Climate Risk Scoring and Rating

Introduction

Original risk indices are seldom employed directly in the risk assessment practice. In this section, we will present some methods applied in the climate risk assessment projects implemented by CLIMsystems over the last 20 years as a reference to end-users.

Reclassify A Spatial Index

An especially useful technique to work with spatial data (such as raster or point cloud) is changing their values or grouping them into categories, which is the so-called reclassification, or more professionally risk regionalization or zoning. In another word, reclassification is the process of reassigning a value, a range of values, or a list of values in a spatial data to new output values. There are several reasons to classify a spatial data layer:

- ◊ Set specific values to NoData to exclude them from analysis,
- ◊ Change values in response to new information or classification schemes,
- ◊ Replace one set of values with an associated set,
- ◊ Assign values of preference, priority, sensitivity, or similar criteria to a raster or point cloud,
- ◊ Others.

There are two categories of classifying methods (Joel Lawhead, 2019). The first one is simple, which is based only on some value distribution algorithm derived from the histogram of spatial data or user-defined groups. This kind of simplest methods is called unsupervised classifications, where no additional input is given other than the data itself. The second category is quite complicated as it may involve training datasets and even computer learning and artificial intelligence. Generally, this kind of methods involves some sort of training data to guide the computer. Therefore, it is called supervised classifications. For example, identifying crop types from satellite images is a kind of typical application of supervised classification.

Here only the unsupervised classification method is touched, where values for grids or points are compared with the range limits in the ***lookup table***, considering the specified comparison criteria. Whenever a value falls into a given range, the class value specified for this range will be used in the output layer. The following image presents an example of how to reclassify the original values from base raster by ranges to new reclassified values.

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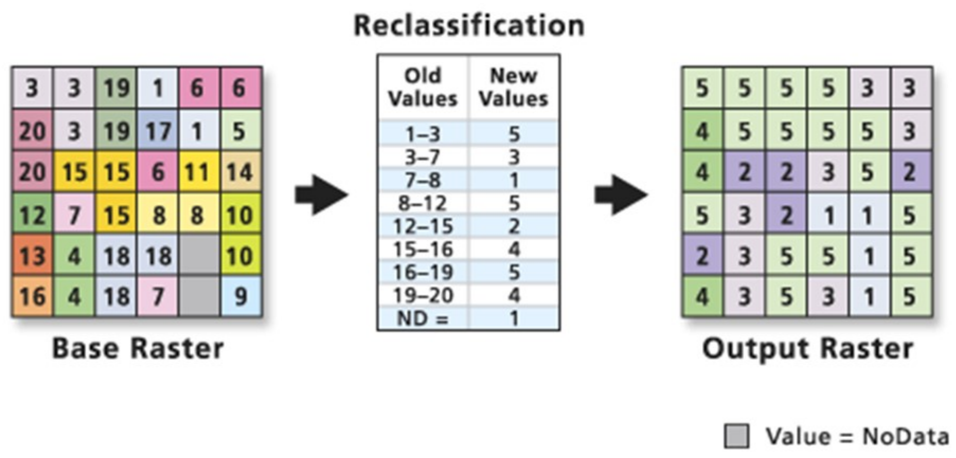
There are two kinds of methods to create the lookup table (i.e., standards for reclassification). The first is relatively simple and depends on statistics or expert opinions. Although many geospatial software such as ESRI ArcMap and QGIS support these functions (noting CLIMsystems is a silver partner of ESRI), using programming language such as Python and R to reclassify rasters is also quite convenient. Sometimes, it is more flexible to figure out and apply more customized classification criteria that fit purpose than using software. A basic list of such kind of classification schemes supported or once applied by CLIMsystems consists of

- ◊ Box_Plot
- ◊ EqualInterval
- ◊ FisherJenks
- ◊ FisherJenksSampled
- ◊ HeadTailBreaks
- ◊ JenksCaspall
- ◊ JenksCaspallForced
- ◊ JenksCaspallSampled
- ◊ MaxP
- ◊ MaximumBreaks
- ◊ NaturalBreaks
- ◊ Quantiles
- ◊ Percentiles
- ◊ StdMean
- ◊ UserDefined-Expert opinions

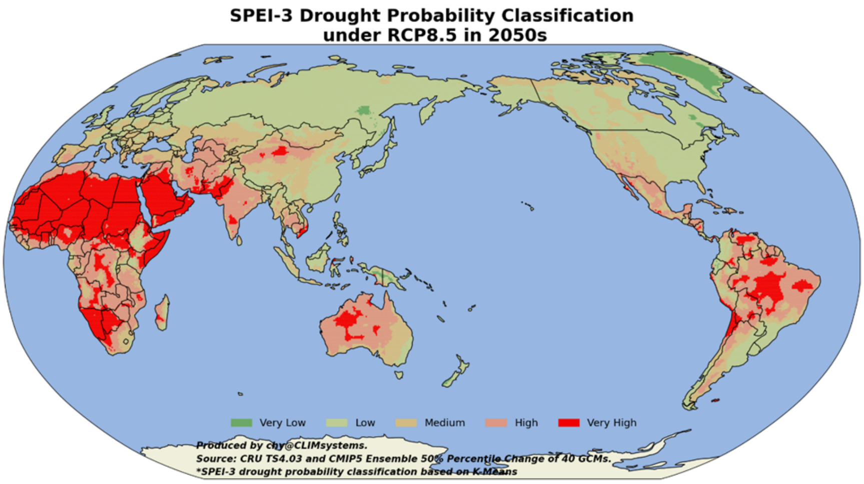


Example of reclassification by value ranges (Image source: ESRI)

The second kind of methods to create lookup table (i.e., classification schemes) is more complicated, which is based on clustering algorithms. There are more than 10 method available, such as:

- ◊ Affinity Propagation
- ◊ Agglomerative Clustering
- ◊ BIRCH
- ◊ DBSCAN
- ◊ HDBSCAN
- ◊ K-Means
- ◊ Mini-Batch K-Means
- ◊ Mean Shift
- ◊ OPTICS
- ◊ Spectral Clustering
- ◊ Gaussian Mixture Model

The most used method by CLIMsystems is the K-Means. All these classification schemes are basically used upon a single Climate Insights data layer, instead of spatial-temporal data. The analysis of spatial-temporal or timeseries data is another story and beyond the scope of this data manual. Interested end-user could refer to some algorithms such as Principal Component Analysis (PCA) and Self-Organized Map (SOM), etc. The following presents a demonstration that applied the K-Means clustering method to re-classify the global map of SPEI-3 based drought probability into five drought risk regions. Keep in mind it is just a demonstration.



A reclassification demonstration applying the K-Means clustering method upon SPEI-3 based drought probability under 2050s, RCP8.5

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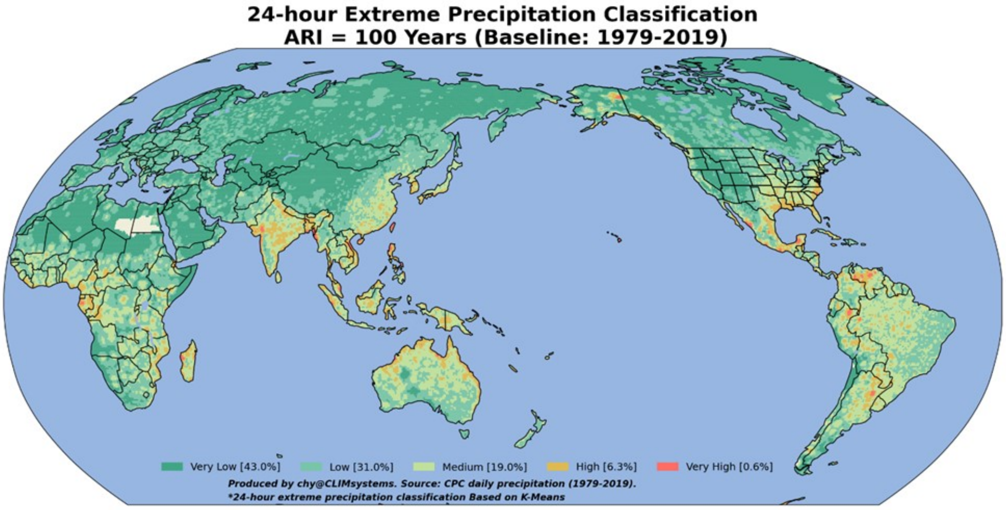
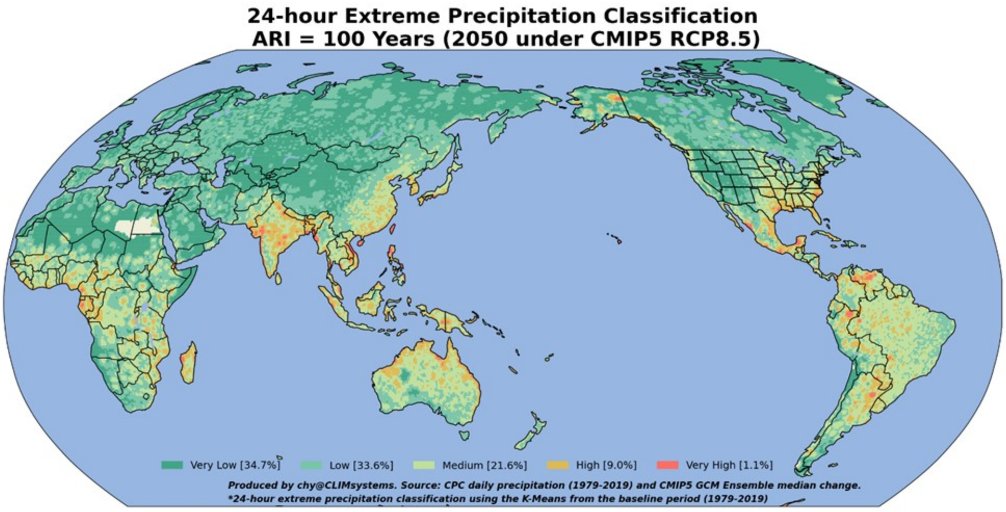
However, it is worth noting that these classification schemes could be applied to an index to obtain its thresholds for the reclassified categories or clusters/classes for a specific period (such as baseline period), and then these thresholds could be further employed to other periods to assess the evolution of the index for each category or cluster/class. For example, taking the extreme precipitation at ARI=100 years as an example, the classification thresholds during the baseline period (1979 - 2019) are employed to reclassify the corresponding future extreme precipitation from the CMIP5 Ensemble projections under RCP8.5 in 2050. Although the changes are not that significant, they are still measurable.





A demonstration of applying the thresholds during the baseline period to reclassify the future projections from CMIP5 ensemble projections under 2050s, RCP8.5 in 2050

Composite Index

Sometime, applying a single risk index is not enough for a specific assessment. Under such a case, the concept of composite index comes into practice. Sometimes, the composite index is titled compound index. A simplest example is mentioned before that heatwave (heatwave frequency (HWF) and total days (HWD) individually would fail to reflect the potential changes of heatwave in the future. Due to climate change, a decrease in the heatwave frequency might company with an increase in its length. That is, heatwave days could become more consecutive in the future. It is suggested that a mean duration should be used that can be calculated from HWF and HWD through simple mathematical operators.

A relatively complicated example is the Climatic Resource Availability Index (CRAI), which is obtained by first calculating a Climatically Determined Biomass Productivity Index (CDBPI), followed by re-scaling in a second step (Pauw and Ramasamy, 2019).

However, it is not difficult to find that the reclassification process was applied twice – one for rating drought probability and the other for reclassifying the composite index of DHI. Moreover, it should be clear that the above analysis utilized a simple rating scheme for drought probability, which is derived from the Jenks natural breaks classification method. The rating scheme is feasible in the analysis because it operated on a homogenous set of indices, all from SPI-3. In practice, it is widely recognized that individual index has a different level of importance (Fekete, 2012; Tate, 2012), but it is difficult to find an acceptable weighting scheme. Indeed, assessing the index weights is seen as a sensitive and controversial step in the development of composite indices. When a composite index is calculated from heterogeneous indices, the weight for individual index is usually obtained from more complicated methods such as the analytic hierarchy process (AHP). The next section presents a brief introduction to the AHP.

The AHP process

The AHP (Saaty, 1980) has widely been applied as a multicriteria decision analysis (MCDA) method (Le et al., 2013). It is based on the experience gained by its developer, T.L. Saaty, while directing research projects in the US Arms Control and Disarmament Agency. It was developed as a reaction to the finding that there is a miserable lack of common, easily understood and easy-to-implement methodology to enable the taking of complex decisions. Since then, the simplicity and power of the AHP has led to its widespread use across multiple domains in every part of the world. The AHP has found use in business, government, social studies, R&D, defence and other domains involving decisions in which choice, prioritization or forecasting is needed.

However, sometimes, and especially when many comparisons are involved, the judgements may be inconsistent. In this case, the priority scales can still be derived by solving the eigenvalue problem, the eigenvector being an approximation of the ideal case (Saaty, 2008b; Sekitani and Yamaki, 1999). The method also provides a framework for evaluating the consistency of the judgements (Saaty, 2008a).

In addition, only a group of experts or stakeholders may not always be enough to produce objective priority scales or weights. Under such as case, multiple group AHPs should be adopted to exploit a broader information basis as well as to achieve a sufficient degree of objectivity (*Fig.28*). Moreover, several AHP rounds must be performed to arrive at a universally acceptable decision.

Keep in mind that AHP is a typical subjective weighting method, where criteria weights are determined solely according to the preferences of decision makers. That is , these weights reflect the subjective judgment of the decision-maker, but analytical results or rankings of alternatives based on the weights can be influenced by the decision maker due to his/her level of knowledge and experience in the relevant field (Ahn, 2011).

Order Preference by Similarity to Ideal Solution (TOPSIS)

TOPSIS was developed by Hwang and Yoon in 1981 and has been used in various MADM problems such as supply chain logistics, marketing management, environmental management, or chemical engineering (Behzadian et al., 2012; Yoon and Hwang, 1981). TOPSIS is preferred over other approaches because of (*i*) its suitability for large number of attributes and alternatives; (*ii*) requirement of limited subjective inputs; (*iii*) its logical and programmable behaviour; and (*iv*) comparative consistency in the alternative ranking (Kalbar et al., 2012).

The methodology of the TOPSIS can be explained in following steps (Yadav et al., 2019):

Step 1: Construction of normalized decision matrix i.e.,

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$$

…..

Step 3: Ranking of alternatives based on C_i^+ .

It is worth noting that TOPSIS could be employed with the AHP method that is used to obtain weights for all criteria and is further applied in Step 2).

Climate Disaster Risk Management

According to the terminology of UNDRR, disaster risk is defined as "the potential loss of life, injury, or destroyed or damaged assets which could occur to a system, society or a community in a specific period of time, determined probabilistically as a function of hazard, exposure, and capacity". In the technical sense, it is defined through the combination of three terms: hazard, exposure, and vulnerability. Risks change, based on the exposure and vulnerability to hazards, which in turn arise from a combination of natural variability and human-induced climate change.

Accordingly, the Risk Index could be expressed as

$$RI = EI * VI * HI$$

where *RI* is the risk index; *EI* is the exposure index, and *VI* is the vulnerability index, while *HI* is the hazard index (i.e., hazardous weather and climate events). For each component of RI (i.e., EI, VI and HI), a set of indicators of indices could be identified from various sources. Then they are used to construct a single composite index based on the *Eq.4.1*. The weight for individual index could be obtained via the AHP process.

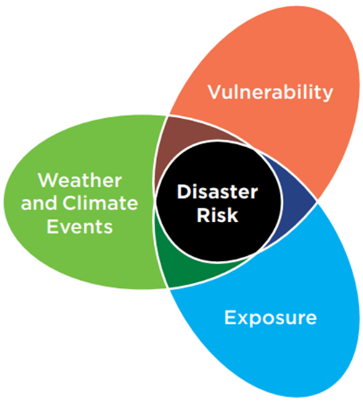
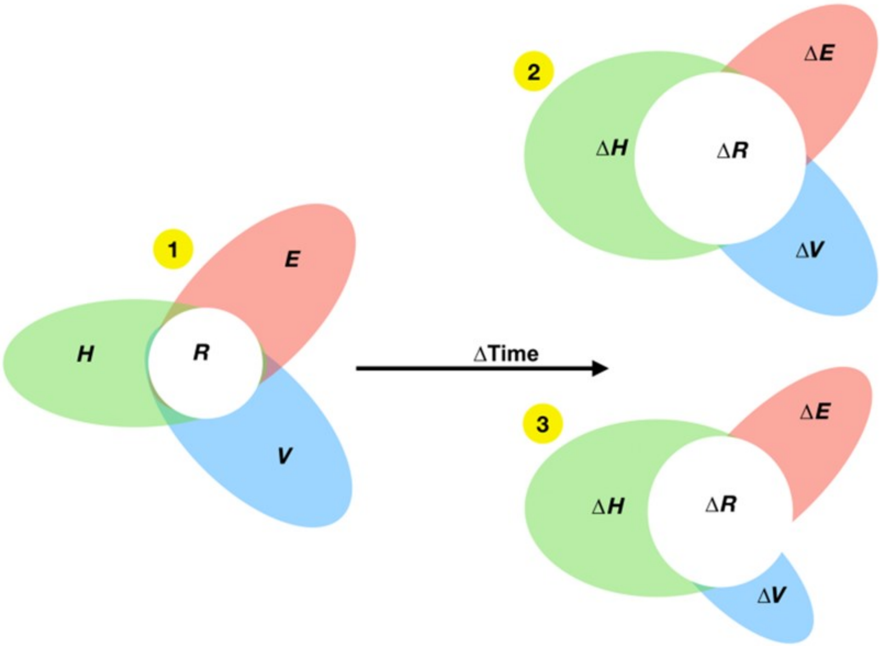


Fig.29 Factors That Influence Risk Include Exposure, Vulnerability, and Hazards (from IPCC 2012)

Understanding the dynamic nature of risk in climate change assessments

The biggest shortcoming of the conventional risk equation (being the product of hazard, exposure and vulnerability) is that it is often estimated with a static perspective, due to its origin from a disaster risk community, where the temporal dimension is significantly shorter compared to the long-term climate change risk assessments, stretching over decades to come. However, risk components, such as exposure and hazard, will change over time.

Climate Insights proposed two kinds of solutions to exploit the dynamics of risk assessments, (1) applying the assessment standards of current climate to measure future risks, (2) putting current and future climate into a uniform timeframe and then taking risk assessments. However, one still needs to choose an appropriate reference period for the solution (2), because some risks would increase monotonically under the context of global warming such as temperature-related risks.

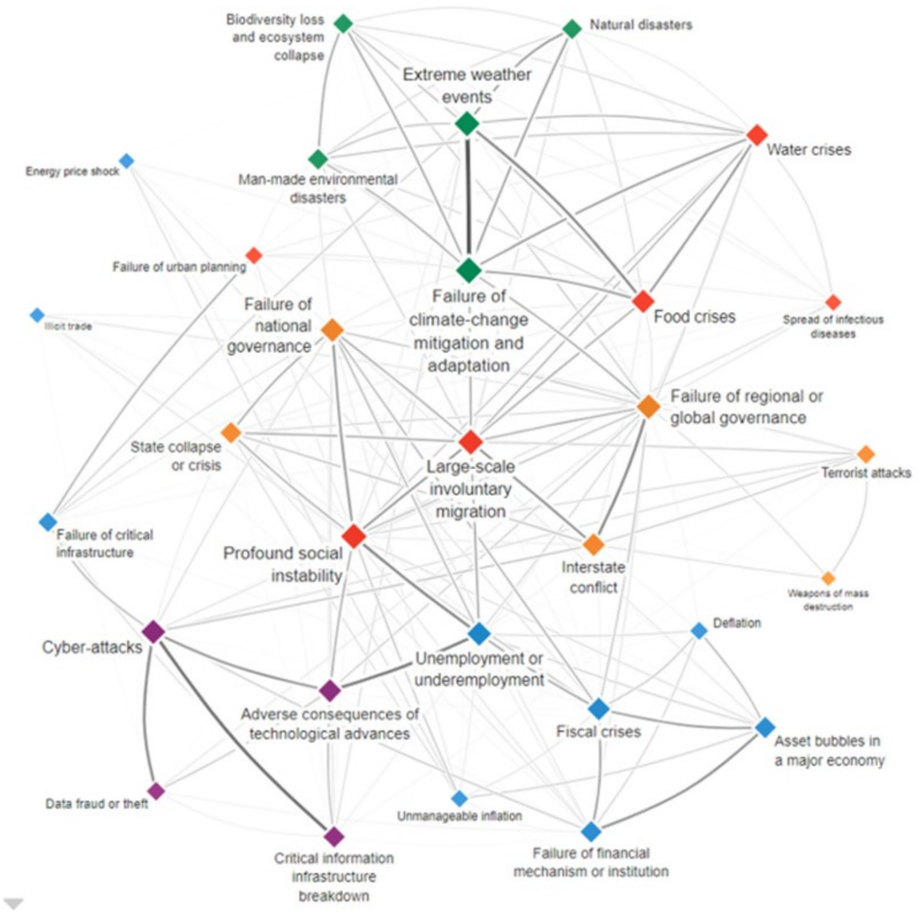


The impact of the dynamic contents of risk upon the measure of risk, where Graphic 1 shows the static current value. Graphic 2 shows the impact of no climate mitigation on the magnitude of the Hazard and the subsequent increase in risk. Graphic 3 shows that even with climate adaptation and resilience response options implemented, risk will increase if the magnitude of the hazard continues to increase (adopted from Viner et al., 2020)

Risk cascades involving compound events and system dynamics

More and more evidences that the combination of hazards, so-called compound events pose the greatest challenges, and such situations demand a multihazard approach (e.g., AghaKouchak et al., 2018). For example, forest fires caused an open forest floor/soil, which was then turned into a mud flood by heavy precipitation. Or an extremely wet January and February, leading to optimal conditions for photosynthesis due to abundant water availability in soils in spring together with favourable temperatures and radiation (sunlight) lead to heavy biomass production—dense vegetation, while the unusually hot and dry summer caused a drying vegetation (much "fuel" for potential fires), which together with strong winds lead to catastrophic fires.

In general, there are three different ways for multiple risks to emerge (Markus et al., 2020). (1) Independent events occurring together (concurrent/same time, different cofactors), (2) Two or more events occurring causally linked to the same root cause (same factor), and (3) Two or more events occurring causally dependent on each other. The type may dictate which are the best defence strategies, for example, cutting the causal chain in (3), or fighting the root cause in (2).



The Global Risks Interconnections Map 2019: How are global risks interconnected? (From World Economic Forum: http://reports.weforum.org/global-risks-2019/survey-results/global-risks-landscape-2019/#risks.)

Ranking and Risk Scoring Methodologies Applied in Climate Insights

Calculation Procedures

(1) Historical and future climate data for each asset according to latitude and longitude, extracted from Climate Insights database.

(2) Process the original data of multiple risk related variables using ranking TOPSIS (Technique of Order Preference Similarity to the Ideal Solution) and RSR (Rank Sum Ratio) algorithms.
Using the indicators from the ranking output, calculate the overall risk score of each asset.

Ranking

(1) Method one: TOPSIS is a multi-criteria decision analysis method, which was originally developed by Ching-Lai Hwang and Yoon in 1981 with further developments by Yoon in 1987, and Hwang, Lai and Liu in 1993. TOPSIS is based on the concept that the chosen alternative should have the shortest geometric distance from the positive ideal solution (PIS) and the longest geometric distance from the negative ideal solution (NIS).

(2) Method two: RSR, The RSR indicator ranges from zero (worst) to one (best) and follows a normal distribution. Additionally, subjects' status (worst/best) could be evaluated using either the RSR order or a set of ordinal classification. Classifications of RSR values use empirical percentiles based on the standard normal deviation.

Risk Score

(1) Method one: K-means clustering is a method of vector quantisation, originally from signal processing, that aims to partition *n* observations into k clusters in which each observation belongs to the cluster with the nearest mean (cluster centers or cluster centroid), serving as a prototype of the cluster.

(2) Method two: Jenks natural breaks (Jenks-Breaks, JB) classification method, is a data clustering method designed to determine the best arrangement of values into different classes. This is done by seeking to minimise each class's average deviation from the class mean, while maximizing each class's deviation from the means of the other groups. In other words, the method seeks to reduce the variance within classes and maximise the variance between classes.