Definition of a drought index to improve disaster preparedness and to support decision making process

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1. Introduction and Aim

Background

Droughts affect communities and environment in many different ways. Economy, agriculture, human health are among the sectors that experience huge impacts. An improvement in risk management capacities is a key point to mitigate the adverse impacts related to droughts [1]. Effective drought monitoring is crucial to reduce the risk, but it is still challenging. Many drought indices have been already developed; few of them aimed at optimising the capability of drought monitoring by using only remote sensed and globally available data [2].

Aim

To propose a **new drought index**, SP&VH, that could be helpful in identifying agricultural droughts. SP&VH combines

- a meteorological drought index (SPI- short aggregation timescale)
- a vegetation index (VHI)

4. Methodology

The following steps were carried out to compute the new index:

1. Precipitation and VHI are brought to the same spatial resolution;
2. Weekly SPI3 has been computed starting from CHIRP precipitation;
3. VHI has been standardized;
4. The indices were combined using a bivariate normal distribution function according to the following equation where x is the SPI3 and y the VHI:

$$f(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} e^{-\frac{x^2}{\sigma_x^2} - \frac{y^2}{\sigma_y^2}}$$

The bivariate normal distribution function is chosen since both the indices have normal distibutions.

2. Datasets

Two **remote-sensing** datasets have been used (Table 1): one for precipitation and one for the VHI. SPI has been computed starting from precipitation and updated every week.

	Precipitation	VHI
Dataset name	CHIRP	STAR VHP
Coverage	Global	Global
Spatial resolution	0.05°	$4km$
Temporal resolution	Daily	Weekly
Starting date	January 1981	August 1981
Reference	[3]	[4]

Table 1: *Main features of the datasets employed.*

5. SPI aggregation timescale

The Receiver Operating Characteristics (ROC) curve was employed in the evaluation procedure [5]. SPI3 was chosen because it's the best performing index in identifying reported drought events (Figure 2). The Area Under the Curve (AUC) for SPI3 was 0.74 while AUC for SPI1, SPI2 and SPI6 were respectively 0.647, 0.712 and 0.725.

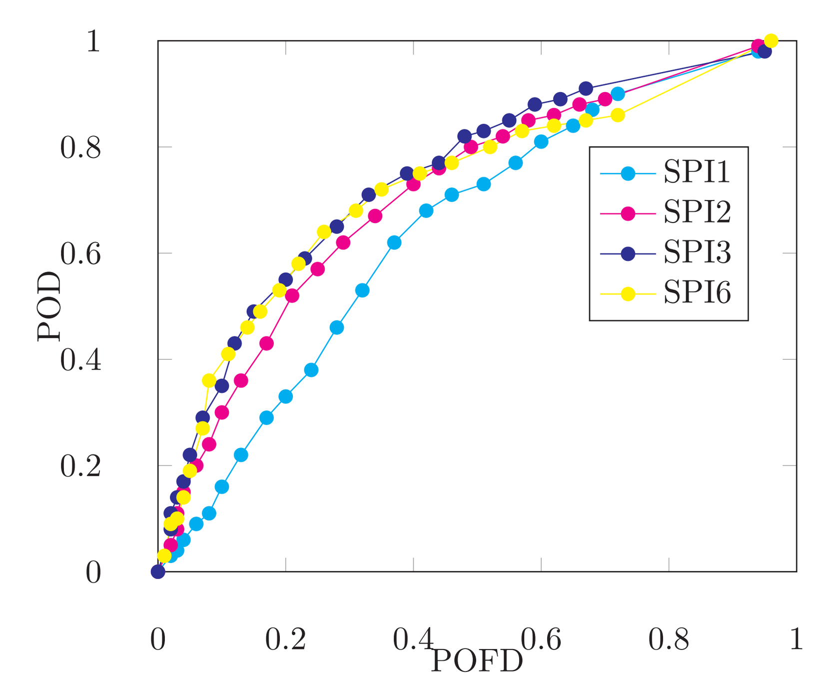

Figure 2: *Comparison among the performances of various SPI aggregation timescale in identifying reported drought events in Haiti.*

3. Case study

Haiti has been selected, since the country was affected by multiple droughts in the last decades (Table 2). Information on reported drought events have been collected from various text-based sources.

Year	Departments	Affected people	% of population
1981	South, Grand Anse, West	103,000	2
1982-1983	South, South East, North West, North East	33,000	5.75
1984-1985	North West	13,500	2
1986	All island		
1990-1991	All island	1,000,000	14
1997	North West, North, North East	50,000	0.64
2000	All island		
2003	North West	35,000	0.41
End 2009	North West		
2011-2012	North, North West, North East, Artibonite, Centre		
2013	All island	143,000	1.5
2014-2017	All island	3,600,000	33

Table 2: *Reported drought events in Haiti over the period 1980-2018.*

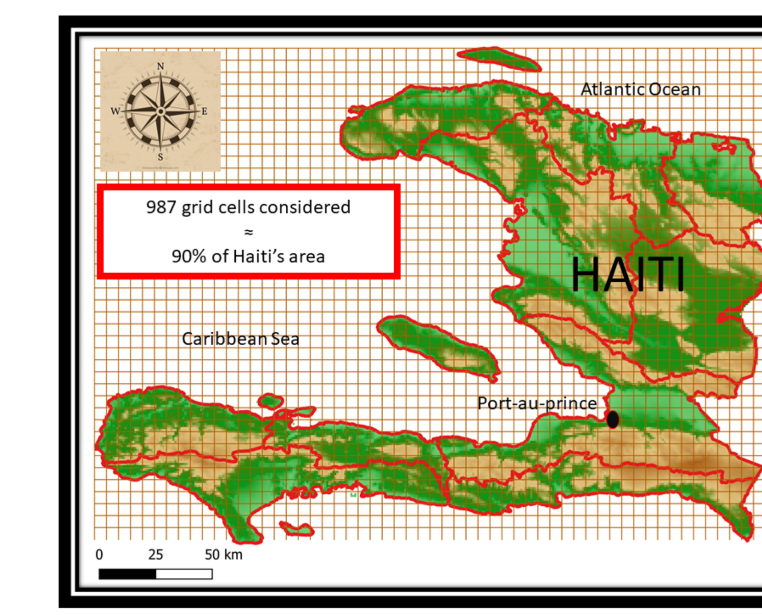

Figure 1: *Haiti: 987 grid cells were considered, 1941 weeks were analysed.*

6. Index Validation

SP&VH has been validated by plotting joint probability values against the empirical copula values [6]. The result is shown in Figure 3.

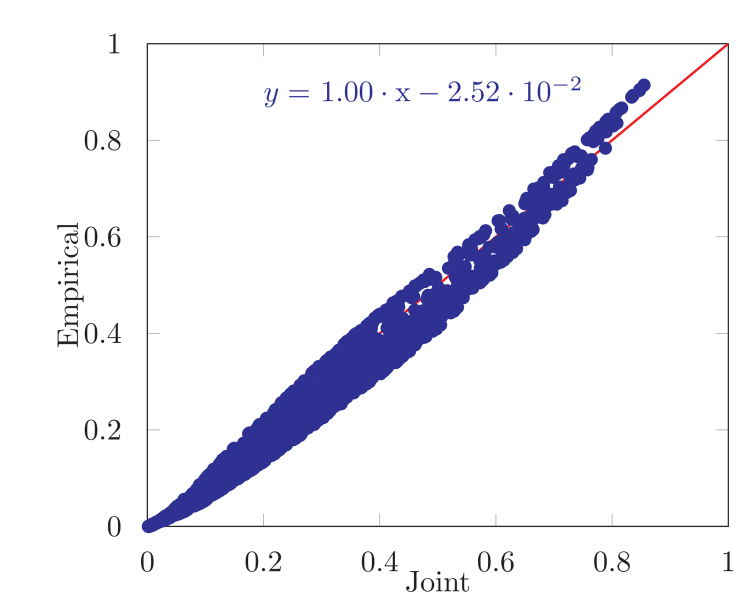

Figure 3: *SP&VH validation: Empirical copulas versus bivariate joint probability function. The red line corresponds to the 45-degree line.*

8. Conclusions and future developments

SP&VH performs better than SPI3 and VHI considered separately regarding the event identification. In addition SP&VH shows various advantages, since it:

1. combines evidence of lack of precipitation with impacts on the ground;
2. is developed using only **remote-sensing** datasets;
3. is **transferable and scalable** over the entire globe.

The research is still ongoing and the next steps will be:

1. the evaluation of droughts **return period** and areal extent by means of Severity-Area-Frequency and Severity-Area-Duration curves. The approach will be included in a framework for agricultural drought risk assessment;
2. the application of SP&VH on a **different county**. This new case study will be selected according to the availability of meteorological ground data to be employed for validation;
3. the development of a link between SP&VH and crop yields. Various growth stage of the crop will be considered.

7. Results

The ROC curve was used once again to evaluate numerically SP&VH performances. SP&VH performed better than SPI3 and VHI considered separately (Figure 4). The ROC curve confirms this hypothesis (Figure 5); AUC for SP&VH was 0.828, while for SPI3 and VHI was respectively 0.741 and 0.784.

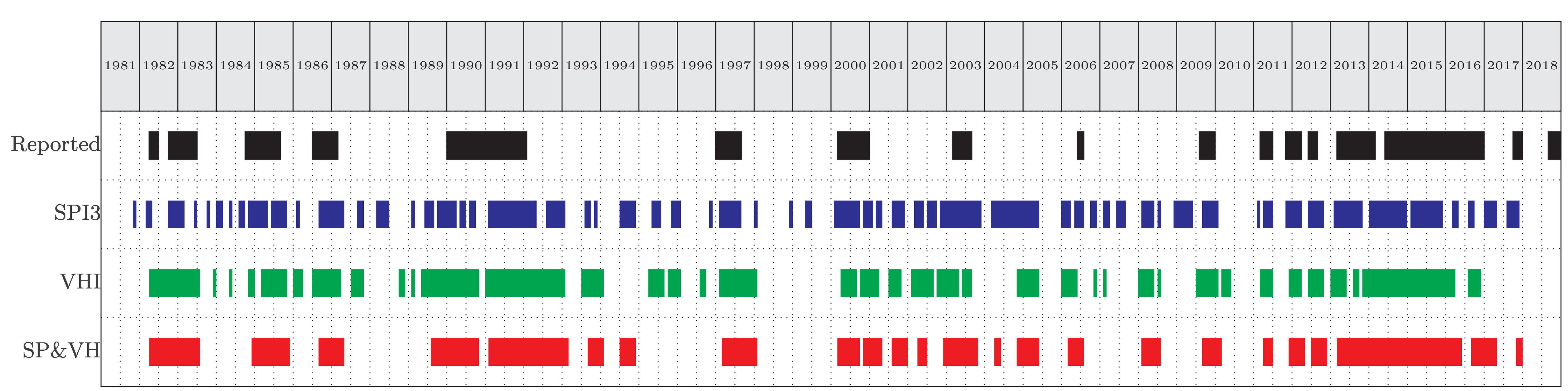

Figure 4: *A visual comparison of the best configurations from the three indices with respect to the reported events*

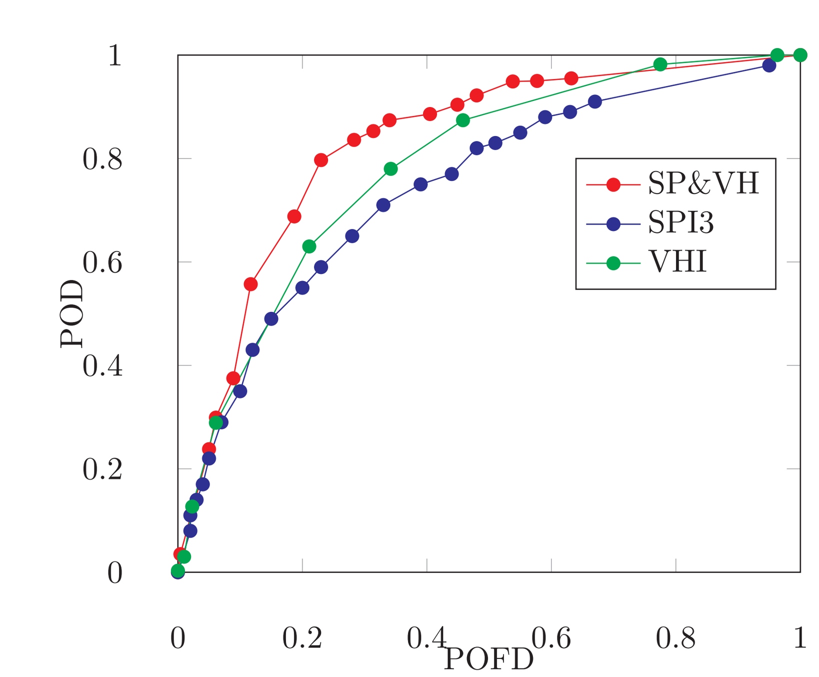

Figure 5: *Comparison among the performances of SPI3, VHI and SP&VH with respect to reported events.*

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