MSTWeatherGen: a multivariate Stochastic Weather Generator

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Non extreme climate events, but with huge impact

2016, 2024: around 25% yield loss on wheat in the "Breadbasket" (France)

Succession of adverse conditions at each stage of the wheat season: sowing, growong and harvesting

Stochastic simulation as a tool to address this complexity

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SWGs

Adapted from Yiou (2024)

SWG are tools that generate random series of meteorological variables such as precipitation, temperature, wind speed, etc., with statistics similar to those of recorded data:

- Mean, variance, quantiles, skewness, extremes
- Covariance (dependence) between variables
- Temporal dependence / coherence (persistence)
- Spatial dependence / coherence

- Calibrated on recorded series
- Computational efficiency ⇒ long series and/or large number of realizations

For what purpose?

Used in impact studies

Outputs of SWGs are used as alternative, plausible weather time series in process-based models

- Assessing complex, non linear, responses to climate in agro-ecological systems
- Explore unmeasured climates
- Explore plant / ecosystem models as functions of climate variability
- Optimal decision under uncertainty: simulate up to year $t + k$, optimize decision
- Disaggregating (downscaling) meteorological variables from GCM outputs
- Also used with energy demand models, hydrological models, insurance models, ...

Some challenges that SWGs pose for spatial statistics

- Building models quantifying spatial, temporal and spatio-temporal variations ⇐ **this talk**

- Doing stochastic simulations, both for the bulk and of the tail
- Building models and methods for multivariate, spatio-temporal extreme events
- Devising new approaches for assessing return levels of impactful compound events

Our context; the project BEYOND

- The **BEYOND** project: towards new tools for epidemiological surveillance (for plants)
- *Xylella Fastidiosa* (Xf) is a plant pathogen propagated by insects
- Major damages: 54,000 ha of dead or uprooted olive orchards in Italy
- Seen in Corsica, Baleares, Tuscany
- Propagation depends on the whole seasonal cycle: not just one "extreme" event

↪ Need for a **stochastic tool able to generate complete cycles over a region**

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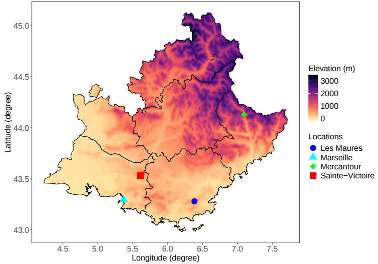
Our domain of interest

- Region of interest: PACA, highly non-stationary
- 6 daily variables: precipitation, humidity, radiation, wind, min and max temperature
- SAFRAN reanalysis data from 2012 to 2021



General architecture

Two main assumptions

- Finite number of weather types over the region, $\mathbf{k} = 1, \ldots, K$
- In each weather type k, the weather variables are modeled as transformed latent Gaussian random fields

$$Y_i(\mathbf{s}, t) = \psi_{\mathbf{k},i,\mathbf{s}}(Z_{\mathbf{k},i}(\mathbf{s}, t)), \qquad \mathbf{k} = \mathbf{X(t)}$$

Weather types | Transformation function | Latent Gaussian field

- Weather states are modeled as 1st order Markov chain with transition matrices $\pi(t)$
- We use empirical transformation for $\psi_{k,i}$ with tail adjustments (Peterson and Cavanaugh, 2019)
- Multivariate spatio-temporal GPs for $\boldsymbol{Z} = (Z_i)_{i=1,p}$

Multivariate Gneiting

Proposition (Allard et al., 2022)

$$C_{ij}(\mathbf{h},u) = \frac{\tau_{ij}}{(\eta_{\mathbf{ij}}(u)+b_{ij}^2)^{\tau}} \mathcal{M}\left(\mathbf{h}; \frac{a_{ij}}{\left(\eta_{\mathbf{ij}}(\mathbf{u})+b_{ij}^2\right)^{b/2}}, \nu_{ij}\right),$$

- $[C_{ij}(\mathbf{h},u)]_{i,j=1}^{p}$ is a multivariate space-time covariance under some conditions on the $p \times p$ matrices $\boldsymbol{b}$, $\boldsymbol{a}$, $\boldsymbol{\nu}$ et $\boldsymbol{\tau}$
- $\boldsymbol{\eta}(\mathbf{u})$ is a $p \times p$ matrix-valued unbounded pseudo-variogram on $\mathbb{R}$

- Each variable has its own set of parameters in space and in time
- Illustrated later

Estimation

Use PL on cleverly chosen sets of pairs.

- Partition the spatial domain D into n_A subgroups of minimal area
- For each $\alpha \in A$, build

$$B_\alpha = \left\{ \mathbf{s}_\beta \in D \mid \mathbb{I}\left(U_\beta \leq \frac{b_\alpha}{\|\mathbf{s}_\alpha - \mathbf{s}_\beta\|^2 + 1} \right) \right\}, \quad (1)$$

with b_α such that $\mathbb{E}[|B_\alpha|] = n_B$.

The set of pairs Λ to be used in PL is then defined as

$$\Lambda = \{(\alpha, \beta, \gamma, \delta) \ : \ \alpha \in A; \beta \in B_\alpha; |t_\gamma - t_\delta| \leq t_{max}, \} \quad (2)$$

Number of pairs approximately equal to $n_S^2/(n_A n_B) \times n_T / t_{max}$

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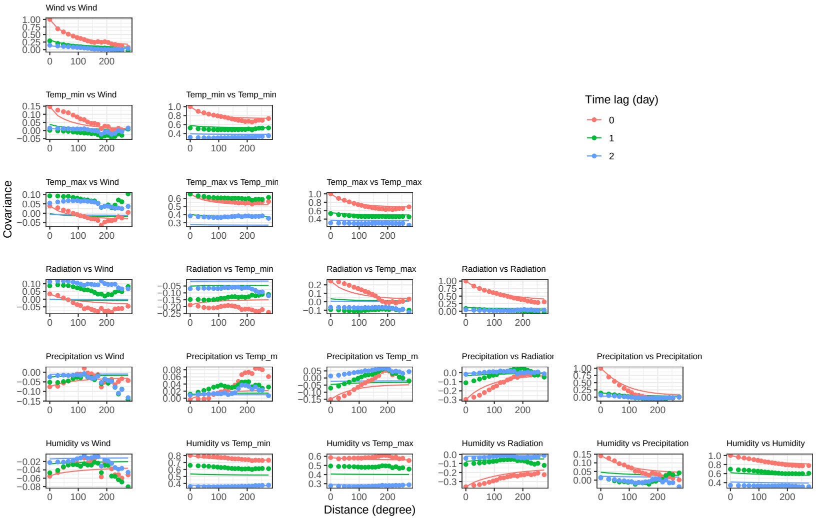
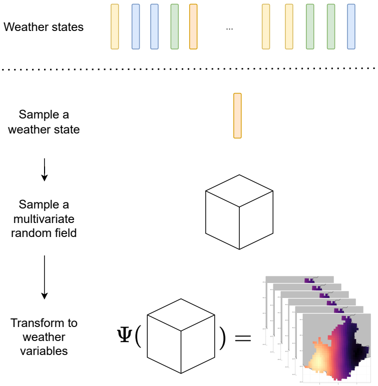
Multivariate covariance

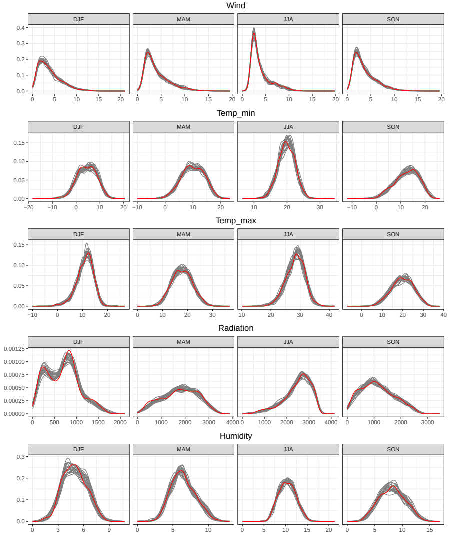


Simulation


Weather states
...
Sample a weather state
Sample a multivariate random field
Transform to weather variables
$\Psi($ $) =$

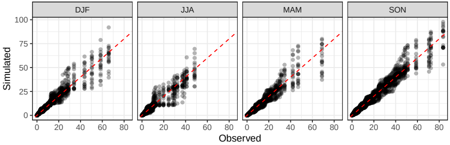
Marginals

All seasons, all continuous variables



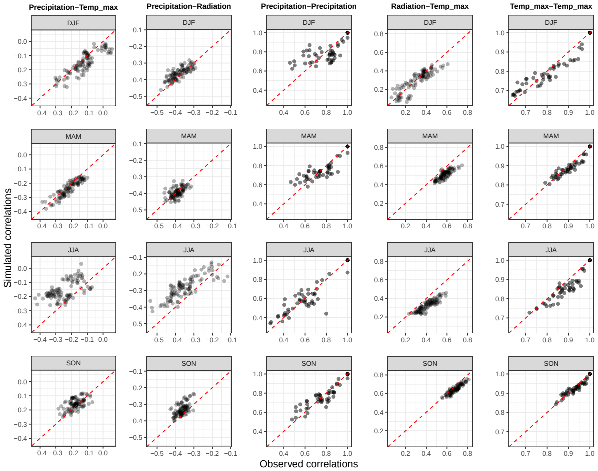
Marginals

All seasons, rainfall



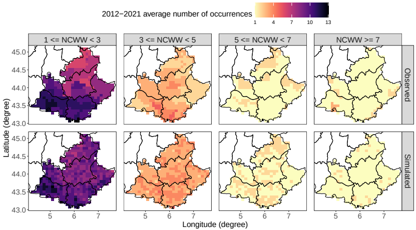
Correlations

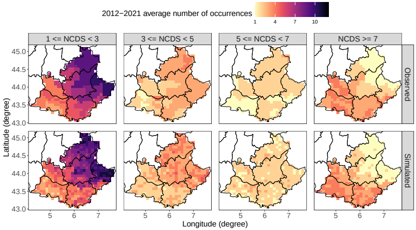
Winter, 10 random locations



Wet and dry spells

Wet winter spells, Dry summer spells





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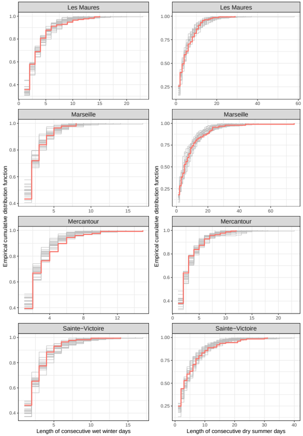
Empirical cumulative distribution function of spells

Wet winter spells, Dry summer spells



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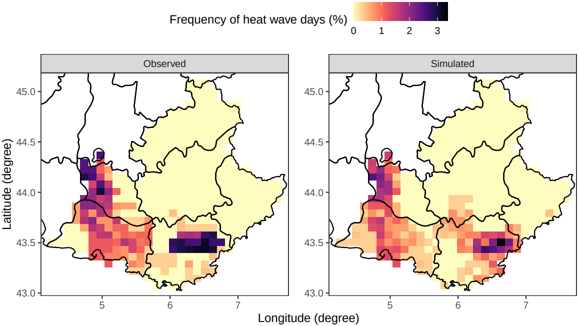
Heat Waves

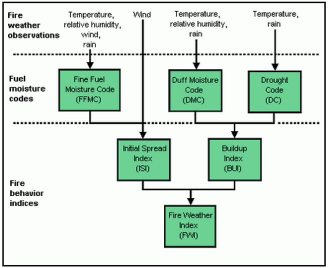
Defined as three successive days with Tmin > 21.5℃ and Tmax >34.5℃



Slight underestimation ⟹ need for better modeling of extremes and their temporal persistence

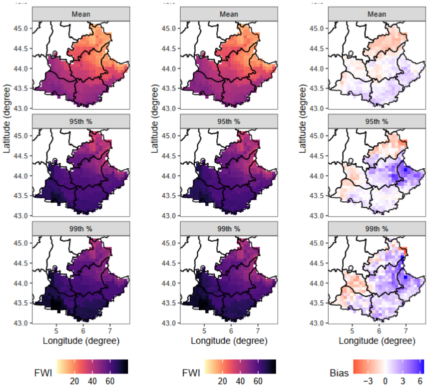
Fire Weather Index

- Developed and maintained by the Candian Forest Service
- consists of six components that account for the effects of fuel moisture and weather conditions on fire behavior.
-
- Updated daily using FWI(day before) and Temp, Rain, Wind, RH
- Used in France for the alert system



Fire Weather Index

Summer average

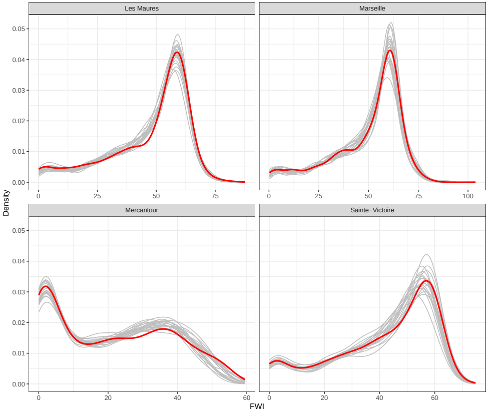


Obs.

Sim.

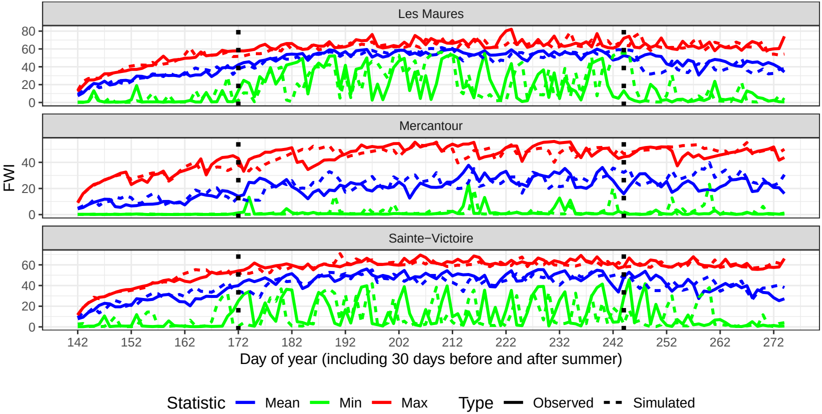
Fire Weather index

Summer density



Fire Weather Index

Summer



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Beyond MSTWeatherGen

MSTWeatherGen

✓Obakrim S., Benoit L., Allard D. (2025) A multivariate and space-time stochastic weather generator using a latent Gaussian framework. *Stochastic Environmental Research and Risk Assessment* (In press).

✓Obakrim S, Benoit L, Allard D, Rey J (2024). MSTWeatherGen: Multivariate Space-Time Weather Generator. R package
`https://sobakrim.github.io/MSTWeatherGen/index.html`

- CDD 2 ans à BioSP financé par la chaire
- Première mission: consolider MSTWeatherGen et l'interface utilisateur
- Au-delà:
  - Intégrer les résultats obtenus par Antoine, Rita, Tiziano etc. (?)
  - Reproduire des séries ou capacité d'interpolation ?
  - Et puis ?

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