

Quantifying the co-occurrence of hydrological, meteorological and agricultural droughts on a global scale

Lauri Ahopelto¹, Marko Kallio^{1,2}, Matias Heino¹, Pekka Kinnunen¹, Amy Fallon¹ and Matti Kummu¹

[1] Water and Development Research Group, School of Engineering, Aalto University, Finland

[2] Geoinformatics Research Group, School of Engineering, Aalto University, Finland

Introduction

In theory, meteorological, agricultural and hydrological drought types are linked. A deficit in precipitation leads to deficit in soil moisture, which in turn leads to hydrological drought with some time lag. Past research, has also shown that different indices used to measure these three drought types have low correlations¹, partially due to the lag effect in one drought type following another, but also because the three physical drought types are influenced by multiple (different) factors.

In our research we quantified the co-occurrence of meteorological, agricultural, and hydrological droughts at global scale. We computed the drought indices at sub-basin scale for years 1981-2010, using HydroATLAS² level 6 (median size of approximately 5575 km²).

To identify drought events, we used 3-month Standardised Precipitation Evaporation Index (SPEI) for meteorological droughts, 1-month Soil Moisture Anomaly (SMA) for agricultural droughts and 3-month Standardised Streamflow Index (SSI) for hydrological droughts. For precipitation we used timeseries by Ruane et al³. For evaporation and soil moisture we used GLEAM v3⁴. For streamflow, we used a recently developed global runoff data product GRUN⁵ which we routed down the basin network in order to estimate discharge. The indices were fitted to the data using gamma distribution. We define a drought event as any continuous time interval where the event is consistently below -1 standard deviation from the mean.

We analysed the co-occurrence of severe droughts – droughts in which the index drops below -1.5 at any timestep – using Association Rules data-mining method⁶. We define here the co-occurrence of two drought events as having at least 50% spatiotemporal overlap. Below, we give brief examples of our initial results.

Association Rules in brief

Here we give a very brief overview of Association Rules (AR) using the apriori-algorithm. AR is a method to derive *rules* describing the relationships between so-called frequent item sets. It outputs rules in the form of $\{A\} \rightarrow \{B\}$ where $\{A\}$ is the antecedent, and $\{B\}$ is the consequent, and is read “given item(s) A in a transaction, we also find item B ”. The rules are characterized by support, confidence and lift. *Support* is the probability of finding all items in the antecedent and consequent in a transaction. *Confidence* is the conditional probability to find item B in a transaction, given item(s) A . *Lift* is the ratio between confidence, and the probability to find B in any transaction – commonly interpreted as the “usefulness” of the rule. The further lift is from one (1), the more information the rule carries.

Results

The results for our global co-occurrence analysis via Association rules are shown in Table 1. We find that of all the drought events identified by any of the three used indices, 43% events do *not* include hydrological drought (SSI, counted as 1-support for the rule $\{\} \rightarrow \{SSI\}$), 36% do *not* include agricultural drought (SMA), and 32 % do *not* include meteorological drought (SPEI). Only 25% of all individually identified events have all three indices co-occurring.

When aggregated to the continents and to the global Hydrobelts ⁷, we find considerable variation, as seen in Figure 1. Interestingly, we find that SMA and SPEI are poor predictors to SSI (lift below 1), which might be attributed to the different nature of the processes, as streamflow is affected by upstream conditions: precipitation and soil moisture are more local processes with weaker links to anthropogenic influence, irrigated areas being an obvious exception. We also find that Southern Subtropical and Southern Dry hydrobelts seem to behave in different way than the other hydrobelts. This is also evident when mapping the result to Hydroregions ⁷ in Figure 2. We also detect an increasing global trend in severe drought events and the co-occurrence of drought types in the study period (1981-2010, trends not shown here).

Table 1. Global association rules, found with 50% event overlap, and the associated support (probability of occurrence), confidence (conditional probability of finding consequent, given the antecedent), lift (usefulness of the rule).

Rule	Support	Confidence	Lift
{SPEI,SSI} -> {SMA}	25 %	73 %	1.13
{SMA,SSI} -> {SPEI}	25 %	73 %	1.07
{SMA} -> {SPEI}	46 %	71 %	1.04
{SPEI} -> {SMA}	46 %	67 %	1.04
{ } -> {SSI}	57 %	57 %	1
{ } -> {SMA}	64 %	64 %	1
{ } -> {SPEI}	68 %	68 %	1
{SMA,SPEI} -> {SSI}	25 %	55 %	0.97
{SMA} -> {SSI}	35 %	54 %	0.94
{SSI} -> {SMA}	35 %	61 %	0.94
{SSI} -> {SPEI}	35 %	61 %	0.89
{SPEI} -> {SSI}	35 %	51 %	0.89

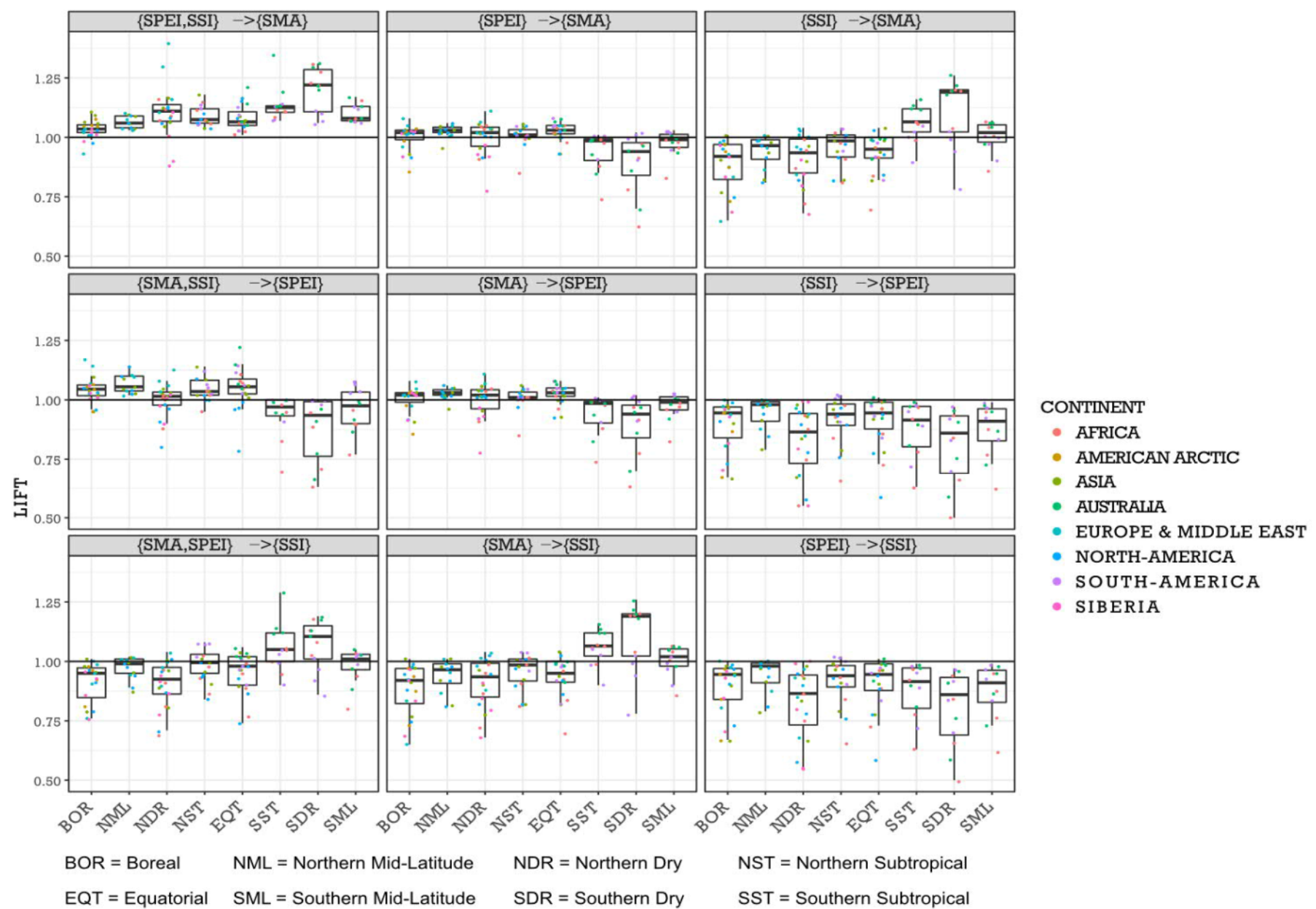


Figure 1. The lift (usefulness of the rule) for each rule aggregated to continents and global hydrobelts. The 1st rows presents the rules where the consequent is SMA, 2nd where it is SPEI and 3rd with SSI.

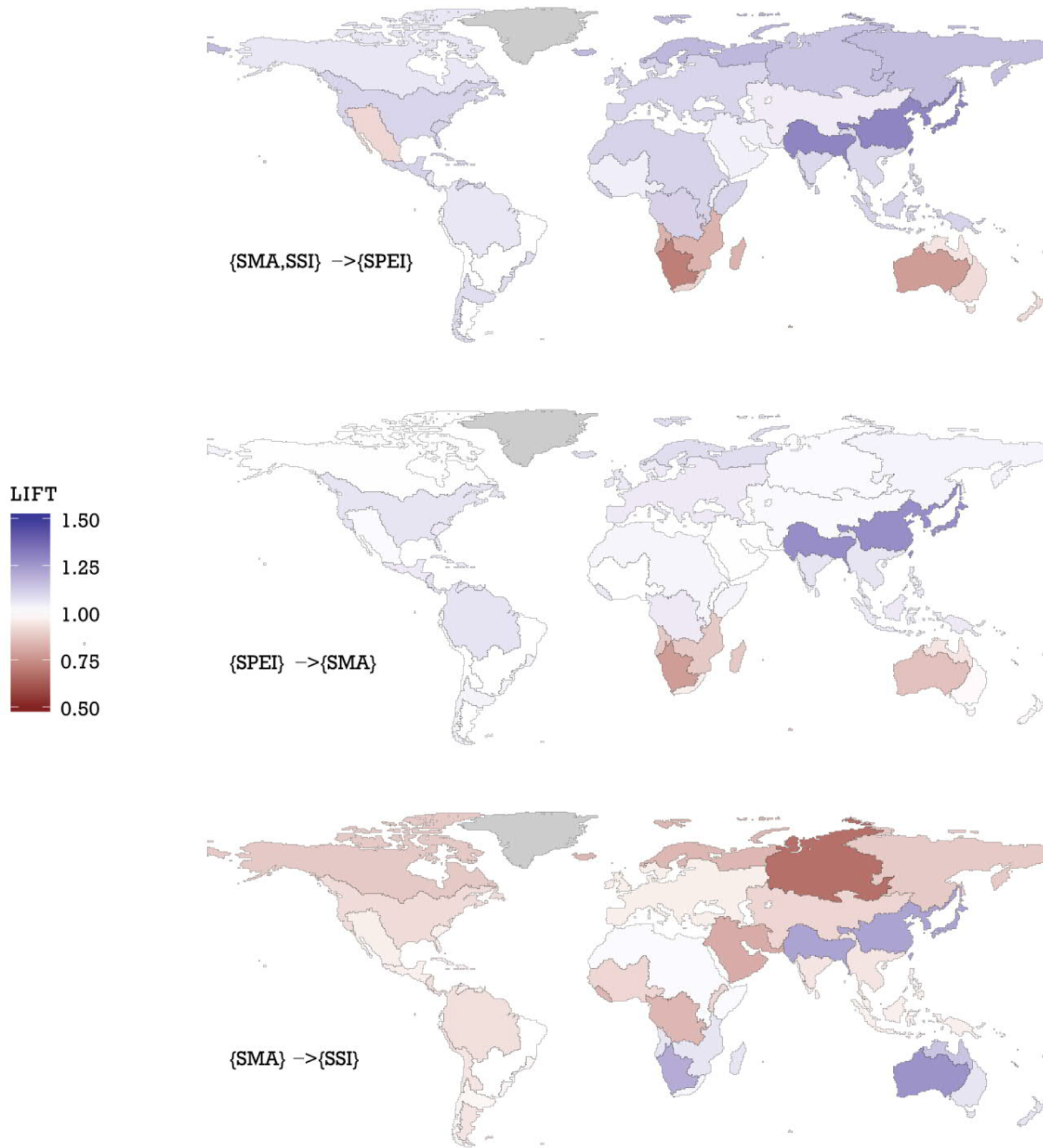


Figure 2. Lift for the global hydroregions for rules $\{SMA, SSI\} \rightarrow \{SPEI\}$, $\{SPEI\} \rightarrow \{SMA\}$ and $\{SMA\} \rightarrow \{SSI\}$. Lift can be read so that in regions with lift 1.5, the consequent occurs 50% more often if also antecedent is present, than it occurs by itself.

Discussion and conclusions

Our results show that different regions in the world have different kinds of relationships with the drought types. Understanding these relationships can provide important information for early warning systems and drought management planning. Deeper understanding of the relationships between drought types and their co-occurrence may support longer-term, proactive drought management planning that is better tailored to regional conditions.

With an increasing amount of environmental data available, we should use more advanced methods for analysing the data. We propose one approach, which still needs further research. We acknowledge that the co-occurrence results are sensitive to the chosen indices, thresholds for drought events and the definition of co-occurrence, thus further development is needed before the method can be truly useful.

References

1. Wanders, N., Loon, A. F. V. & Lanen, H. A. J. V. Frequently used drought indices reflect different drought conditions on global scale. *Hydrol. Earth Syst. Sci. Discuss.* 1–16 (2017) doi:<https://doi.org/10.5194/hess-2017-512>.
2. Linke, S. *et al.* Global hydro-environmental sub-basin and river reach characteristics at high spatial resolution. *Sci. Data* **6**, 283 (2019).
3. Ruane, A. C., Goldberg, R. & Chryssanthacopoulos, J. Climate forcing datasets for agricultural modeling: Merged products for gap-filling and historical climate series estimation. *Agric. For. Meteorol.* **200**, 233–248 (2015).
4. Martens, B. *et al.* GLEAM v3: satellite-based land evaporation and root-zone soil moisture. *Geosci. Model Dev.* **10**, 1903–1925 (2017).
5. Ghiggi, G., Humphrey, V., Seneviratne, S. I. & Gudmundsson, L. GRUN: an observation-based global gridded runoff dataset from 1902 to 2014. *Earth Syst. Sci. Data* **11**, 1655–1674 (2019).
6. *Data mining: the textbook*. (Springer Science+Business Media, 2015).
7. Meybeck, M., Kummerow, M. & Dürr, H. H. Global hydrobelts and hydroregions: improved reporting scale for water-related issues? *Hydrol. Earth Syst. Sci.* **17**, 1093–1111 (2013).