

# Beat the Heat

## The Impact of Heat Waves and Droughts on Regional EU Economies

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IFC Satellite Seminar, October 4<sup>th</sup>, 2025

# Presentation Overview<sup>1</sup>

- ① Introduction
- ② Heat Waves & Droughts
- ③ Nowcasting Exercise
- ④ Assessment of Models

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<sup>1</sup>Disclaimer: This paper should not be reported as representing the views of the authors' national banks, ECB or the Eurosystem.

# Motivation: Role of Heat Waves & Droughts in Production

- Climate change exacerbates **regional disparities**, threatening economic stability (Seneviratne et al., 2021)
- **Severe heat** caused 0.3–0.5% losses in EU GDP and could reduce it fivefold by 2060 (García-León et al., 2021)
- By 2100, **drought** damages may increase fivefold with 3°C warming (European Commission et al., 2020)
- **AIM:** Nowcast RGVA per capita for sectoral aggregations A, B-E & C at NUTS-3 level, using economic and climate data



# Literature Gaps and Contributions

## Gaps in the Literature:

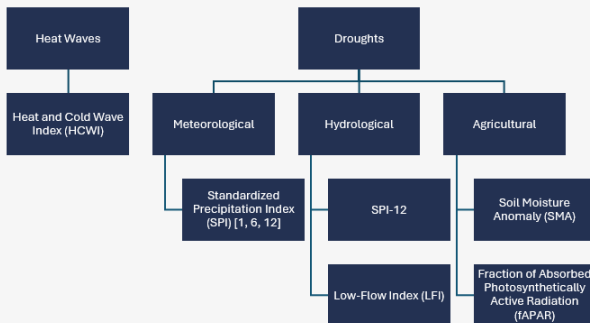
- Earlier work has focused on **long-term impacts** of temperature and precipitation on GDP (Motta et al., 2025; Khan, 2021; Dellink et al., 2019)
- Research is often **sector-specific** (mainly agriculture) (Wang et al., 2018; Praveen & Sharm, 2019) and at **low spatial and temporal resolution**
- Methods remain largely **linear** (Usman et al., 2024)
- Few studies integrate **economic and climate data** for macroeconomic forecasting (Rossi et al., 2023), but compounding events remain understudied

## Our Contributions:

- Apply **ML methods** (Random Forest, XGBoost)
- Targeting **climate extremes** (heat waves & droughts)
- Capture **compounding effects** across time, events, & neighbouring regions
- Contrast **linear regression** with non-linear ML approaches

# Capturing Heat Waves & Droughts

We incorporate a set of temperature- and precipitation-based climate features, restricted to reflect only heat waves and droughts.



- Variable standardisation allows numerical thresholds to directly map to climate conditions
- HCWI & LFI: values  $> 0$  indicate heat waves and hydrological drought, respectively
- SPI, SMA, & fAPAR: values  $\leq -1$  denote drier-than-normal conditions

# Compounding Climate Effects

- **Temporal:** Event duration is included in climate variable calculations, with longer events implying greater severity
- **Geographic:** For region  $r$  with a set of neighbours  $r^*$ , the geographic compounding of indicator  $X$ , where  $X$  excludes agricultural droughts, is:

$$GC_{t,r}^X = \frac{1}{|N_{r^*}|} \sum_{i \in N_{r^*}} X_{t,i}$$

- **Event-based:** Concurrent heat waves and droughts are captured via an interaction of scaled HCWI and SPI:

$$EC_{t,r}^f = \begin{cases} HCWI_{t,r} \times |SPI_{t,r}^f|, & HCWI_{t,r} > 0, SPI_{t,r}^f \leq -1 \\ 0, & \text{otherwise} \end{cases}$$

where SPI periods ( $f$ ) capture impacts at different temporal scales

# Nowcasting Production with Heat Waves & Droughts

- The general structure of our models express the growth rate of RGVA per capita ( $Y_{t,r,s}$ ) using the functional forms: [▶ Variable Map](#)

$$Y_{t,r,s} = f_{ECON}(Y_{t-1,r,s}, E_{t,r,s}, G_{t-1,c}, M_r, R_r, C_r, N_r; \theta_{ECON,s})$$

$$Y_{t,r,s} = f_{CLIM}(Y_{t-1,r,s}, E_{t,r,s}, G_{t-1,c}, \mathbf{HCWI}_{t,r}, \mathbf{SPI01}_{t,r}, \mathbf{SPI06}_{t,r}, \mathbf{SPI12}_{t,r}, \mathbf{LFI}_{t,r}, \mathbf{SMA}_{t,r}, \mathbf{fAPAR}_{t,r}, M_r, R_r, C_r, N_r; \theta_{CLIM,s})$$

- Models:** Linear Regression, Random Forest & XGBoost
- Data Setup:** Mixed-Frequencies with Train-Test Split of 2002-17 & 2018-22
- Model Structures:** Yearly Medians & St. Deviations, and Feature Extraction Techniques for Climate Variables (PCA, MIDAS) [▶ Further Details](#)

# Nowcasting Results

We find no evidence that our climate features improve the nowcasting performance of linear regressions, but they can **improve nowcasting in non-linear models, particularly in agriculture.**

**Table 1:** Nowcast RMSEs

Model	Linear Regression			Random Forest			XGBoost		
	A	B E	C	A	B E	C	A	B E	C
Economic ( $f_{ECON}$ )	21.64	14.11	77.90	23.05	13.83 <sup>†</sup>	72.81	28.15	13.89 <sup>†</sup>	76.73 <sup>†</sup>
Climate ( $f_{CLIM}$ )									
- Medians & St. Deviations	22.12	14.20	77.95	20.93 <sup>*†§</sup>	14.01 <sup>†</sup>	73.64	20.54 <sup>*†§</sup>	13.95 <sup>†</sup>	77.69
- PCA Features	22.23	14.17	77.91	21.05 <sup>*†</sup>	13.94 <sup>†</sup>	74.03	21.52 <sup>*†</sup>	14.03 <sup>†</sup>	77.80
- MIDAS Features	22.98	14.36	78.03	21.18 <sup>*†</sup>	14.06 <sup>†</sup>	75.19	21.72 <sup>*†</sup>	13.97 <sup>†</sup>	85.34

Note: RMSEs are calculated over annual nowcasts of real GVA per capita growth from 2018 to 2022. Sector A covers agriculture; B–E includes mining (B), manufacturing (C), utilities (D), and waste management (E), with C also modelled separately to obtain direct predictions for manufacturing. The symbols to denote statistically significant improvements in predictive performance are:

\*  $p < 0.05$  indicates predictive improvements relative to the respective economic counterpart of the same model type;

<sup>†</sup>  $p < 0.05$  indicates predictive improvements relative to the respective linear regression model counterpart; and

§  $p < 0.05$  indicates predictive improvements relative to the respective linear economic model for the same sector.



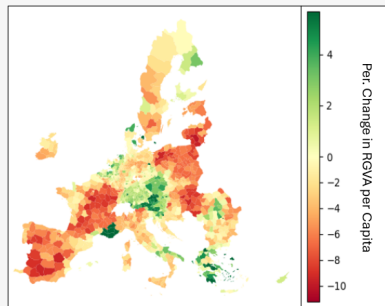
# Importance of Climate Features

- SHAP values measure how much each feature contributes to shifting a model's prediction away from the average prediction, providing a clear, additive decomposition of model outputs.
- SHAP values and factor loadings suggest that:
  - **HCWI** consistently ranked among the most **important** features, while **drought** indicators showed **sector-specific relevance**.
  - **Geographic compounding** indicators contributed strongly, reflecting both competitive and complementary regional effects.
  - **Event-based compounding** gained importance in models using feature extraction, with factor loadings non-linearly distributed over short-, medium-, and long-term droughts.
  - **Climate variables** had the largest impact in regions with **below-median RGVA per capita**.

# Applying Models for Simulations

- **Climate Scenario:** Heat Wave with the intensity of the 99<sup>th</sup> percentile per region
- **Simulation Process:**
  - 1 Select the model with the optimal nowcasts
  - 2 Generate predictions using 2022 data for 2 scenarios:
    - no heat waves and droughts baseline, &
    - a tailored climate scenario
  - 3 Subtract values of the desired climate scenario from baseline

**Figure 1.** Heat Waves Simulation for Agriculture in 2022



# *Thank You*

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# Variables Map

► Nowcasting Approach

Notation	Description
$t$	Time
$r$	Region
$s$	Sector
$c$	Country
$Y$	RGVA per capita
$E$	$\frac{Employed_{t,r,s}}{Population_{t,r}}$
$G$	RGDP per capita
$M$	Mountainous Terrain (0,1)
$R$	Rural Terrain (0,1)
$C$	Coastal Terrain (0,1)
$N$	Encoded Region Indicator
$HCWI$	Heat & Cold Waves Index
$SPI$	Standardised Precipitation Index
$LFI$	Low Flow Index
$SMA$	Soil Moisture Anomaly
$fAPAR$	Fraction of Absorbed Photosynthetically Active Radiation
$\theta$	Model Hyperparameters

# Feature Extraction

► Nowcasting Approach

- Feature extraction techniques are used to map monthly climate data with yearly economic variables
- Extracting 1 feature from the set of high-frequency data of each climate feature maintains a degree of interpretability
- **Principal Component Analysis (PCA):**  
Transforms correlated features into one component capturing the maximum variance in the data
- **Mixed Data Sampling (MIDAS):**  
MIDAS uses  $\beta$  distributed lag weights to summarise climate data, with the prediction used as the extracted feature

for X in [HCWI, SPI-01, ...]:

Year	NUTS 3	X [1]	X [2]	...	X [12]

Component Extraction for X:

Opt. 1 → PCA

Opt. 2 → MIDAS

Year	NUTS 3	$\hat{X}$

Y =