Econometric Methods for Meteorological Drought

Giuseppe Cavaliere[1] Enzo D'Innocenzo[1] Luca Fanelli[1]

[1]Department of Economics
Alma Mater Studiorum Università di Bologna

December 2-3, 2024
Venice, Campus San Giobbe, Italy
2nd **Workshop on Sustainable Finance Spoke 04 - GRINS**

Econometrics in Drought Analysis: Strategic Decision-Making

- Econometric Tools: A Bridge to Informed Decisions
  - Econometrics leverages data analysis to quantify relationships, predict outcomes, and evaluate policies.
- Families & Households:
  - *Water Conservation Planning:* Predicting water shortages to adjust household usage effectively.
- Businesses:
  - *Agricultural Planning:* Forecasting crop yields and optimizing irrigation strategies.
- Public Administrations:
  - *Resource Allocation:* Targeting drought relief funding and water supply management.
- Political Decision Makers:
  - *Policy Design:* Creating drought mitigation policies based on predictive climate and economic models.

$\Rightarrow$ Econometric analysis of droughts empowers data-driven strategies for water management and resource planning, minimizing impacts across society.

Drought Analysis

Why is drought so important?

- Drought is complex and poorly understood, with non-linear spatial and temporal characteristics.
- Severe economic, social, and environmental effects.
- A review of drought modeling can be found in Mishra and Singh (2011).

The variables and associated types of drought include:

- Precipitation for meteorological drought analysis.
- Groundwater levels for ground water drought.
- Reservoir hydrologic drought analysis.
- Soil moisture and crop yield for agricultural drought.

⇒ **Key Index:** The **Standardized Precipitation Index (SPI)** is widely used for drought monitoring.

The SPI and its Analysis

The Standardized Precipitation Index (SPI)

- Quantifies precipitation as a standardized deviation from a probability distribution of raw data.
- Recognized worldwide for quantifying **meteorological drought** across various climates and time periods.
- Linked to **soil moisture** (short-term) and to **groundwater** and **reservoir storage** (long-term).

$\Rightarrow$ **Research gaps:**

- Multivariate and non-linear dynamic econometric methods have not been thoroughly investigated for drought modeling.
- Dynamic econometric tools for quantifying and reporting drought conditions in Italy are currently unavailable.

Goal & Contributions

⇒ **Our goal:**

- To develop a unified econometric approach to:
  1. Model, forecast, and evaluate the impacts of climate change on extreme events related to droughts.
  2. Understand the links between extreme events and global-change-type droughts.
  3. Assess drought impacts and monitor extreme drought-related climate events in Italy at the regional scale.

⇒ **Our Contributions:**

- With this research project, we:
  1. Provide a useful **econometric tool** for quantifying and reporting drought conditions in Italy, based on monthly-updated maps of the SPI calculated at different timescales.
  2. Develop freely available **Matlab code** to efficiently implement our methods using real SPI time series data.

⇒ The integration of our tool and code within the **AMELIA** platform will be crucial for strategic decision-makers.

Some empirical evidence from Italian data

- The SPI can be computed for an observation of 3 months total of precipitation, for short-term drought index up to 48 months of precipitation, for long-term drought index.

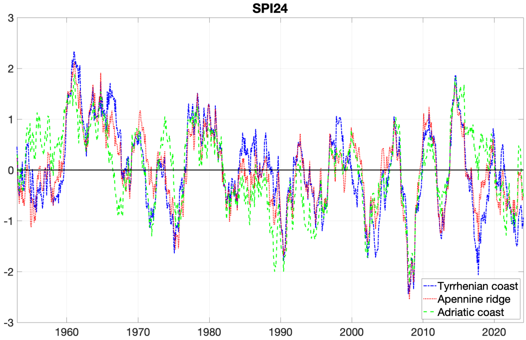

Figure: SPI24 time series averaged over the three reference areas. The time series spans from January 1953 to February 2024.

Some empirical evidence from Italian data: Non-Gaussianity

- Testing the multivariate distribution of SPIs.

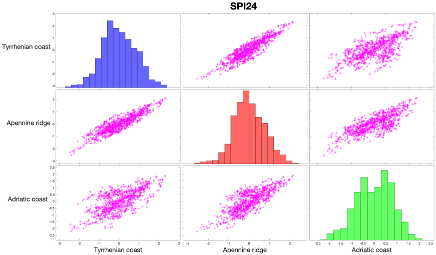

Figure: Scatter-plot matrix of the monthly SPI24 time series.

Table: Mardia's multivariate asymmetry skewness and kurtosis.

Note: The symbol * denote statistical significance 5 percent level.

Multivariate	Coefficient	Statistic	df	*p*-value
Skewness	0.495	70.429	10	0.000*
Kurtosis	13.885	-2.975		0.002*

Some empirical evidence from Italian data: Stochastic Correlations

- Is there empirical evidence that correlations stochastically vary over time?

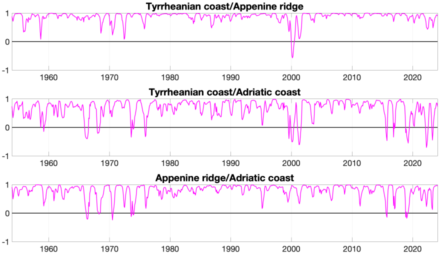

Figure: Empirical correlation computed using a rolling window of 12 months of the monthly SPI24 time series.

- The regions' climate indices are often synchronized but can experience intermittent divergences.
  ⇒ **Empirical evidence:** Focusing solely on a univariate statistical analysis of the three SPIs would likely lead to *misleading conclusions* due to the multivariate and dynamic nature of the data.

RVAR-DCC-GARCH Models for Drought Analysis

- **Purpose:** Model complex relationships among climate variables or indexes (e.g., SPIs, rainfall, soil moisture) and their changing correlations over time.
- **Components:**
  - *Vector AutoRegression (VAR(p)):* Models interdependence among multiple variables (Lütkepohl, 2005).

$$\boldsymbol{y}_t = \boldsymbol{\delta} + \boldsymbol{\Phi}_1 \boldsymbol{y}_{t-1} + \cdots + \boldsymbol{\Phi}_p \boldsymbol{y}_{t-p} + \boldsymbol{\epsilon}_t, \qquad \boldsymbol{\epsilon}_t \sim F\left(\boldsymbol{0}, \boldsymbol{\Sigma}_t\right).$$

  - *Generalized AutoRegressive Conditional Heteroskedasticity (GARCH):* Captures time-varying volatility (Francq and Zakoian, 2019).

$$\boldsymbol{\Sigma}_t = \boldsymbol{D}_t \boldsymbol{R}_t \boldsymbol{D}_t, \quad \boldsymbol{D}_t = \operatorname{diag}\left(\sigma_{1,t}, \ldots, \sigma_{N,t}\right),$$
$$\sigma^2_{i,t} = \omega_i + \alpha_i \epsilon^2_{i,t} + \beta_i \sigma^2_{i,t-1}.$$

  - *Dynamic Conditional Correlations (DCC):* Tracks changing correlations (Engle, 2002).

$$\boldsymbol{R}_t = \boldsymbol{\Delta}_t^{-1} \boldsymbol{Q}_t \boldsymbol{\Delta}_t^{-1}, \quad \boldsymbol{\Delta}_t = \operatorname{diag}\left(\sqrt{q_{1,t}}, \ldots, \sqrt{q_{N,t}}\right), \quad \boldsymbol{\eta}_t = \boldsymbol{D}_t^{-1/2} \boldsymbol{\epsilon}_t,$$
$$\boldsymbol{Q}_t = \boldsymbol{\Omega} + \boldsymbol{B}^{1/2} \boldsymbol{Q}_{t-1} \boldsymbol{B}^{1/2} + \boldsymbol{A}^{1/2} \boldsymbol{\eta}_{t-1} \boldsymbol{\eta}_{t-1}^\top \boldsymbol{A}^{1/2}.$$

⇒ **What we use:** We substitute a "long" VAR model for a VARMA system, achieving identification, easy estimation and enhancing result interpretability.
⇒ **Final model:** The *Restricted* VAR (RVAR) DCC-GARCH.

Empirical analysis of Italian SPIs: In-Sample fit

- The selected RVAR(25) model, with **significant lags 1, 24, and 25**, takes into account for short and seasonal dependencies.
- The contemporaneous relationships are captured with the DCC-GARCH model.

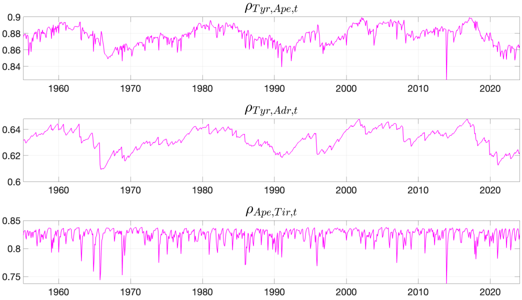

Figure: DCC-GARCH correlation filtered from the monthly SPI24 time series.

- Strong and stable correlations between Italian regions' climates.
- The notable variability in specific periods reveals how geographical proximity and distinct atmospheric influences shape regional climate dynamics.

Empirical analysis of Italian SPIs: Out-of-sample forecasting

- We employ our RVAR(25)-DCC-GARCH for both *point* and *density forecasts*
  - **Point forecasts:** provide the best guess based on historical data.
  - **Density forecast:** present a full probability distribution of potential outcomes.

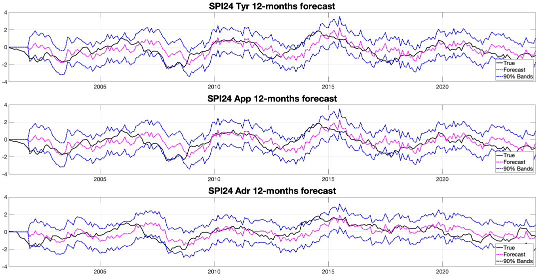

Figure: 12 step-ahead forecast of the monthly SPI24 time series.

- Density forecasts enable decision-makers to assess the probability of extreme drought events and outliers.
- Accurate forecasts are crucial for effective water allocation strategies and risk management.

Discussion & Future research

⇒ **Achieved objectives:**

- The empirical results demonstrate that the proposed multivariate dynamic model can be effectively employed for drought monitoring.
- The estimation results are straightforward to interpret and align with climatic expectations.
- The RVAR(25)-DCC-GARCH model demonstrates great robustness across all regions and horizons, making it a suitable choice for model and forecast SPI values.
- We also extended our multivariate dynamic model to include **Teleconnection Indexes** and other climate-related variables in order to separate the periodic patterns of precipitation from climate oscillations.

⇒ **Further analysis:** Can we extend the empirical analysis to other **Italian areas?**

- We aim to determine if an SPI-like measure can be developed for Emilia Romagna (ER) or its surrounding area, as understanding the impact of recent extreme weather events on drought risk is critically important.

Brockwell, P. J. and Davis, R. A. (1986). *Time series: theory and methods*. Springer-Verlag, Berlin, Heidelberg.

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics*, 20(3):339–350.

Francq, C. and Zakoian (2019). *GARCH Models, 2nd Edition*. John Wiley & Sons.

Lütkepohl, H. (2005). *New Introduction to Multiple Time Series Analysis*. Springer Berlin Heidelberg.

Mishra, A. K. and Singh, V. P. (2011). Drought modeling – a review. *Journal of Hydrology*, 403(1):157–175.