Stochastic generators for spatial fields of ecoclimatic agricultural indicators in France

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joint with

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Focus project *CLIMATHS* (PEPR Maths VivES)
Project *LOST OXIGEN* (INRAE-CLIMAE)
Chair of Geolearning

SWGEN 2025, Grenoble
December 4, 2025

Save-the-date (for another workshop)

Extreme events in agriculture and forestry: challenges, methods and applications

9-11 June 2026

Avignon University

Organized by:
Focus project *CLIMATHS* (PEPR Maths VivES)
Project *LOST OXIGEN* (INRAE-CLIMAE)

Focus topics (in alphabetical order):

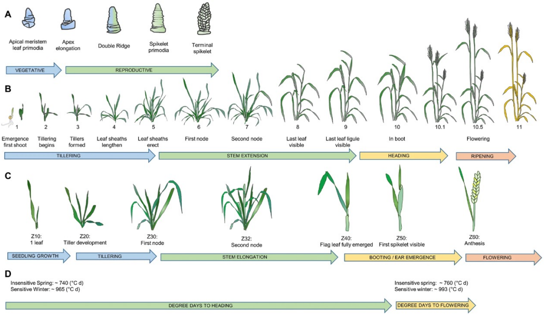
- Climate indicators
- Compound events and risks
- Extreme value theory
- Heatwaves and droughts
- Interactions between biotic and abiotic risks
- Physical processes and climate dynamics of extreme events
- Phenology and ecophysiology of plants
- Rare-event algorithms
- Stochastic weather generators for impact models

Programme and website are under under construction.
Soon available at
`https://extremes2026.sciencesconf.org/`

- **Weather impacts** on crop development and yield depend on **timing** in **life cycle**
- Modeling based on **"crop time"**, not calendar time, to consider crop vulnerability
- **Ecoclimatic indicator:** A meaningful weather summary for a crop risk during a specific phase of the life cycle

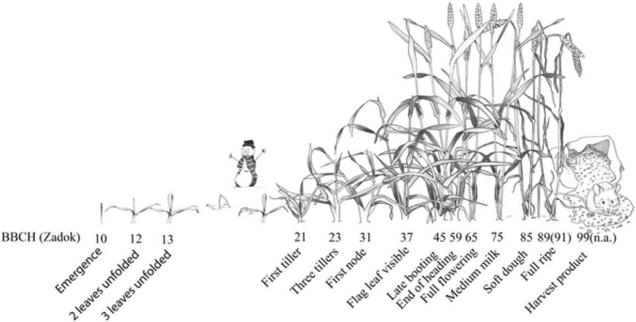
Goal: Development of a low-cost stochastic multivariate spatial ecoclimatic generator

Different representations of wheat phenology events



Source: [Hyles et al., 2020]

- Typically sowing in autumn of year $Y-1$, harvest in summer of year Y
- BBCH scale with 10 development stages from *Germination* (0) to *Senescence* (9)
- **In this work:** Focus on **drought risk** during **spring growing stages** 2–5



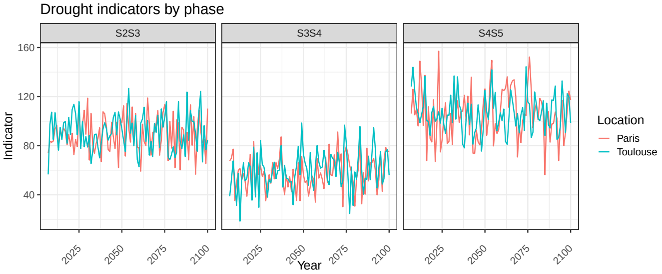
Source: Wikipedia; Group of Crop Science, ETH Zürich

One value per combination of

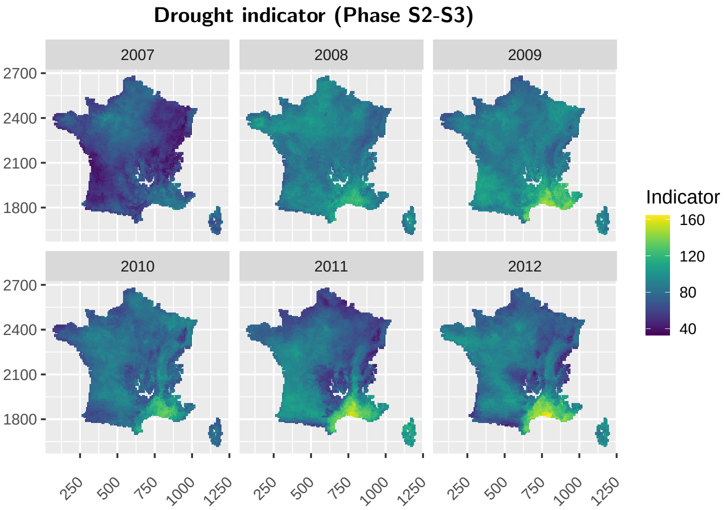
Location + Year + Phase + Indicator + Wheat ideotype

- **Gridded (8km) training data from DRIAS platform:**
  - Scenario RCP8.5, 2007–2100, GCM-RCM model of CNRM, bias-corrected
  - Provides plausible simulations of variability in present and future ecoclimate
- Data based on PhD work of Maël Aubry using 31 indicators for 14 risk categories [Aubry et al., 2025]
- Fixed wheat ideotype common in France
- Phenological phases determined using the STICS crop model
- **Drought indicators** based on Precipitation and Potential Evapotranspiration

Three drought indicator series for Paris and Toulouse pixels
(BBCH phases S2-S3, S3-S4, S5-S5)



Ecoclimate has spatial structure



↪ Stochastic structures with spatial trends and correlation

Some **desirata** (and **solutions**) for a stochastic ecoclimate generator

- **Spatial correlation** for capturing spatial compound events
  $\hookrightarrow$ **Spatial Gaussian copula**
- **Space-varying correlation range** for **large-scale modeling** (France)
  $\hookrightarrow$ **SPDE approach** for Gaussian fields with Matérn-like covariance
  $\hookrightarrow$ **Pre-estimated local range coefficient** as covariate
- **Multivariate modeling** (compound events) with many indicators
  $\hookrightarrow$ **Spatial Blind Source Separation**
  $\hookrightarrow$ Estimate weight matrix W and independent zero-mean Gaussian fields ε_j with

$$\begin{pmatrix} \mathrm{Indicator}_1(s,t) \\ \vdots \\ \mathrm{Indicator}_m(s,t) \end{pmatrix} = W \begin{pmatrix} \varepsilon_1(s,t) \\ \vdots \\ \varepsilon_m(s,t) \end{pmatrix} \quad \text{jointly for all pixels } s \text{ and years } t$$

- **Large numbers of spatial locations** (~ 8000)
  $\hookrightarrow$ **Gauss–Markov Random Fields** (GRMFs)
  $\hookrightarrow$ **INLA-based estimation**
- **Extrapolation** for generating larger extremes than in training data
  $\hookrightarrow$ **Extreme-Value Theory** (Peaks-over-Threshold)
  $\hookrightarrow$ **Conditional GMRF simulation**

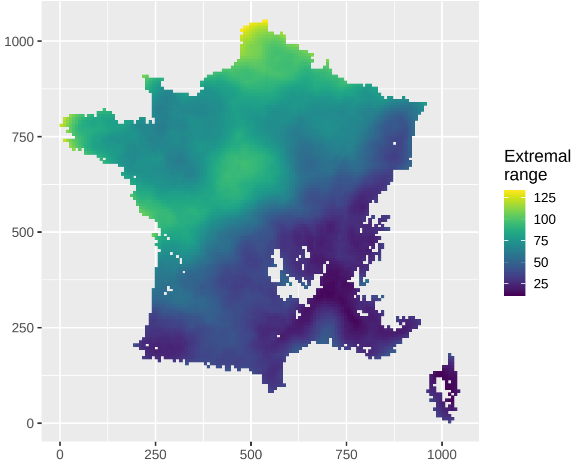
Towards a modular, fast and robust estimation procedure

1. **Estimate pixel-wise marginal model** for each indicator
   ↪ Hybrid distribution with continuous density: kde bulk, Generalized Pareto tail [Opitz et al., 2021]
2. **Transform each indicator to standard Gaussian** using distributions from Step 1
3. **Run Spatial Blind Source Separation** (`stbss` package) on multivariate space-time indicator data
4. **Calculate local range covariate** for each univariate space-time source from Step 3
5. **Fit second-order nonstationary INLA-SPDE models** separately to each source field using the covariate calculated in Step 4 (`R-INLA` package)
6. **Simulate new source field data** (GMRF simulation in `R-INLA` package) and **backtransform** to original fields and marginal distributions
   ↪ GMRF simulation allows conditioning on extreme weighted spatial averages

Example: Constructed covariate for the correlation range

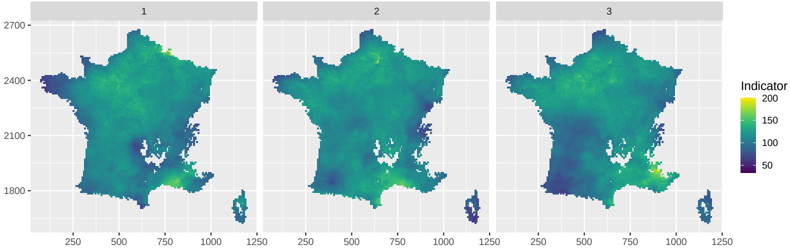
- Covariate = Estimated **median exceedance range** at each pixel [Cotsakis et al., 2024]
- Exceedance range = Distance to nearest non exceedance of a high marginal quantile (given that it is exceeded at the pixel)
- **Nonstationary SPDE Matérn range** estimated as $\rho(s) = \rho_0 \times \text{Covariate}^{\,\rho_1}$

Covariate for Drought indicator (Phase S2-S3) with $\hat{\rho}_1 = 0.7$

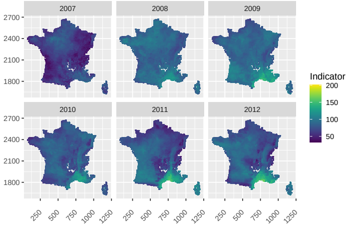


- **Proof-of-concept for a univariate model:** Drought indicator (Phase S2-S3)
- Simulation conditional on **spatial average of two Gaussian standard deviations**

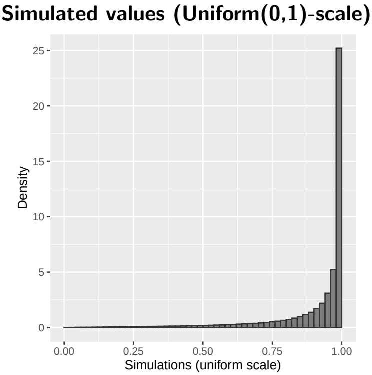
Three new simulations of the Drought indicator (Phase S2-S3)

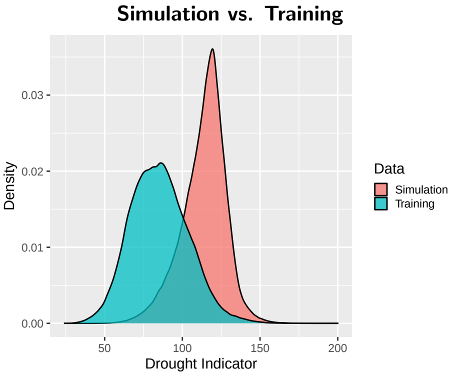


Training examples (same color scale)



New conditional simulations are much more extreme





- **Proof-of-concept for a spatial multivariate ecoclimatic generator:**
  - Construct a **modular and interpretable model** with separately estimable components
  - Enable **scalability** to many components and many locations
  - **Extrapolate** towards new extremes
- **Next steps:**
  - Estimate the **full multivariate spatial model**
  - **Validate** the simulation model
  - Transform indicators into yield distribution with a **statistical yield prediction model**
  - Assess extremes of **aggregated yield losses** at **large spatial scales**

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