla Valle, as an external consultant and the back-end IT developer of the database, system and website, executed the implementation phase of the INFORM Covid-19 Warning activities and wrote part of the report.

Oluwatosin John Orenaike, as a trainee, developed the method to introduce the seasonality of the meteorological hazards in the model of the INFORM Risk and wrote the dedicated chapter.

Luca Galimberti, as visiting scientist, developed the prototype of the COVID-19 impact predictions based on the database of INFORM Covid-19 Warning in Tableau and wrote part of the report.

Abstract

During the Covid-19 pandemic, the humanitarian and development community of INFORM partnership expressed a need for analytical tool to monitor how the ongoing pandemic affects the existing risks of humanitarian crisis. The Covid-19 pandemic is far more than a health crisis: it is affecting societies and economies at their core. While the impact of the pandemic will vary from country to country, it will most likely increase poverty and inequalities at a global scale, increasing the risk of humanitarian crises.

This report describes the INFORM Covid-19 Warning tool developed by JRC, the scientific and technical lead of INFORM. The objective of INFORM Covid-19 Warning is to identify, monitor and anticipate where Covid-19 could compound existing risks to cause new, or exacerbate existing, humanitarian crises. It aims to provide analysis that can be used to support decisions on preparedness and anticipatory action to mitigate the direct and indirect humanitarian impacts of the Covid-19 pandemic.

It essentially concerns the collection, aggregation and presentation of information about crisis risk that is dynamic rather than structural in nature. The INFORM Covid-19 Warning collects and presents risk trends, seasonal risks and severity trends. It compares them to thresholds to monitor how risks change in the short-medium term compared to the baseline. The tool has a global coverage with continuous automatic updates of data and results in a dashboard of information that shows how risk changes with time at the country level.

The INFORM Covid-19 Warning tool serves also as a case study for the conceptualisation of the INFORM Warning, one of the three main products of INFORM Suite, by piloting solutions that will be adopted in the main tool.

1 Introduction

The Covid-19 pandemic demonstrates that the international response system needs to be prepared for a new order of crises, for an era in which large-scale systemic shocks may overlay and aggravate existing risks and significant long-standing humanitarian needs (NRC, 2020).

The Joint Research Centre of European, as a scientific and technical lead of INFORM, responded to needs expressed through INFORM partnership mechanism with development and implementation of the two COVID-19 specific analytical tools together with UN OCHA: INFORM Covid-19 Risk Index (Poljanšek, 2020a) and INFORM Covid-19 Warning tool presented in this report.

UN OCHA is coordinator of INFORM, which is a multi-stakeholder forum for developing shared, quantitative analysis relevant to humanitarian crises and disasters. INFORM includes organisations from across the multilateral system, including the humanitarian and development sector, donors, and technical partners. The work program of INFORM is development of a suite of quantitative, analytical products to support decision-making on humanitarian crises and disasters. These help make decisions at different stages of the disaster management cycle, specifically prevention, preparedness and response. INFORM develops methodologies and tools for use at the global level and also supports their application at subnational level.

In April 2020 JRC released the INFORM Covid-19 Risk Index (Poljanšek, 2020a). INFORM Covid-19 Risk Index identifies: “countries at risk from health and humanitarian impacts of Covid-19 that could overwhelm current national response capacity, and therefore lead to a need for additional international assistance”. The INFORM Covid-19 Risk Index is primarily concerned with structural risk factors, i.e. those that existed before the outbreak. It does not consider the current evolution of the pandemic, nor the mechanisms behind potential indirect impacts - for example how it could lead to increased food insecurity and conflict, worse health outcomes for other diseases, or less effective responses to new crises and disasters. The tool was very useful at the very beginning of the Covid-19 pandemic, providing important indication of the potential impact of the Covid-19 outbreak in the countries where the virus didn’t yet arrived.

But as consequence of the further spreading of the Covid-19, the world has been caught in ongoing crisis of global pandemic. The model and information used in the INFORM Covid-19 Risk were not designed to follow the ongoing situation. The global pandemic has completely changed the scenario. The indicators for potential drivers for the probability of the virus spreading in INFORM Covid-19 Risk, such as the daily reporting of the Covid-19 cases, have become a measure of direct impact of crisis as well as a driver for exceeding the health system capacity, a potential secondary impact of crisis. Similarly, the government’s measures to restrict the mobility of people in order to contain the pandemic have on the other side been causing the undesired impact in economy sector.

After the first-tier response to Covid-19 aiming at life savings and life extension, humanitarian actors have started to analyse what other dimensions of fragile societies will be overwhelmed by the secondary impact of the virus outbreak: schools closure determines the halt of nutrition programs in several countries where an entire generation can be out of schooling and facing nutritional constraints, the changes in mobility of seasonal workers will impact crop harvest in several marginalized and mixed farming systems, while the advancements made on gender and inclusion of marginalized groups are threat by the drop in access to the persons of concern.

Yet, the secondary effects of Covid-19 won’t impact all societies with the same intensity, hence the need for a tool that can identify where, when and how the risk of an overwhelming humanitarian impact is materializing. In April 2020, the United Nations (GHRP, 2020) declares that “the COVID-19 pandemic is characterized by the rapidity of its spread and difficulty to project how the epidemic will evolve at country level. As a result, a monitoring mechanism of the situation, needs and response achievements is indispensable to rapidly adjust the interventions.”

In response to this need, JRC developed another tool to provide a more dynamic and up-to-date picture of how the pandemic is evolving and how the impact of Covid-19 pandemic interacts with other hazards, vulnerabilities and coping capacities indicators and affects crisis risk. In August 2020, the beta version of INFORM Covid-19 Warning has been release.

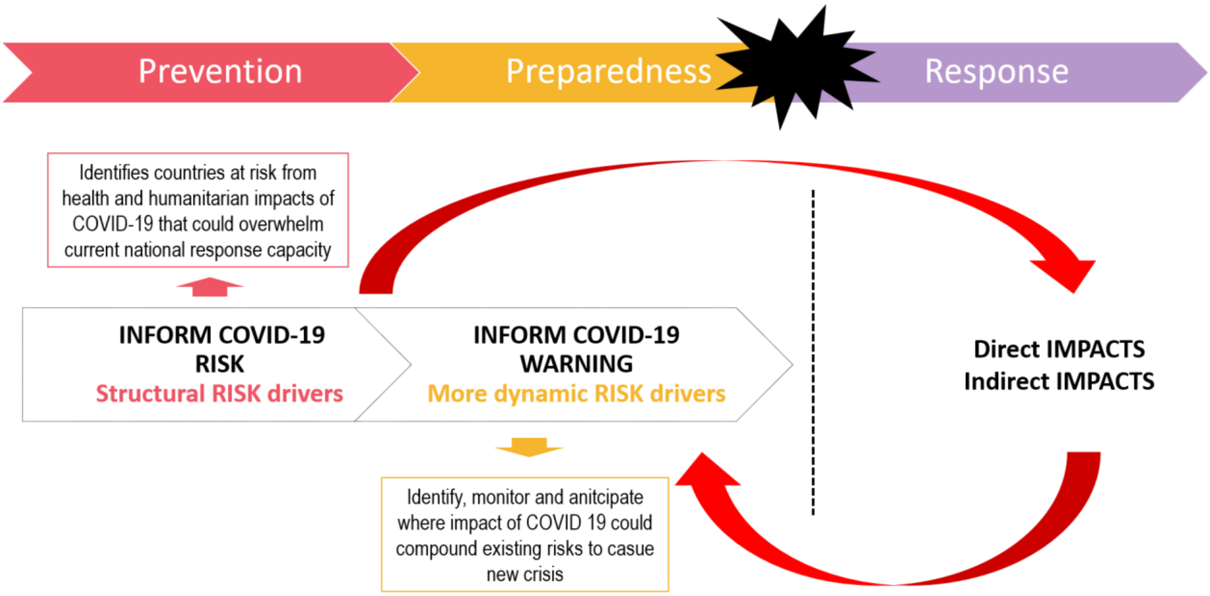
This report covers all phases of the development of the INFORM Covid-19 warning tool: from scoping, development of the conceptual framework and model to the technical requirements of the implementation of the model. Model introduced has three modules: risk monitor, dashboard and impact predictor. Risk monitor and dashboard are already operational while impact predictor is presented as a case study using casual loop approach to deduce the timeline and type of possible impacts from the monitoring data. The specific focus has been also on development of seasonal hazard calendar, the never published work done by JRC and it has been found very useful in this context.

2 Objective and Scope

The epidemic situation of Covid-19 is in continuous evolution. Countries experienced seconds or third waves following the first global impact of the virus. The different containment measures strategies adopted by the of the governments, together with the public health capacity, and finally the vaccination campaigns, are dynamically influencing the impact of Covid-19 in the different countries. It is therefore important to have more dynamic measures to reflect current and changing risks.

The objective of INFORM Covid-19 Warning is to "identify, monitor and anticipate where Covid-19 could compound existing risks to cause new, or exacerbate existing, humanitarian crises". It aims to provide analysis that can be used to support decisions on preparedness and anticipatory action to mitigate the direct and indirect humanitarian impacts of the Covid-19 pandemic (**Figure 1**).

Figure 1. INFORM Covid-19 Warning



Source: authors

3 Conceptual framework

We are addressing time window, when we are already monitoring the direct impacts of a crisis but it is still relevant for anticipatory actions (or interventions) to prevent or mitigate or prepare for risk to grow, escalate or cascade into major whole-of-society problem with a snow-ball effect and increases the potential for both, economic, environmental and further human losses. The characteristics of this time window most fit to early warning phase of managing risk.

An early warning systems should combine four interrelated elements: (1) disaster risk knowledge, (2) monitoring and warning service, (3) dissemination and communication of warnings, and (4) response capability (UNISDR, 2006). The INFORM Covid-19 Warning focuses on the first two pillars: risk knowledge and the monitoring & warning service.

INFORM Covid-19 Warning aims to monitor the potential humanitarian impacts of Covid-19 in combination with other pre-existing crisis risks. It does this by combining structural risk indicators (as already defined by the INFORM Covid-19 Risk Index) and dynamic risk indicators (risk monitoring).

The conceptual frameworks already developed for the INFORM Covid-19 Risk Index (Poljanšek, 2020a) and the broader INFORM Risk Index provide a starting point for the identification of risk factors that require monitoring.

Broadly the approach taken defines 4 levels of INFORM Covid-19 Warning framework (**Figure 2**)

Figure 2. Conceptual framework of INFORM Covid-19 Warning

1.level	**2.level**	**3.level**	**4.level**
INFORM Covid-19 Risk	Covid-19 related risks	Covid-19 unrelated risks	Impact areas
Provides the baseline of the risk for humanitarian crisis of Covid-19 based on pre-pandemic **structural risk drivers**	Identifies and organises key **dynamic risk indicators directly relating to Covid-19** (e.g. spread of the virus, movement of people, impacts on the health system) **and indirectly relating to Covid-19** (e.g. food insecurity, socio-economic vulnerabilities, violent events)	Identifies and organises key **dynamic risk indicators not related to Covid-19** (e.g. natural hazards, other diseases), but that could increase compound risks	Identifies 'impact areas' (e.g. health, food security, conflict) to highlight where and how all the risk drivers could contribute to humanitarian crises

Source: authors

3.1 INFORM Covid-19 Risk

The first level in INFORM Covid-19 WARNING provides with INFORM Covid-19 Risk the country's baseline for the risk of humanitarian crisis due to health and humanitarian impacts of Covid-19 that could overwhelm current national response capacity.

Figure 3: INFORM COVID-19 risk model

Risk	INFORM COVID-19 RISK					
Dimension	RISK FORMULA					
	Hazard & Exposure		Vulnerability		Lack of Coping Capacity	
Category	P2P		GEOMETRIC AVERAGE		GEOMETRIC AVERAGE	
	ARITHMETIC AVERAGE		INFORM Vulnerability	Covid-19 Vulnerability	INFORM Lack of Coping Capacity	Covid-19 Lack of Coping Capacity
	WaSH	Population				

Source: Poljanšek et al., 2020a

Figure 4: COVID-19 Vulnerability and Covid-19 Lack of Coping Capacity subdimensions

Covid-19 Vulnerability	Movement (25%)	International movement
		Internal movement
	Behaviour (25%)	Awareness
		Trust
	Demographic and Comorbidities (50%)	***Proportion of the population at increased risk of severe COVID-19 disease***

Covid-19 Lack of coping capacity	Health Capacity	***Health system capacity specific to Covid-19***	International Health Regulations Core Capacities average score
			Country Preparedness and Response Status for COVID-19

Source: Poljanšek et al., 2020a

3.2 Covid-19 related risk

The second level in INFORM Covid-19 WARNING looks at monitoring the impact of the Covid-19 (direct or indirect) on the risk drivers. Starting from the INFORM Covid-19 Risk Analytical Framework (Poljanšek, 2020a), we first identified the risk components that are influenced directly or indirectly by the Covid-19 pandemic. We show the INFORM Covid-19 Risk scores for each component as benchmark, presenting the level of risk without containment measures.

We then identify and visualize a set of dynamic indicators that help the users to monitor the ongoing situation. These monitoring indicators are not meant to directly update the INFORM Covid-19 Risk scores, but to facilitate the interpretation of the evolving situation, towards a worsening or improvement of the risk. The INFORM Covid-19 Risk Index uses the absolute value of the indicators (i.e. how good or bad the country performs in each risk driver), while the INFORM Covid-19 Warning look at the changes and trends of the indicators. It is based on the assumption that changes in risk drivers could trigger a humanitarian crisis

Examples of direct effects of Covid-19 pandemic are the increasing of the mortality rate, or the overwhelming of the health systems.

As examples for indirect effects, the containment measures from governments (i.e. restriction of movements, closure of schools, lockdown) have reduced the direct impact of the Covid-19 on the health of people, but increased the economic impact (unemployment, reduce income), the food security (access to food, food prices), education, and health system capacity (access to health services not related to Covid-19).

3.3 Covid-19 unrelated risks

Risks are often assessed and monitored in isolation – with monitoring tools focused on singular issues (such as food security, conflict or seasonal hazard). This can lead to incomplete understanding of where risk is concentrated, and potential biases in estimates of the probability and severity of adverse shocks. Humanitarian crises often are not caused by a single event, but by the combination of natural hazards, socioeconomic drivers, conflicts and disease outbreaks. The COVID-19 pandemic is a major example of cascading events, with the initial public health impacts followed by economic contraction. Moreover, the consequence of Covid-19 did not come in isolation; but it interacted with existing natural hazards, such as drought, floods or tropical cyclones, and violent conflict (OCHA, 2020).

The third level consists of compounding factors that lead to humanitarian crisis and that the Covid-19 pandemic can amplify their impact. Natural hazards and human-induced risk with a seasonality component have been identified and displayed in a fixed timeline, allowing to identify critical times for risk becomes a humanitarian impact (e.g. in the case of the tropical cyclone season).

Countries with existing humanitarian crises are particularly exposed to the effects of the pandemic, in terms of both direct impacts on people's health, and indirect effects, such as disruption of livelihoods, food supply chains and access to food, basic services as well as humanitarian assistance (FAO[1]). The baseline for understanding the potential deterioration of the ongoing humanitarian crisis is provided by the monthly update of the INFORM Severity[2] (Poljanšek et al.., 2020b), which is presented as part of the information.

A preliminary list of dynamic information would include:

- Seasonal (monthly) natural hazards
- Weather forecasting (short, medium, long term)
- Violent events
- Election calendar
- Severity of the ongoing humanitarian crisis
- Other disease outbreaks

3.4 Impact areas

The fourth level (not yet implemented) analyses looks at the potential impact (direct and indirect) of Covid-19 on the different type of humanitarian crises. The monitoring indicators will be organised towards the impacts across a wide range of relevant themes such as economy, health, migration and education.

A preliminary list of impact areas includes:

- Health
- Food security
- Conflict
- Education
- Economy
- Displacement

[1] http://www.fao.org/3/ca8464en/CA8464EN.pdf
[2] http://drmkc.jrc.ec.europa.eu/inform-index/INFORM-Severity

4 Model of the INFORM Covid-19 Warning tool

The Conceptual Framework (Chapter 3) provides basis for the selection of single indicators and the rules how to combine them into meaningful model that would fit the purpose of the tool designed.

The INFORM Covid-19 Warning collects structural risk indicators (INFORM COVID-19 RISK) and dynamic risk indicators directly or indirectly related to Covid-19 (COVID RELATED WARNING), or not related to Covid-19 (COVID UNRELATED WARNING), and combines them in order to predict potential impacts.

The model of the INFORM Covid-19 Warning can be divided in three modules:

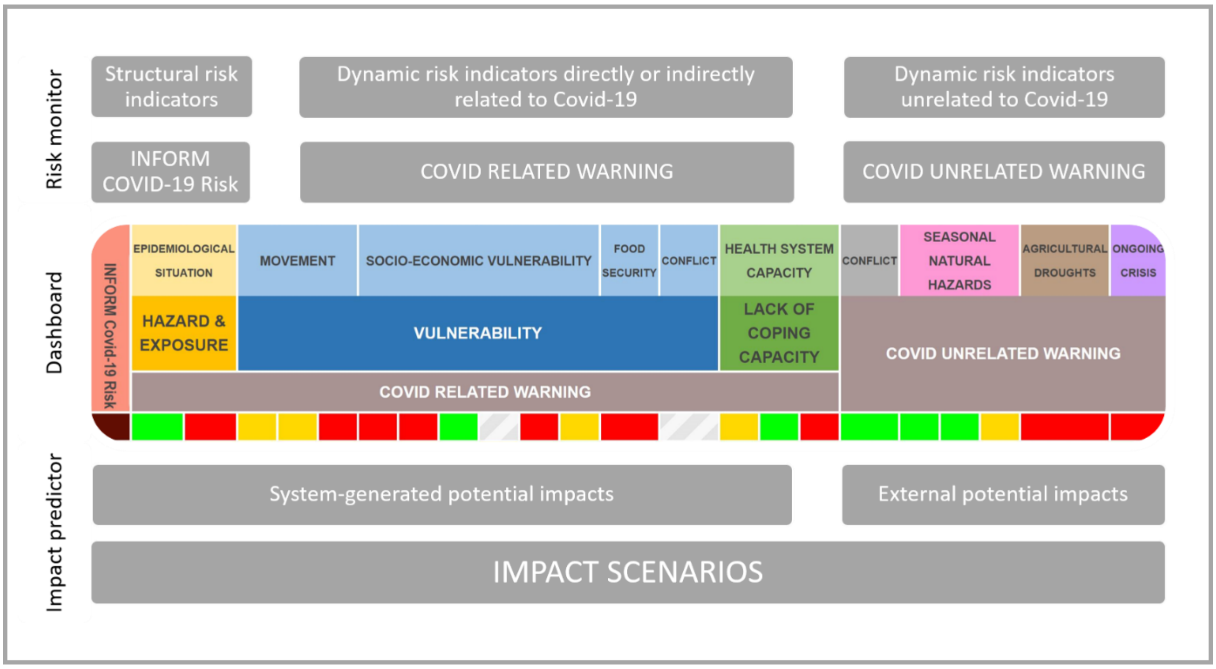
1. Risk monitor
2. Dashboard
3. Impact predictor

In the Risk monitor the indicators values are compared to thresholds to monitor how risks change in the short-medium term compared to the baseline. It has global coverage, is automated and results in country profiles.

The dashboard presents an overview of the warning status for all the countries. The dashboard consists the access point for the country details (Chapter 5.3), showing a larger range of information.

The third module for predicting the impacts is still in development. The used approach and the first results are presented in the Chapter 7.

Figure 5. Model of the INFORM Covid-19 Warning tool



Source: authors

The tool should be user-friendly, providing a clear and efficient way to access to the presented information.

To facilitate the interpretation and the comparability, all the risk monitoring indicators are classified in three warning levels, red, orange and green according to predefined criteria (Annex 2).

5 The implementation of the INFORM Covid-19 Warning tool

5.1 Technical requirements

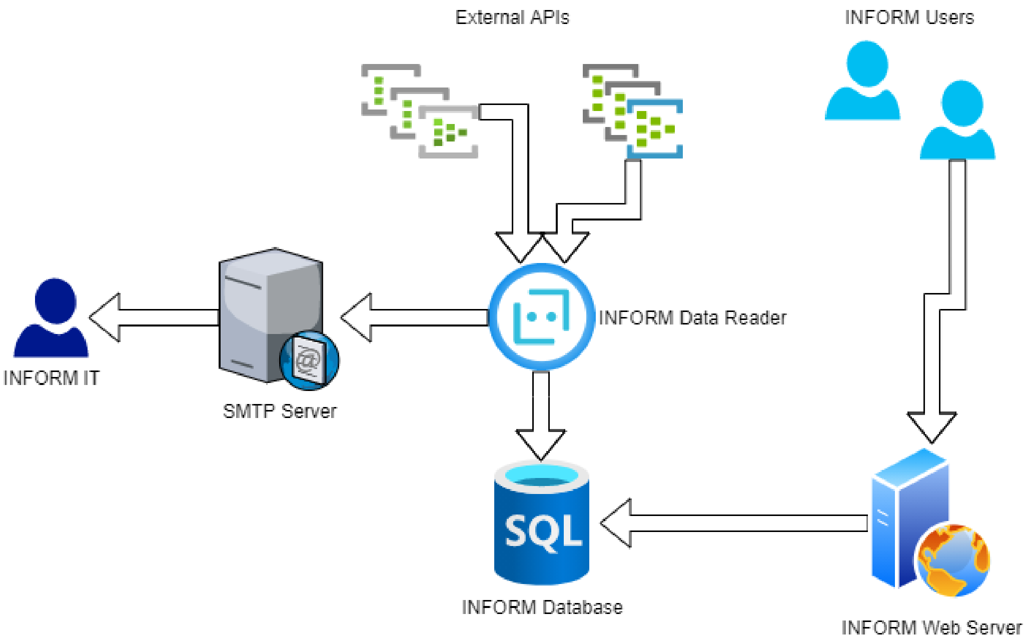
The main goal for the tool was to gather, process, and expose a variety of information to be always updated and available for the final user.

The sources comprise data in different formats, such as JSON, CSV, MS Excel, and with different update timeframes. Few sources are updated daily, others weekly, and so on up to a yearly update.

With such a variety in formats and update frequency an automated process for gathering and processing information was among the main requirements. An INFORM Data Reader has been developed and runs on the INFORM Server, taking care of downloading the datasets from the External APIs, with their URLs specified in a dedicated database table in the INFORM Database, after a certain amount of time has passed from the previous update, said amount specified along with the URL.

INFORM Data Reader traps any possible error, e.g. an URL or the structure of a dataset has changed, and send a notification to the IT department through an SMTP Server, allowing for a timely intervention and fix.

Figure 6. INFORM Covid-19 Warning IT schema



Source: authors

The data sources have been listed in a dedicated web page, as well as being shown below each indicator in the country detail web page.

Another main requirement was to present the information in a simple and clear way. With the INFORM Web Site being hosted in the European Commission domain[3] we had to ensure the EC look and feel was preserved. When developing a new web application in the EC domain a dedicated visual library is available, it contains guidelines, building blocks and tools that can be used to assemble the foundations of the new application.

For the INFORM Covid-19 Warning application, maps and charts are part of the EC library tools, indicators are derived from an EC library building block and every visual component, from colours to fonts and styles, follows the EC library guidelines[4].

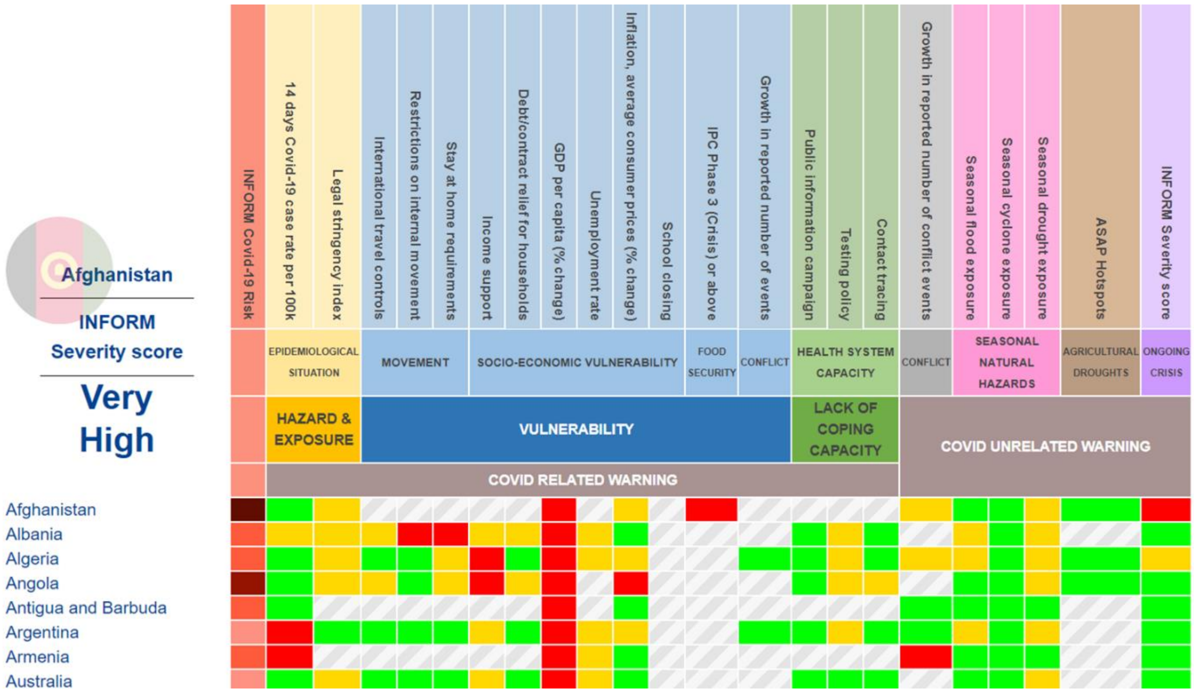
[3] https://wikis.ec.europa.eu/display/WEBGUIDE/
[4] https://ec.europa.eu/component-library/ec/guidelines/

5.2 The INFORM Covid-19 Warning (beta version) dashboard

There is a need to provide to the users a simple and clear understanding of the situation of all the countries among the different risk drivers.

The INFORM Covid-19 Warning (beta version) dashboard (**Figure 7**) provides the global overview of the warning status of the selected risk factors. Each risk monitoring indicator is classified in three warning levels, red, orange and green according to the criteria presented in the Annex 2. These criteria are still preliminary and subjected to revision.

Figure 7. The INFORM Covid-19 Warning (beta version) dashboard (when moving the mouse over a cell to get more information, e.g., INFORM Severity score for Afghanistan)



Source: INFORM website

The indicators included in the dashboard have been selected according to four criteria:

1. representativeness,
2. relevance,
3. consistency, and
4. comparability.

They should well describe the different risk drivers and being recognised as reference by the specific community, they should be available over time and continuously updated, and finally allowing comparability among the different countries.

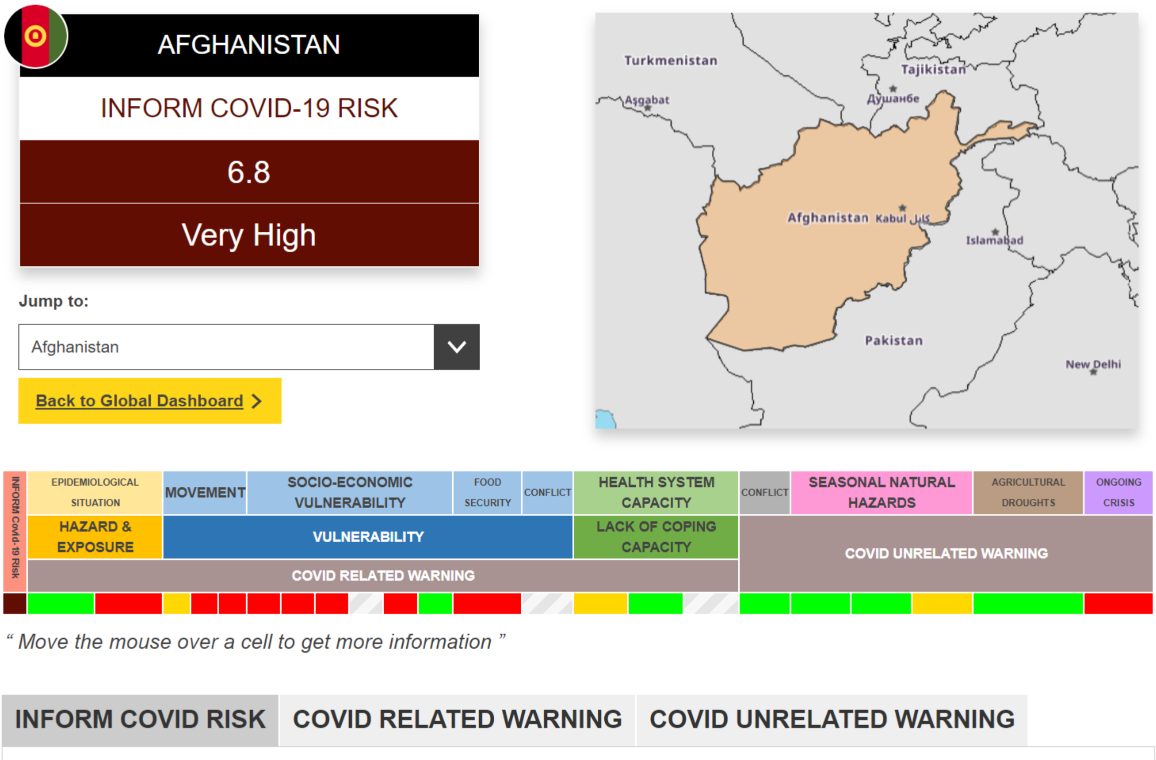
The dashboard is updated automatically overnight and you can download all the daily results in a CSV format.

5.3 Country profiles

The INFORM Covid-19 Warning (beta version) dashboard provides also the access to the country details by clicking on the country names.

The country profiles are composed by a header with the INFORM Covid-19 Risk score, an overview map and the INFORM Covid-19 Warning (beta version) dashboard data for the selected country (**Figure 8**).

Figure 8. Country profile



Source: INFORM website

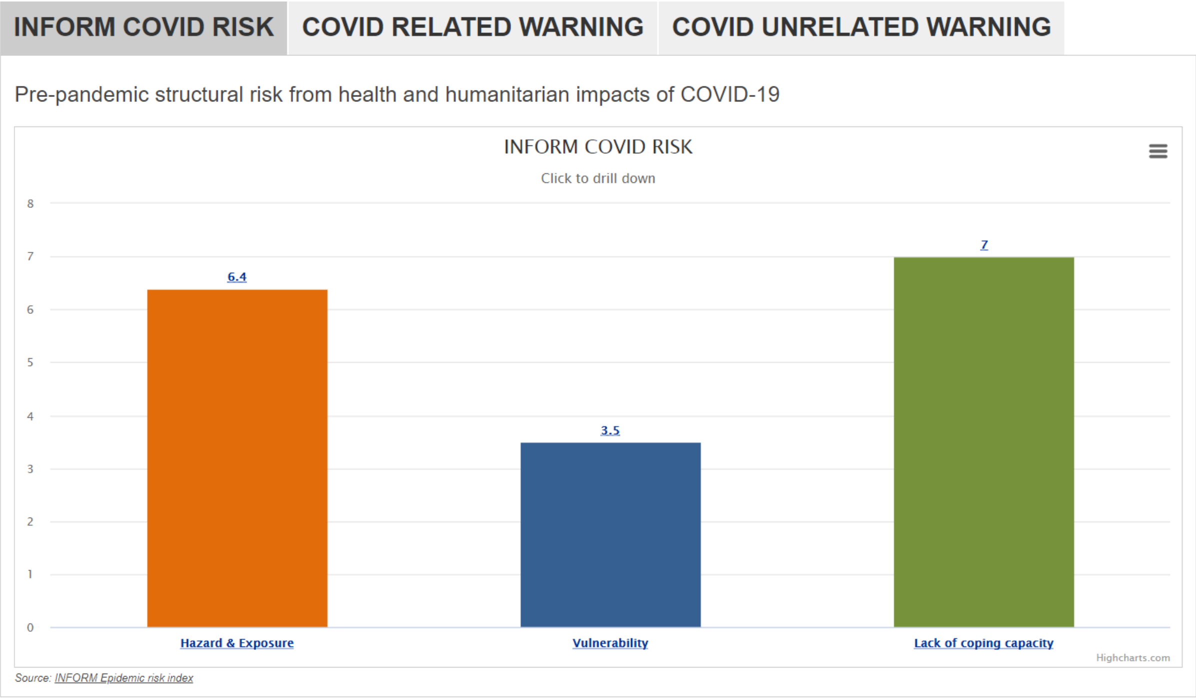
The country profile is divided in three sections:

- INFORM COVID RISK (structural risk indicators)
- COVID RELATED WARNING (dynamic risk indicators directly or indirectly related to Covid-19)
- COVID UNRELATED WARNING (dynamic risk indicators not related to Covid-19)

5.3.1 INFORM Covid-19 Risk

The INFORM COVID-19 Risk Index (Poljanšek et al., 2020) is primarily concerned with structural risk factors, i.e. those that existed before the outbreak. Showing the potential impact of Covid-19 before the outbreak, it provides the baseline for the monitoring indicators presented in the "Covid related warning" section (**Figure 9**).

Figure 9. INFORM Covid-19 Risk tab



Source: INFORM website

5.3.2 Covid-19 related warning

The "Covid-19 related warning" section presents key dynamic risk indicators that are:

- directly related to Covid-19 (e.g. spread of the virus, movement of people, impacts on the health system) and
- indirectly related to Covid-19 (e.g. food insecurity, socio-economic vulnerabilities, violent events).

The monitoring indicators are organised according to the INFORM Covid-19 Risk analytical framework (**Figure 3**: INFORM COVID-19 risk model**Figure 3**) which follows the INFORM Risk dimensions: Hazards & Exposure, Vulnerability and Lack of coping capacity.

The **Hazards & Exposure** dimension shows the Covid-19 *Epidemiological Situation* and its immediate health impact on people. Monitored indicators are for example: "cumulative cases", "cumulative fatalities", "14 days Covid-19 case notification rate per 100k".

The **Vulnerability** dimension includes the category of:

- *Movement* that is made of two components showing restrictions in
  - *International travel* and
  - *internal movements*

  that are imposed to contain the spread of the virus. Identified restrictions on mobility add to the pass-through effects of the global economic recession as well as other compound risks and aggravate the shocks from conflict, civil violence and natural disasters as they further hamper the access and delivery of humanitarian assistance and protection services.
- *Socio-economic vulnerability* that covers

- *Development & Deprivation*,
- *Economic Dependency* and
- *Education* components.

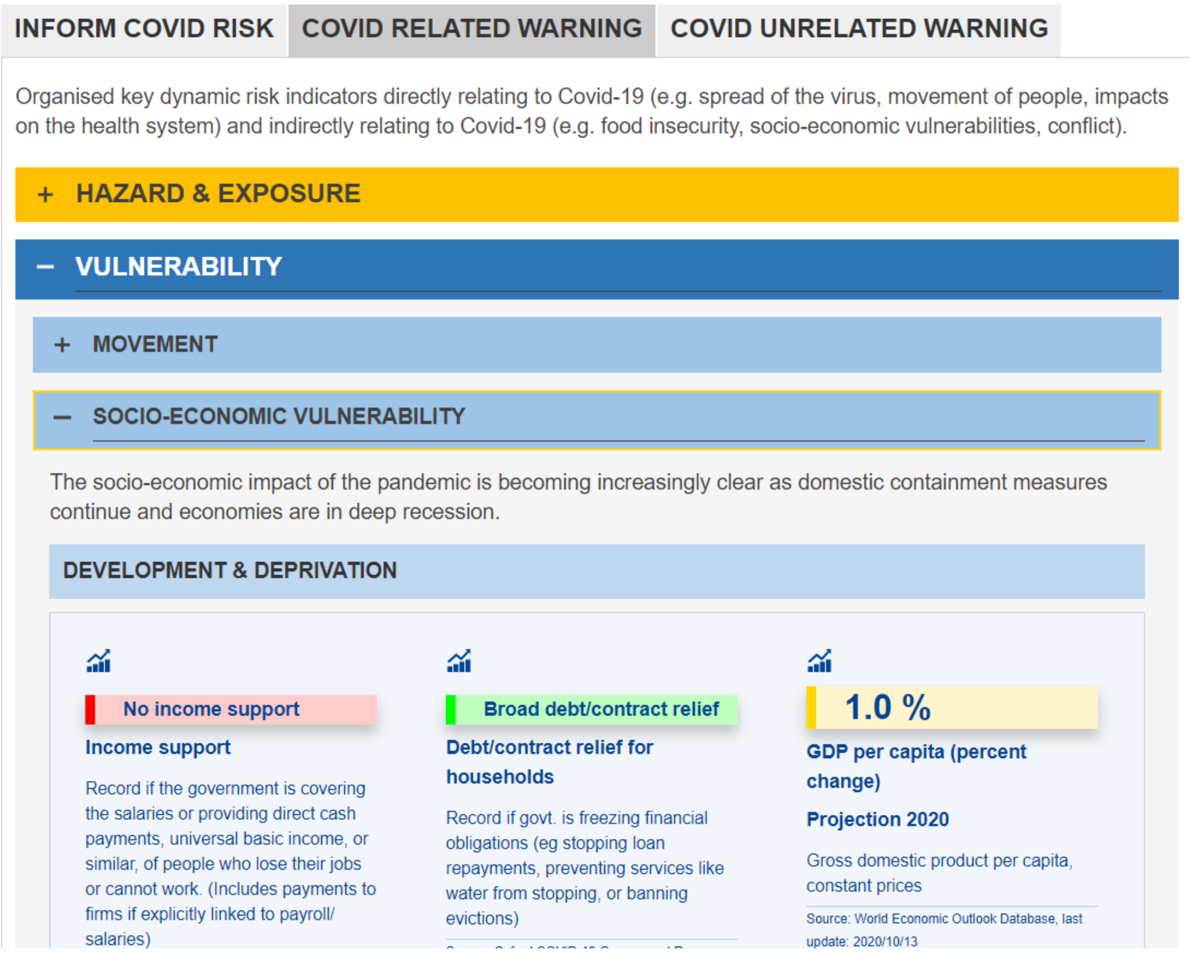
Development & Deprivation and *Economic Dependency* highlight another aspect of the increasing impact of the pandemic as domestic containment measures continue and economies are in deep recession. While Education considers the likely indirect impact of school closures on future earnings and human capital for students, increase educational and broader inequalities particularly for the poorest students, girls, and students with disabilities, and contribute to hunger and malnutrition from the suspension of school feeding programmes.

- *Food security* showing how Covid-19 is deepening the hunger crisis in the world's hunger hotspots and creating new epicentres of hunger across the globe.
- *Conflict* represented with disorder events that are directly related to the coronavirus pandemic.

The **Lack of coping capacity** dimension looks at the capacity to the health systems in relation to the Covid-19 pandemic.

The indicators can be quantitative as well as qualitative. For each indicator, we show the value classified in three warning levels, red, orange and green. The information is complemented by the description of the indicator, the source and the date of the last update.

Figure 10. Covid-19 related warning tab



Source: INFORM website

5.3.3 Covid unrelated warning

Finally, the "Covid-19 unrelated warning" section shows key dynamic risk indicators not directly related to Covid-19 (e.g. extreme weather events), that could increase compound risks.

It currently includes indicators about (sources in Annex 1):

1. conflicts
2. seasonal natural hazards: flood, cyclone and drought exposure (more in Chapter 6)
3. agricultural droughts
4. ongoing humanitarian crises
5. on-going epidemic outbreaks (currently not available)

As for the "Covid related warning" section, the indicators can be quantitative as well as qualitative. Each indicator is classified in three warning levels, red, orange and green. The information is complemented by the description of the indicator, the source and the date of the last update.

Figure 11. Covid-19 unrelated warning tab

Source: INFORM website

6 Development of seasonal hazards calendars

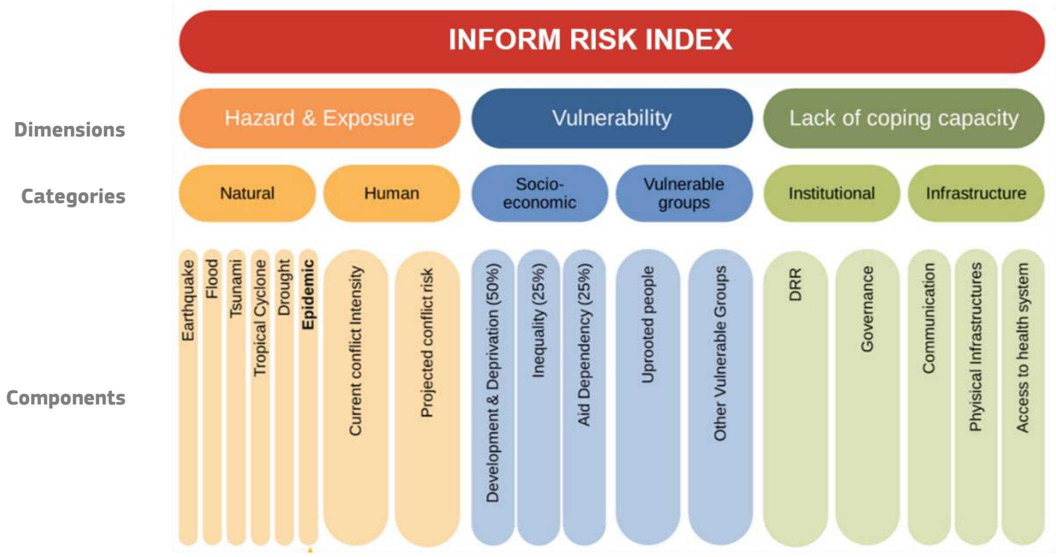
Meteorological hazards such as floods, tropical cyclones and droughts have elements of changes due to their relations to weather cycles. This modifies the frequency, magnitude of hazardous events that take place within the year. Globally, different countries are seasonally affected by different hazards. **Seasonality** in this report refers to variation in the probabilities of occurrence of different magnitude of events within one year time window, e.g., assessed monthly or quarterly. Such recorded seasonal variation in occurrences of the hazardous events we call **seasonal hazard calendars**.

We have used the INFORM methodology to translate the existing knowledge (local as well as most recent data) about variability in seasonal hazard risk into quantitative information and convert it into a score. That way the results

1. are comparable at global scale and through time (Marin-Ferrer et al., 2017, Poljanšek et al., 2018), and
2. provide an opportunity to introduce the seasonal variations through the natural hazard category into INFORM Risk model and test the challenges of composite indicator approach, i.e., not being very sensitive on dynamic changes.

The components within Natural Hazard category of INFORM Risk Index assess the annual average exposure to hazards such as earthquakes, tsunamis, floods, epidemics, droughts and tropical cyclones. To introduce seasonal hazard calendars we analysed the monthly variability of the meteorological hazards included in INFORM Risk (**Figure 12**), i.e., floods, tropical cyclones and droughts based on historical events data (**Table 1**).

Figure 12: The position of flood, tropical cyclone and drought components within INFORM Risk model



Source: Poljanšek et al., 2018

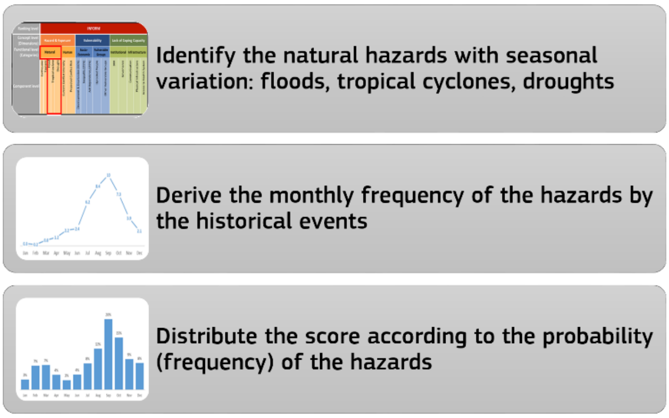
Table 1: Data used for assessing the seasonality of the meteorological hazards

Dimensions	Categories	Components	Data Provider	Description	Citation
Hazard & Exposure	Natural	Tropical Cyclones	The International Best Track Archive for Climate Stewardship(IBTrACS)v04	The International Best Track Archive for Climate Stewardship(IBTrACS) collects and combines histroical best track from Regional Speciazed Metrological Centres(RSMCS) and other agencies.	Knapp, K. R., Kruk, M. C., Levinson, D. H., Diamond, H. J., & Neumann, C. J. (2010). The international best track archive for climate stewardship (IBTrACS) unifying tropical cyclone data. Bulletin of the American Meteorological Society, 91(3), 363-376.
	Natural	Floods	EM-DAT and CRED	D. Guha-Sapir, R. Below, Ph. Hoyois - EM-DAT: International Disaster Database – www.emdat.be – Université Catholique de Louvain – Brussels – Belgium.	D. Guha-Sapir, R. Below, Ph. Hoyois - EM-DAT: International Disaster Database – www.emdat.be – Université Catholique de Louvain – Brussels – Belgium.
	Natural	Drought	JRC-ASAP	ASAP is an online support system for early warning about hotspots for agricultural production anomaly, which was developed by JRC for food crises prevention and response. Link . The dataset contains warnings about low or delayed vegetation performance at sub-national level for crops and rangelands	Rembold, F., Meroni, M., Urbano, F., Csak, G., Kerdiles, H., Perez-Hoyos, A., ... & Negre, T. (2019). ASAP: A new global early warning system to detect anomaly hot spots of agricultural production for food security analysis. Agricultural systems, 168, 247-257.

Source: authors

The monthly frequencies of the historical events are used as probability for distributing the INFORM scores within each month for each country. The INFORM annual score[5] corresponds to the peak month of the monthly scores (**Figure 13**).

Figure 13: The approach to derive the monthly distribution of natural hazard components INFORM score



Source: Authors

6.1 Seasonality of floods

Floods are a climate related event that account for more than 90 percent of the world's disasters according to the number of people affected (OCHA, 2019). Floods are influenced by characteristics of climatic system such as precipitation and temperature. They change along the year and, thus, the risk of flood events. The floods occurrence is affected also by drainage basin condition, soil characteristics, rate of urbanisation as well as dikes and dams (WMO-UNEP, 2008).

6.1.1 INFORM seasonal floods: methodology and assessment

The flood score within INFORM Risk Index is based on the estimated number of people exposed to floods per year. It results from the combination of the hazard zones and the total population living in those spatial units. It indicates the expected number of people exposed in the hazard zone in one year.

To estimate the monthly variation, historical events from the EMDAT database (CRED) has been used.

6.1.2 Findings and Results

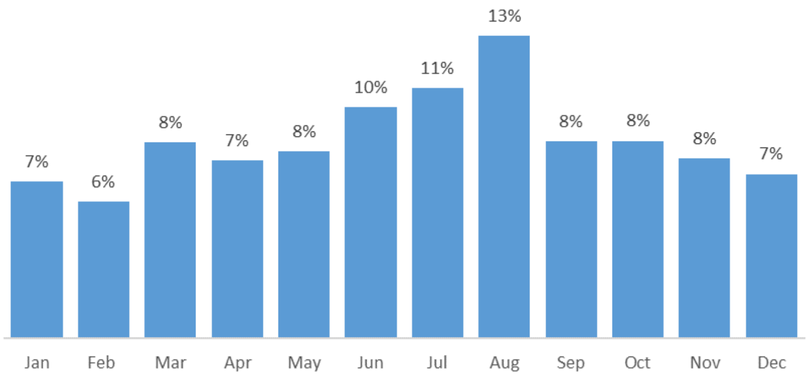
The final result of the flood is presented based on the monthly distribution globally, regionally, and spatially.

[5] In this report the INFORM Risk 2018 was used for calculation of hazard component score distributions

6.1.2.1 Monthly Distribution of Floods Globally

Figure 14 shows the monthly global distribution of floods. Globally, floods are recorded all year around with a minimum of 6% rate of occurrence in February, while June, July and Aug are experiencing more events.

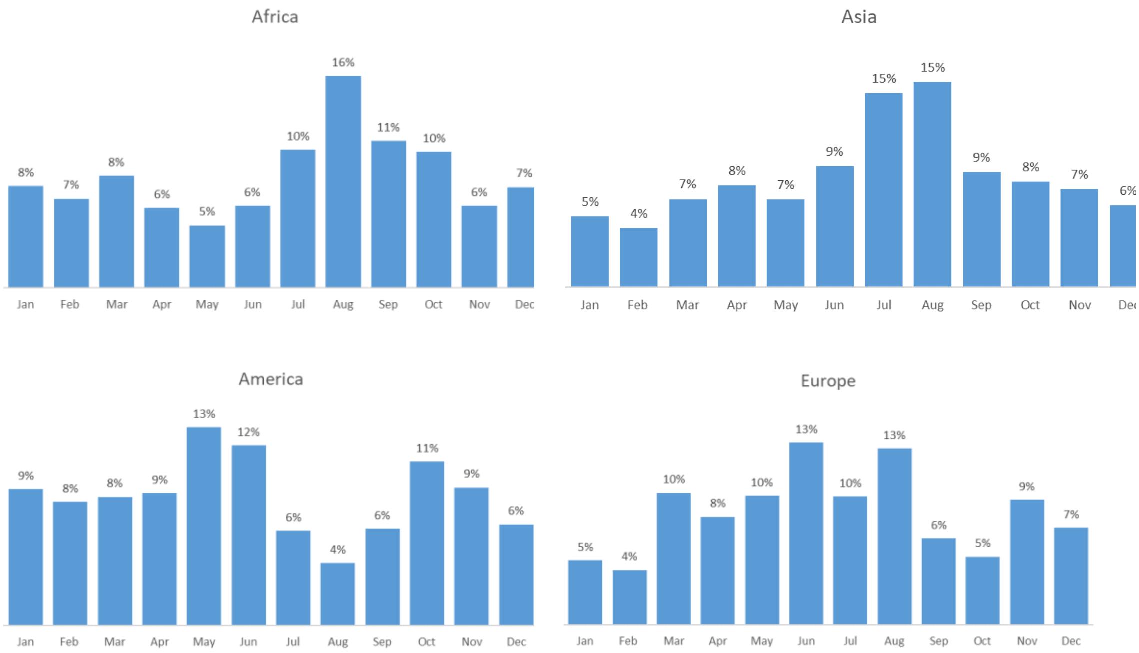
Figure 14: Monthly Distribution of Global Flood



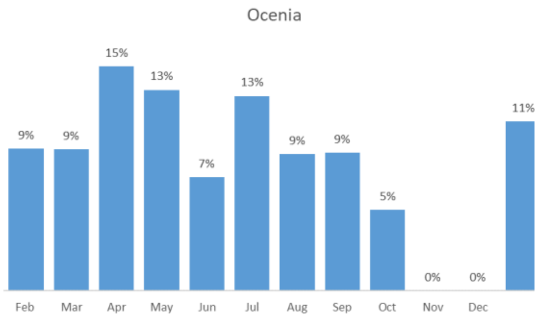
Source: authors

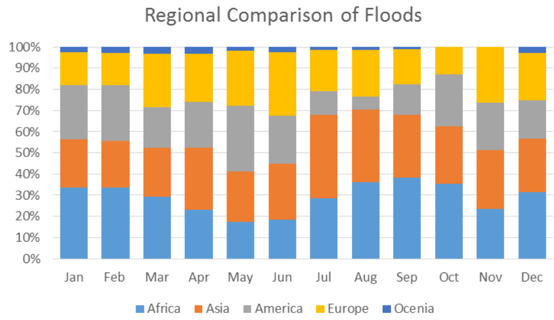
6.1.2.2 Monthly Distribution of Floods by Regions

Figure 15. Monthly distribution of floods by regions[6] and regional comparison



[6] UN Geographical Region Classification https://unstats.un.org/unsd/methodology/m49/





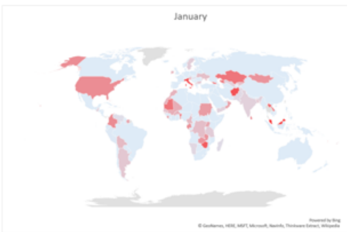
Source: authors

6.1.2.3 INFORM Seasonal Flood Scores: Monthly and Spatial Distribution

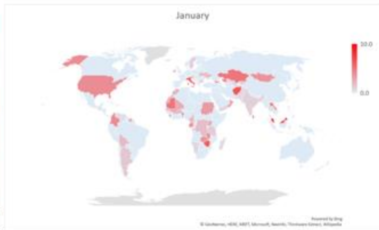
This section shows spatial distribution of INFORM flood scores, the list of top ten countries and their average by INFORM flood scores in each month. Observing those averages there is relatively low variation in the monthly difference.

Figure 16. Spatial Distribution of monthly floods

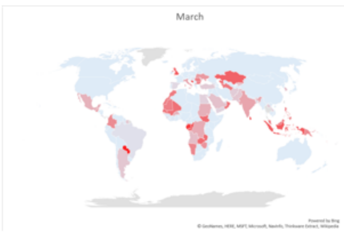
January	Countries	Scores
1	Indonesia	8
2	Brazil	8
3	Philippines	7
4	Mozambique	7
5	France	7
6	Zimbabwe	6
7	Ecuador	6
8	Bolivia	6
9	Malaysia	6
10	Malawi	5
	Avg	7



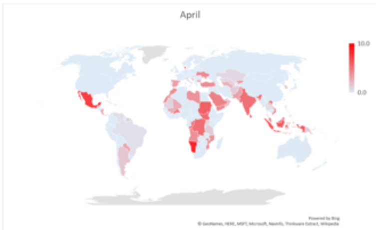
February	Countries	Score
1	Madagascar	8
2	Indonesia	7
3	Peru	7
4	Uzbekistan	6
5	Bolivia	6
6	Guyana	5
7	Zimbabwe	5
8	Zambia	5
9	Botswana	4
10	Brazil	4
	Avg	6



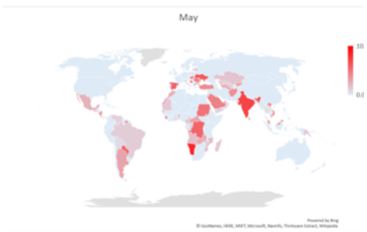
March	Countries	Score
1	Serbia	9
2	Madagascar	8
3	Hungary	8
4	Ecuador	7
5	Argentina	7
6	Uzbekistan	6
7	Belarus	6
8	Kazakhstan	6
9	Namibia	6
10	Colombia	6
	Avg	7



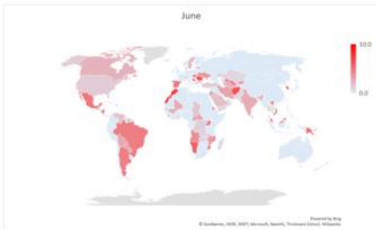
April	Countries	Score
1	Russia	8
2	Bosnia and Herzego	7
3	Colombia	7
4	Argentina	7
5	Belarus	6
6	Tanzania	6
7	Kyrgyzstan	6
8	Syria	5
9	Kenya	5
10	Afghanistan	5
	Avg	6



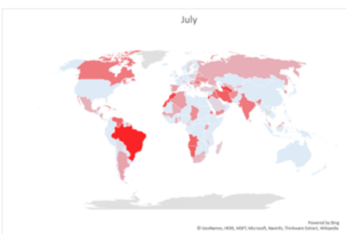
May	Countries	Score
1	Suriname	9
2	Russian Federati	8
3	Hungary	8
4	Afghanistan	7
5	Croatia	7
6	USA	6
7	Serbia	6
8	Kenya	6
9	Tajikistan	6
10	Tanzania	5
	Avg	7



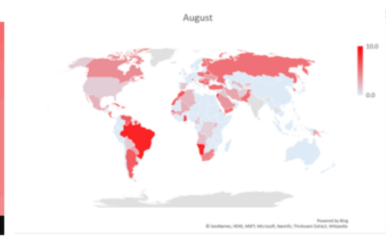
June	Countries	Score
1	Bangladesh	9
2	Suriname	9
3	China	8
4	Hungary	8
5	Romania	7
6	Slovakia	7
7	France	7
8	Russian Federati	6
9	Chile	6
10	Côte d'Ivoire	6
	Avg	7



July	Countries	Score
1	Bangladesh	10
2	India	9
3	Myanmar	8
4	Korea DPR	8
5	Romania	7
6	Ukraine	7
7	China	7
8	Nepal	7
9	Pakistan	6
10	Liberia	6
	Avg	7

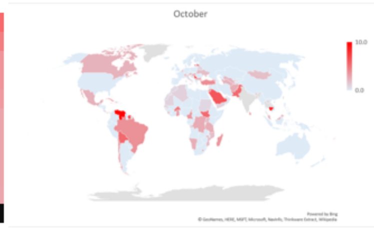


August	Countries	Score
1	Myanmar	10
2	Cambodia	10
3	Lao PDR	9
4	Pakistan	9
5	India	9
6	Russian Federat	8
7	South Sudan	8
8	Bangladesh	8
9	Nigeria	8
10	Sudan	8
	Avg	9



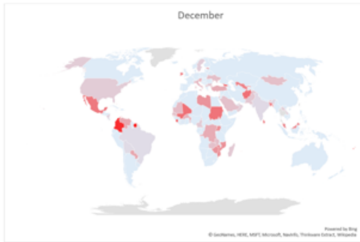
September	Countries	Score
1	Chad	8
2	Nigeria	8
3	Viet Nam	8
4	Mexico	7
5	Croatia	7
6	Thailand	7
7	India	6
8	Bangladesh	6
9	Mauritania	5
10	Azerbaijan	5
	Avg	7

October	Countries	Score
1	Viet Nam	10
2	Belize	8
3	South Sudan	7
4	Thailand	7
5	Somalia	6
6	Guatemala	6
7	Spain	6
8	Nicaragua	6
9	Honduras	6
10	Algeria	5
	Avg	7



November	Countries	Score
1	Iraq	10
2	Serbia	9
3	Viet Nam	8
4	Somalia	8
5	Congo	7
6	Thailand	7
7	France	7
8	Morocco	6
9	Cambodia	6
10	Argentina	6
	Avg	7

December	Countries	Score
1	Thailand	9
2	Egypt	8
3	Congo DR	7
4	Croatia	7
5	Malaysia	7
6	Sri Lanka	6
7	Indonesia	6
8	France	5
9	Papua New Guin	5
10	Tanzania	5
	Avg	7

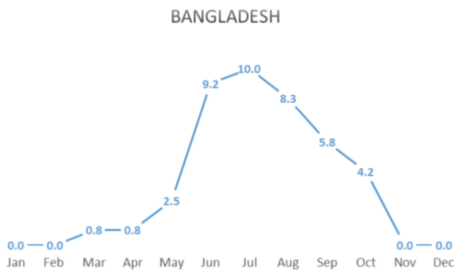
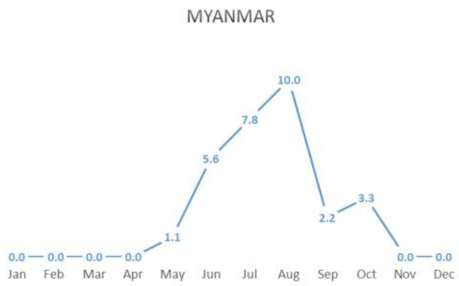


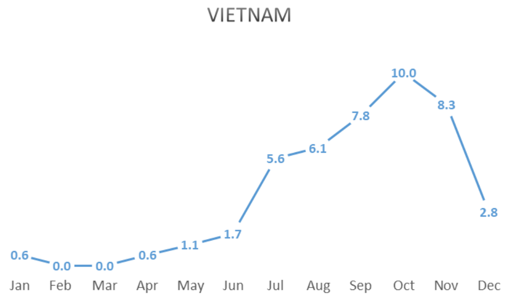
Source: authors

6.1.3 Case Study: Bangladesh, Myanmar, Viet Nam

Bangladesh (10), Myanmar (10), Viet Nam (10) ranked top in terms of flood exposure according to INFORM Risk. These countries were then considered as a case study to show their dynamics. The three countries under consideration though have a score of 10 according to INFORM Risk, however the peak month differs; with Bangladesh being July, Myanmar August and Viet Nam October.

Figure 17: Monthly dynamic of the INFORM Drought component: Bangladesh, Myanmar, Viet Nam

Country	INFORM annual score	INFORM monthly score
Bangladesh	10	
Myanmar	10	

Viet Nam	10	

Source: authors

6.2 Seasonality of tropical cyclones

Tropical cyclones (TCs) are among the most destructive weather, bringing with it torrential rainfall, storm surge thus causing threat to those living close to the coast (Ramsay, 2017b). TCs vary in Intensity, frequency and magnitude as well as exposure (Peduzzi et al., 2012), thus posting various degrees of threat.

Tropical cyclones can form in any month of the year. Studies has been conducted on the months within which TCs mostly occur. Ramsay (2017) noted that two-third of the storms in the Northern hemisphere happens in the months of June to November and peaks in August – September. The quietest period in the Northern hemisphere, January to March, happens to be the most active cyclone season in Southern Hemisphere. And vice-versa, the off season in the Southern hemisphere, i.e. June-November, coincides with the active period in the Northern hemisphere. Globally, the most active month of TCs are August to September, while the month of May see the fewest TCs (Peduzzi et al., 2012; Ramsay, 2017a). This shows there is a level of dynamics in the level of TCs occurrence throughout the year. However, fewer studies has looked into the dynamics of the TCs occurrence at the country level and the risk therein.

6.2.1 INFORM seasonal tropical cyclones: methodology and assessment

The probability of occurrence of tropical cyclones events are dynamic along with the frequency and magnitude within a year time (Peduzzi et al., 2012). In INFORM Risk Index, the annually averaged exposed population to tropical cyclones is calculated from the probabilistic hazard maps provided by the UNISDR Global Risk Assessment 2015 (UNISDR, 2015).

In order to assess the seasonality of tropical cyclones, the datasets from the International Best Track Archive for Climate Stewardship (IBTrACS) was considered, since it has a long records of TCs tracks recorded by month. For this study we used track's data from 2000 to 2019. The TCs tracks from IBTrACS are divided into 7 basins and sub basins (Matsui, Compo, & Hartten, 2011; Ramsay, 2017a) from which tropical cyclones originates. As first approximation, the TC tracks have been process by basins, assigning the same value to all the countries among the same basin. Regarding the TC magnitude, out of the seven wind speed categorization (Saffir-Simpson Hurricane Scale information[7]) in IBTrACS, the TCs within categories up to 1 and up to 3 where considered for the analysis in order to match the INFORM Risk indicators (Marin Ferrer et al.., 2017). We classified the TCs considering the maximum wind speed value for each of the TCs.

6.2.2 Findings and results

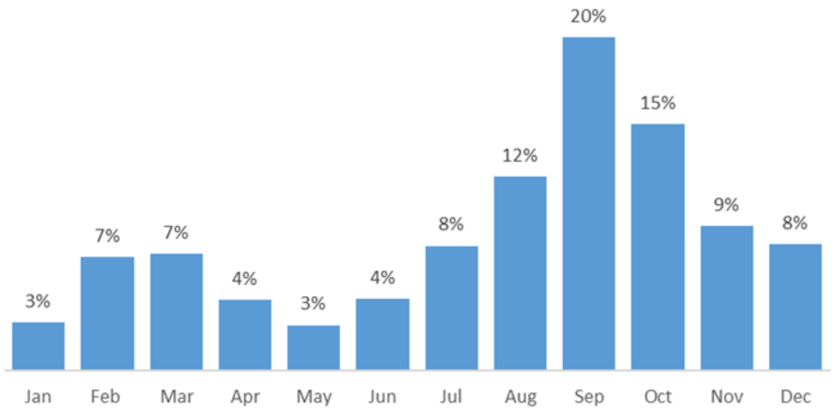
The final result of the weighted TCs is presented based on the monthly distribution globally, regionally, and spatially.

6.2.2.1 Monthly Distribution of Tropical Cyclones Globally

Figure 18 shows the monthly distribution of TCs globally. August, September and October account for almost half of the all TCs globally. This is similar to the findings of (Ramsay, 2017), where he noted that the most active months of TCs is August and September.

[7] The Saffir-Simpson Hurricane Wind Scale is a 1 to 5 rating based on a hurricane's sustained wind speed. https://www.nhc.noaa.gov/aboutsshws.php

Figure 18. Monthly Distribution of Tropical Cyclones globally

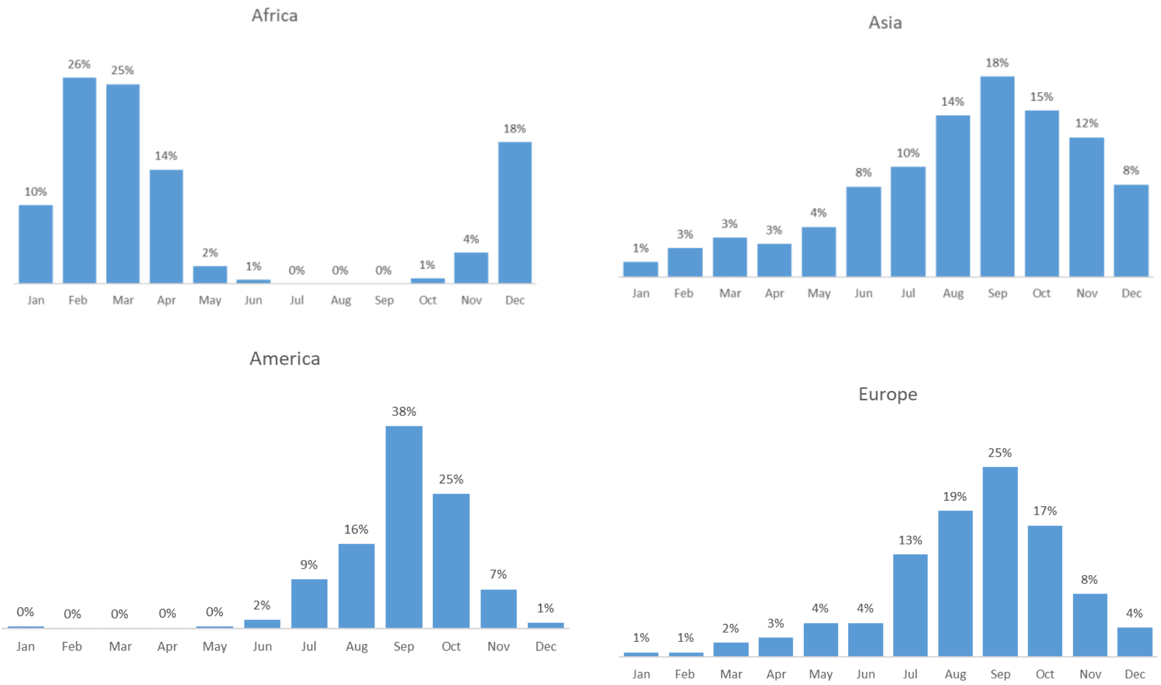


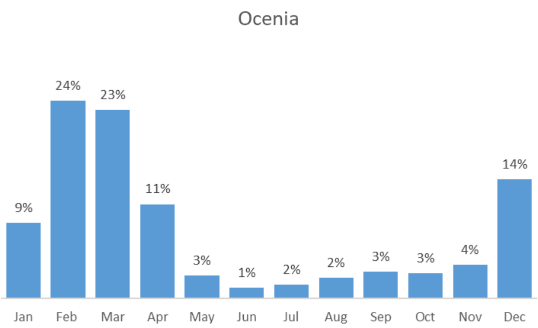
Source: authors

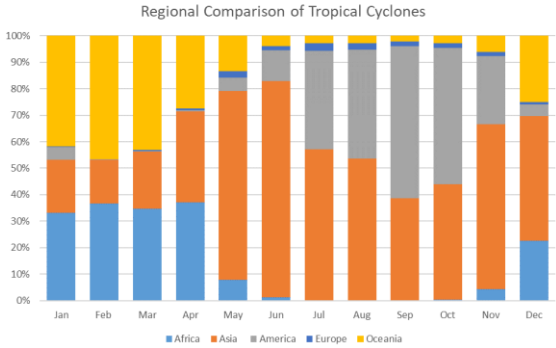
6.2.2.2 Monthly Distribution of Tropical Cyclones by Regions

Figure 19 shows the regional distribution of TCs and a comparison of the regional distribution of the events. Africa and Oceania experienced more TCs in February, March and April. On the contrary, Asia and America had more events in the later part of the year, August September and October, though Asia, experience the most events overall, the peak of event running from August till November.

Figure 19. Monthly Distribution of TCs by regions and regional comparison







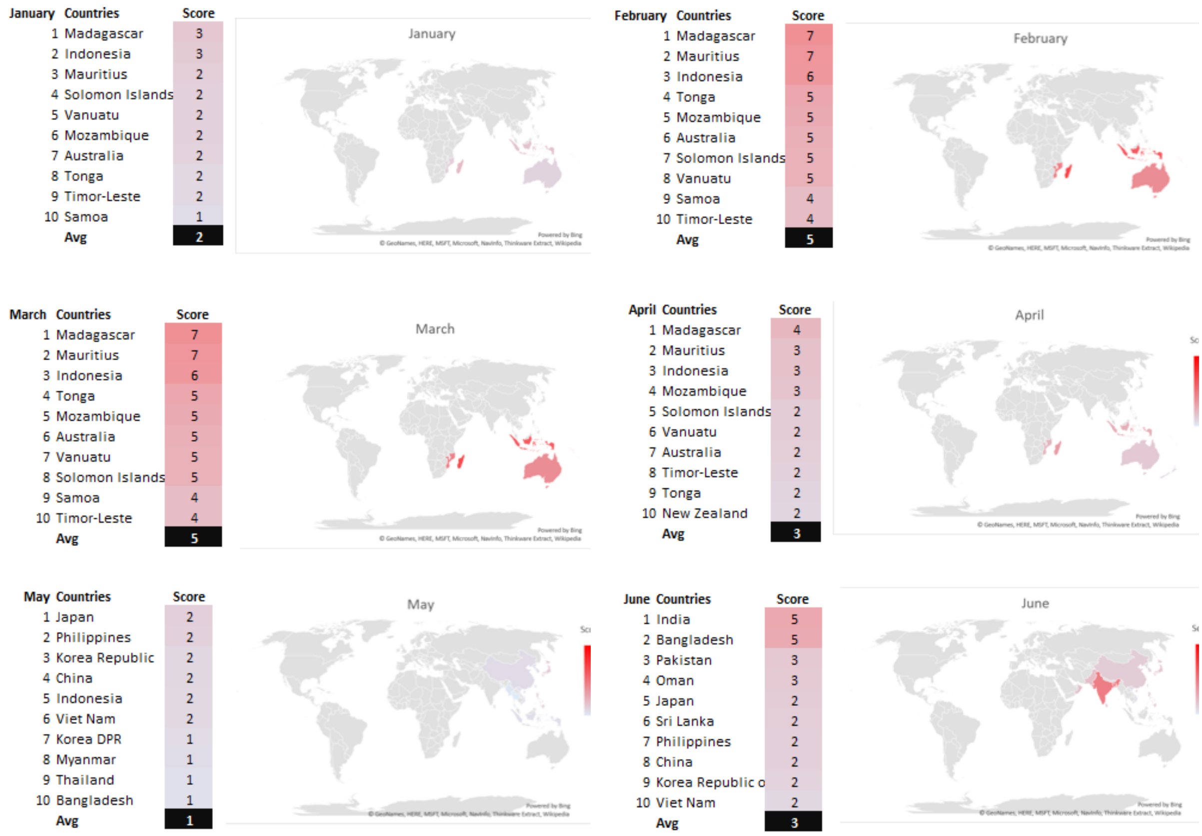
Source: authors

In particular, Africa and Oceania have a larger share of events in the early part of the year, January, February and March, while Asia experience more events from May to August, November and December. America peaks in September and October.

6.2.2.3 INFORM Seasonal Tropical Cyclone Scores: Monthly and Spatial Distribution

This section shows spatial distribution of INFORM tropical cyclone component scores, the list of top ten countries and their average by INFORM tropical cyclone in each month. Month September has more countries with score higher than 8, followed by August and October, meaning these months have more countries with high exposure to tropical cyclone hazard.

Figure 20: Monthly Distribution of Tropical Cyclones and top ten countries



January	Countries	Score
1	Madagascar	3
2	Indonesia	3
3	Mauritius	2
4	Solomon Islands	2
5	Vanuatu	2
6	Mozambique	2
7	Australia	2
8	Tonga	2
9	Timor-Leste	2
10	Samoa	1
	Avg	2

February	Countries	Score
1	Madagascar	7
2	Mauritius	7
3	Indonesia	6
4	Tonga	5
5	Mozambique	5
6	Australia	5
7	Solomon Islands	5
8	Vanuatu	5
9	Samoa	4
10	Timor-Leste	4
	Avg	5

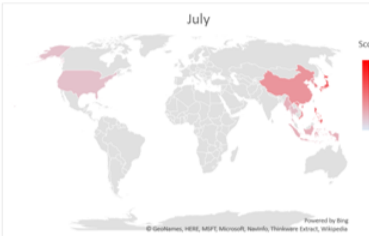
March	Countries	Score
1	Madagascar	7
2	Mauritius	7
3	Indonesia	6
4	Tonga	5
5	Mozambique	5
6	Australia	5
7	Vanuatu	5
8	Solomon Islands	5
9	Samoa	4
10	Timor-Leste	4
	Avg	5

April	Countries	Score
1	Madagascar	4
2	Mauritius	3
3	Indonesia	3
4	Mozambique	3
5	Solomon Islands	2
6	Vanuatu	2
7	Australia	2
8	Timor-Leste	2
9	Tonga	2
10	New Zealand	2
	Avg	3

May	Countries	Score
1	Japan	2
2	Philippines	2
3	Korea Republic	2
4	China	2
5	Indonesia	2
6	Viet Nam	2
7	Korea DPR	1
8	Myanmar	1
9	Thailand	1
10	Bangladesh	1
	Avg	1

June	Countries	Score
1	India	5
2	Bangladesh	5
3	Pakistan	3
4	Oman	3
5	Japan	2
6	Sri Lanka	2
7	Philippines	2
8	China	2
9	Korea Republic o	2
10	Viet Nam	2
	Avg	3

July	Countries	Score
1	Japan	6
2	Philippines	6
3	Korea Republic o	5
4	Viet Nam	5
5	China	4
6	Korea DPR	4
7	Indonesia	3
8	Myanmar	3
9	Thailand	3
10	USA	3
	Avg	4



August	Countries	Score
1	Japan	8
2	Philippines	8
3	Korea Republic o	7
4	Viet Nam	6
5	China	6
6	Korea DPR	5
7	Myanmar	5
8	Indonesia	5
9	Thailand	4
10	United States of	4
	Avg	6

September	Countries	Score
1	Japan	10
2	Philippines	10
3	Bahamas	9
4	Korea Republic o	9
5	Antigua and Barb	8
6	China	8
7	Cuba	8
8	Viet Nam	8
9	Dominican Repu	8
10	Jamaica	7
	Avg	8

October	Countries	Score
1	Japan	7
2	Philippines	7
3	Mexico	6
4	China	6
5	Korea Republic o	6
6	Bahamas	6
7	Viet Nam	5
8	United States of	5
9	Antigua and Barb	5
10	Cuba	5
	Avg	6

November	Countries	Score
1	India	7
2	Bangladesh	6
3	Japan	4
4	Oman	4
5	Pakistan	4
6	Philippines	4
7	China	4
8	Sri Lanka	4
9	Korea Republic o	3
10	Viet Nam	3
	Avg	4

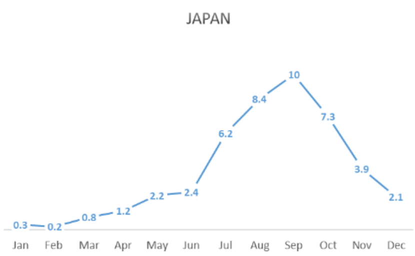
December	Countries	Score
1	Madagascar	5
2	Indonesia	5
3	Mauritius	4
4	India	4
5	Bangladesh	4
6	Mozambique	4
7	Solomon Islands	3
8	Vanuatu	3
9	Tonga	3
10	Australia	3
	Avg	4

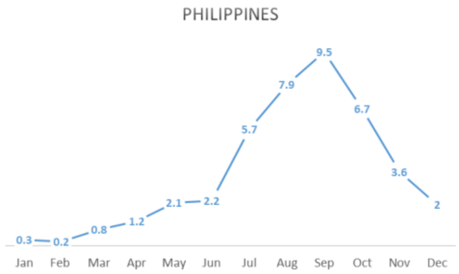
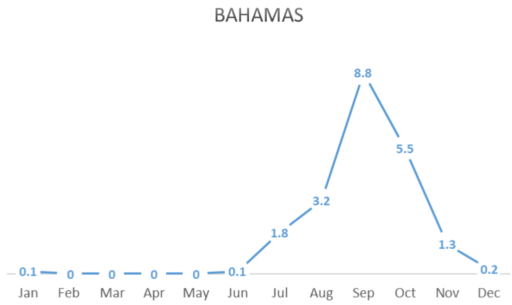
Source: authors

6.2.3 Case Studies: Japan, Philippine and Bahamas

Japan (10), Philippine (9.5) and Bahamas (8.8) have the highest INFORM tropical cyclone components scores. The three countries under consideration have September as the peak months, even though the basin of origins differs (See **Figure 21**).

Figure 21. Monthly dynamic of the INFORM TCs component: Japan, Philippines, Bahamas

Country	INFORM annual score	INFORM monthly score
Japan	10	

Philippines	9.5	
Bahamas	8.8	

Source: authors

6.3 Seasonality of droughts

Drought is a recurrent climate event that results from a shortfall in precipitation over an extended period of time.

Droughts are commonly grouped into three basic types. A **meteorological drought** is generally defined as a period with an abnormal precipitation deficit, in relation to the long-term average conditions for a region. When a meteorological drought leads to a soil moisture deficit that limits water availability for natural vegetation and crops, the result is an **agricultural drought**. A **hydrological drought** is associated with the effects of periods of shortfalls of precipitation, on surface or sub-surface water supply (JRC, EDO).

6.3.1 INFORM seasonal drought: methodology and assessment

In INFORM Risk Index, the exposure to drought (Marin Ferrer et al., 2017) is measured by a combination of two factors:

1. risk for drought, calculated as the probability for an agricultural drought and
2. population affected by droughts in recent years.

To assess the monthly distribution of drought events, we used the data from the Anomaly Hotspots of Agricultural Production (ASAP) (Rembold et al., 2019)**.** ASAP is an online support system for early warning on hotspots for agricultural production anomaly, which was developed by JRC for food crises prevention and response. The dataset contains warnings about low or delayed vegetation performance at sub-national level for crops and rangelands. The warning classification scheme is applied globally and is based 10-day rainfall estimate (RFE) products of the European Centre for Medium-Range Weather Forecasts (ECMWF) at 0.25° spatial resolution and observations of the Normalized Difference Vegetation Index (NDVI) from the European Space Agency MetOp mission (operated by EUMETSAT, European Organization for the Exploitation of Meteorological Satellites) at 1 km spatial resolution.. The results are reliable warning of hydrological stress for agricultural production and the warning level ranges from 1 to 4. The warning group 2, 3, and 4 were considered as drought events for this analysis.

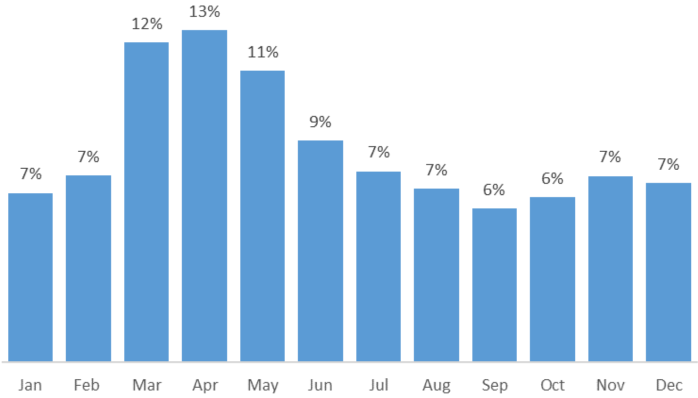
6.3.2 Findings and results

The outcome analysis presented in this section is based on the monthly distribution of events, globally, regionally and the monthly spatial weights based on the average of INFORM drought component score of top 10 countries.

6.3.2.1 Monthly distribution of Drought Globally

Figure 22 shows the monthly global distribution of droughts. Globally, droughts are recorded all year around with a minimum of 6%, while March, April and May experiencing more events.

Figure 22: Monthly distribution of Global Drought

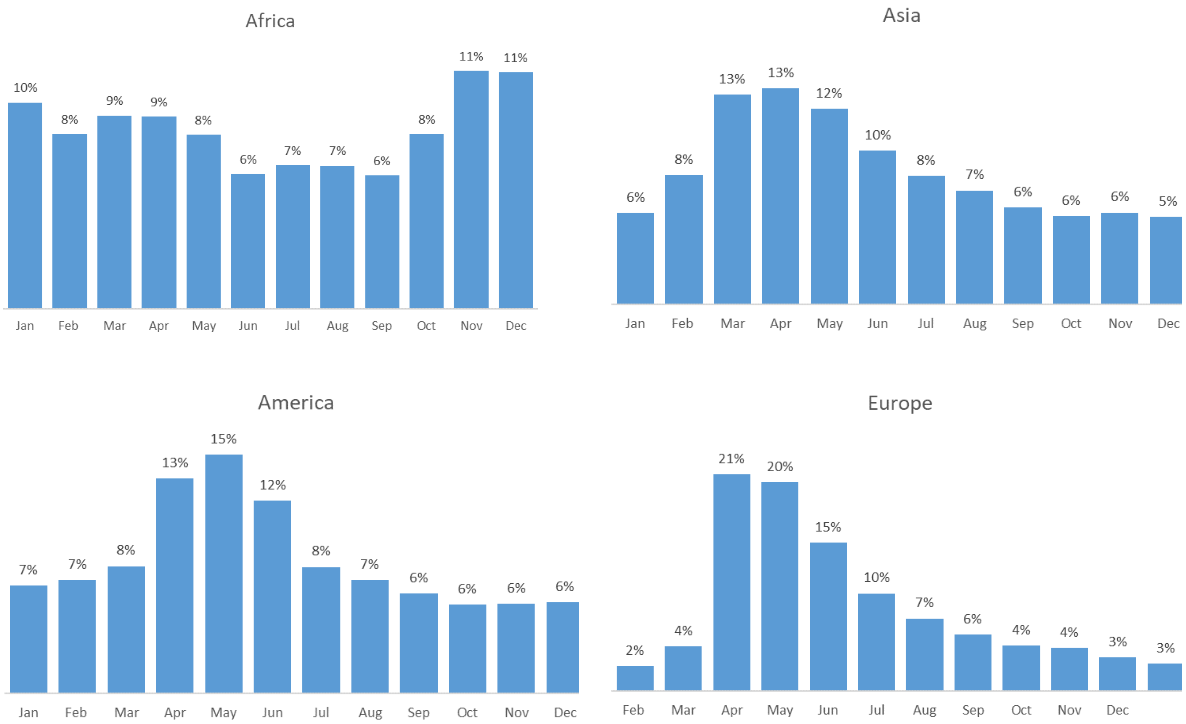


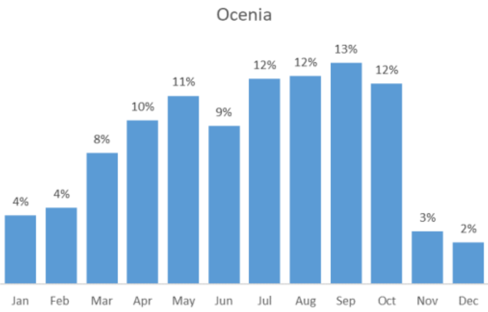
Source: authors

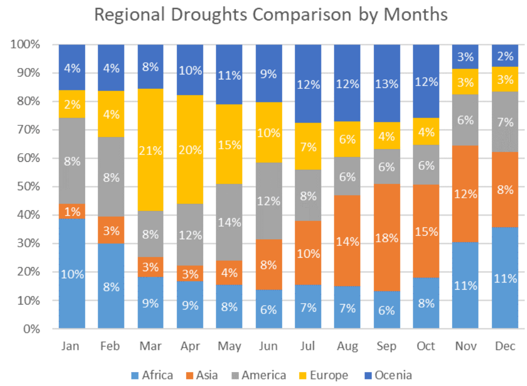
6.3.2.2 Monthly distribution of Drought by Regions

Drought events in each regions shows similarities in pattern in Asia, Europe, Oceania and America, with April being the peak month, in contrast, Africa shows a different pattern, having its peak in the early and late part of the year.

Figure 23: Monthly Distribution of Droughts by Regions







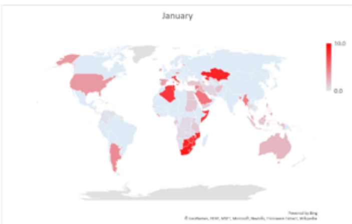
Source: authors

6.3.2.3 INFORM Seasonal Drought Scores: Monthly and Spatial Distribution

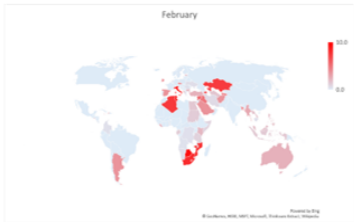
This section shows spatial distribution of the INFORM drought component scores and the monthly average of top ten countries using the INFORM drought component rating. Observing those averages there is relatively low variation in monthly differences

Figure 24: Monthly Distribution of Spatial Droughts and Average scores

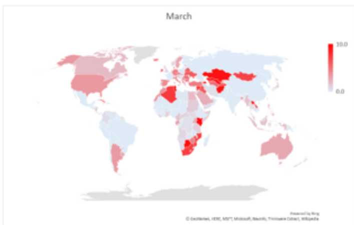
January	Countries	Score
1	Namibia	9
2	South Africa	9
3	Botswana	8
4	Jordan	8
5	Tunisia	8
6	Morocco	8
7	Algeria	8
8	Somalia	8
9	Israel	8
10	Libya	8
	Avg	8



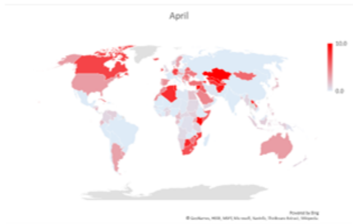
February	Countries	Score
1	Botswana	9
2	Libya	9
3	Israel	9
4	Tunisia	9
5	South Africa	8
6	Morocco	8
7	Namibia	8
8	Algeria	8
9	Jordan	8
10	Azerbaijan	7
	Avg	8



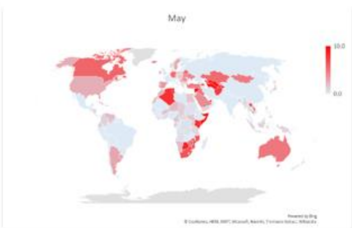
March	Countries	Score
1	Kazakhstan	10
2	Jordan	10
3	Tunisia	9
4	Uzbekistan	9
5	Syria	9
6	Azerbaijan	9
7	Afghanistan	9
8	Tajikistan	9
9	Kyrgyzstan	9
10	Botswana	8
	Avg	9



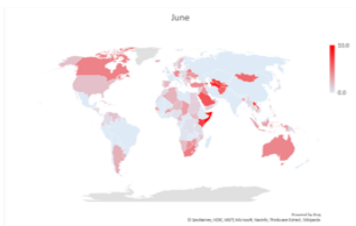
April	Countries	Score
1	Kazakhstan	10
2	Jordan	10
3	Tunisia	10
4	Uzbekistan	10
5	Syria	10
6	Azerbaijan	9
7	Afghanistan	9
8	Tajikistan	9
9	Kyrgyzstan	9
10	Botswana	8
	Avg	9



May	Countries	Score
1	Syria	10
2	Tajikistan	10
3	Uzbekistan	10
4	Somalia	9
5	Turkmenistan	9
6	Botswana	8
7	Tunisia	8
8	Azerbaijan	8
9	Kazakhstan	8
10	UAE	8
	Avg	9

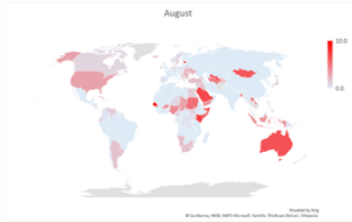


June	Countries	Score
1	Somalia	10
2	Turkmenistan	8
3	Kyrgyzstan	8
4	Tajikistan	8
5	Kazakhstan	7
6	Uzbekistan	7
7	Saudi Arabia	6
8	Azerbaijan	6
9	Egypt	6
10	Afghanistan	6
	Avg	7

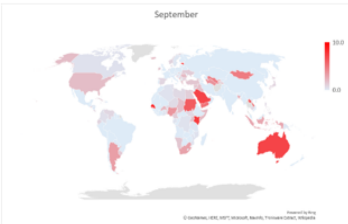


July	Countries	Score
1	Eritrea	10
2	Senegal	8
3	Saudi Arabia	8
4	Mongolia	8
5	Mauritania	7
6	Kazakhstan	7
7	Moldova	7
8	Kyrgyzstan	7
9	Somalia	7
10	Australia	6
	Avg	8

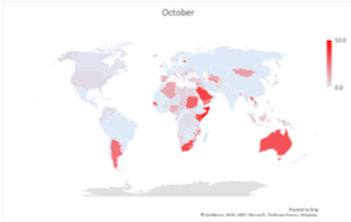
August	Countries	Score
1	Eritrea	10
2	Senegal	10
3	Mauritania	10
4	Mongolia	8
5	Kazakhstan	7
6	Saudi Arabia	7
7	Australia	6
8	Moldova	6
9	Uzbekistan	6
10	Kyrgyzstan	6
	Avg	8



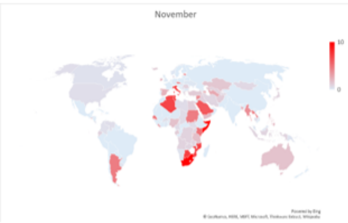
September	Countries	Score
1	Eritrea	9
2	Senegal	9
3	Kazakhstan	7
4	Australia	7
5	Saudi Arabia	7
6	Mauritania	7
7	Kyrgyzstan	6
8	Sudan	6
9	Mongolia	6
10	Yemen	5
	Avg	7



October	Countries	Score
1	Somalia	9
2	Eritrea	9
3	Saudi Arabia	7
4	Kazakhstan	7
5	South Africa	7
6	Mauritania	7
7	Kyrgyzstan	7
8	Australia	6
9	Senegal	6
10	Sudan	6
	Avg	7



November	Countries	Score
1	Somalia	10
2	South Africa	10
3	Tunisia	8
4	Israel	8
5	Botswana	7
6	Morocco	7
7	Algeria	7
8	Namibia	7
9	Saudi Arabia	6
10	Zimbabwe	6
	Avg	8



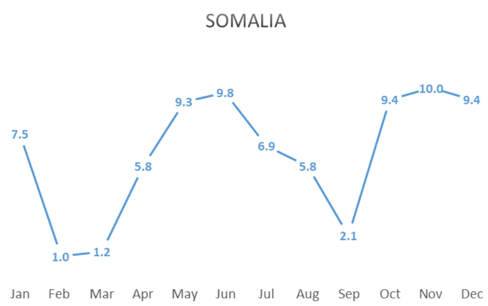
December	Countries	Score
1	Israel	10
2	Botswana	10
3	Zimbabwe	10
4	South Africa	10
5	Somalia	9
6	Morocco	9
7	Namibia	9
8	Tunisia	8
9	Algeria	8
10	Jordan	7
	Avg	9

Source: authors

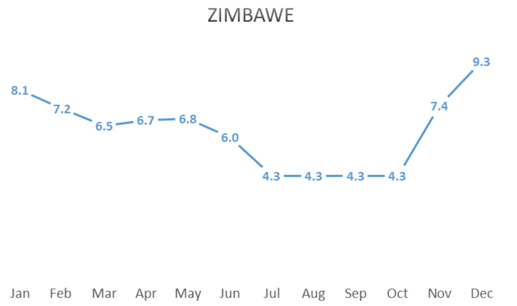
6.3.3 Case studies: Somalia, Zimbabwe, Mauritania

Somalia (10), Zimbabwe (9.3) and Mauritania (8.6) ranked top in terms of exposure to drought hazards according to INFORM Risk Index. This countries were then considered as a case study to show their seasonal dynamics. The three countries under consideration have distinctive peak months. Somalia though with a hazard score of 10 has the peak months in November (10) and June (9.8), while Zimbabwe with an INFORM drought component score of 9.3 has the peak in December (9.3) (See **Figure 25**). Mauritania on the contrary has August as its peak month and a constant low dynamic score in the beginning of the year (from January to June).

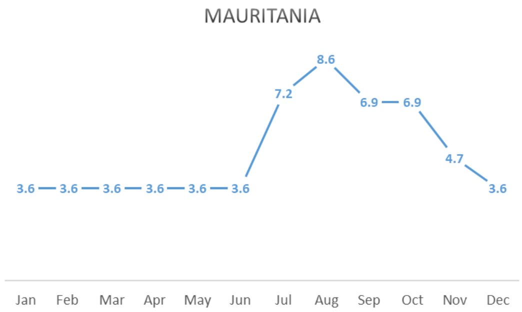
Figure 25. Monthly dynamic of the INFORM Drought component: Somalia, Zimbabwe, Mauritania

Country	INFORM annual score	INFORM monthly score
Somalia	10	

Zimbabwe 9.3



Mauritania 8.6

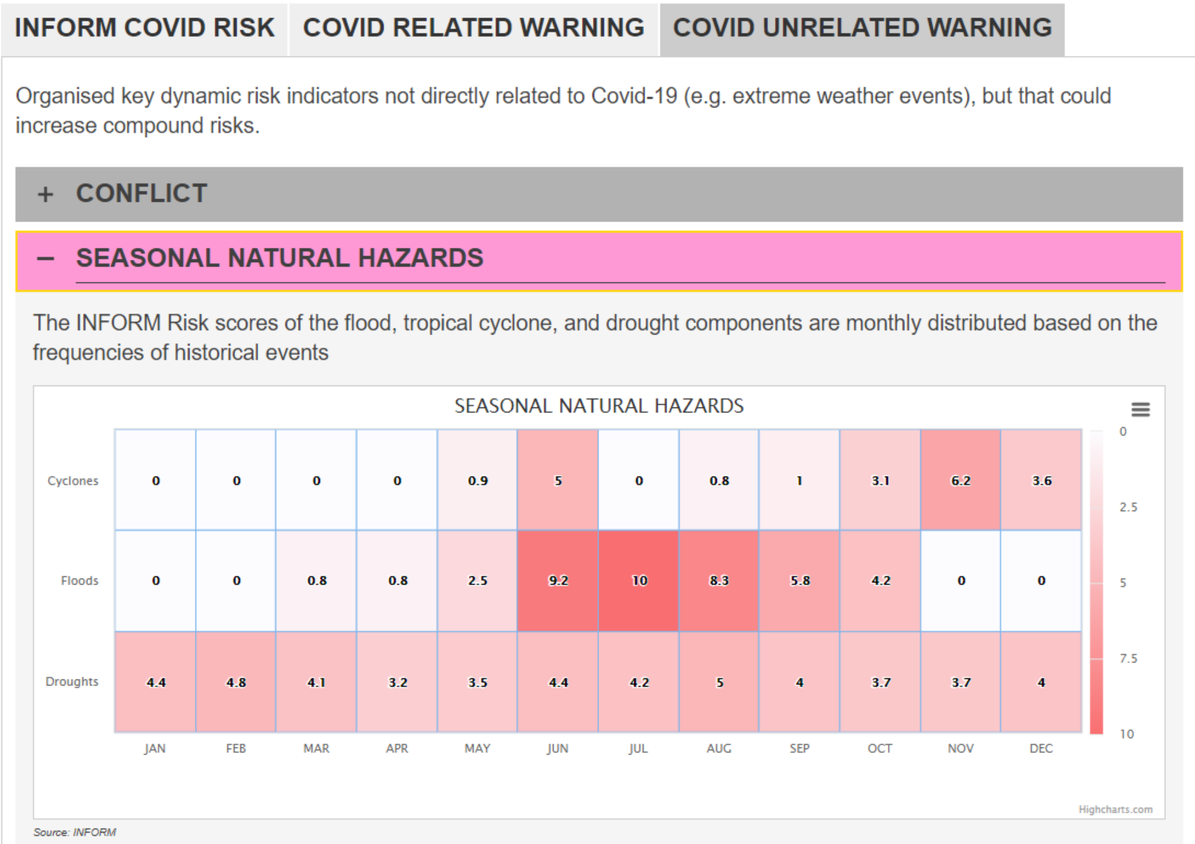


Source: authors

6.4 Presentation of the seasonal hazards data in the INFORM Covid-19 Warning

The INFORM seasonal hazards data are presented for each country in the “Covid unrelated warning” section. The aims is to provide an indication of the expected level of exposure to climate hazards in the coming months.

Figure 26. Seasonal natural hazards



Source: INFORM website

7 From the monitoring to the impact predictor

The dashboard provides a first level of aggregation of the risk drivers. However, it doesn't give any indications on the possible impact, such as possible occurrence of new humanitarian crises or deterioration of ongoing crises.

The challenge is to identify potential crisis scenarios from the risk drivers we are monitoring?

First, we need to define the **interlinkages** between key drivers of humanitarian crises. Risk drivers are connected to each other in a causal relation, from the triggers to the impacts.

We need also to add the **time dimension** to the cause-consequence pathway. The consequence of a change in one or more drivers will (might) be observed with a delay that depends on many factors including the type of driver, the magnitude of the change and the baseline conditions. This allows to define the *time of the potential impact*.

Finally, we need to link the risk drivers with the potential **impacts** in order to define the *scale of impacts* and the *certainty.*

All these elements helps to identify **compounding risks**. The increased public health crisis caused by the COVID-19 pandemic is compounding existing crises. This includes conflict, food insecurity, climatic hazardous events and displacement. According to the INFORM Severity Index, half of the countries under the Humanitarian Response Plan (HRP) have increased in severity since the beginning of the year (OCHA, 2021).

Herein we present a case study on tentative mock-up of impact predictor (**Figure 5**) using casual loop approach based on INFORM Covid-19 Warning dashboard with monitoring data available from August 2020 to March 2021.

7.1 Causal loop approach

Dynamic data needs dynamic methods to exploit their potentiality. We experimented the causal loop approach for building the scenarios of future humanitarian crises. Causal loop diagrams (CLDs) are tools to depict the causal connections between components of a system, and illustrate how changes in one component cascade in changes in others and back to itself, via feedback loops, potentially affecting the status of the entire system (Kirkwood, 1998).

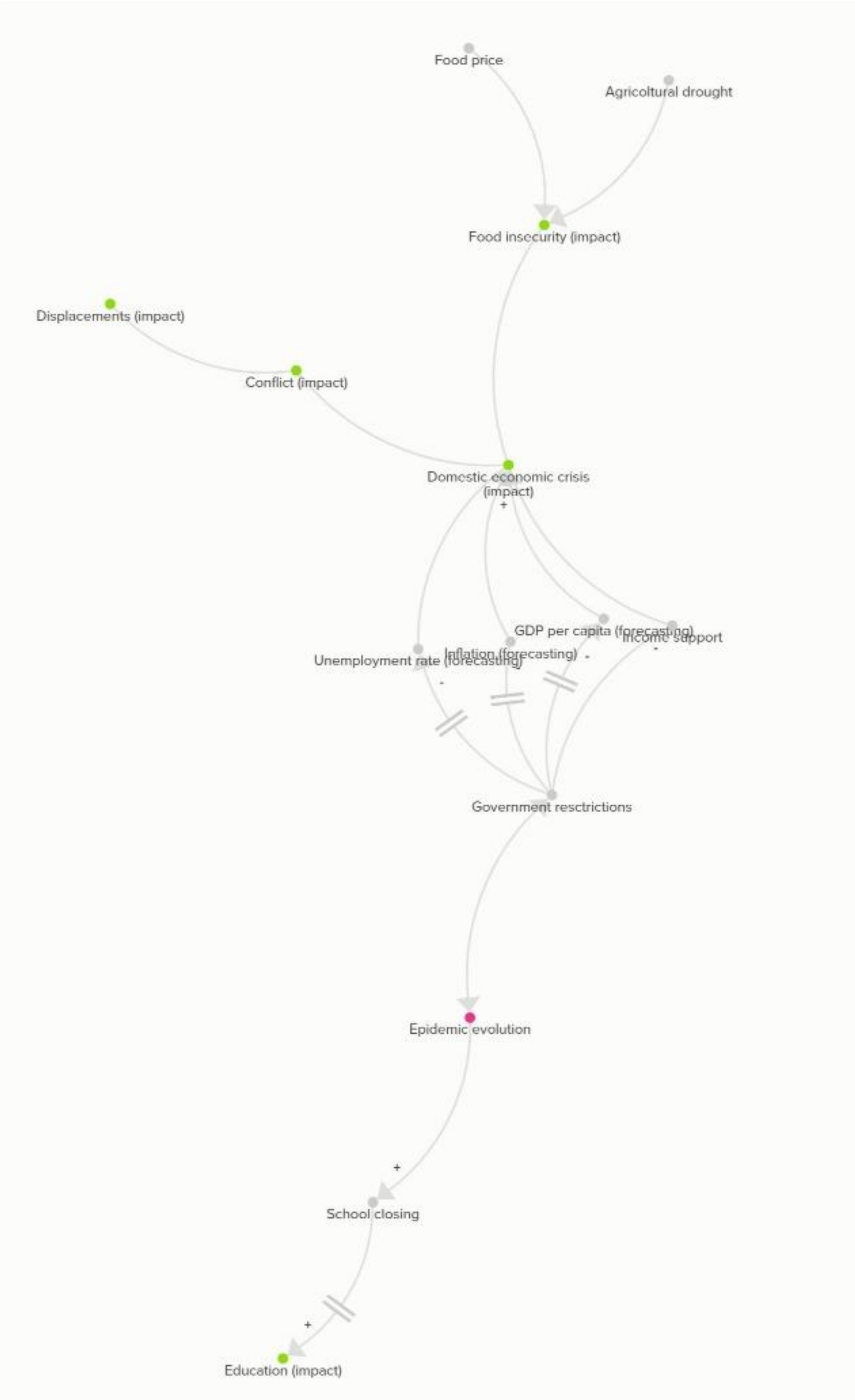
With the causal loop approach we are able to connect certain changes in monitored risk data to specific types of future outcomes. For example, an increase of the Covid-19 incidence rate would generate restriction and closures in order to contain the infections, and as consequence people will start to suffer of economic restrictions, access to food and lack of education, all factors that could lead to a new crisis or increase the severity of an ongoing crisis. This can be of course generalised to others drivers than Covid-19 pandemic ones. For example, droughts not only cause food and nutrition insecurity, they also increase the burden of waterborne diseases, and can lead to displacement, or school dropouts.

ACAPS has a long experience of conducting scenario building exercise in the humanitarian contexts to predict impacts on people affected. ACAPS proposes a step by step methodology (ACAPS, 2016) to build scenarios, based on the chain of plausibility approach.

Defining the real problem is the starting point of the scenario building exercise. The INFORM Covid-19 Warning aims to "identify, monitor and anticipate where Covid-19 could compound existing risks to cause new, or exacerbate existing, humanitarian crises". Having articulated the problem, we have identified key variables (risk drivers) that are likely to trigger a chain of events resulting in a humanitarian impact (Chapter 5.2, Annex 2).

Once the variables are selected, we identify the relationships between them. A relationship implies that a change in direction of variable A impacts the behaviour of variable B. The **Figure 27** shows the map of the causal relations used in the test.

Figure 27. The causal loop diagram illustrating the interacting variables related to the threat of COVID-19.



Source: authors

Nine variables, starting with the Covid-19 as a trigger (14 days Covid-19 case notification rate per 100k), were identified as the main factors determining the humanitarian consequences of Covid-19: Epidemic evolution, Government restrictions, Unemployment rate, Inflation, GDP per capita, Income support, school closing, Food price, Agricultural drought.

The selected impact types were (Chapter 3.4):

- Health,
- Domestic economic crisis,
- Food insecurity,
- Education,
- Conflict,
- Displacements.

The causal loop approach finds its application in some complex models, such as Bayesian network models or System dynamics (SD) models that have been recently experimented in different humanitarian contexts. For example, Foresight model[8] from Danish Refugee Council and IBM aimed at providing long term forecasts on forced displacement volumes and causal analysis of drivers of displacement.

Bayesian network models determine where those linkages can be found in the data and what the values of the linkages are (Kjærum, 2020).

System dynamics (SD) models provide foresights about situational behaviour changes in a system over time (Hodicky, 2020). SD modelling has demonstrated considerable value across a number of different fields, ranging from ecology to economics, and recently to humanitarian crises (Queenan, 2020; Herrera de Leon, 2020), to help understanding and predicting the dynamic behaviour of complex systems (Currie, 2018).

7.2 Description of the implementation and first results

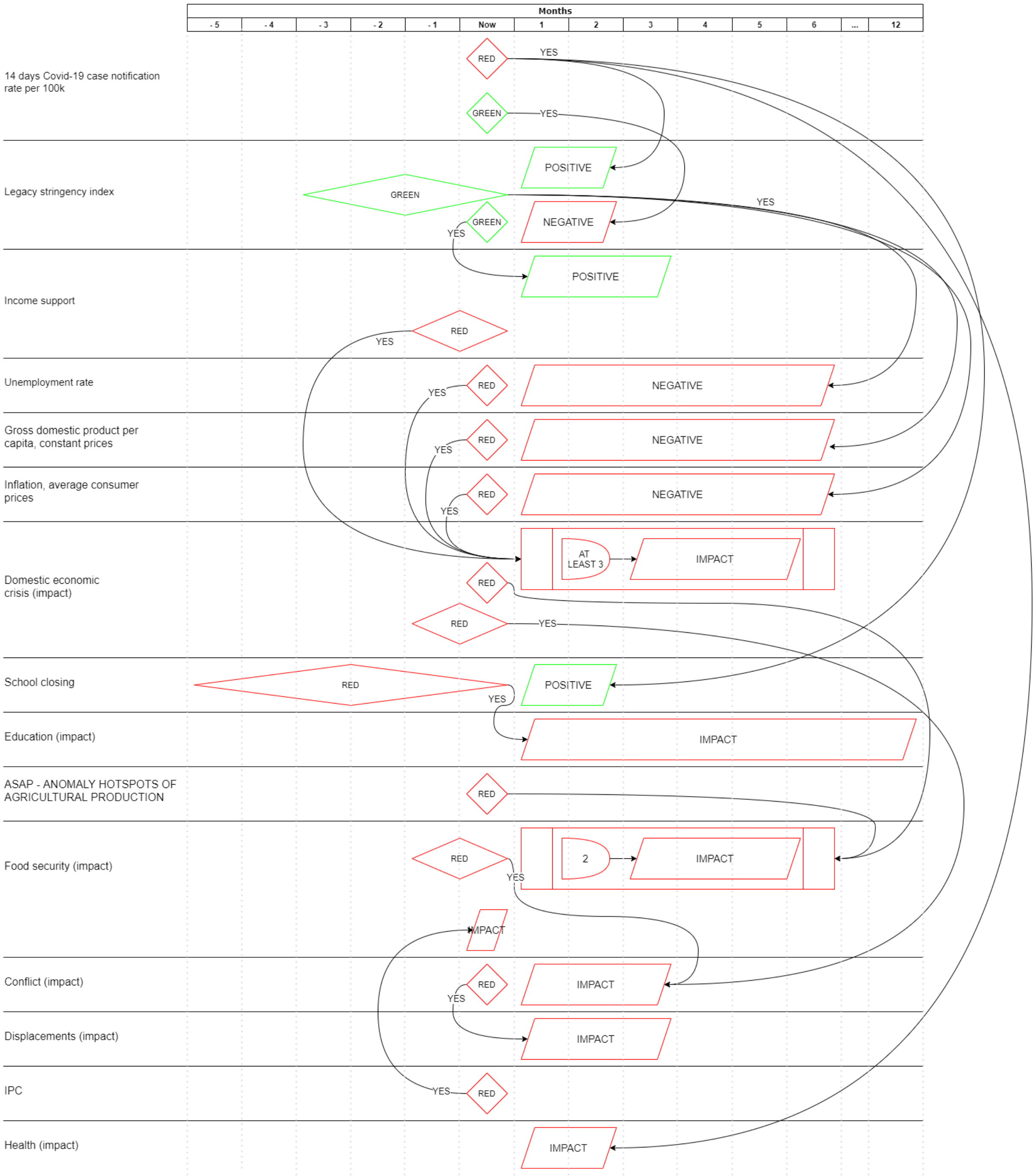
We implemented causal loop map of the Covid-19 in the INFORM system for the automatic calculation of the potential impacts. The implementation takes into consideration several factors based on data already collected and data generated by the model for each country.

The implemented diagram (**Figure 28**) with the pre-defined meanings of the symbols (**Table 2**) takes into account negative (i.e. increasing of the Covid-19 incidence) and positive (i.e. releasing of the containment measures) consequence on the connected risk drivers and the delay with these consequence happen (i.e., 4 consecutive months of government restrictions will generate an impact on the economic variables).

The diagram is developed observing a time frame that spans across several months, starting in the past. The algorithm starts evaluating conditions today, for each country and indicator, verifying the indicator's actual value or the continuity of that trend value for a certain number of months up to today. Each evaluation generates either a series of data to be evaluated in subsequent iterations or an impact. For certain impacts a group of indicators must be evaluated together. At the end of the evaluation for the current month the process is repeated considering the current month = current month +1, up to 2 months in the future.

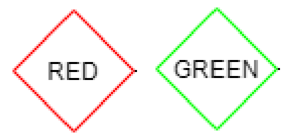
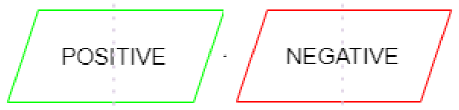
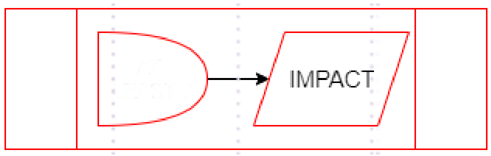
[8] https://mixedmigration.org/wp-content/uploads/2018/07/MM4Sight_1pager.pdf

Figure 28. Diagram of the causal loop approach tested for predicting scenarios



Source: authors

Table 2: Legend of the causal loop schema

	Evaluate a condition and produce a record for the specified indicator. The colour indicates whether the value must be under or above the specific threshold. The amplitude indicates for how long (months) the condition must be satisfied.
	The record generated after the condition evaluation. The value is determined by the polarity, and it will be used for evaluation in subsequent iterations. Its amplitude determines how many records will be produced, one for each month.
	The record generated after the condition evaluation, the impact for a specific indicator means a warning should be raised for that area. The impact could depend on more than one conditions.
	The process verifies that more than one condition are satisfied at the same time before producing an impact.

Source: Authors

We then combined the predicted impacts produced by the causal loop approach with the others predictions available in the INFORM Covid-19 Warning, such as seasonal hazards and IPC Food insecurity.

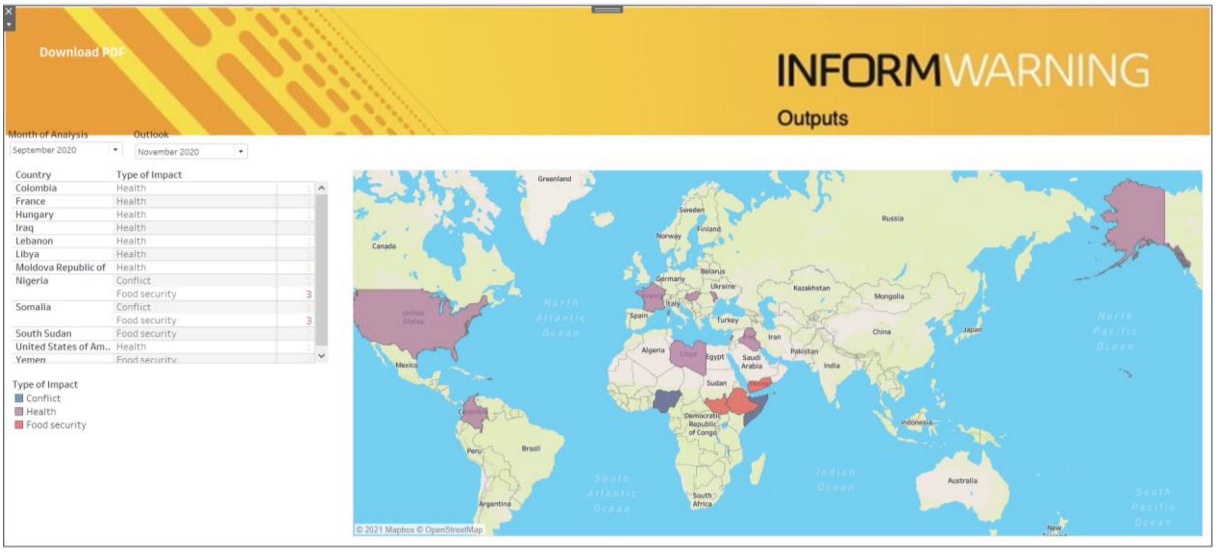
The algorithm has been migrated into an analytics platform Tableau[9] where all the inputs data and the predicted ones have been connected in order to be displayed in a dashboard. The **Figure 29** shows the mock-up with the first results of the tested approach. The goal of the prediction module of INFORM Covid-19 Warning is to present an overview of predictions from:

1. system-generated predictive information and
2. already existing, external models.

The tool allows to visualise the countries for which there are predicted impacts in a list and in the map, and to select the outlook from 1 to 12 months. It also allows to move back to the past predictions in order to assess their reliability.

[9] https://www.tableau.com/

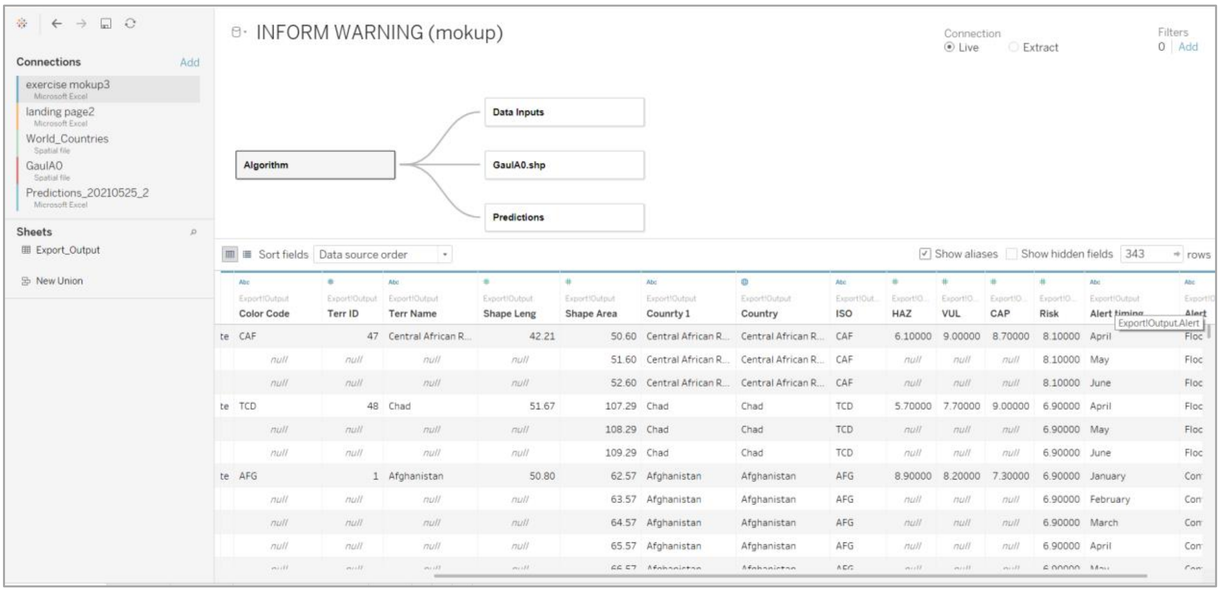
Figure 29. Mock-up of the impact prediction model in Tableau



Source: authors

The structure of the analytics database shown in **Figure 30** facilitates the connection of above mentioned collected data inputs and the combinations of conditions that determined the Warning for each specific field with predictions.

Figure 30: The structure of the analytics database



8 Lessons learned and remaining challenges

When you need to deal with a large set of data and indicators as in this project, the most important thing is to have a solid conceptual framework. This is the precondition in order to properly collate the data and provide an interpretation key. The conceptual framework already developed for the INFORM Covid-19 Risk Index provided the starting point for the identification of risk factors that require monitoring. Showing the potential impact of Covid-19 before the outbreak, it provides the baseline for the monitoring indicators presented in the "Covid-19 related risks" section.

The monitoring indicators have been divided in two groups:

— Covid-19 related risks: indicators directly and indirectly relating to Covid-19.

— Covid-19 unrelated risks: indicators not directly related to Covid-19, but that could increase compound risks.

The effort to develop the INFORM Covid-19 Warning gave us a clear understanding of the COVID-19 data landscape and the broader availability of inputs for modelling.

However, many challenges remain:

- Considerable **data gaps** remain, with some drivers better represented than others.
- Integration of **global, regional** and **local** information.
- How to define the **warnings** (risk thresholds, triggers) and identify the relevant indicators.
- **Calibration** of the thresholds and **validation** of the warnings.
- How to guarantee the **comparability** among the different countries/warnings.
- Quantifying **interactions between different drivers**.
- How to link **risk information** with **early actions**.

All these elements, the lessons learned and the remaining challenges, are helping the conceptualisation and the development of the INFORM Warning.

9 Conclusions

INFORM has developed into the suite of tools fit for decision making in different phases of disaster risk management. The most known is INFORM Risk index, existing from 2014, for the prevention, INFORM Warning, at the moment in development stage, for the preparedness and early warning and the INFORM Severity Index for the response. The most interesting is that each of these tools has its Covid-19 variant, showing how flexible INFORM can be.

In particular, the development of INFORM Covid-19 Warning acts as an accelerated and conceptually ring-fenced case study that can contribute to the future development of the broader INFORM WARNING product.

The development has been triggered with Covid-19 emergency in 2020 and further worries of humanitarian community on when and how the risk of an overwhelming humanitarian impact is materializing.

The INFORM COVID-19 Warning allows users to monitor how risks of health and humanitarian impacts are changing dynamically. As a result, it will be more suited to support decisions on ongoing response and preparedness.

The tool (risk monitor and dashboard module) is publicly available on the INFORM website (https://drmkc.jrc.ec.europa.eu/inform-index/INFORM-Covid-19/INFORM-Covid-19-Warning-beta-version).

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List of figures

Annexes

Annex 1. Sources

Dataset	Source	Citation	Licence
The Armed Conflict Location & Event Data Project	ACLED	Armed Conflict Location & Event Data Project (ACLED); acleddata.com	Non-Commercial Licenses - ACLED's full dataset is available for use free of charge by non-commercial entities and organizations (e.g., non-profit organizations, government agencies, academic institutions) using the data for non-commercial purposes, subject to these Terms of Use. Non-commercial licenses may also be granted to for-profit media outlets or journalists citing ACLED's content in works of journalism; provided that such works are made available to the general public and benefit public discourse on the topic, subject to ACLED's prior, written approval.
Oxford COVID-19 Government Response Tracker (OxCGR)	Blavatnik School of Government, University of Oxford	Hale, Thomas, Sam Webster, Anna Petherick, Toby Phillips, and Beatriz Kira (2020). Oxford COVID-19 Government Response Tracker, Blavatnik School of Government. Data use policy: Creative Commons Attribution CC BY standard.	Creative Commons Attribution CC BY standard
Geographic distribution of COVID-19 cases worldwide	ECDC	© European Centre for Disease Prevention and Control (ECDC) 2020	https://www.ecdc.europa.eu/en/copyright
Humanitarian Appeals and Response plans	FTS, OCHA	Financial Tracking Service (FTS), Date, http://fts.unocha.org/	Site visitors may copy, download or print content for personal use, and may include FTS data in documents, presentations, blogs, websites and teaching materials, provided that suitable attribution of FTS as data source is given. Such attribution should cite the Financial Tracking Service (FTS), the publication date of the figures used and the relevant URL.
INFORM Seasonal	INFORM		

Dataset	Source	Citation	Licence
INFORM Severity Index	INFORM https://drmkc.jrc.ec.europa.eu/inform-index/INFORM-Severity/Results-and-data		
Inflation, average consumer prices	International Mon etary Fund	World Economic Outlook Database, April 2020 Edition	https://www.imf.org/external/terms.htm
ASAP - ANOMALY HOTSPOTS OF AGRICULTURAL PRODUCTION	JRC https://mars.jrc.ec.europa.eu/asap/	Rembold, Felix (2018): Ten-daily automatic warnings about agricultural vegetation anomalies. European Commission, Joint Research Centre (JRC) [Dataset] PID: http://data.europa.eu/89h/jrc-10112-10001	https://ec.europa.eu/info/legal-notice_en
IPC	National IPC Technical Working Groups	National IPC Technical Working Groups	Public Domain / No Restrictions
Global School Closures COVID-19	UNESCO		Creative Commons Attribution International
% Reduction on food purchase power	WFP		
Alert for Price Spikes (ALPS)	WFP		
WHO Disease Outbreak News (DONs)	WHO		

Annex 2. Dashboard indicators thresholds

	Monitoring indicator	Dataset	From	To	From	To	From	To
1	14 days Covid-19 case notification rate per 100k	Geographic distribution of COVID-19 cases worldwide	119	∞	20	119	∞	20
2	Legal Stringency Index	Oxford COVID-19 Government Response Tracker (OxCGR)	∞	20	20	80	80	∞
3	Gross domestic product per capita, constant prices	Inflation, average consumer prices	∞	-1	-1	1	1	∞
4	Inflation, average consumer prices	Inflation, average consumer prices	5	∞	∞	0	0	3
5	ASAP Hotspots	ASAP - ANOMALY HOTSPOTS OF AGRICULTURAL PRODUCTION	0.9	2			∞	0
6	Debt/contract relief for households	Oxford COVID-19 Government Response Tracker (OxCGR)	∞	0	0	1	1	2
7	Growth in reported number of disorder events	The Armed Conflict Location & Event Data Project	0.2	∞	-0.2	0.2	∞	-0.2
8	Income support	Oxford COVID-19 Government Response Tracker (OxCGR)	∞	0	0	1	1	∞
9	International travel controls	Oxford COVID-19 Government Response Tracker (OxCGR)	∞	0	0	3	3	∞
10	Number of people in IPC Phase 3 (Crisis) or above	IPC	1000000	∞	0	1000000		
11	Restrictions on internal movement	Oxford COVID-19 Government Response Tracker (OxCGR)	∞	0	0	1	1	∞
12	School Closing	Global School Closures COVID-19	∞	0	0	1	1	2
13	Stay at home requirements	Oxford COVID-19 Government Response Tracker (OxCGR)	∞	0	0	2	2	∞
14	Unemployment rate	Inflation, average consumer prices	20	∞	5	20	∞	5
15	Contact tracing	Oxford COVID-19 Government Response Tracker (OxCGR)	∞	0	0	1	1	∞
16	Public information campaign	Oxford COVID-19 Government Response Tracker (OxCGR)	∞	0	0	1	1	2
17	Testing policy	Oxford COVID-19 Government Response Tracker (OxCGR)	∞	0	0	2	2	∞
18	Seasonal flood exposure	INFORM Seasonal	6.99	∞	2	6.99	∞	2
19	Seasonal cyclone exposure	INFORM Seasonal	6.99	∞	2	6.99	∞	2
20	Seasonal drought exposure	INFORM Seasonal	6.99	∞	2	6.99	∞	2

	Monitoring indicator	Dataset	From	To	From	To	From	To
21	Growth in reported number of conflict events	The Armed Conflict Location & Event Data Project	0.2	∞	-0.2	0.2	∞	-0.2
22	INFORM Severity score	INFORM Severity Index (beta version)	3	∞	0	3		

Annex 3. INFORM Covid-19 Risk Index Analytical Framework

Position in the INFORM COVID-19 Risk model			Name of core indicator	
Hazard & Exposure	Person to person	Population	Population density	
			Urban population growth	
			Population living in urban areas	
			Population living in slums	
			Household size	
		WaSH	Sanitation	
			Drinking water	
			Hygiene	
Vulnerability	Covid-19 Vulnerability	Movement (25%)	International movement	Air transport, passengers carried
				International tourism, number of arrivals
				Point of entry
			Internal movement	Access to Cities
				Road density
		Behaviour (25%)	Awareness	Adult literacy rate
				Mobile cellular subscriptions
				Internet users
			Trust	
		Demographic and Comorbidities (50%)	Proportion of the population at increased risk of severe COVID-19 disease	1+ underlying conditions plus 0 conditions (50+ yrs)
	INFORM Vulnerability	Socio-Economic Vulnerability	Development & Deprivation	Human Development Index
				Multidimensional Poverty Index
			Inequality	Gender Inequality Index
				Gini Index
			Economic Dependency Index	Public Aid per capita (US$)
				Net ODA received (% of GNI)
				Volume of remittances
		Vulnerable Groups	Uprooted people	
			Gender Based Violence	
			Health Conditions	HIV
				Incidence of Tuberculosis
				Malaria incidence per 1,000 population at risk
				People requiring interventions against neglected tropical diseases
			Food Security	Food Availability Score
				Food Utilization Score
Lack of coping capacity	Covid-19 Lack of coping capacity	Health Capacity	Health system capacity specific to Covid-19	International Health Regulations Core Capacities average score
				Country Preparedness and Response Status for COVID-19
	INFORM Lack of coping capacity	Institutional	Governance	Corruption Perception Index
				Government Effectiveness
		Infrastructure	Access to health care	Health system capacity
				Immunization coverage
				Per capita public and private expenditure on health care
				Maternal Mortality ratio

Annex 4. INFORM Covid-19 related Warning Analytical Framework

Position in the model of COVID-19 related warning		Monitoring indicator	
Hazard&Exposure	Epidemiological situation	14 days Covid-19 case notification rate per 100k	
		Legal Stringency Index	
		Number of cumulative cases*	
		Number of cumulative cases / 1M inhabitants*	
		Number of cumulative fatalities / 1M inhabitants*	
		Number of cumulative fatalities*	
		Number of new cases*	
		Number of new fatalities*	
Vulnerability	Movement	International movements	International travel controls
		Internal movements	Restrictions on internal movement
			Stay at home requirements
	Socio-economic Vulnerability	Development& Deprivation	Income support
			Debt/contract relief for households
			Gross domestic product per capita, constant prices
			Unemployment rate
			Inflation, average consumer prices
		Economic Dependency	Humanitarian Appeals and Response plans required*
			Humanitarian Appeals and Response plans coverage*
		Education	School Closing
	Food Security	Number of people in IPC Phase 3 (Crisis) or above	
	Conflict	Growth in reported number of disorder events	
Lack of Coping Capacity	Health System Capacity	Public information campaign	
		Testing policy	
		Contact tracing	
		Investment in Covid-19 vaccines*	

*provided only in the country profiles

Annex 4. INFORM Covid-19 unrelated Warning Analytical Framework

Position in the model of COVID-19 unrelated warning	Monitoring indicator
CONFLICT	Growth in reported number of conflict events
SEASONAL NATURAL HAZARDS	Seasonal flood exposure
	Seasonal cyclone exposure
	Seasonal drought exposure
AGRICULTURAL DROUGHTS	ASAP Hotspots
ONGOING CRISIS	INFORM Severity score

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