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A Tailored Fine Fuel Moisture Content Model for Improving Wildfire Danger Rating Systems

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1. Background

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1. Background

The estimation of Fine **Fuel Moisture Content (FFMC)** is a key factor in any Forest Fire Danger Rating System, to determine ignition-prone fuel conditions and fire behavior. The difficulty in obtain frequent and spatialized real-time measurements of FFMC leads to the use of models to assess and predict it.

The FFMC model represents the core and dynamic component of RISICO [4], the Forest Fire Danger Rating System used operatively by the Italian Civil Protection Department and developed in 2000 by CIMA Research Foundation.

In the framework of the new release of RISICO in 2023, the FFMC model has been reformulated and calibrated on the basis of fuel stick data.

In this presentation:

1. **the calibration procedure on fuel stick data is presented, with a description of the new FFMC model;**
2. **the results of FFMC model performance on past wildfires events in Italy from 2007 to 2021 are presented.**

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2. Calibration

2.1. Fuel Stick Data → *2.2. FFMC Model* → *2.3. Parameter Optimization* → *2.4. Goodness-Of -Fit measures*

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2. Calibration

2.1. Fuel Stick Data

- *2.1.1. Data Collection and Analysis*
- *2.1.2. Time-serie Sampling*
- *2.1.3. Time-serie Clustering*
- *2.1.4. Calibration and Validation Datasets*

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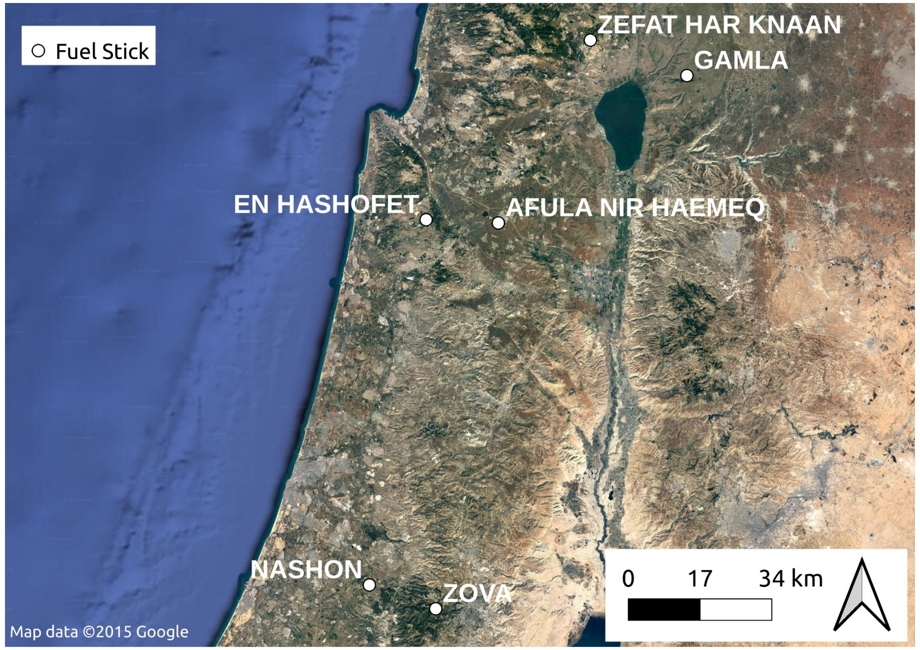
2.1. Fuel Stick Data

2.1.1. Data Collection and Analysis

Fuel stick data has been collected from **5 fuel sticks** allocated in **Israel** (see [1]). Data refers from 2017 to 2021.

We thank the authors of the paper for sharing the data with us.

	Latitude	Longitude	Altitude [m]	Distance from the sea [km]
Zefat Mt. Kenaan	35.5070	32.9800	936	38
Zova	35.1203	31.7803	715	43
Afula Nir Haemeq	35.2769	32.5960	60	33
Gamla	35.7484	32.9056	405	63
Nahshon	34.9544	31.8308	180	26



[1] Shmuel, A., Ziv, Y., & Heifetz, E. (2022). Machine-Learning-based evaluation of the time-lagged effect of meteorological factors on 10-hour dead fuel moisture content. Forest Ecology and Management, 505, 119897.

2.1. Fuel Stick Data

2.1.1. Data Collection and Analysis

The 5 fuel sticks have been located next to meteorological stations.

Data has been provided at
1 hour time resolution

Rain
[mm]

Temperature
[°C]

Wind
Speed
[m/s]

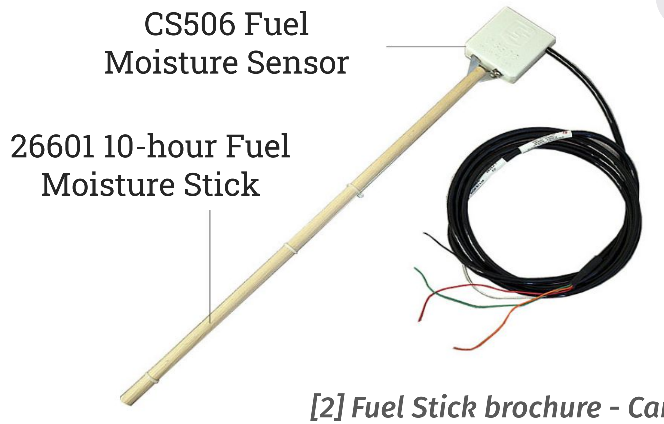
Air
Humidity
[%]

Time series of weather conditions and fuel moisture

Variable of interest:
Fuel Moisture Content

Measuring instrument:
Campbell [2] Fuel Stick

Fuel sticks are often used for wildfire danger forecasting systems, providing real-time data of fuel moisture.



[2] Fuel Stick brochure - Campbell Scientific
https://www.campbellsci.com/pn26601

2.1. Fuel Stick Data

2.1.1. Data Collection and Analysis

W: Water content [g]

F: fuel weight in dry conditions [g]

The fuel stick measures fuel moisture calculated as the **water content over the dry fuel weight** (FFMC dry).

$$\varphi(x) = \frac{x}{100+x}100$$

$$FFMC_{dry} = \frac{W}{F}100$$

$$FFMC = \frac{W}{W+F}100$$

$$\varphi^{-1}(x) = \frac{x}{100-x}100$$

The original FFMC model of RISICO simulates the **water content over the total weight** (FFMC).

For this reason, the following fuel moisture measures are reported with respect to the total weight, according to the proper conversion.

2.1. Fuel Stick Data

2.1.1. Data Collection and Analysis

	Fuel Moisture time span	Completeness *	Continuity **
Zefat Mt. Kenaan	04.2018–07.2021	0.689	0.999
Zova	04.2017–07.2021	0.935	0.998
Afula Nir Haemeq	04.2017–01.2021	0.812	0.999
Gamla	08.2017–07.2021	0.804	0.999
Nahshon	05.2017–02.2021	0.851	0.998

These time series cover a **wide range of weather conditions** thanks to their continuity and completeness, and their length of about 4 years.

The **continuity index is 1 for a continuous time-series, while it is zero for a time series that alternates missing data with valid data

$$Continuity = 1 - 2 \times \frac{Number\ of\ invalid\ intervals}{Number\ of\ times}$$

A time interval is valid if composed by all valid times.

*The **completeness index** is 1 if all the data are present for each time of the timeseries.

$$Completeness = \frac{Number\ of\ valid\ times}{Number\ of\ times}$$

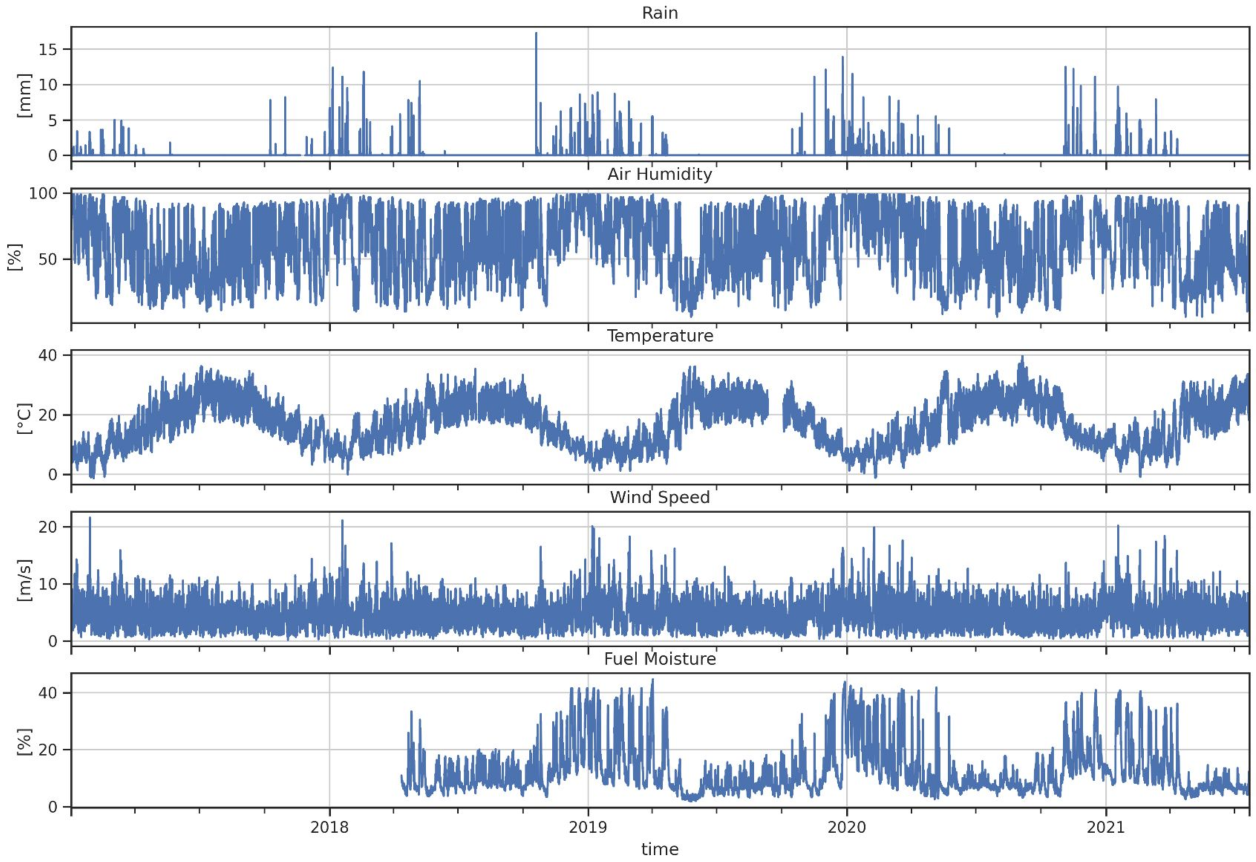
A time instant is valid if all weather data are present.

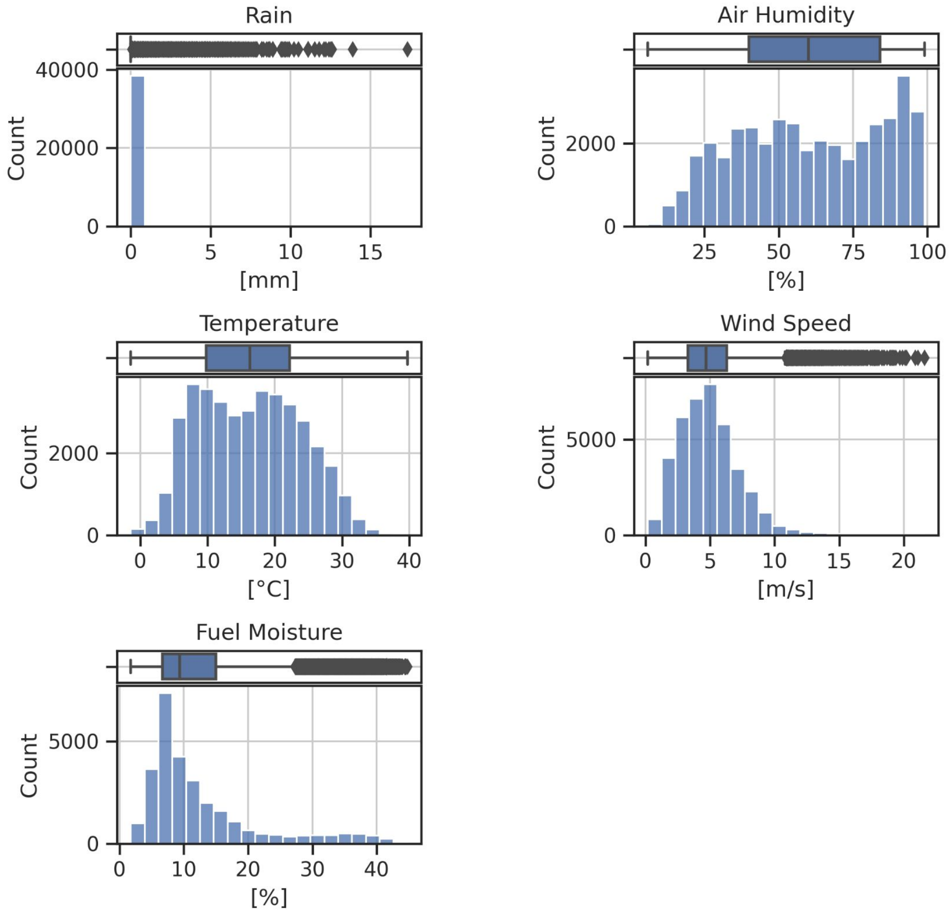
2.1. Fuel Stick Data

2.1.1. Data Collection and Analysis

Variables distribution

- **Zefat Mt. Kenaan**



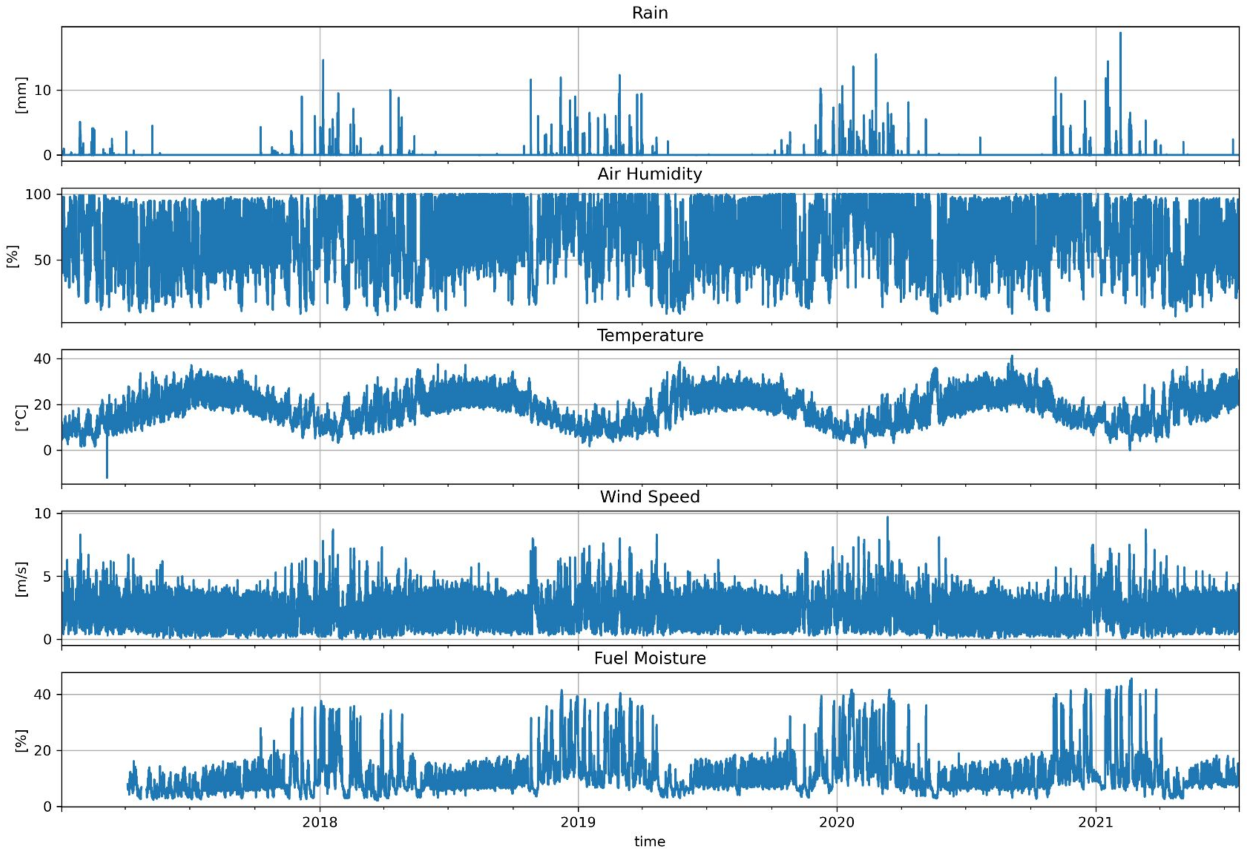


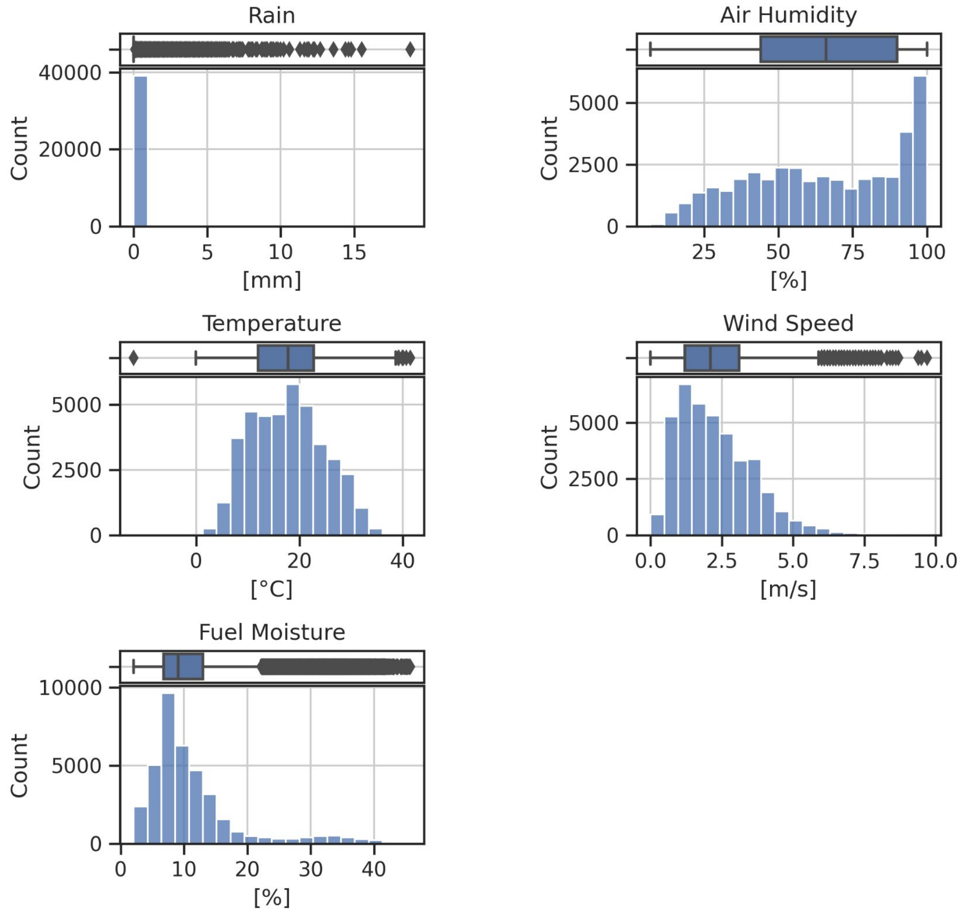
2.1. Fuel Stick Data

2.1.1. Data Collection and Analysis

Variables distribution

- **Zova**





2.1. Fuel Stick Data

2.1.1. Data Collection and Analysis

Variables distribution

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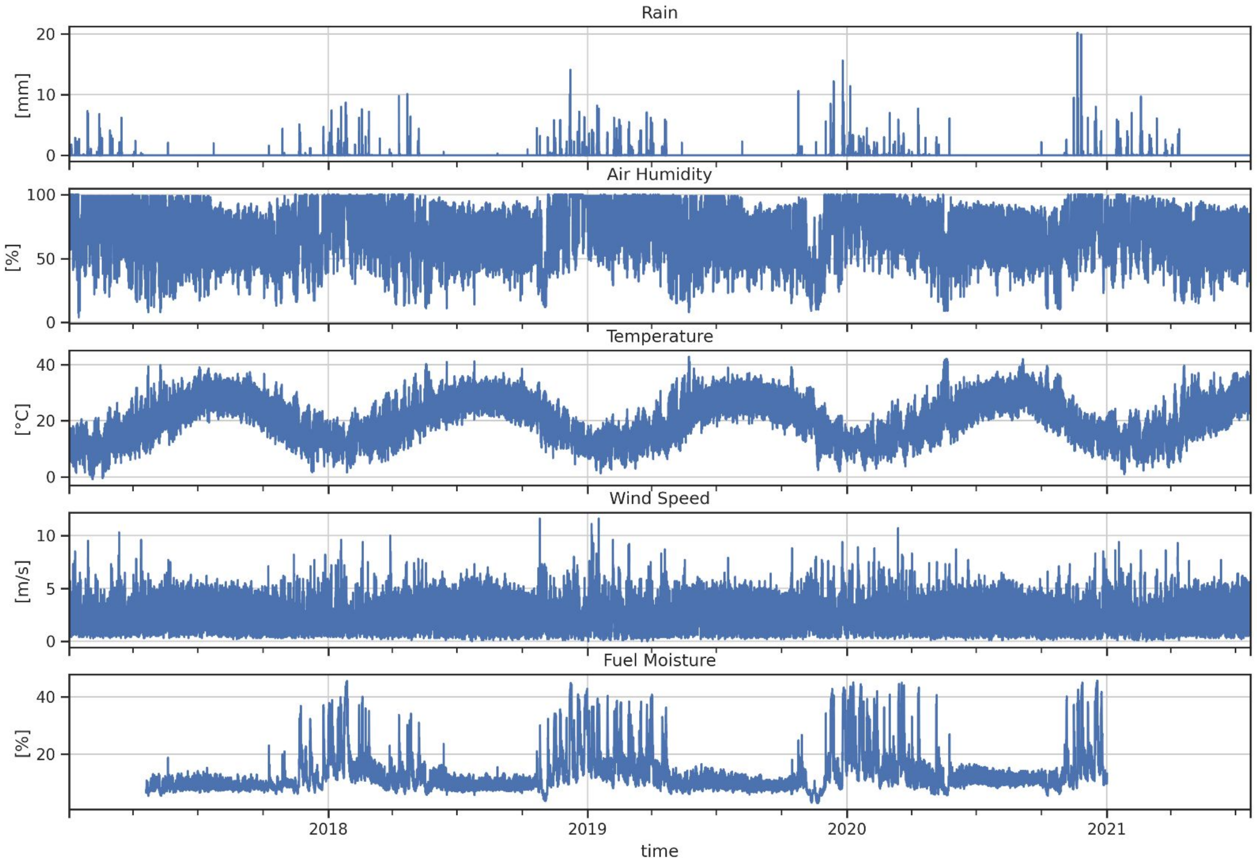
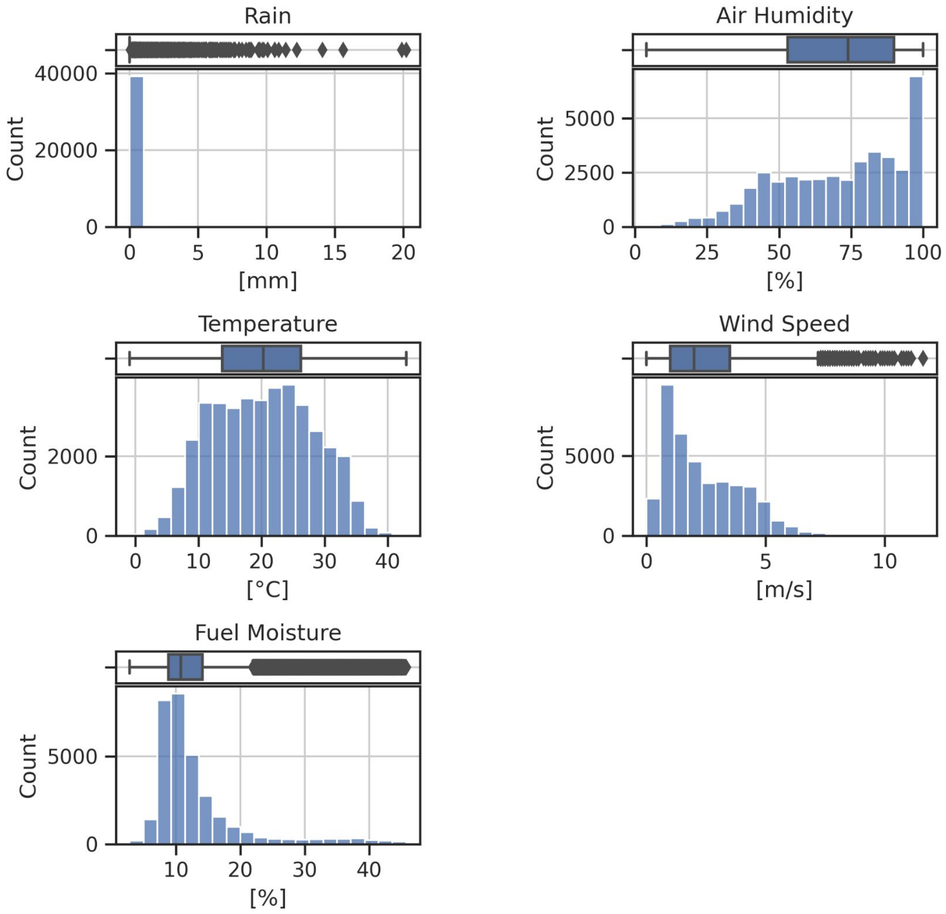
- **Afula Nir Haemeq**



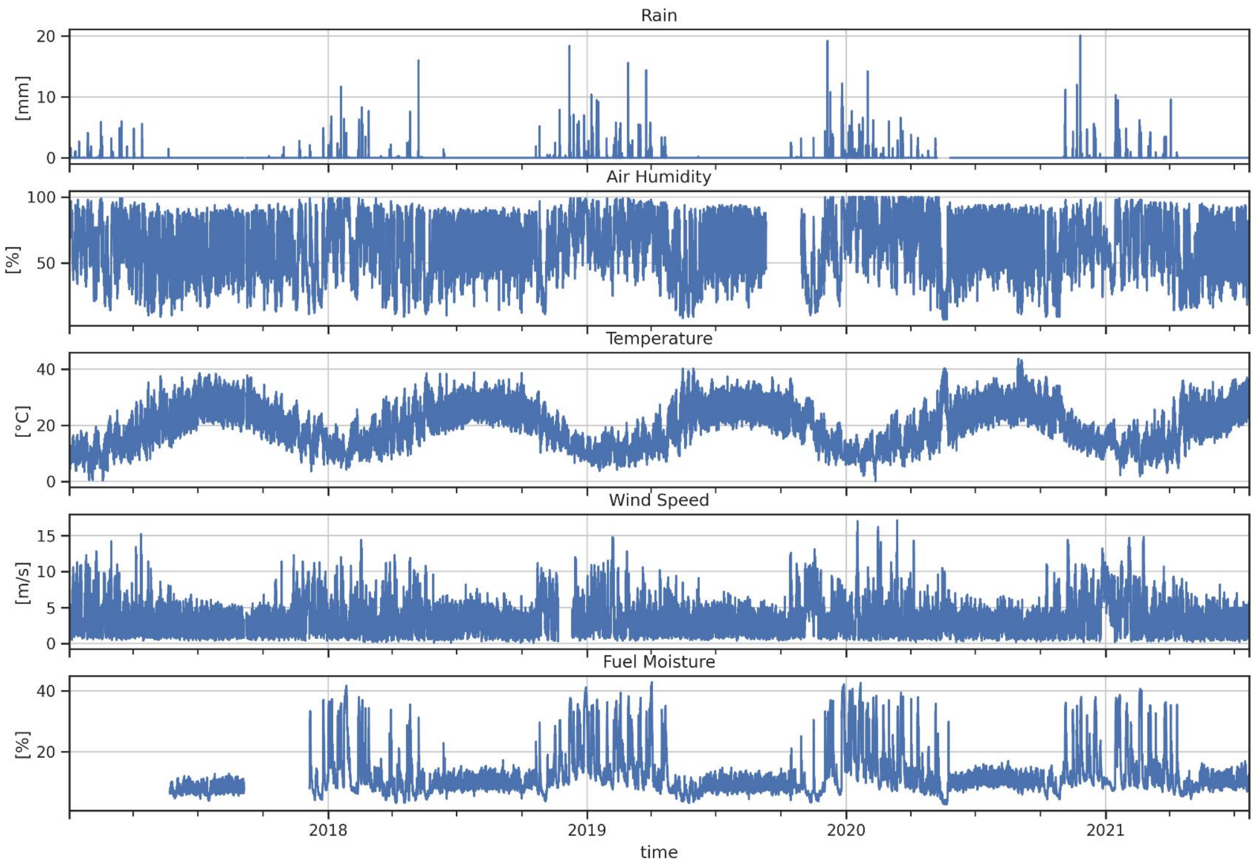


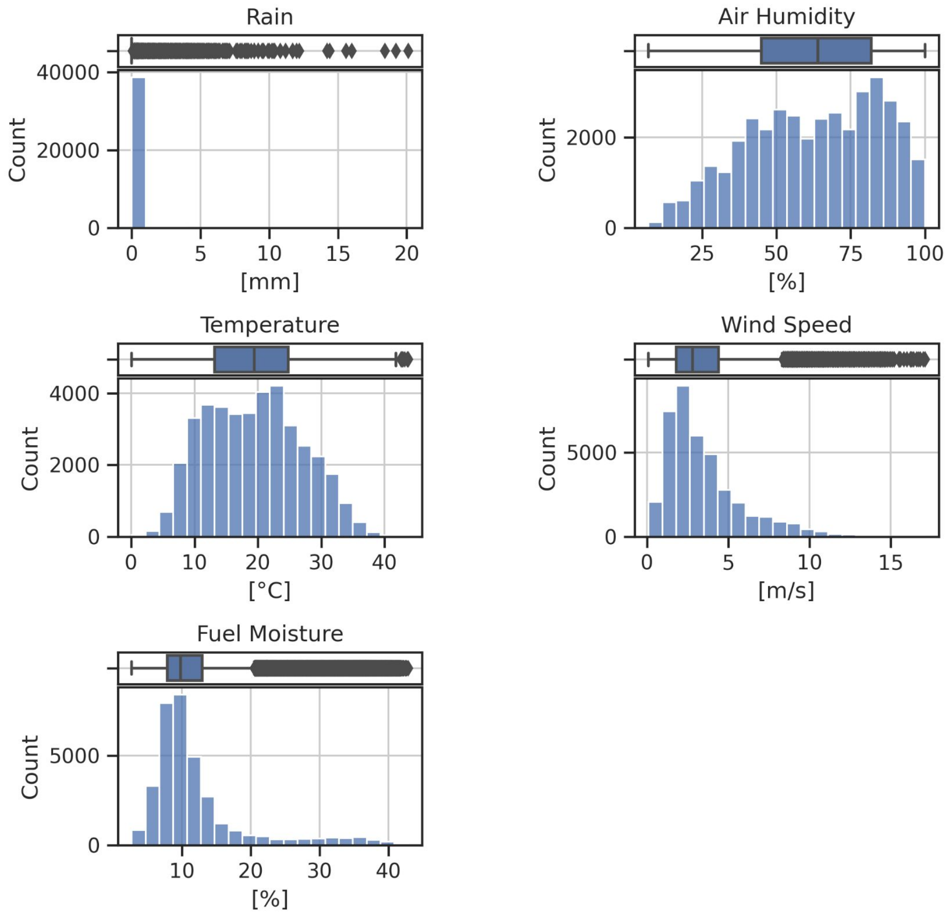
2.1. Fuel Stick Data

2.1.1. Data Collection and Analysis

Variables distribution

- **Gamla**



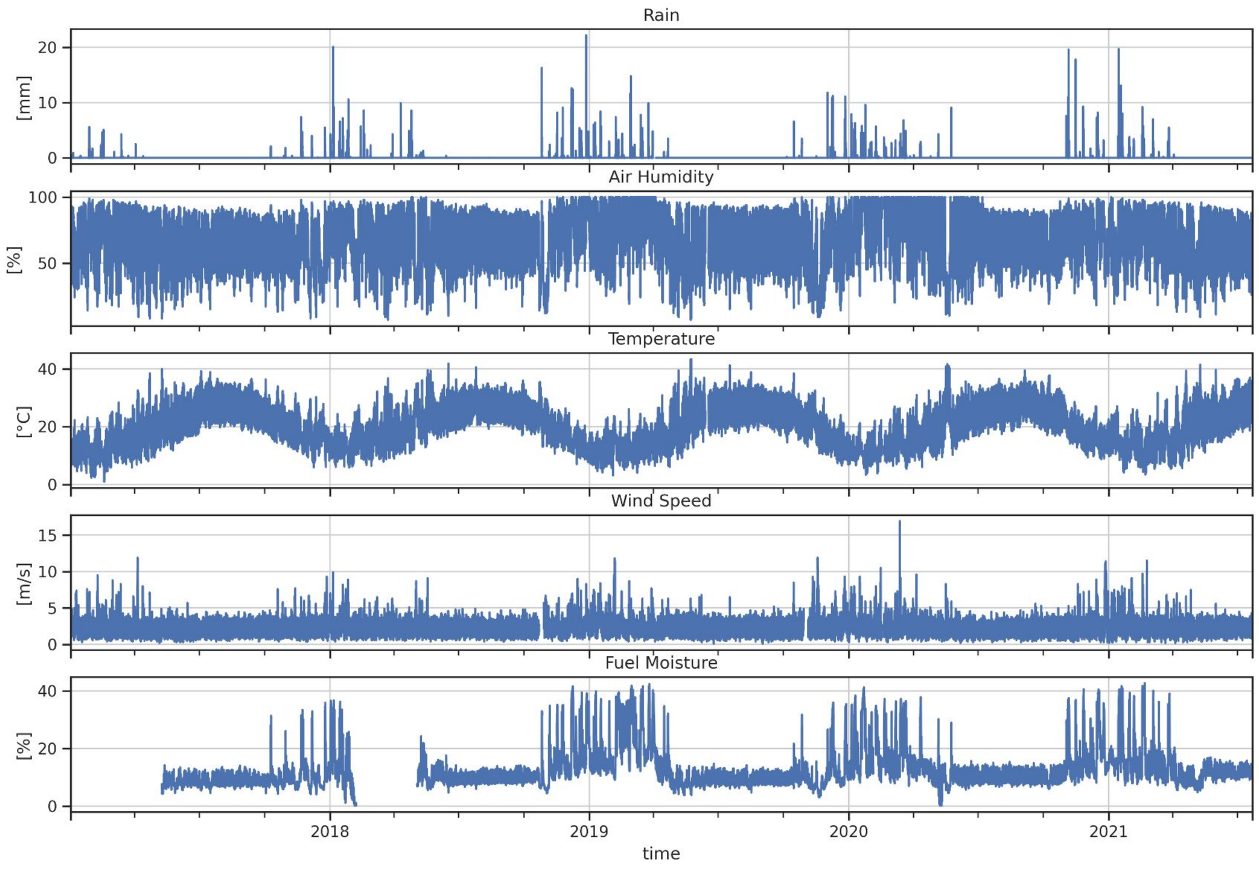


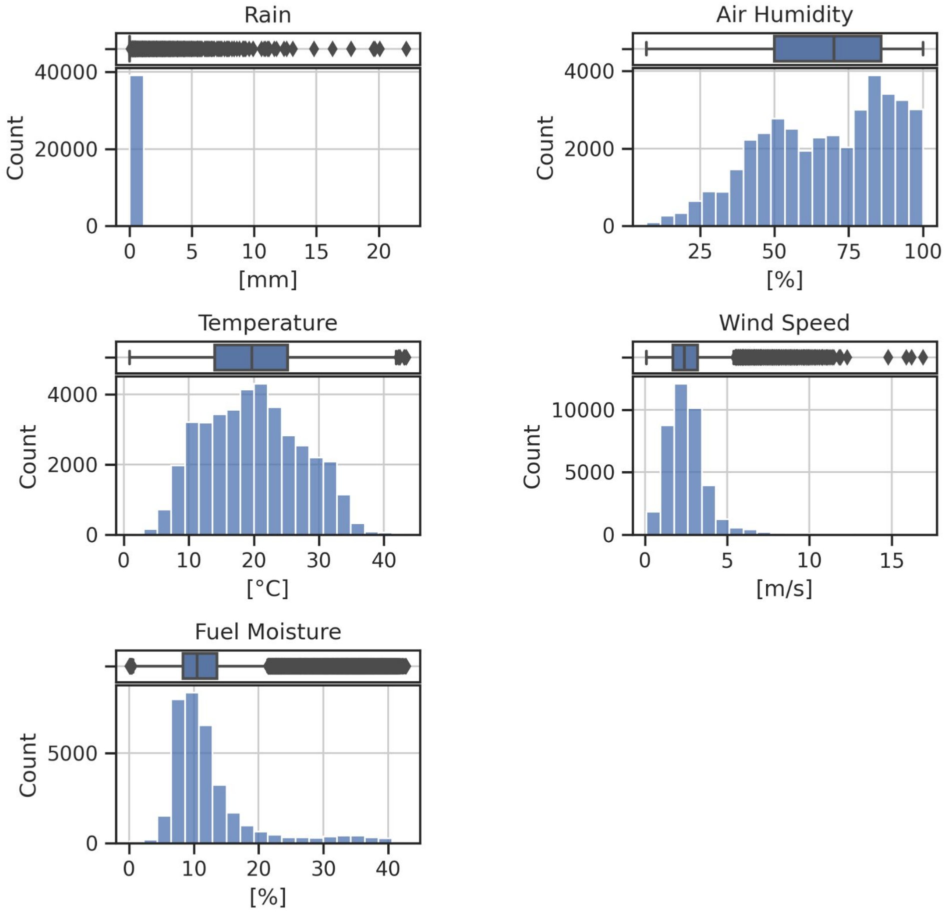
2.1. Fuel Stick Data

2.1.1. Data Collection and Analysis

Variables distribution

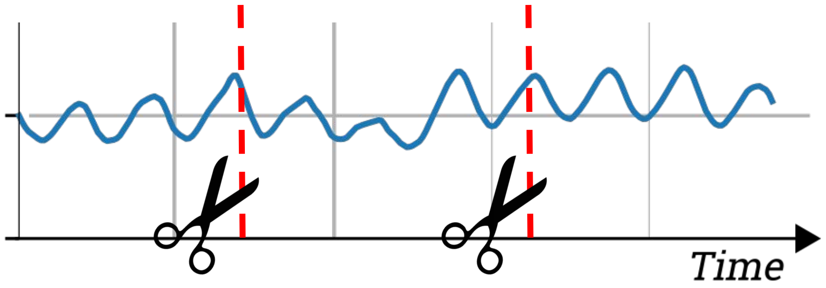
- **Nahshon**

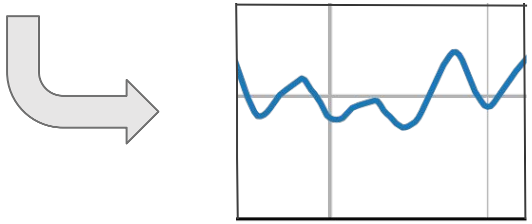




2.1. Fuel Stick Data

2.1.2. Time-serie Sampling





Sub-timeseries have been sampled.

Three groups of sub-time-series have been selected:

1. **No-rain:** time-series without rain to calibrate the no-rain phase
2. **Rain:** time-series with rain have to calibrate the rain phase
3. **Mixed:** generic time-series to evaluate the final calibrated model

	Sampling criteria		
	No-rain phase	**Rain phase**	**Mixed**
Timeseries length	240 h (10 days)	6 h	240 h (10 days)
Presence of rain	no	yes, for all the times	not strictly requested
Distance from no-data	24 h	24 h	24 h
Minimum temperature	0 °C	0 °C	0 °C
Buffer between timeseries	72 h (3 days)	6 h	120 h (5 days)
Number of sampling	**277**	**351**	**408**

Sampling method: stochastic

1. data clusters that meet the selection criteria are identified
2. a cluster is randomly drawn from possible clusters
3. the time-serie is selected from the cluster and removed from the possible choices
4. the procedure is repeated until possible clusters are available

2.1. Fuel Stick Data

2.1.2. Time-serie Sampling

As expected, the no-rain samples are mostly from Summer period, while rain samples are from Spring and Winter period.

	Number of samples		
	No rain	Rain	Mixed
Zefat Mt. Kenaan	46	89	67
Zova	64	58	92
Afula Nir Haemeq	53	61	86
Gamla	58	79	81
Nahshon	56	64	82

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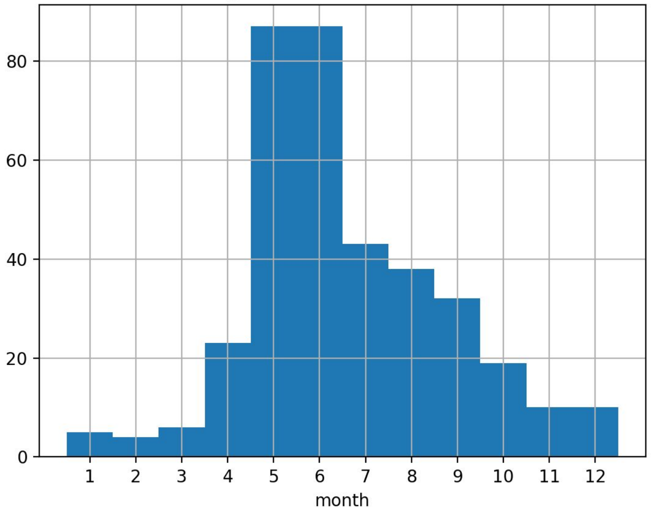
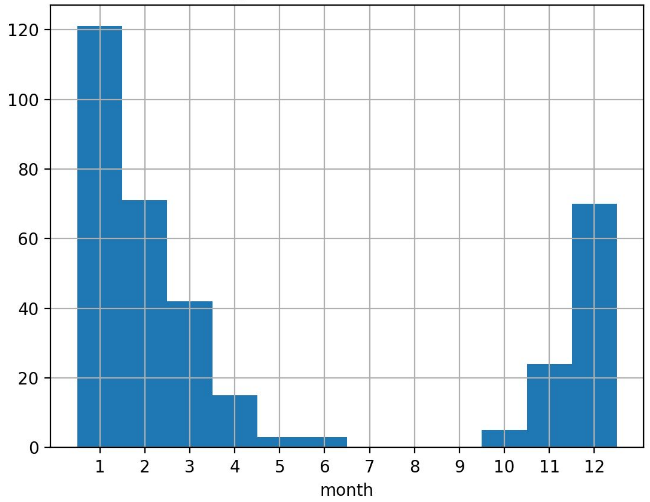
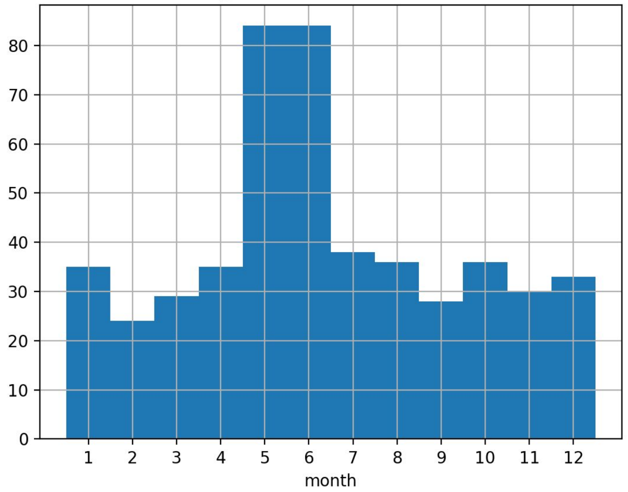
No-rain



Rain



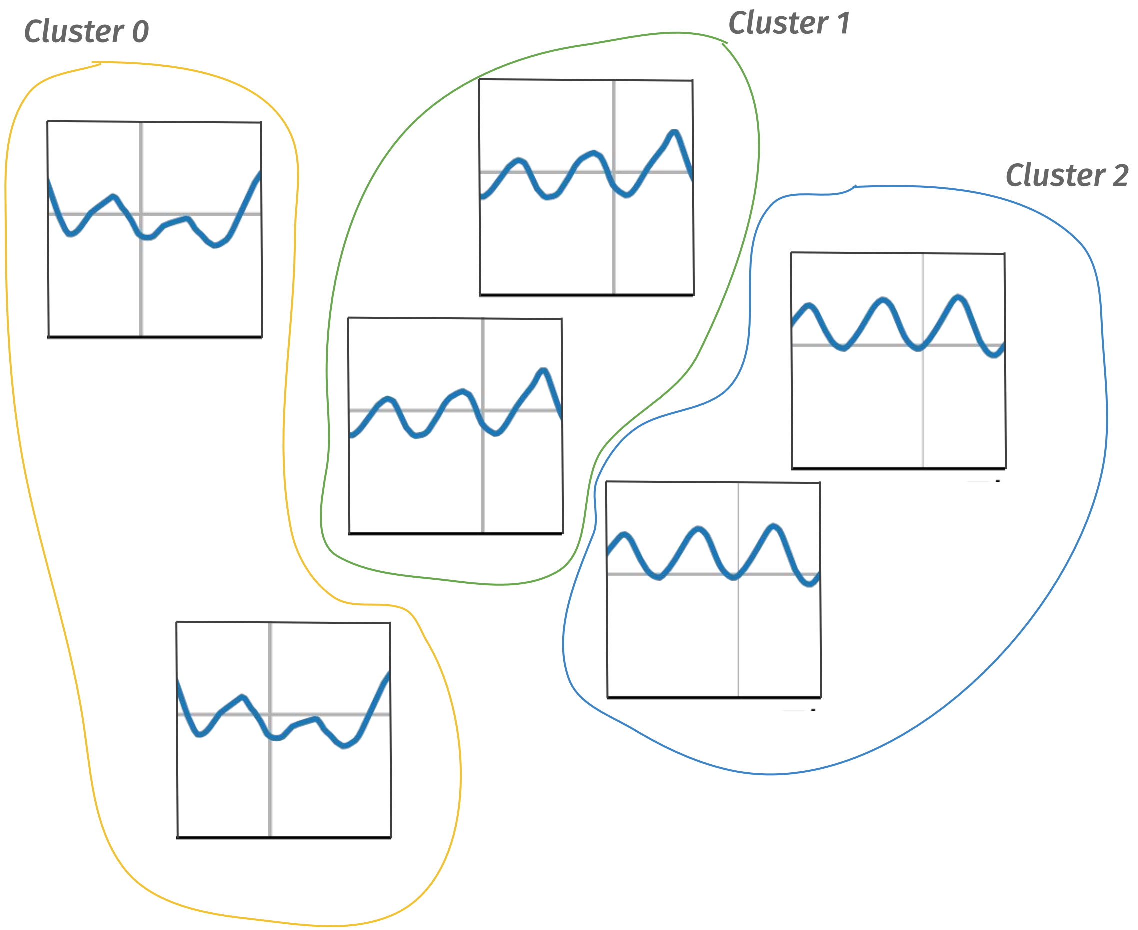
Mixed



2.1. Fuel Stick Data

2.1.3. Time-serie Clustering

For each group of timeseries, clusters are computed.



Data clustering has been performed to:

1. identify structures on the timeseries
2. select properly the datasets for calibration and validation

Method: K-means **[3]**

Metric: Dynamic Time Warping (DTW)

Number of clusters: 3

Variable for clustering: Fuel Moisture

[3] Aghabozorgi, S., Seyed Shirkhorshidi, A., & Ying Wah, T. (2015). Time-series clustering - A decade review. Information Systems, 53, 16–38. https://doi.org/10.1016/j.is.2015.04.007

2.1. Fuel Stick Data

2.1.3. Time-serie Clustering

No-rain samples

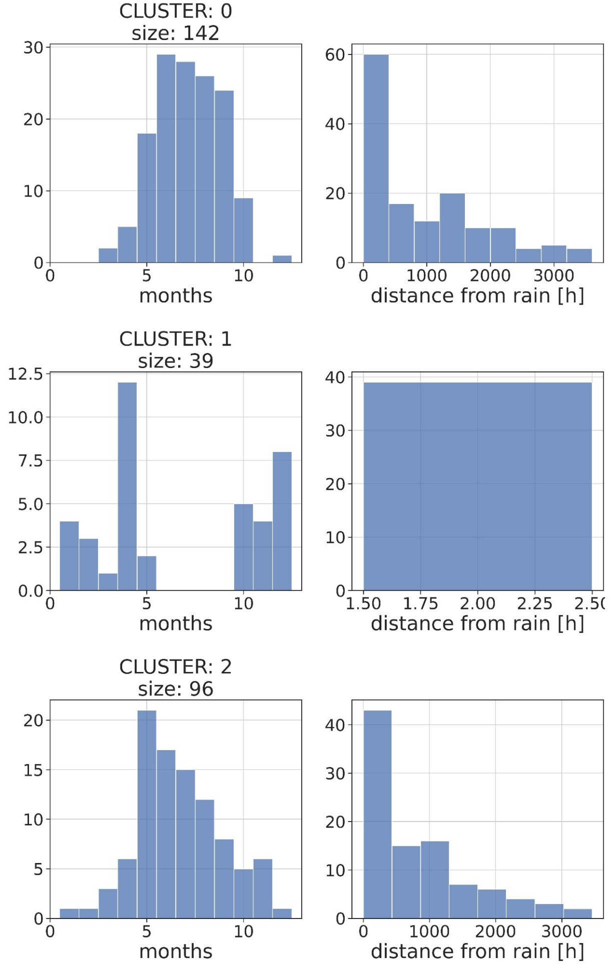
Clusters statistics

	Number of samples	Mean values			
		Fuel Moisture [%]	Air Humidity [%]	Temperature [°C]	Wind speed [m/s]
Cluster 0	142 (51%)	9.98	65.90	24.42	2.59
Cluster 1	39 (14%)	10.39	56.38	15.65	3.75
Cluster 2	96 (35%)	7.46	51.99	23.26	3.07

CLUSTER 0: the biggest cluster, characterized by time-serie samples in Summer, with low values of fuel moisture

CLUSTER 1: the smallest cluster, with time-series in Spring, Autumn or Winter very close to rains (less than 2 hours from the last registered rain)

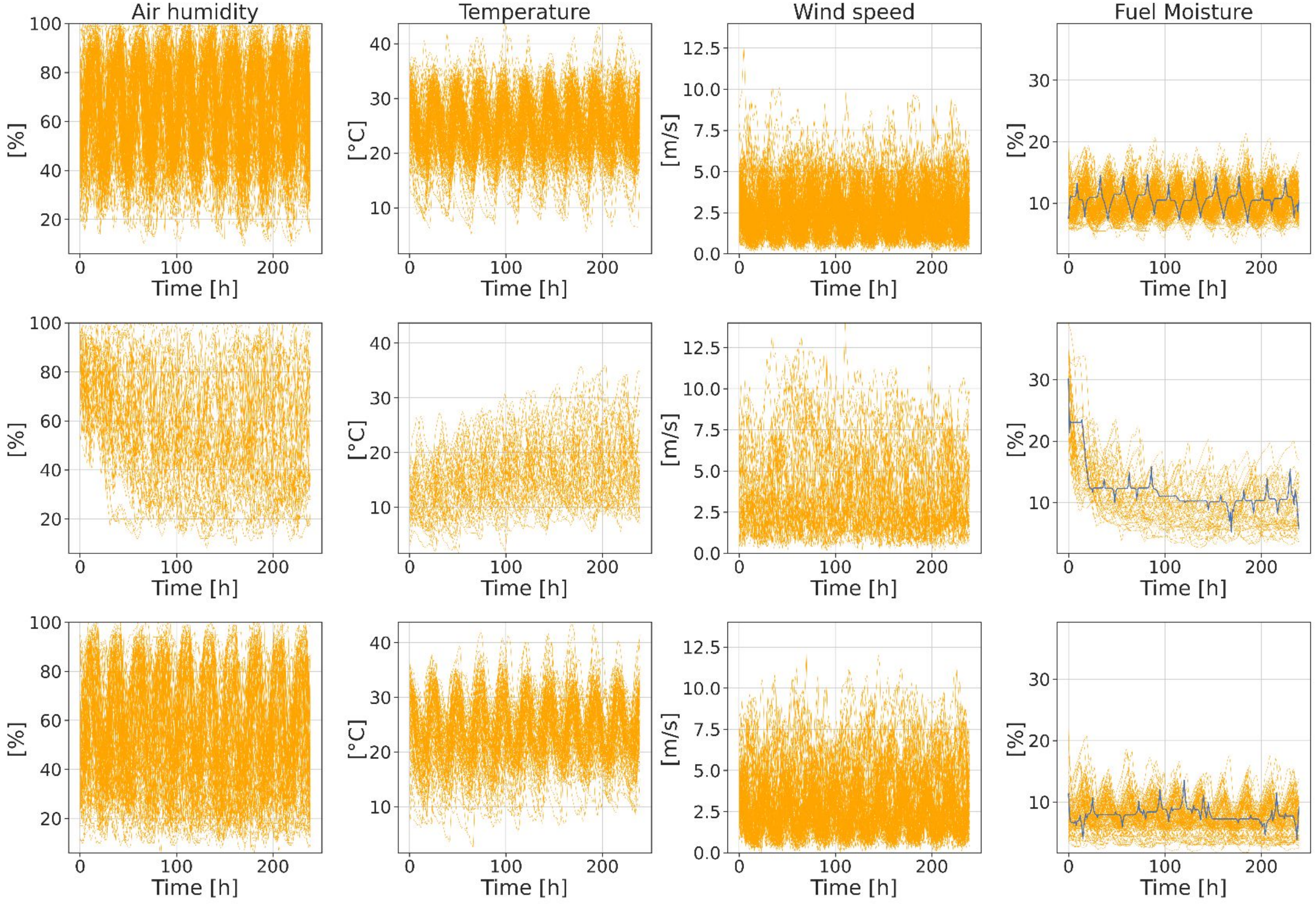
CLUSTER 2: especially in Spring and Summer, very low values of fuel moisture



2.1. Fuel Stick Data

2.1.3. Time-serie Clustering

No-rain samples



Clusters plot

CLUSTER 0: regular behavior, alternating between absorption and desorption of moisture

CLUSTER 1: after-rain behavior, with a decrease in moisture content

CLUSTER 2: low values of moisture, not particularly regular behavior

Timeseries

Centroid of the cluster (only for fuel moisture)

2.1. Fuel Stick Data

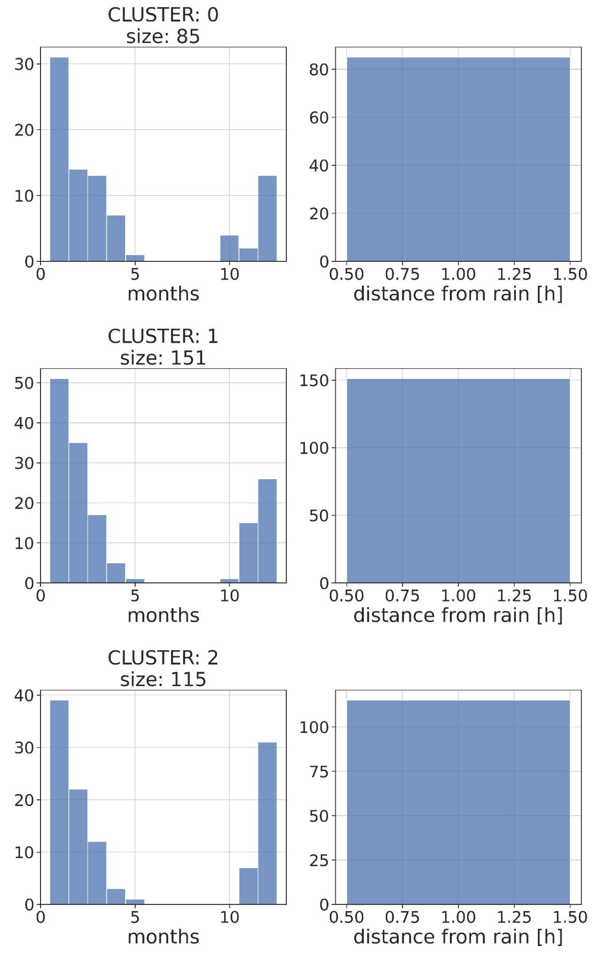
2.1.3. Time-serie Clustering

Rain samples

Clusters statistics

	Number of samples	Mean values				
		Fuel Moisture [%]	Rain [mm/h]	Air Humidity [%]	Temperature [°C]	Wind speed [m/s]
Cluster 0	85 (24%)	26.86	1.95	89.75	10.92	4.79
Cluster 1	151 (43%)	33.43	2.25	95.64	9.21	4.94
Cluster 2	115 (33%)	39.40	1.92	97.10	8.39	4.72

As expected, all the clusters are referred to timeseries near rains (or inside rain events), in Spring/Winter period, with high values of fuel moisture

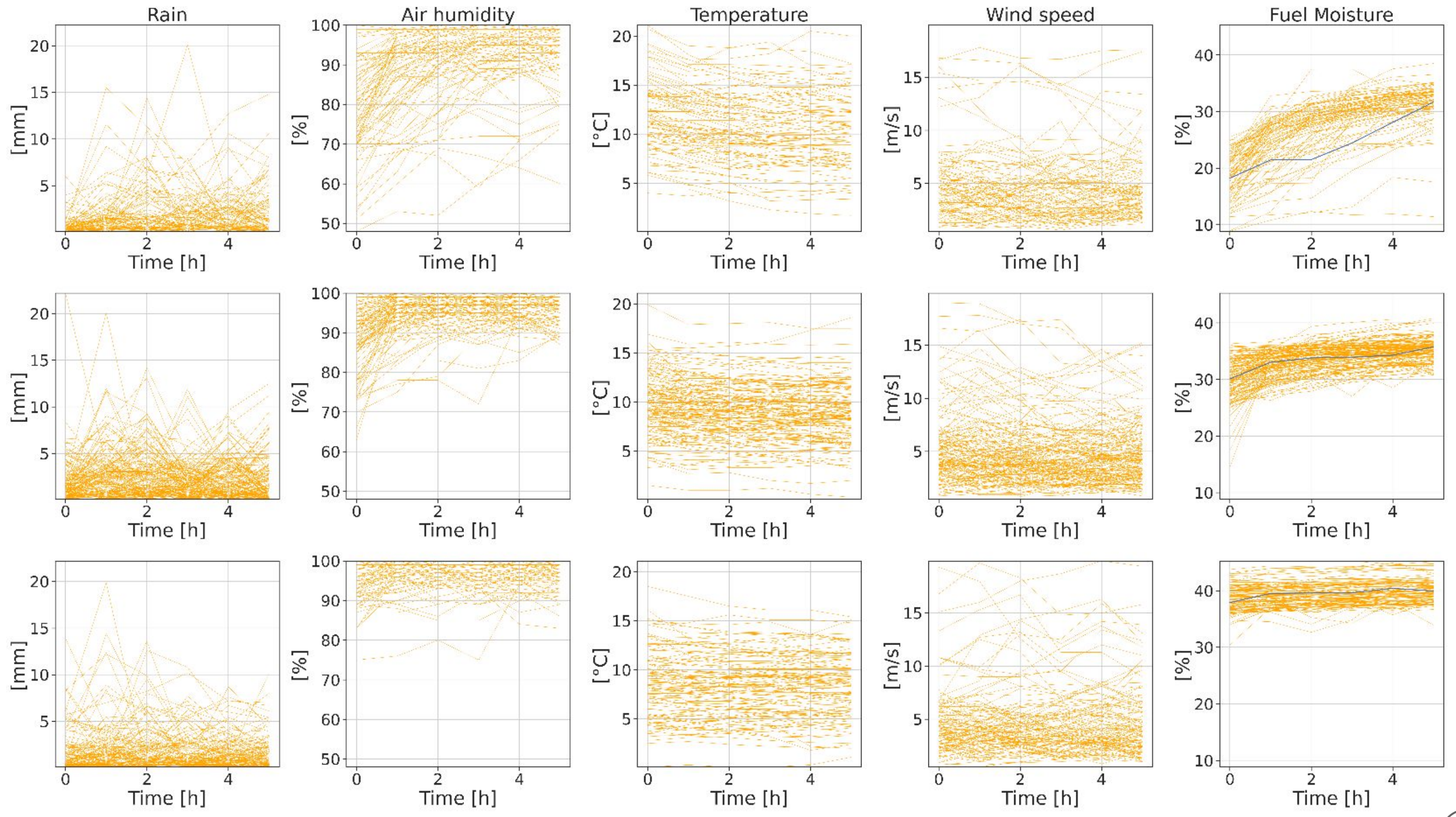


2.1. Fuel Stick Data

2.1.3. Time-serie Clustering

Clusters plot

Rain samples



CLUSTER 0: fuel moisture is increasing from low values due to rain events

CLUSTER 1: fuel moisture is increasing from previous quite high fuel moisture values

CLUSTER 2: fuel moisture is not increasing, since it is already near the saturation values

Timeseries
Centroid of the cluster (only for fuel moisture)

2.1. Fuel Stick Data

2.1.3. Time-serie Clustering

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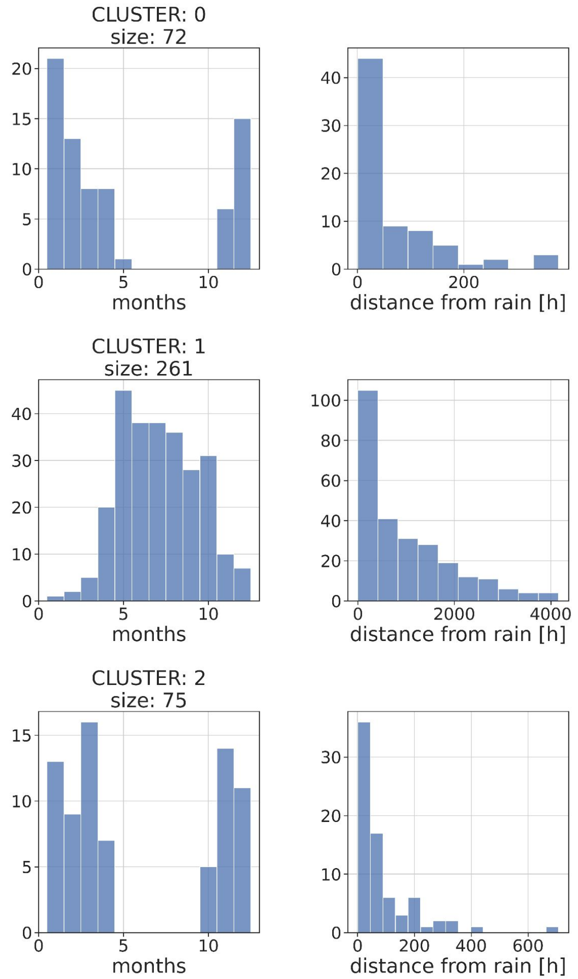
Mixed samples

Clusters statistics

	Number of samples	Mean values				
		Fuel Moisture [%]	Rain [mm/h]	Air Humidity [%]	Temperature [°C]	Wind speed [m/s]
Cluster 0	72 (18%)	18.69	0.19	75.23	11.95	3.40
Cluster 1	261 (64%)	9.22	0.004	60.87	23.0	2.88
Cluster 2	75 (18%)	16.63	0.17	72.93	19.95	3.33



CLUSTER 0: characterized by time-serie samples in Spring or Winter, with high values of fuel moisture

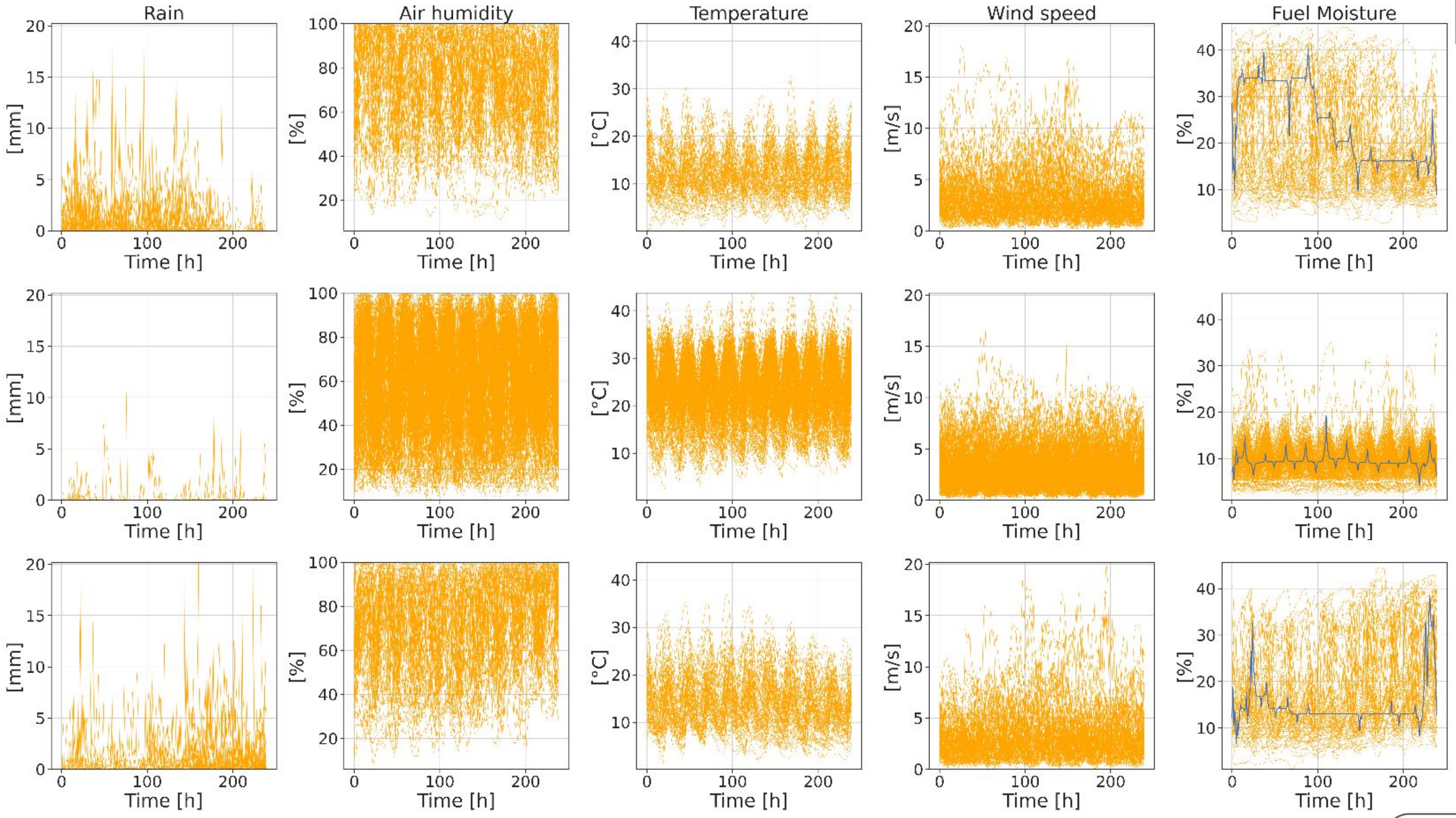
CLUSTER 1: the biggest cluster, with time-series mainly in Summer period, and with very low values of fuel moisture

CLUSTER 2: similar to cluster 0; characterized by time-serie samples in Spring or Winter, with high values of fuel moisture

2.1. Fuel Stick Data

2.1.3. Time-serie Clustering

Mixed samples



Clusters plot

CLUSTER 0: characterized by quite high values of fuel moisture, with a decreasing behavior

CLUSTER 1: regular behavior, with low values of fuel moisture (no or few rain)

CLUSTER 2: characterized by quite high values of fuel moisture

Timeseries

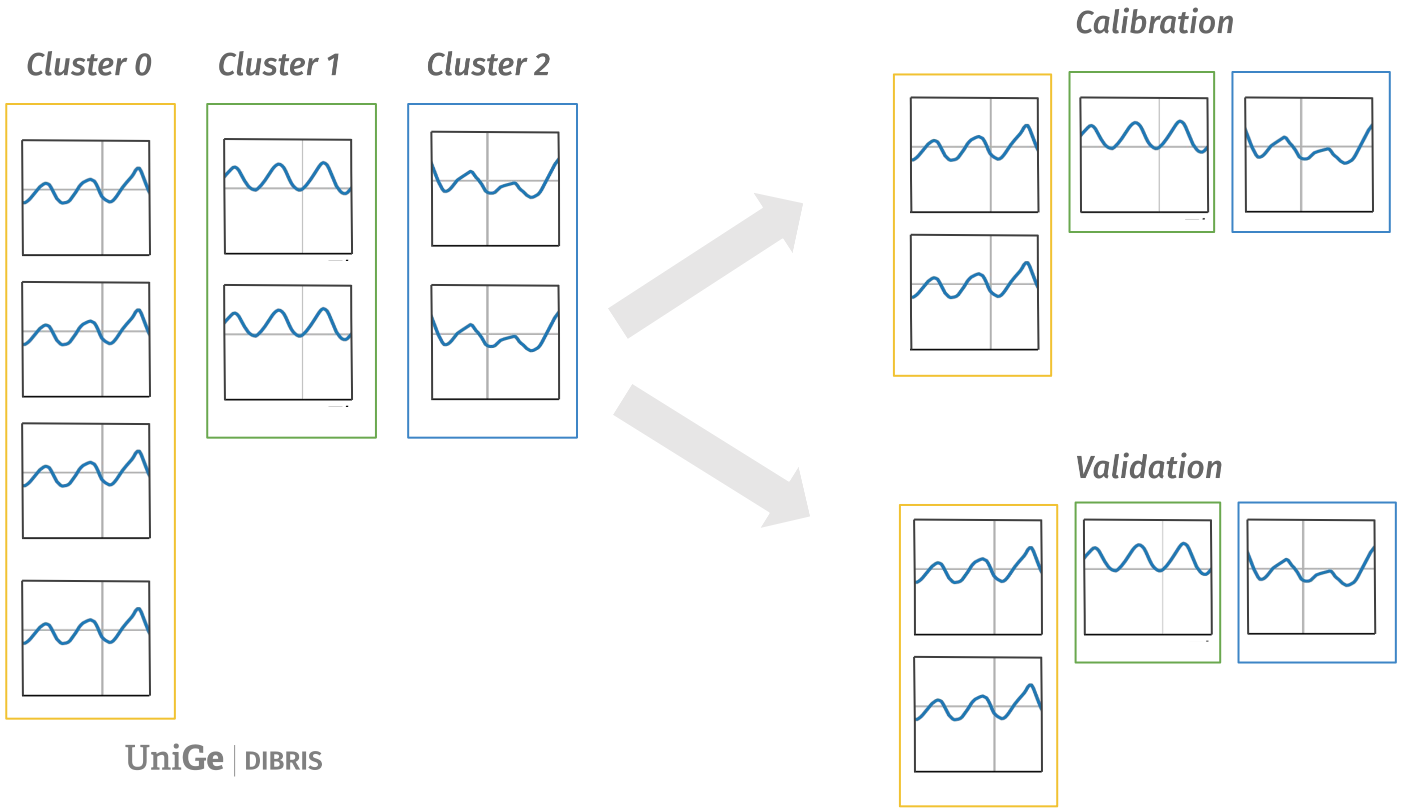
Centroid of the cluster (only for fuel moisture)

2.1. Fuel Stick Data

2.1.4. Calibration and Validation Datasets

- The **No-rain** and **Rain** groups of samples have been then splitted into a calibration dataset (**80%**) and validation dataset (**20%**), maintaining for each of the two datasets **the same distribution of clusters** identified in the initial dataset.

- The **mixed** group have been all used for validation of the calibrated model.



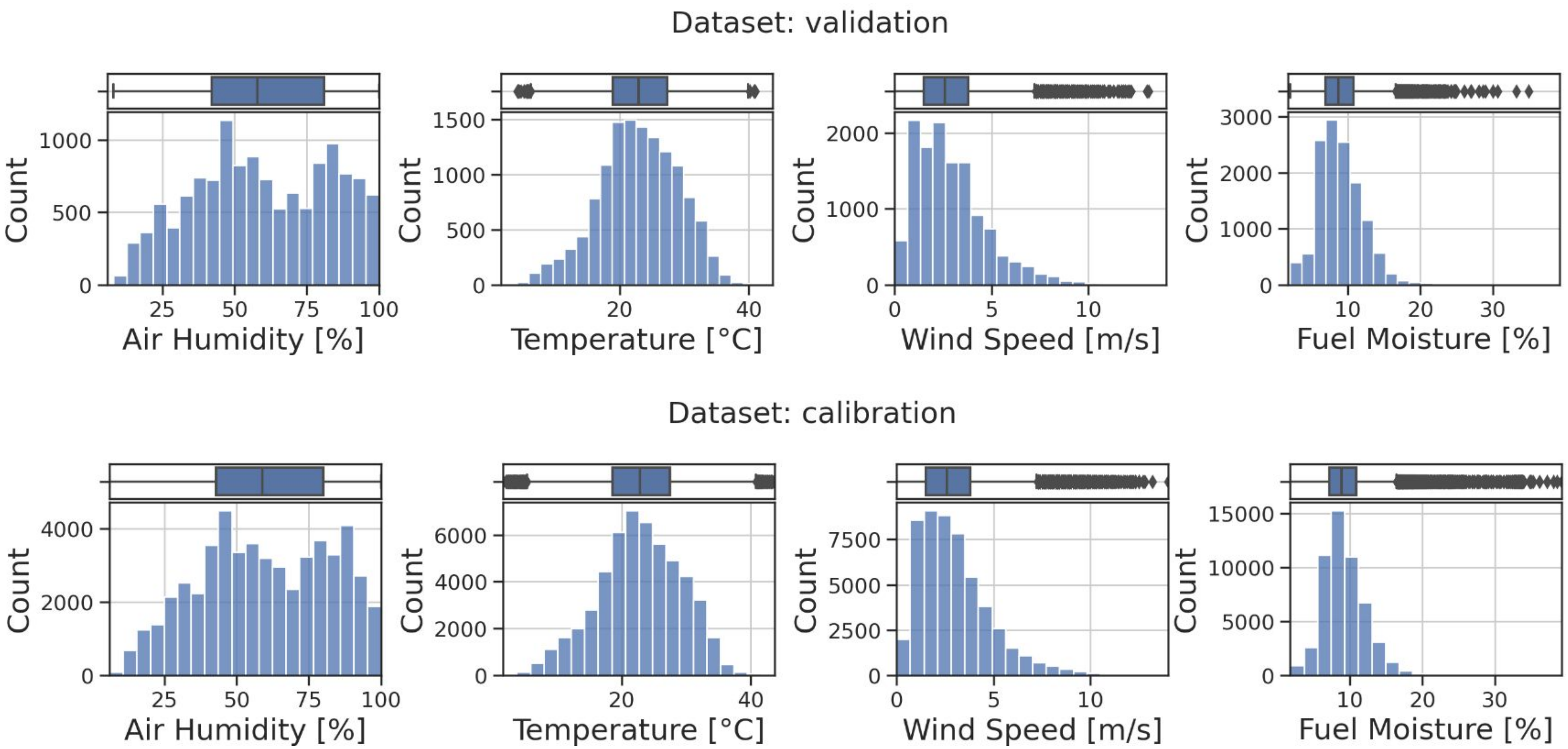
	Number of samples	
	Calibration	Validation
No-rain	220	54
Rain	280	70
Mixed	/	408

2.1. Fuel Stick Data

2.1.4. Calibration and Validation Datasets

Data distribution

No-rain samples

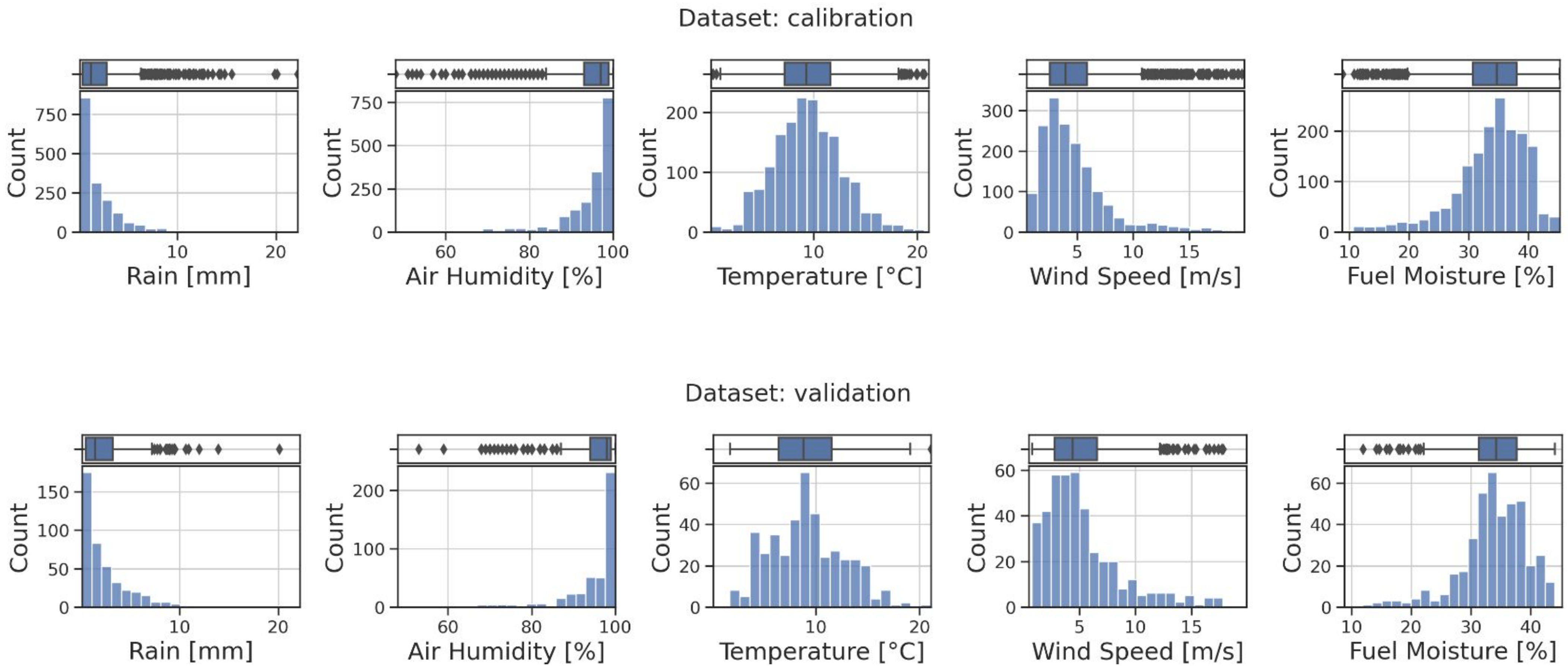


2.1. Fuel Stick Data

2.1.4. Calibration and Validation Datasets

Data distribution

Rain samples

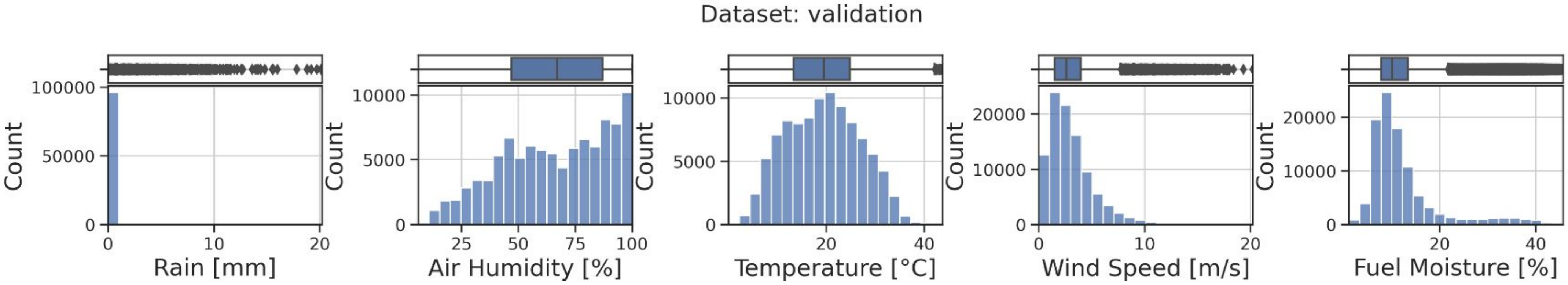


2.1. Fuel Stick Data

2.1.4. Calibration and Validation Datasets

Data distribution

Mixed samples



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2. Calibration

2.2. FFMC Model

2.2.1. General Structure → *2.2.2. No-rain Phase* → *2.2.3. Rain Phase*

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2.2. FFMC Model

2.2.1. General Structure

The new FFMC model has been developed as modification of the original FFMC model of RISICO system [4], which was developed in the 2000s based on the FFMC model of the well-known Canadian Fire Weather Index.

The FFMC model of RISICO system presents some important differences with respect to FWI:

1. the model incorporates **diversification of fuel types** in some key parameters: **standard response time** and **saturation level**;
2. the model is **flexible with respect to different time steps**, as it is represented by a dynamic equation.

The model is composed by two different phases: **No-Rain Phase** and **Rain Phase**

[4] Paolo Fiorucci, Francesco Gaetani, and Riccardo Minciardi. "Development and application of a system for dynamic wildfire risk assessment in Italy". In: Environmental Modelling and Software 23.6 (June 2008), pp. 690–702. issn: 13648152. doi: 10.1016/j.envsoft.2007.05.008.

2.2. FFMC Model

2.2.2. No-Rain Phase

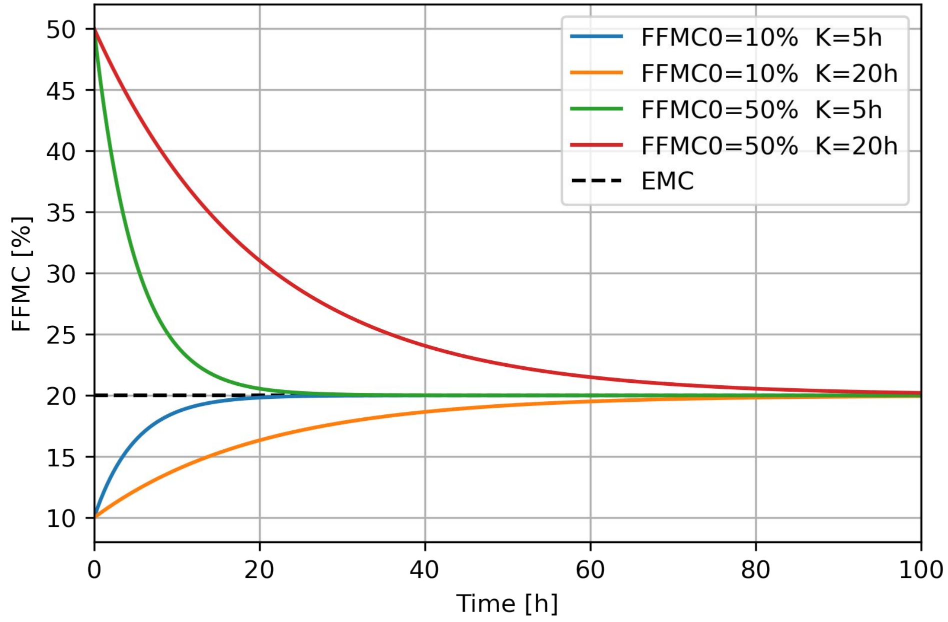
As reported in the literature [5], the fuel moisture content presents an **exponential behavior** toward an Equilibrium Moisture Content (EMC) value, with a response time (K).

- The **Equilibrium Moisture Content** is widely recognised to be function of t**emperature and air humidity**
- The **response time** is considered function of **fuel characteristics** (dimension, type) and **weather conditions**

Dynamic Equation $K\,(FFMC)' + FFMC = EMC$

simulated time [h]

FFMC dynamics $$FFMC = \mathrm{EMC} + (\underbrace{FFMC_0}_{\text{initial condition}} - \mathrm{EMC})e^{-\frac{t}{K}}$$



[5] Stuart Matthews. "Dead fuel moisture research: 1991-2012". In: International Journal of Wildland Fire 23.1 (2014), pp. 78–92. issn: 10498001. doi: 10.1071/WF13005.

2.2. FFMC Model

2.2.2. No-Rain Phase

$$FFMC = \mathrm{EMC} + (FFMC_0 - \mathrm{EMC})e^{-\frac{t}{K}}$$

$$EMC(H,T) = A_1 H^{A_1} + A_3 e^{\frac{H-100}{10}} + A_4(3 - \min[T,30])(1 - e^{-A_5 H})$$

T: temperature [°C]
H: humidity [%]

A1	TO BE CALIBRATED
A2	0.555
A3	10.6
A4	0.5022
A5	0.0133

Some parameters have been kept from the original model to avoid large-dimension optimization problem.

The parameter has been identified as having the greatest impact on EMC behaviour in the calibration dataset.

FFMC can go through a **desorption (or drying)** or **absorption (or wetting)** phase depending on whether the initial value is above or below the equilibrium value respectively

The EMC value is considered the same for both the phases

2.2. FFMC Model

2.2.2. No-Rain Phase

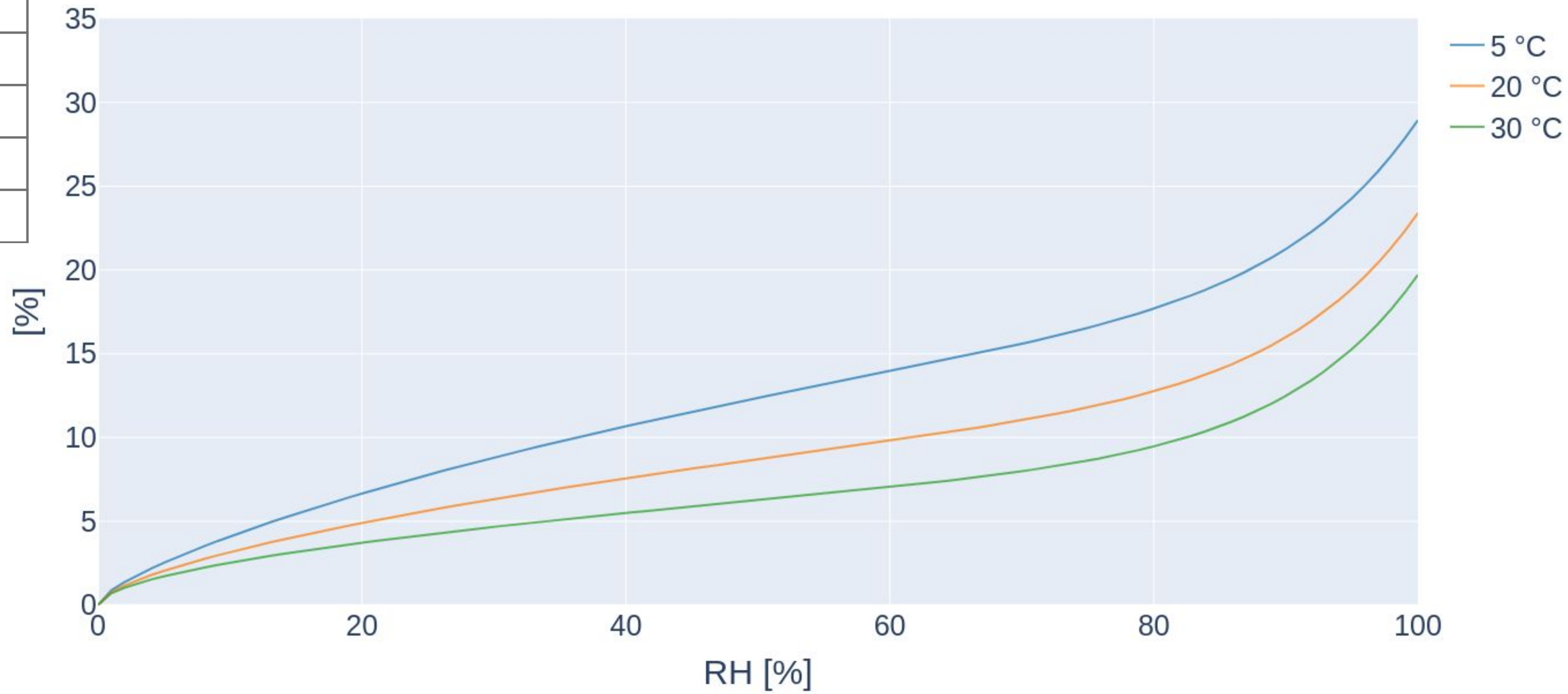
$$FFMC = \mathrm{EMC} + (FFMC_0 - \mathrm{EMC})e^{-\frac{t}{K}}$$

$$EMC(H,T) = A_1 H^{A_1} + A_3 e^{\frac{H-100}{10}} + A_4(3 - \min[T,30])(1 - e^{-A_5 H})$$

T: temperature [°C]
H: humidity [%]

A1	0.7063
A2	0.555
A3	10.6
A4	0.5022
A5	0.0133

Results of calibration



2.2. FFMC Model

2.2.2. No-Rain Phase

$$FFMC = \mathrm{EMC} + (FFMC_0 - \mathrm{EMC})e^{-\frac{t}{K}}$$

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$$K_i(T,W) = T_0 \cdot \frac{D_i}{1 + B_{1,i}T^{C_{1,i}} + B_{2,i}W^{C_{2,i}}} \qquad i = \{drying, wetting\}$$

T: temperature [°C]
W: wind speed [m/s]

B1,drying	TO BE CALIBRATED
C1,drying	TO BE CALIBRATED
B2,drying	TO BE CALIBRATED
B3,drying	TO BE CALIBRATED
B1,wetting	TO BE CALIBRATED
C1,wetting	TO BE CALIBRATED
B2,wetting	TO BE CALIBRATED
C2,wetting	TO BE CALIBRATED
D drying	constrained
D wetting	constrained

$$D_i \quad so\ that \quad K_i(T = T_{st}, W = W_{st}) = 1$$

different coefficients have been calibrated for the drying and wetting phases

The response time K is considered function of:

1. weather conditions: it is decreasing with **temperature** and **wind speed**
2. **fuel characteristics**, represented by the parameter **T0**

T0: Standard response time, in standard conditions [6]:

$$T_{st} = 27\,°C \quad W_{st} = 0\ m/s$$

It is used to differentiate between different fuel types

For the calibration process, T0 has been set to 10 h, the standard response time of the fuel stick

[6] Nelson, J. (2000). Prediction of diurnal change in 10-h fuel stick moisture content. Canadian Journal of Forest Research, 30(7), 1071–1087. https://doi.org/10.1139/cjfr-30-7-1071

2.2. FFMC Model

2.2.2. No-Rain Phase

$$FFMC = \mathrm{EMC} + (FFMC_0 - \mathrm{EMC})e^{-\frac{t}{K}}$$

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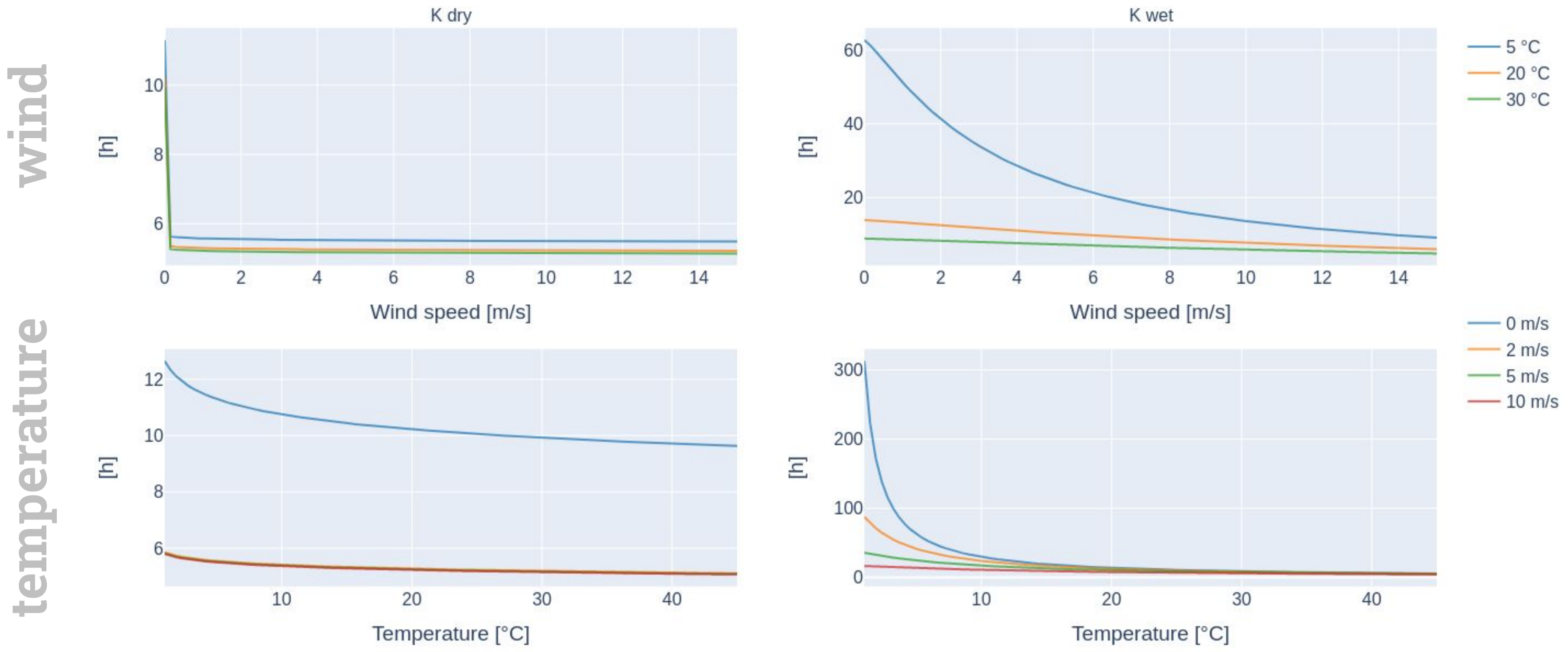
$$K_i(T,W) = T_0 \cdot \frac{D_i}{1 + B_{1,i}T^{C_{1,i}} + B_{2,i}W^{C_{2,i}}} \qquad i = \{drying, wetting\}$$

T: temperature [°C]
W: wind speed [m/s]

B1,drying	3.165
C1,drying	0.091
B2,drying	4.785
C2,drying	0.011
B1,wetting	4.130
C1,wetting	1.108
B2,wetting	5.738
C2,wetting	1.207
D drying	5.267
D wetting	160.436

Results of calibration



2.2. FFMC Model

2.2.2. No-Rain Phase

The FFMC model has been calibrate to simulate the **water content over the total weight**

$$FFMC_{all} = \frac{W}{W+F}100$$

W: Water content [g]

F: fuel weight in dry conditions [g]

Since the well-known equation presented before is referred to the FFMC with respect to the dry weight, the equation has been modified accordingly with respect to the transforming relation.

$$x(t) = EMC^d + (x_0 - EMC^d)e^{-\frac{t}{K^d}}$$

$$y(t) = \frac{EMC^a - 100Ge^{-\frac{t}{K^d}}}{1 - Ge^{-\frac{t}{K^d}}}$$

$$\varphi(x) = \frac{x}{100+x}100$$

$$G = \frac{EMC^a - y_0}{100 - y_0}$$

2.2. FFMC Model

2.2.3. Rain Phase

$$\underbrace{FFMC}_{}=\underbrace{FFMC_0}_{\text{initial condition}}+\underbrace{R_1\cdot r\cdot e^{-\frac{R_2}{sat-FFMC_0+1}}\cdot\left(1-e^{\frac{R_3}{r}}\right)}_{\text{Delta FFMC}}$$

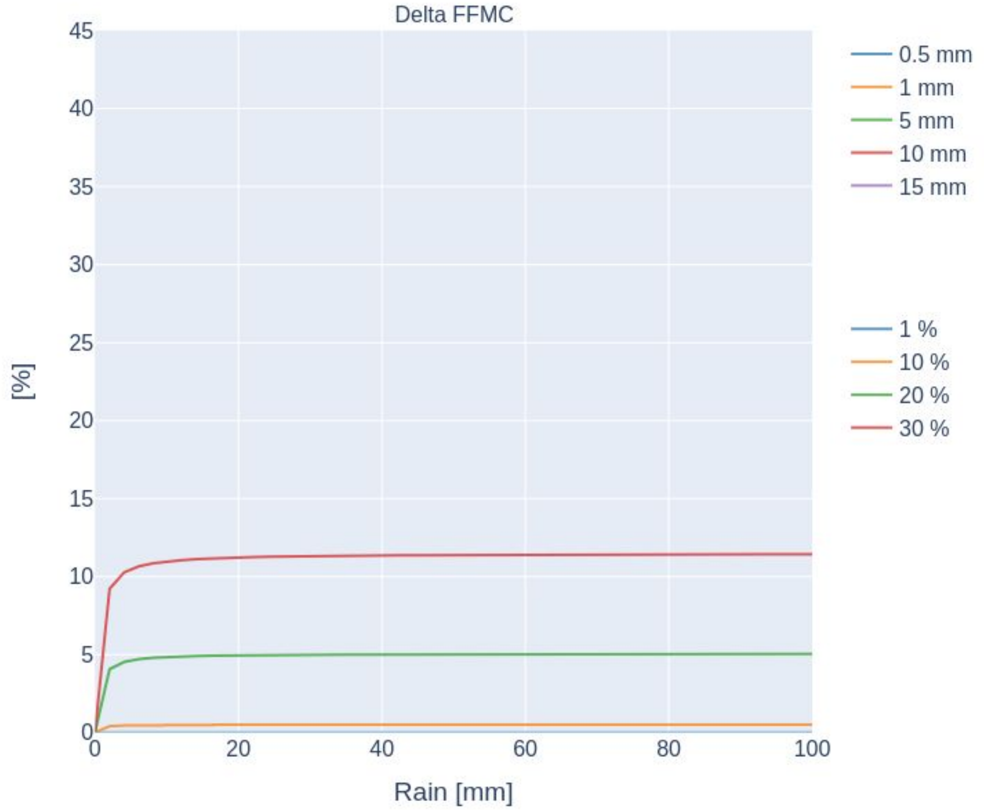
r: rain[mm]

In the rain phase, the fuel moisture increases at each simulated step, according to the amount of rain occurred and the distance from the **saturation value (sat).**

The equation is independent from the time step, depending only on the amount of rain occurred.

R1	68.546
R2	53.313
R3	0.936

For the calibration process, saturation has been set to 45% (FFMC over all weight), the standard saturation value of the fuel stick



2. Calibration

2.3. Parameters Optimization

2.3.1. Objective Function

2.3.2. Optimization Algorithm

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2.3. Parameters Optimization

2.3.1. Objective Function

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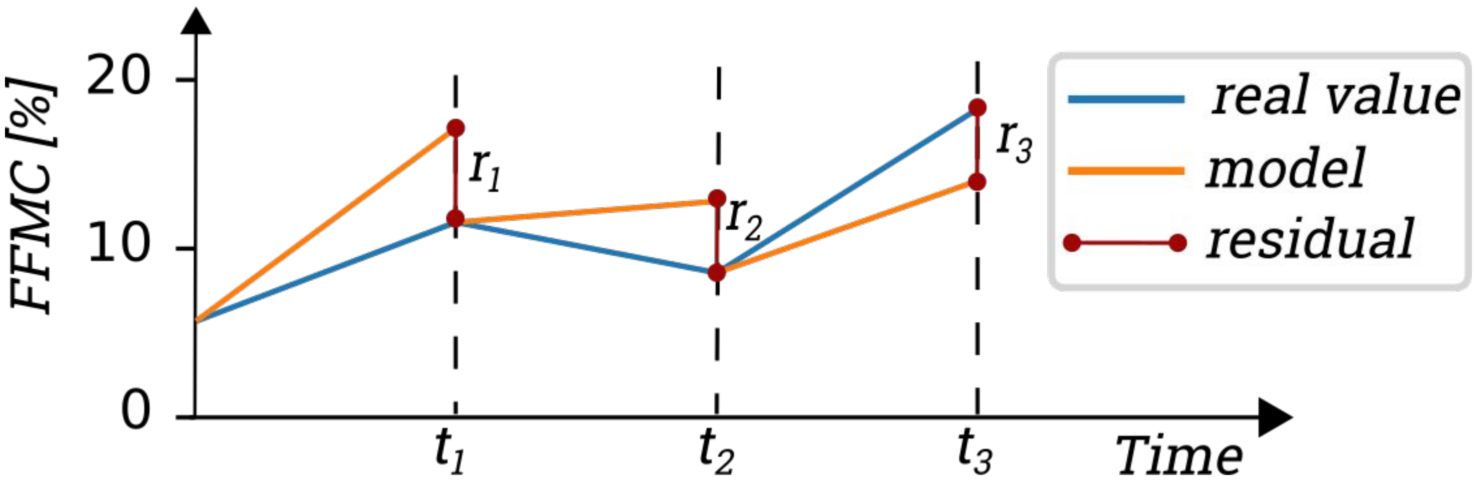

1. Given the observed value of fuel moisture at time t, the model runs to compute the **next** forecasted fuel moisture value

2. the residuals are computed at each time step, for each time-serie

3. the objective function is composed by the **sum of the squared values of residuals** for each time steps, and each time-serie

Number of time-series

Number of time steps

Real value

Simulated value with parameters set Θ

$$\sum_{j=1}^{N}\sum_{k=1}^{T}\left(\hat{y}_j(t_k) - y_j(t_k,\theta)\right)^2$$

For each time-series

For each time steps

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2.3. Parameters Optimization

2.3.2. Optimization Algorithm

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To minimize the objective function, a **Particle Swarm Optimization** (PSO) algorithm has been identified

What is it?

PSO-type algorithms are **metaheuristics** that try to optimize a problem iteratively improving a candidate solution with respect to a measure of quality (e.g. the objective function)

PROs

1. no assumptions about the problem
2. can search very large spaces of candidate solutions

CONs

1. do not guarantee an optimal solution is found: affected by local minima problem
2. difficulties in deal with large dimension problems

How does it work?

1. The swarm is initialized with different particles.
   A particle is characterized by:
   a. the position, that is **a set of parameters**
   b. the velocity

2. The swarm moves into the parameters space, probing different positions (e.g combination of parameters)

3. The position and the velocity is update trying to move toward the best solution found (**swarm intelligence**)

4. A randomness is introduced to promote exploration

2.3. Parameters Optimization

2.3.2. Optimization Algorithm

Different modification of the original PSO algorithm have been proposed.

Multi-strategy learning particle swarm optimization **(MSL-PSO)** [7]

Pseudocode

1. initialize the swarm, with N_POP elements
2. while i<MAX_ITER:
   a. for n=1:N_POP:
      i. probe N_PROBES positions following the social learning paradigm
      ii. save the best probed position for the element n
   b. a new swarm of best probed positions is identified
   c. for n=1:N_POP:
      i. for each element, identify two different sub-swarms for the social learning paradigm
   d. i = i+1

Two different learning processes to balance between the **convergence** to the global solution and the **diversity** of the population

The particle learns from the other particles that present a better fitness (smaller values of the objective function) **[convergence]** and from the barycenter of the swarm **[exploration]**

The particle learns from the other new probed particles that present a better fitness **[convergence]** and from the some particles that present worse fitness **[exploration]**

TO AVOID LOCAL MINIMA, THE ALGORITHM RUNS MANY TIMES PER EACH TEST, KEEPING THE BEST SOLUTION.

[7] Wang, H., Liang, M., Sun, C., Zhang, G., & Xie, L. (2021). Multiple-strategy learning particle swarm optimization for large-scale optimization problems. *Complex and Intelligent Systems*, *7*(1), 1–16. https://doi.org/10.1007/s40747-020-00148-1

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2. Calibration

2.4. Goodness-Of-Fit

2.4.1. GOF Meaures

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2.4 Goodness-Of-Fit

2.4.1. GOF Measures

Goodness-Of-Fit (**GOF**) measures are introduced to assess the goodness of the fit achieved by the parameter optimization procedure.

$$Bias = \frac{1}{T}\sum_{k=1}^{T}(y_j(t_k,\theta) - \hat{y}_j(t_k)) \quad for \quad j = 1, \dots, N$$

The Bias measures the mean deviation between model and observation

Bias>0 : overestimation (WETTER VALUES)
Bias<0 : underestimation (DRYER VALUES)
Bias=0 : perfect correspondence between model and observation

$$RMSE = \sqrt{\frac{1}{T}\Sigma_{k=1}^{T}(\hat{y}_j(t_k) - y_j(t_k,\theta))^2} \quad for \ j = 1, \dots, N$$

The RMSE is an estimator of the standard deviation of the errors

RMSE=0 : perfect correspondence between model and observation

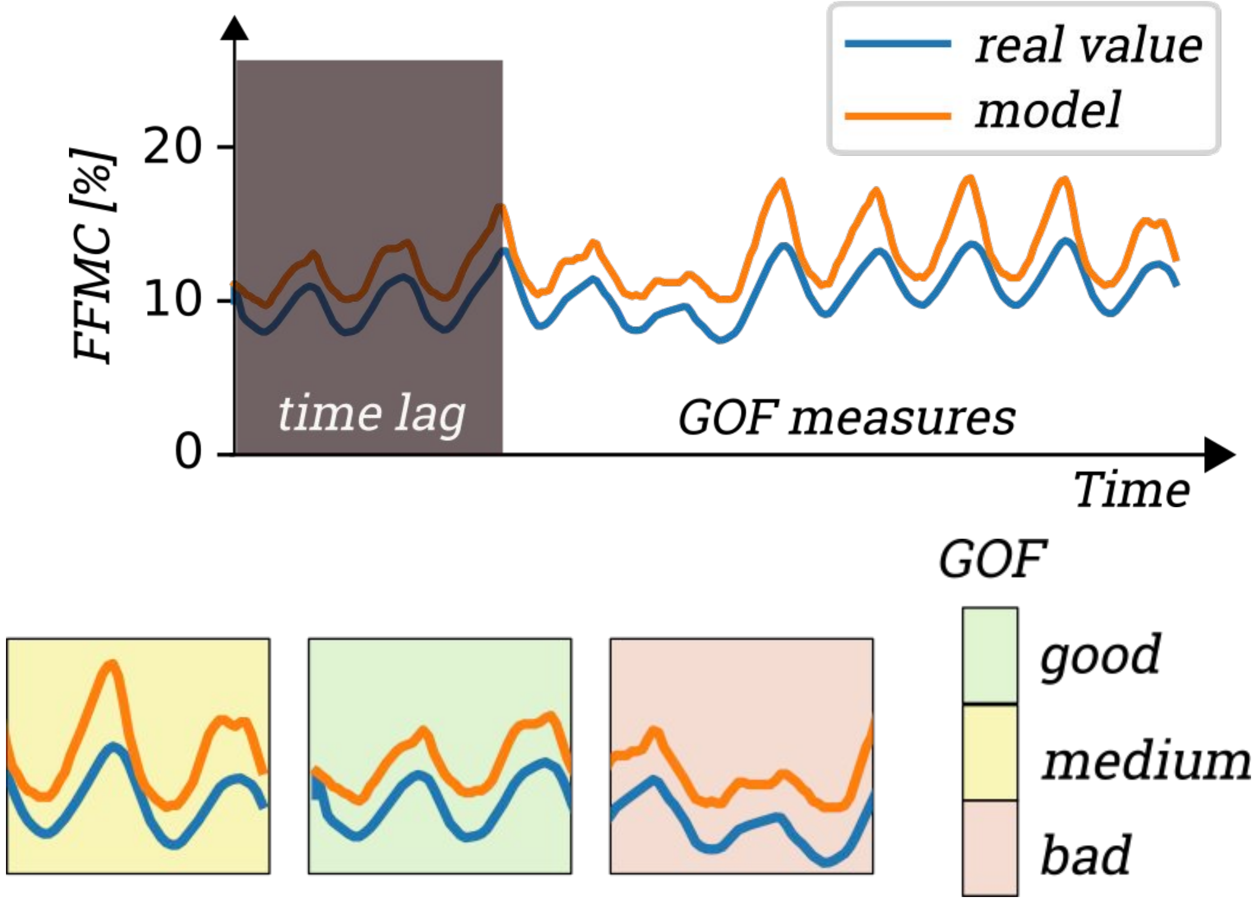
2.4 Goodness-of-fit

2.4.1. GOF Measures

Goodness-Of-Fit (**GOF**) measures are evaluated **for each time-series separately**, to identify specific conditions on which the model does not properly fit observations.

How to compute the GOF measures?

1. from the first fuel moisture observation, the model is run independently for all the time steps
2. the model results are used to compute the GOF measures
3. a time lag is imposed, to consider a transitory behavior of the model. The time lag depends on the time-serie type:
    a. **No-rain:** 72 hours
    b. **Rain:** 1 hour
    c. **Mixed:** 72 hours



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3. Results

3.1. Results on Validation Datasets → ***3.2. FFMC Model for Wildfire Danger Assessment***

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3. Results

3.1. Calibration Results

In the Table, the results of the objective function and goodness-of-fit metrics are shown for the original model of RISICO and for the calibrated one, for all the three calibration datasets: No-Rain, Rain and Mixed.
The calibrated model **shows better performance on all validation datasets**, with slightly negative bias. This behavior can be accepted as precautionary measure to avoid underestimation of wildfire danger conditions.

		Calibration				Validation					
		No-Rain		Rain		No-Rain		Rain		Mixed	
		Original	New	Original	New	Original	New	Original	New	Original	New
Objective Function		408 389	98 060	28 078	7 114	110 389	27 569	7 963	1 136	1 766 703	471 359
RMSE	min	0.381	0.449	0.106	0.03	0.461	0.587	0.203	0.25	0.397	0.459
	max	7.020	3.796	14.263	10.019	6.910	4.041	10.726	5.139	14.501	9.133
	median	2.643	1.328	3.164	1.177	3.022	1.358	3.599	1.163	3.966	1.895
BIAS	min	-0.884	-3.657	-8.14	-7.620	-0.263	-2.754	-2.664	-5.130	2.584	-8.577
	max	6.678	2.811	13.779	9.538	6.618	3.720	10.692	3.874	14.117	5.861
	median	2.456	-0.255	2.492	-0.369	2.769	-0.062	3.223	-0.356	3.407	-0.2

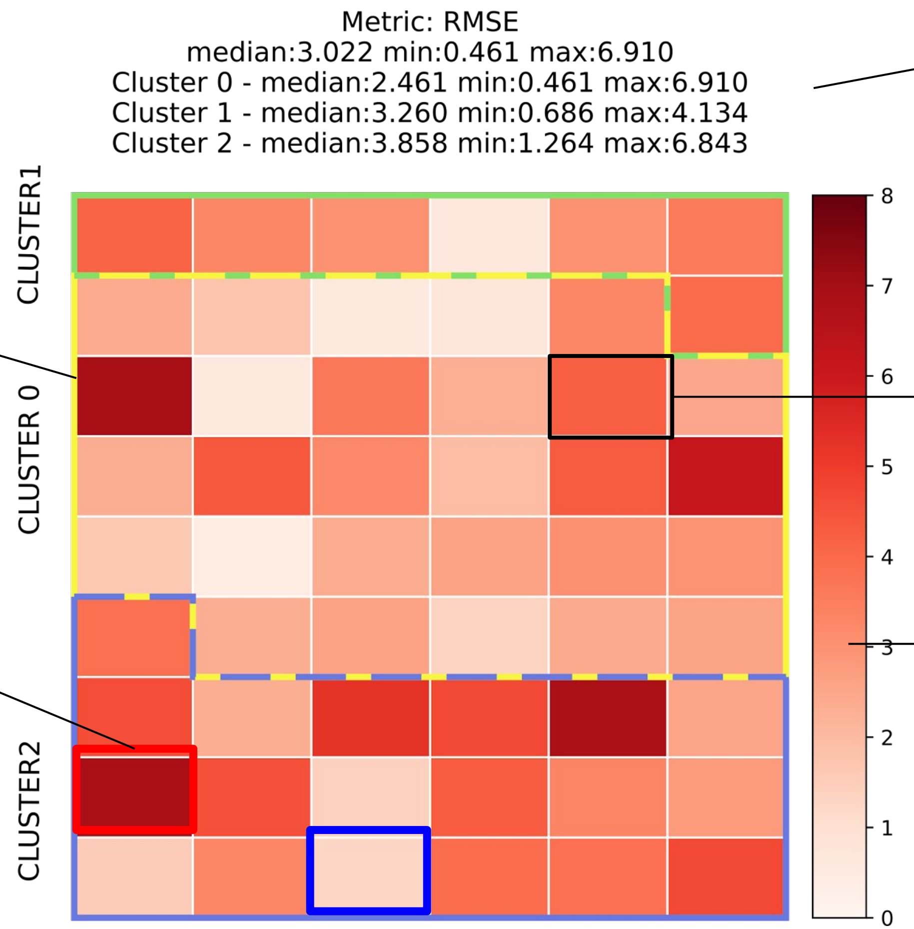
3. Results

3.1. Calibration Results

How to read the plots?

Information about minimum, maximum and median values, for all the time-series and for each cluster

The different clusters are highlighted



Each tile represents a different time-serie

Worst (in red) and best (in blue) time-series are selected

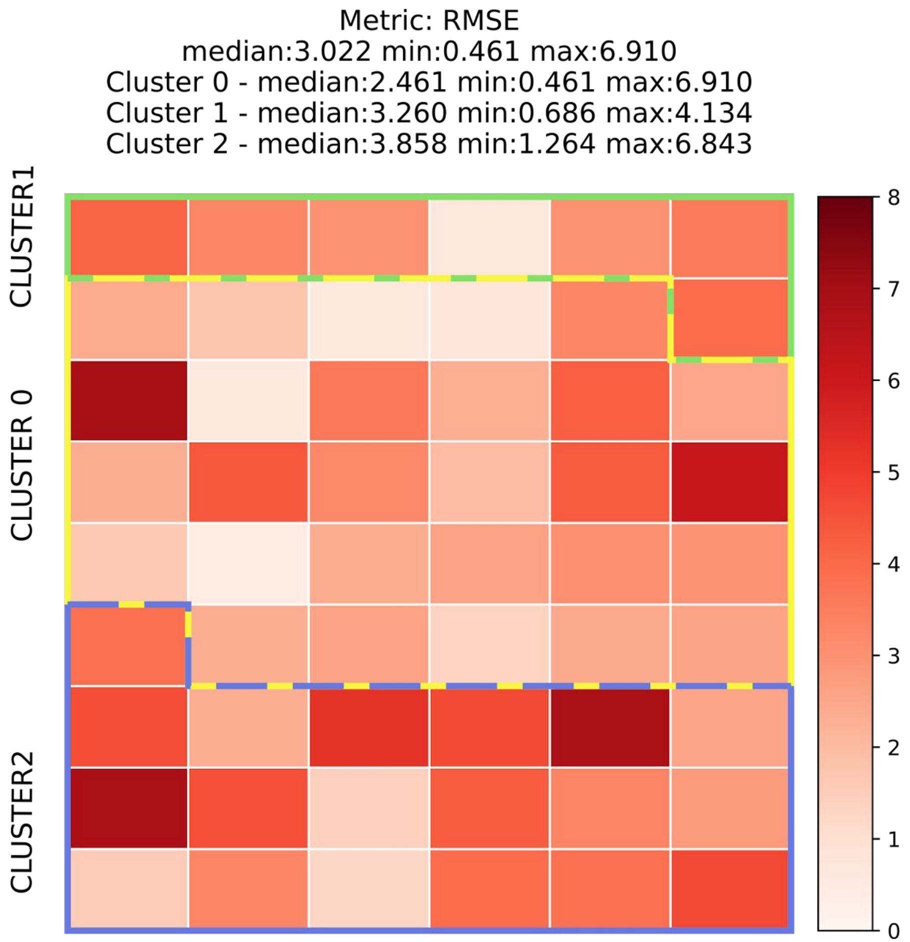
The color is related to the metric value of the time-serie

3. Results

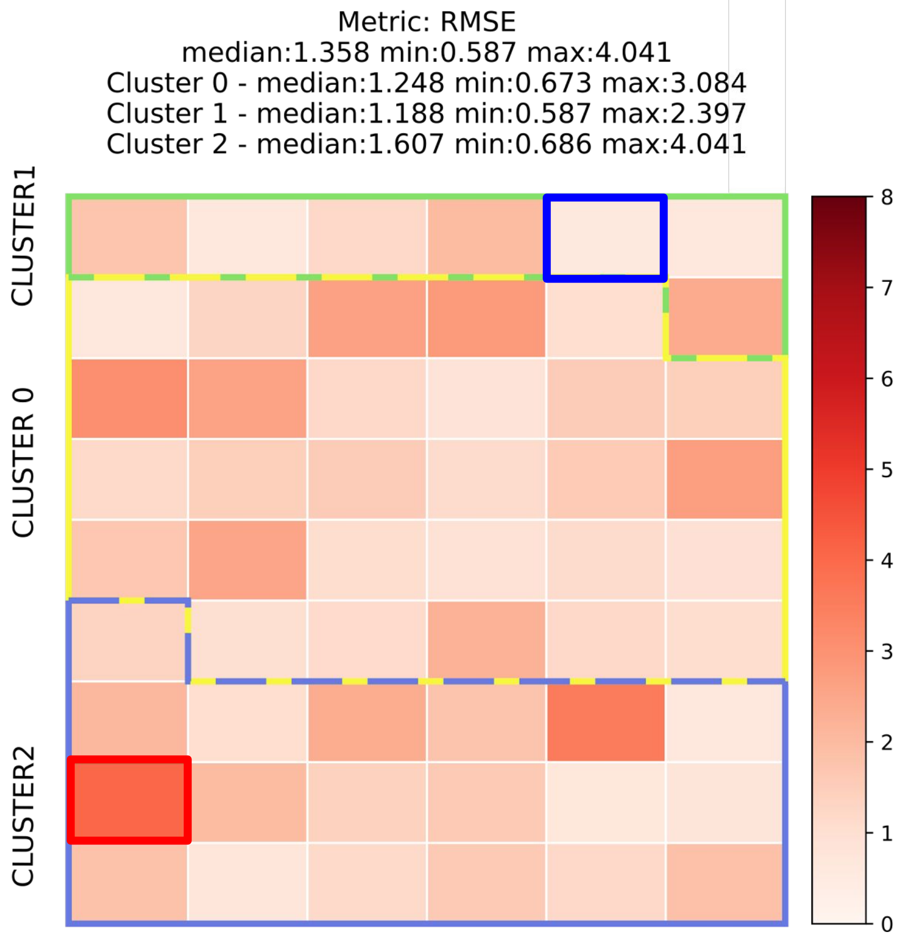
3.1. Calibration Results

No Rain
Validation Dataset

RMSE



ORIGINAL MODEL



NEW MODEL

Worst

Best

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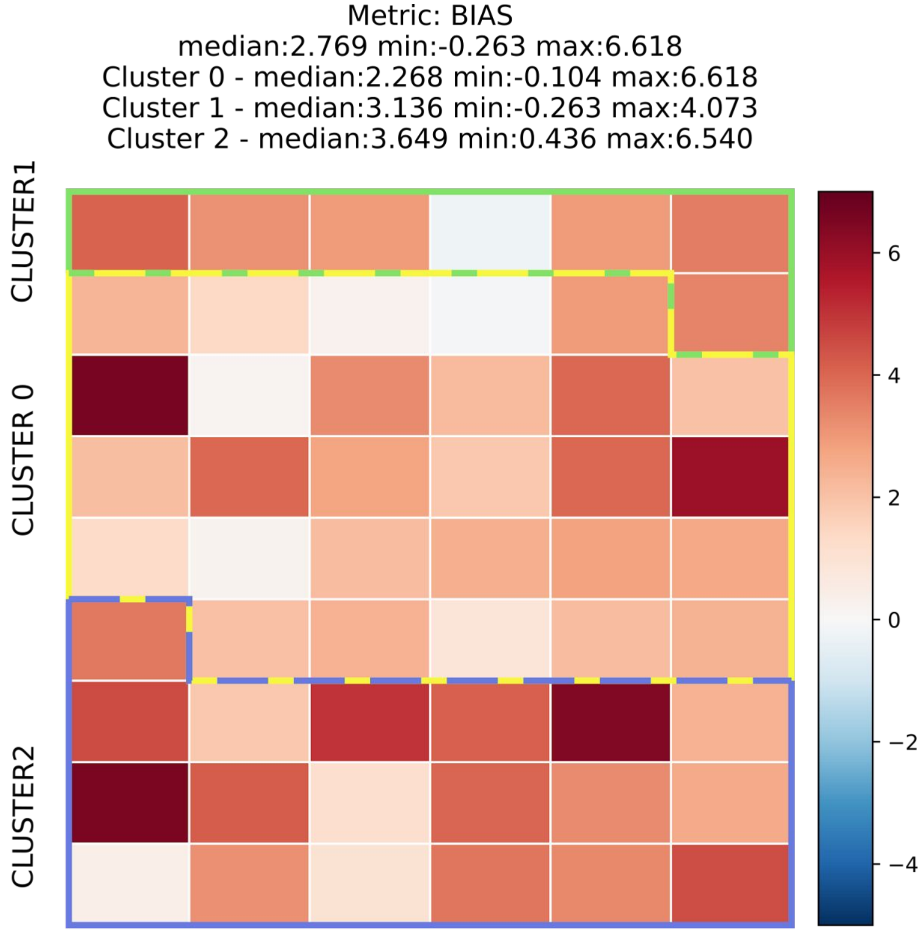
3. Results

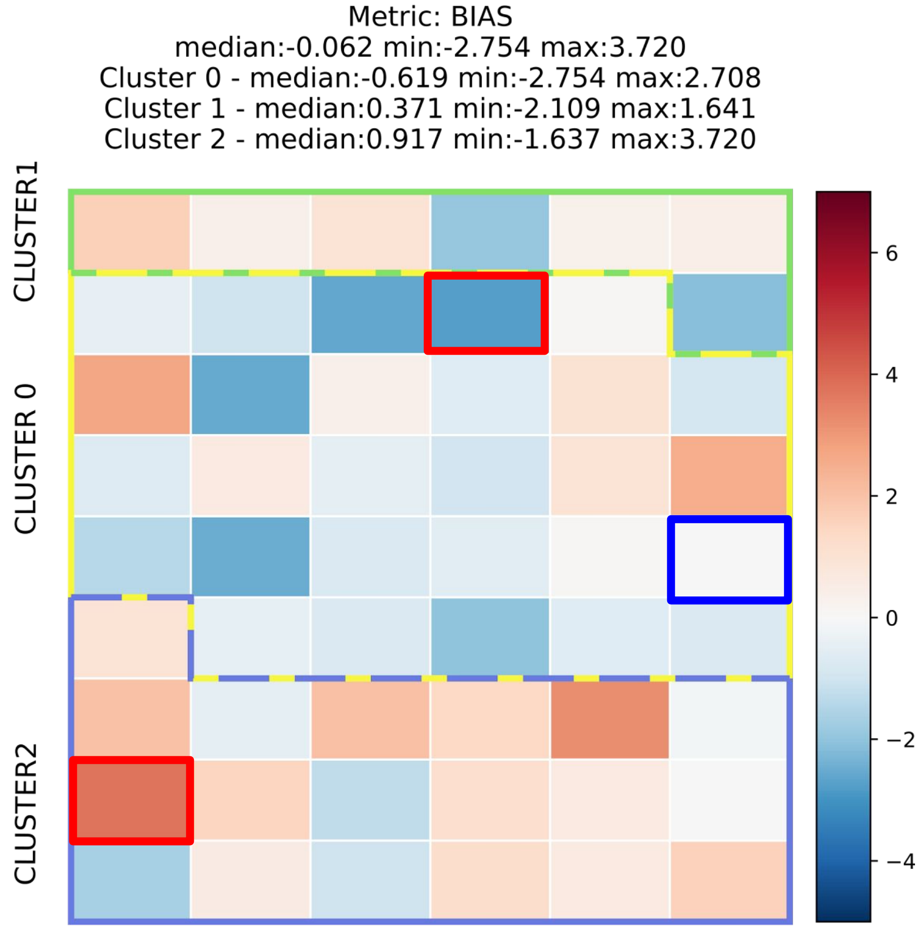
3.1. Calibration Results

No Rain
Validation Dataset

BIAS



ORIGINAL MODEL



NEW MODEL

Worst

Best

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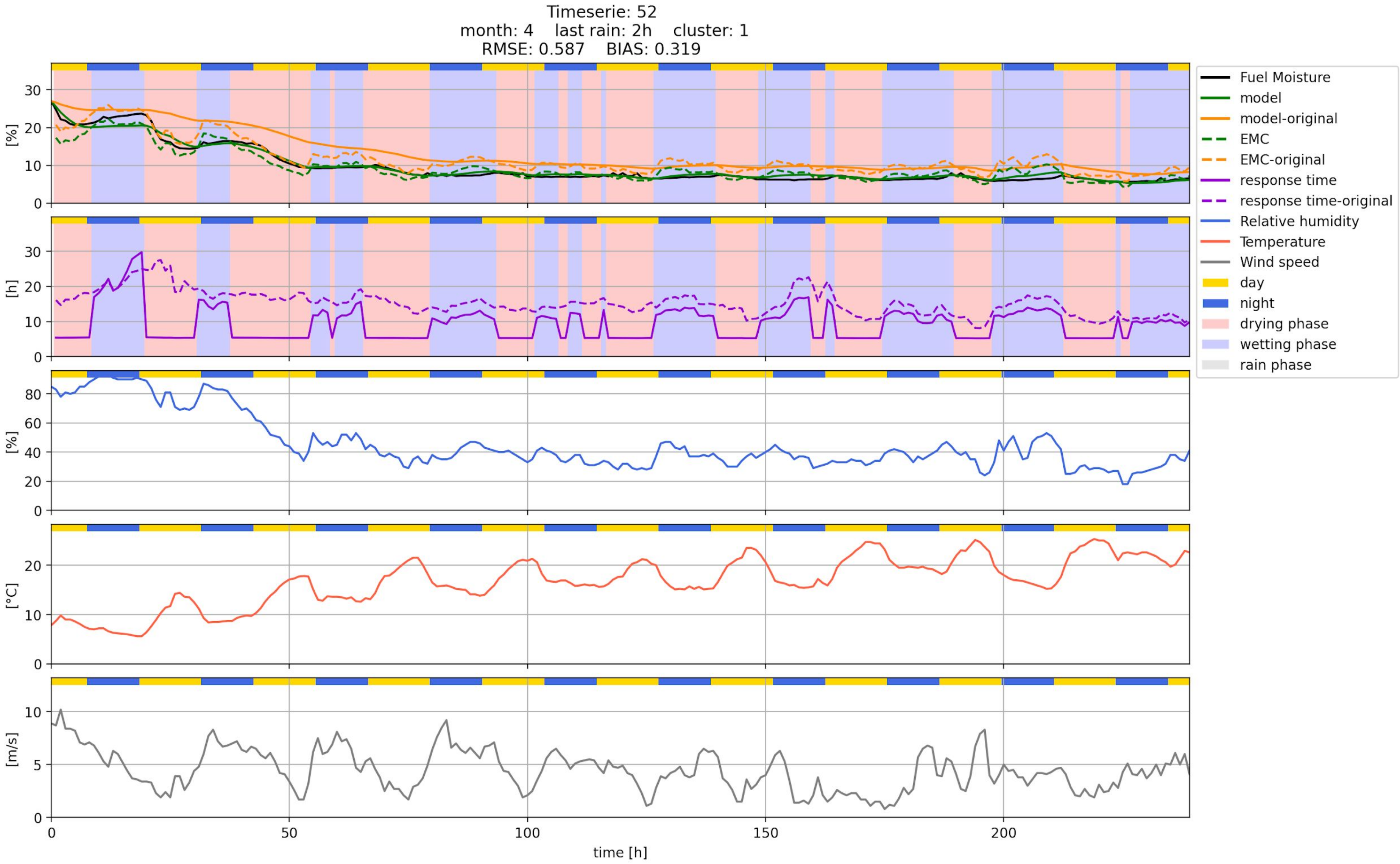
3. Results

3.1. Calibration Results

No Rain
Validation Dataset

Best time-serie
Metric: RMSE



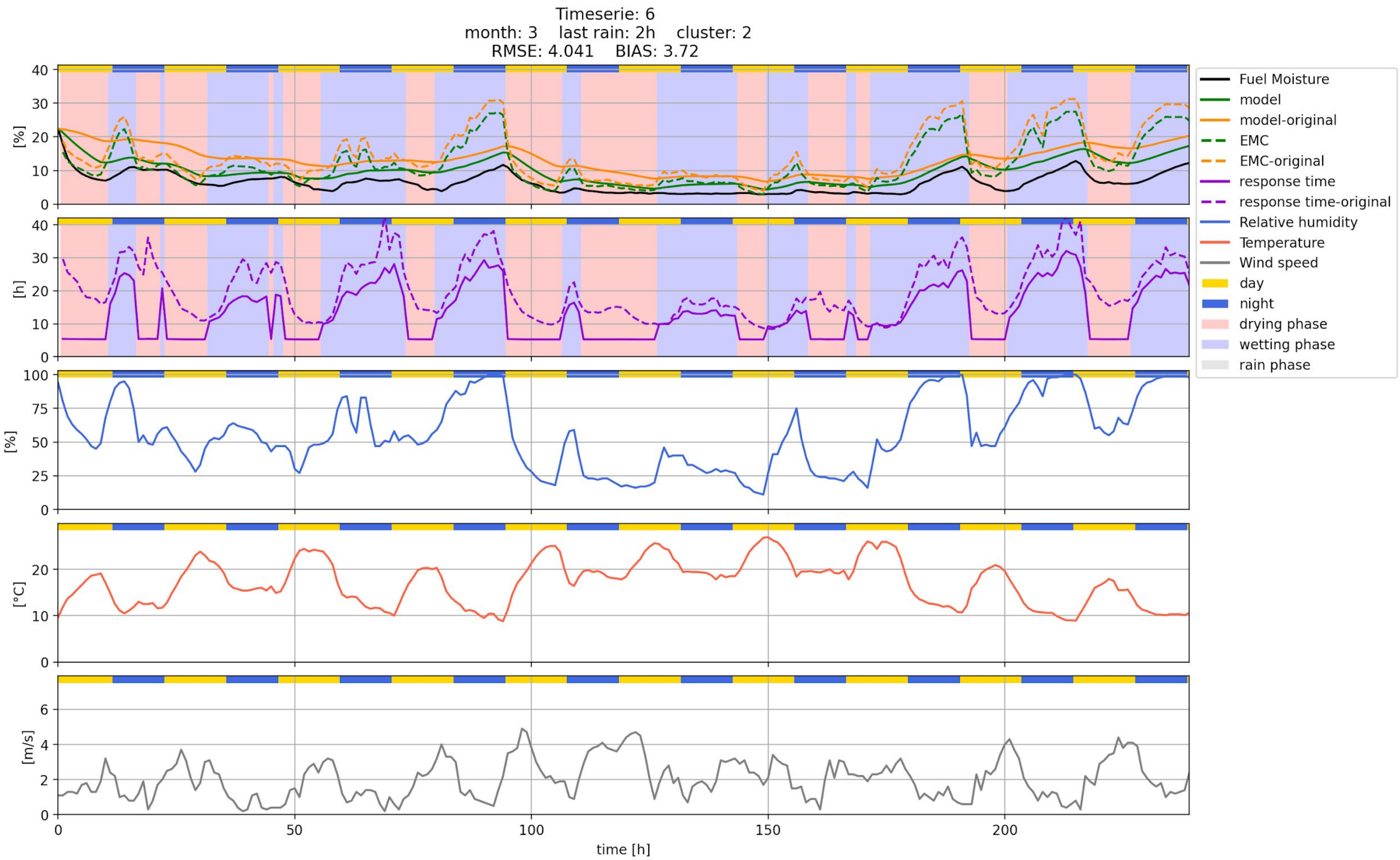
3. Results

3.1. Calibration Results

No Rain
Validation Dataset

Worst time-serie
Metric: RMSE

Worst time-serie
overestimation
Metric: BIAS

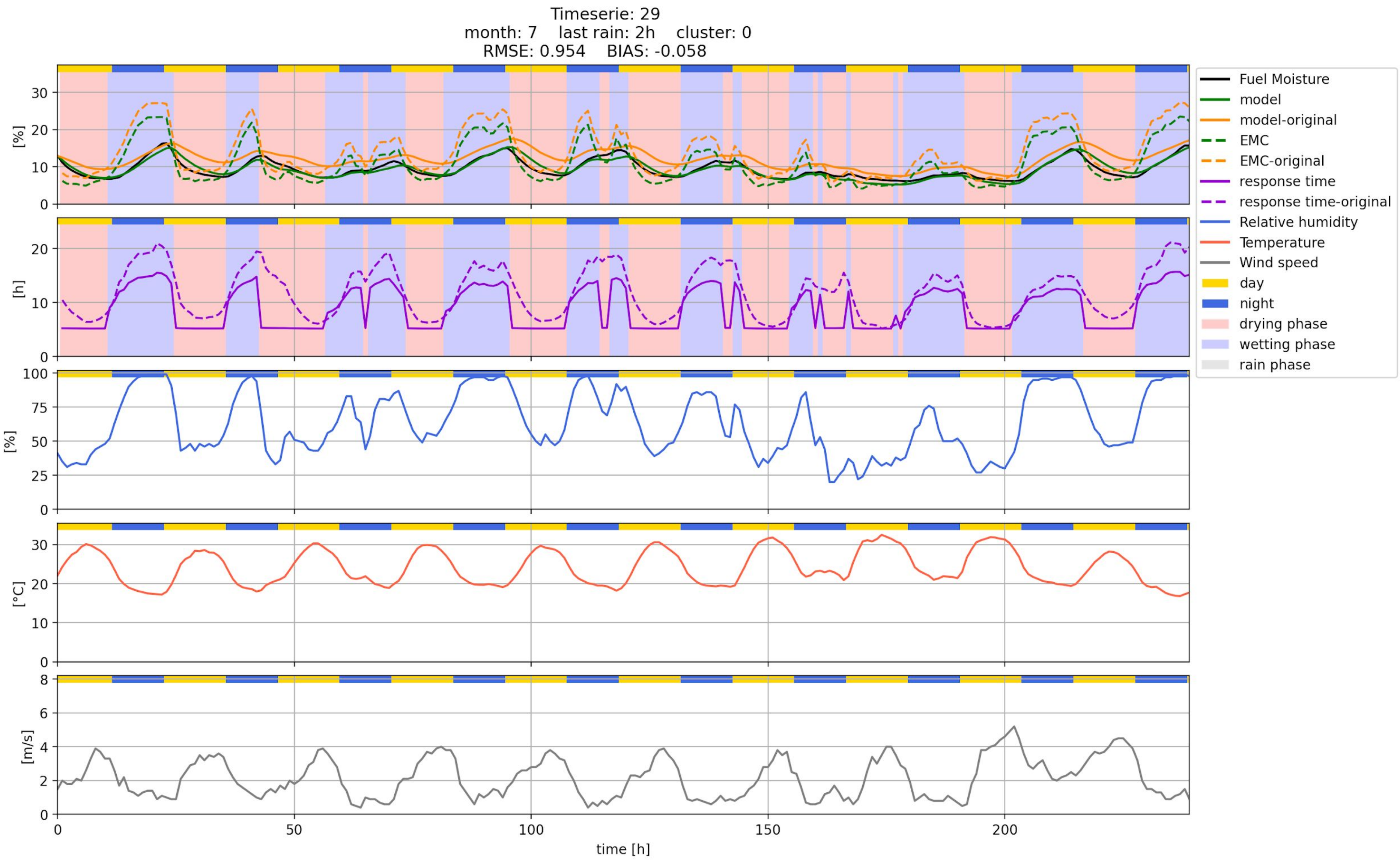


3. Results

3.1. Calibration Results

No Rain
Validation Dataset

Best time-serie
Metric: BIAS

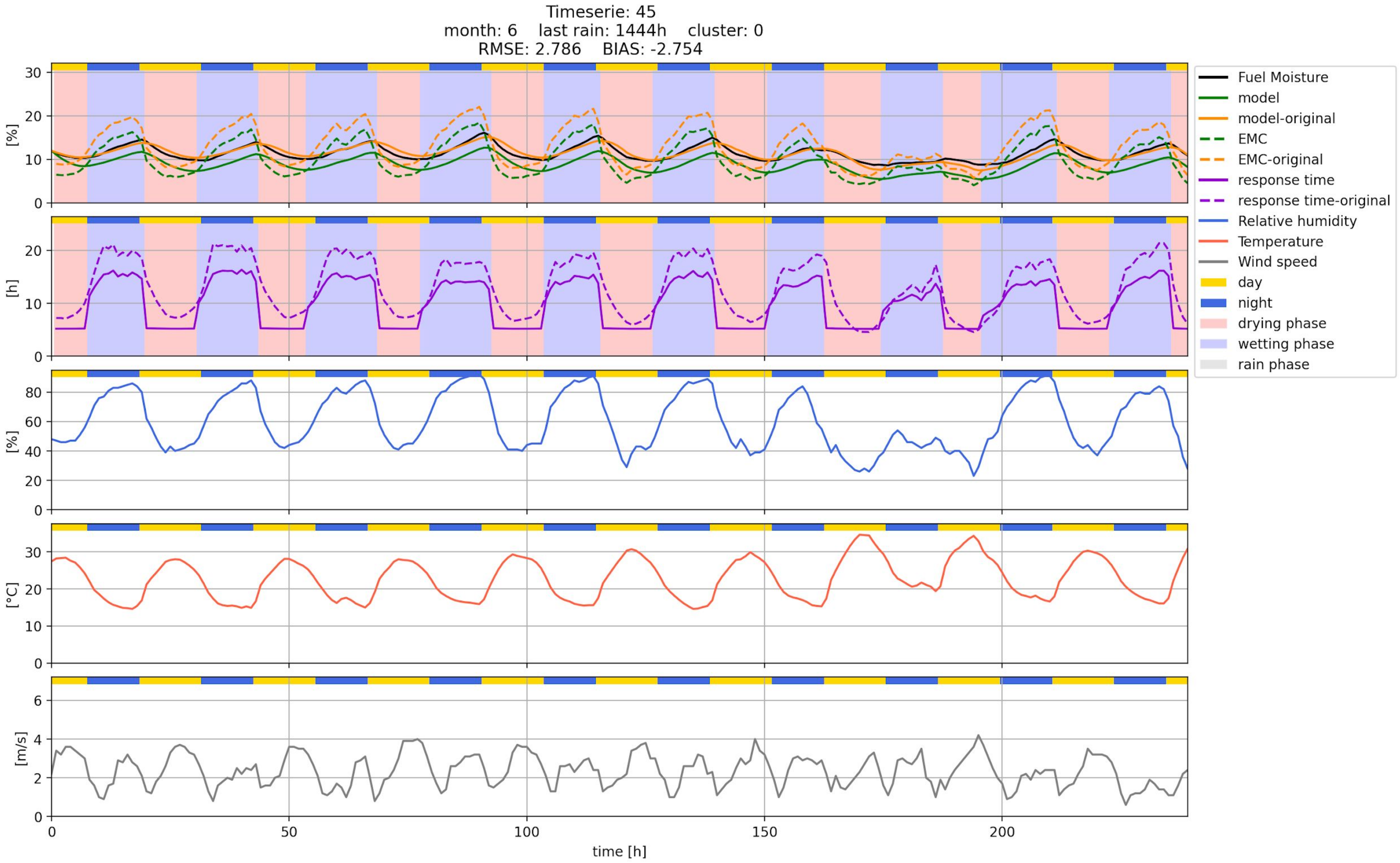


3. Results

3.1. Calibration Results

No Rain
Validation Dataset

Worst time-serie
underestimation
Metric: BIAS

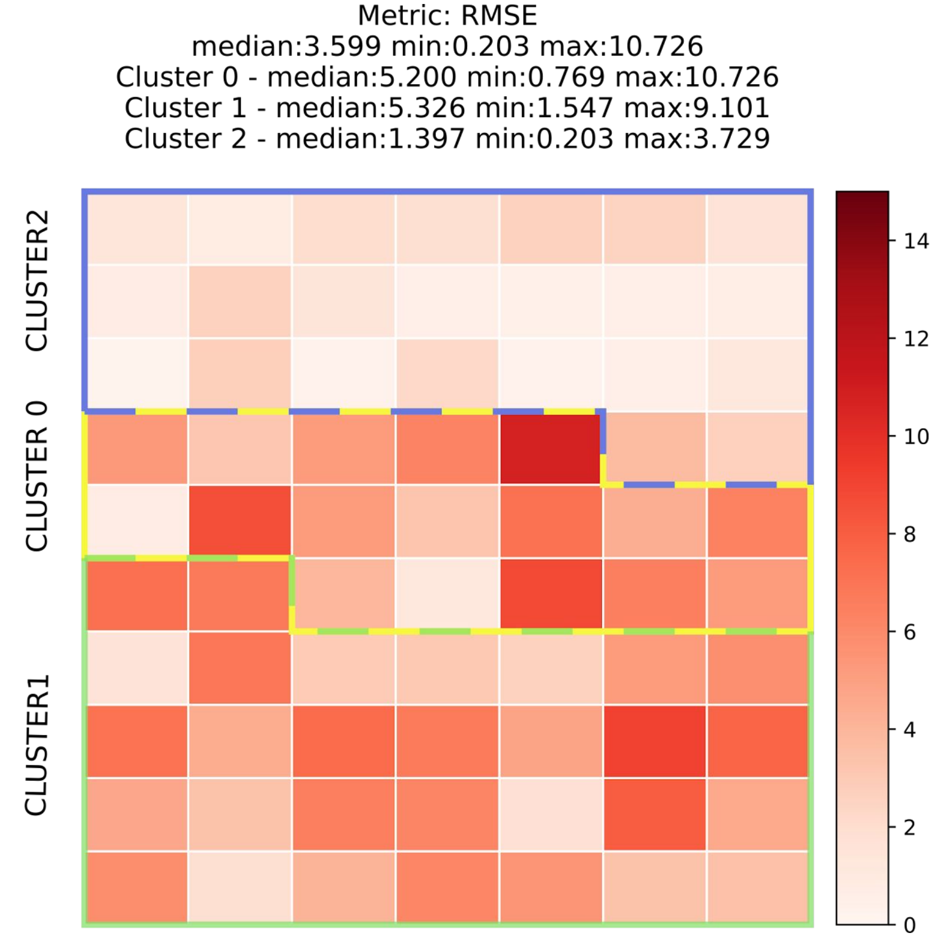


3. Results

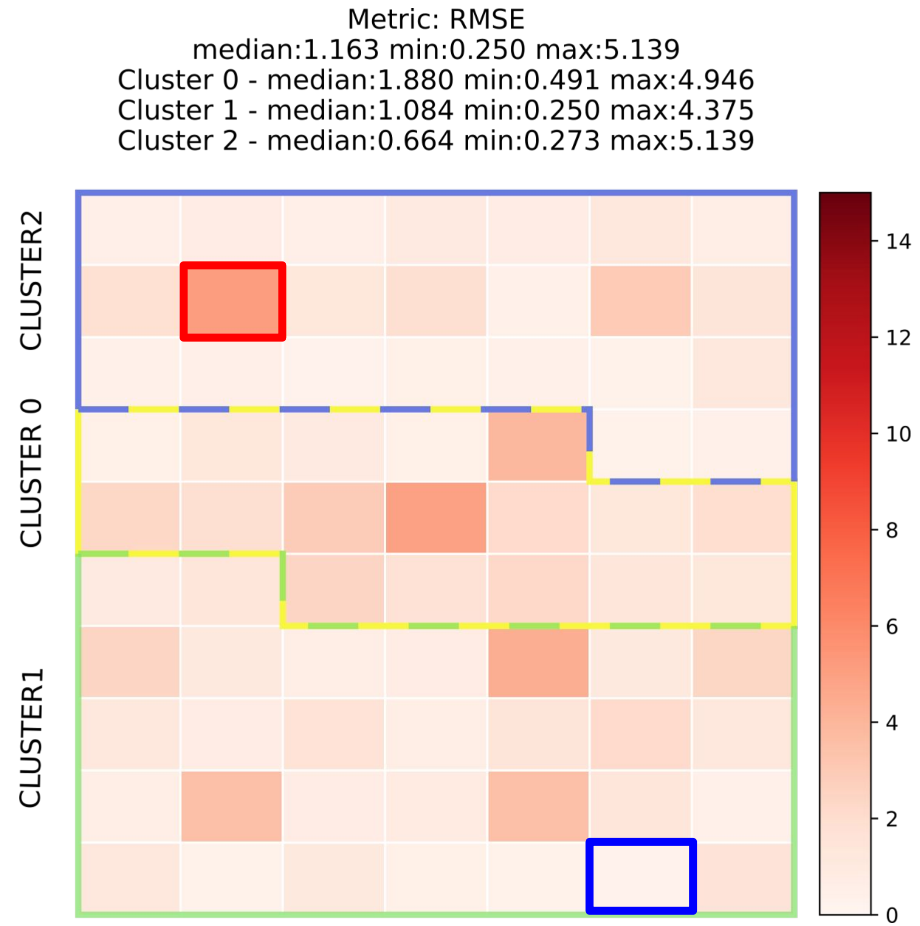
3.1. Calibration Results

Rain
Validation Dataset

RMSE



ORIGINAL MODEL



NEW MODEL

Worst

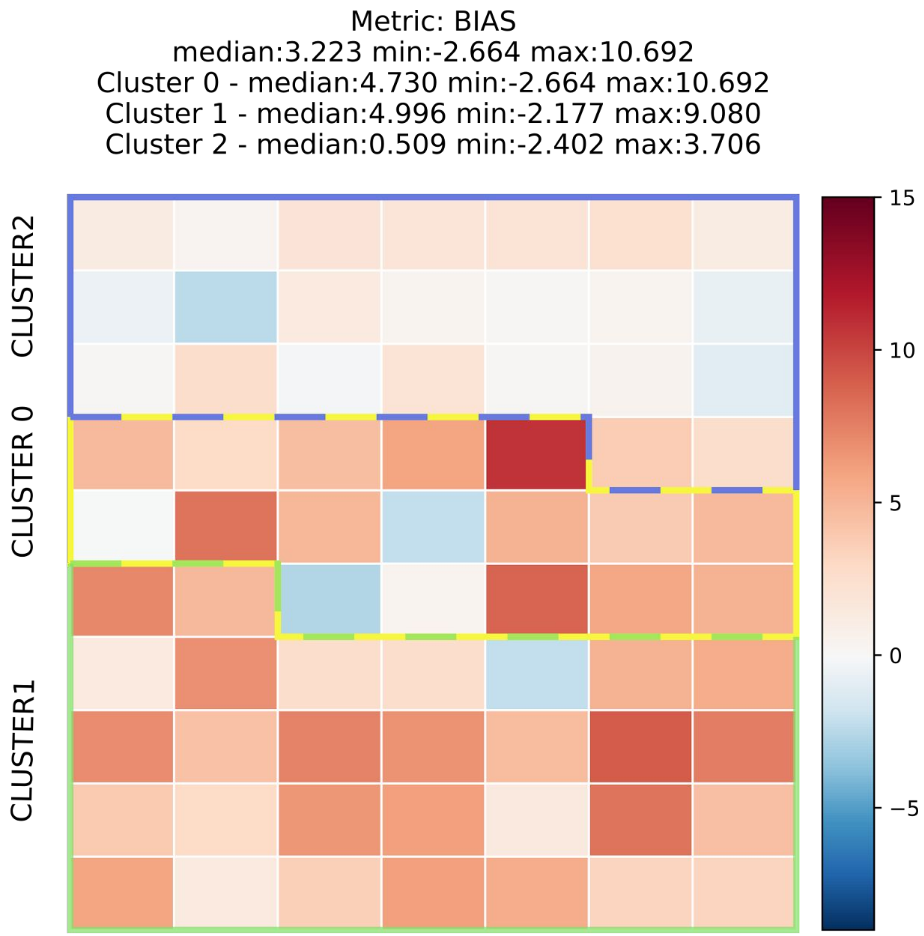
Best

3. Results

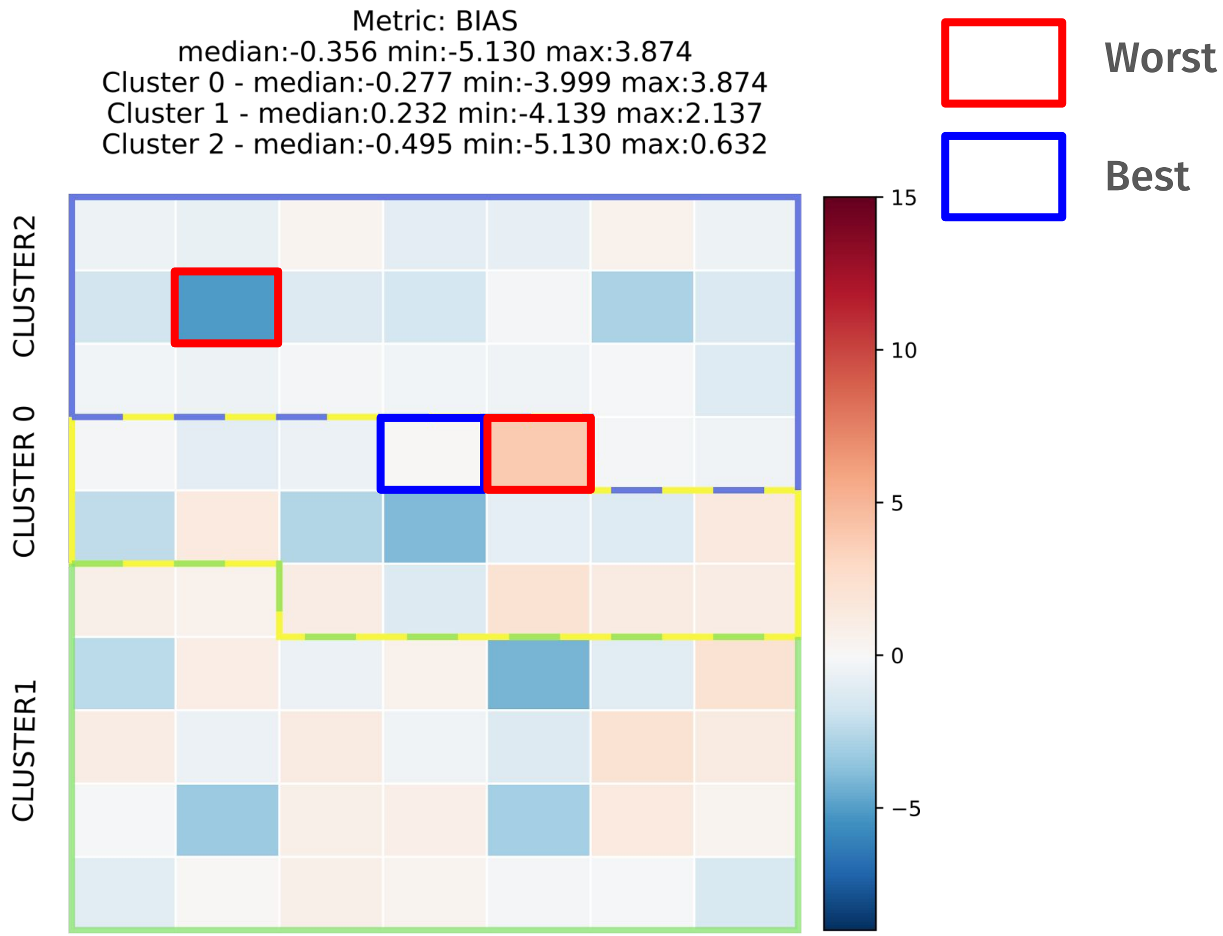
3.1. Calibration Results

Rain
Validation Dataset

BIAS



ORIGINAL MODEL



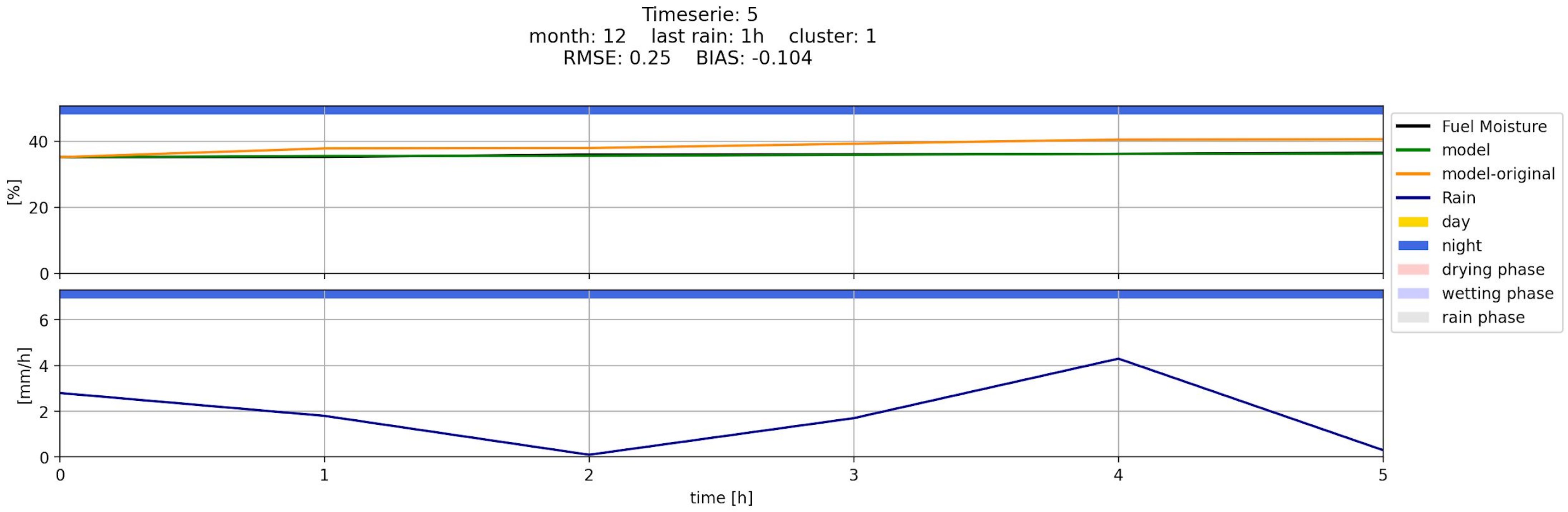
NEW MODEL

3. Results

3.1. Calibration Results

Rain
Validation Dataset

Best time-serie
Metric: RMSE



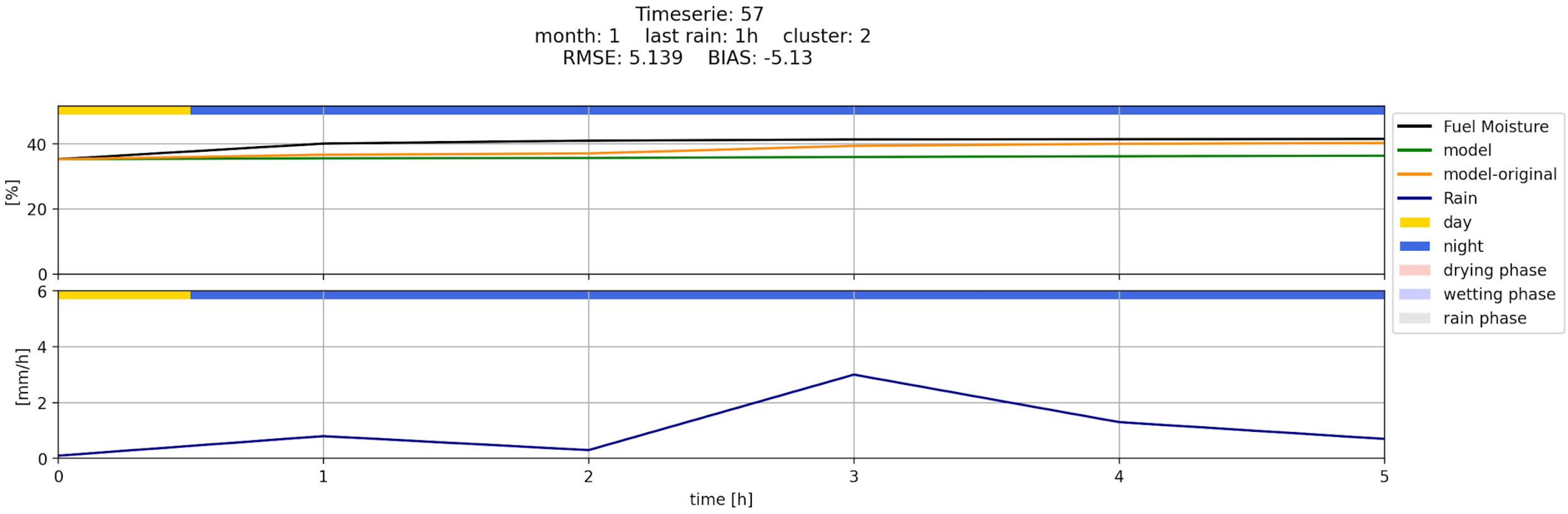
3. Results

3.1. Calibration Results

Rain
Validation Dataset

Worst time-serie
Metric: RMSE

Worst time-serie
underestimation
Metric: BIAS



3. Results

3.1. Calibration Results

Rain
Validation Dataset

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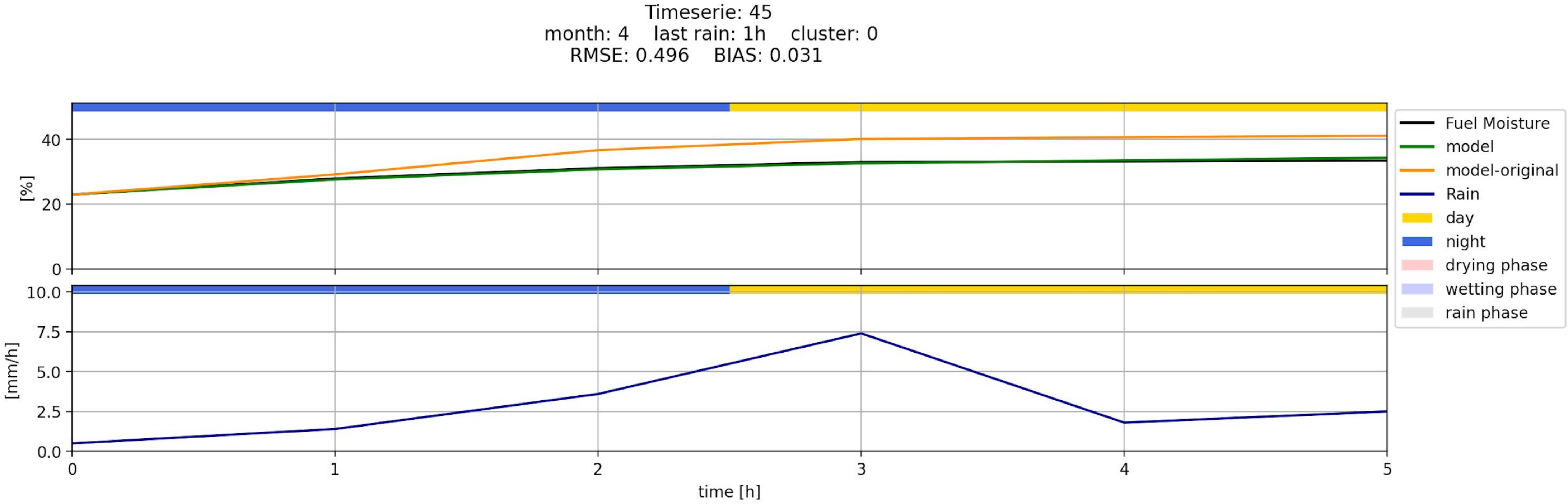
Best time-serie
Metric: BIAS

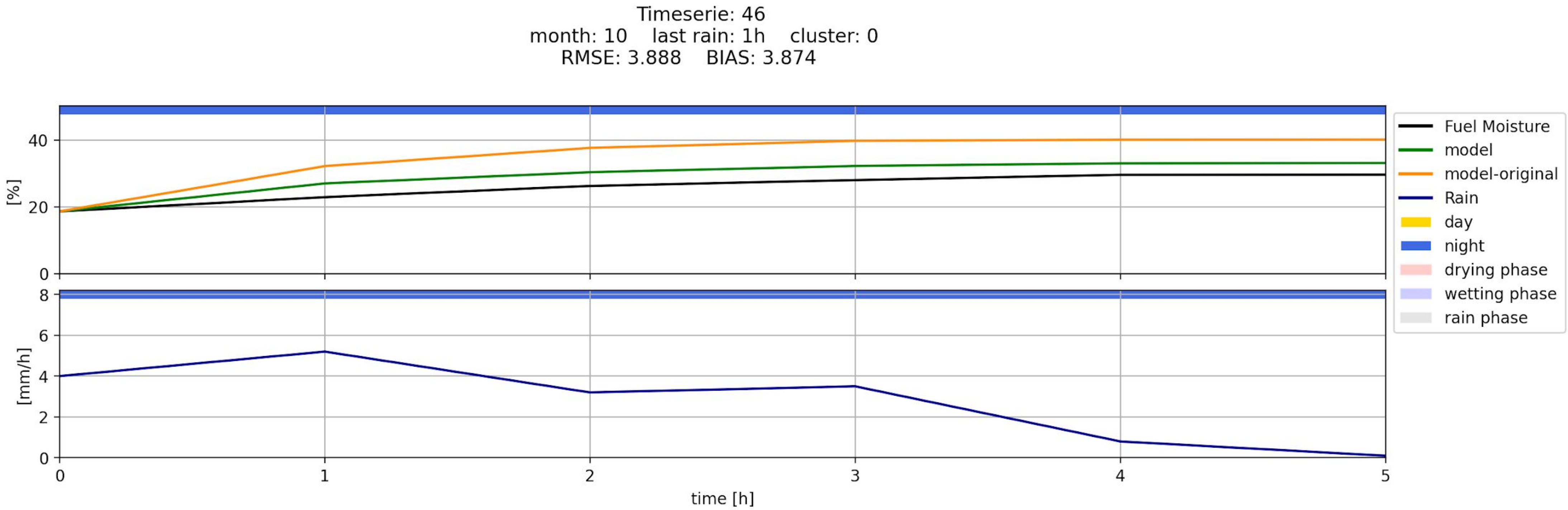


3. Results

3.1. Calibration Results

Rain
Validation Dataset

Worst time-serie
overestimation
Metric: BIAS

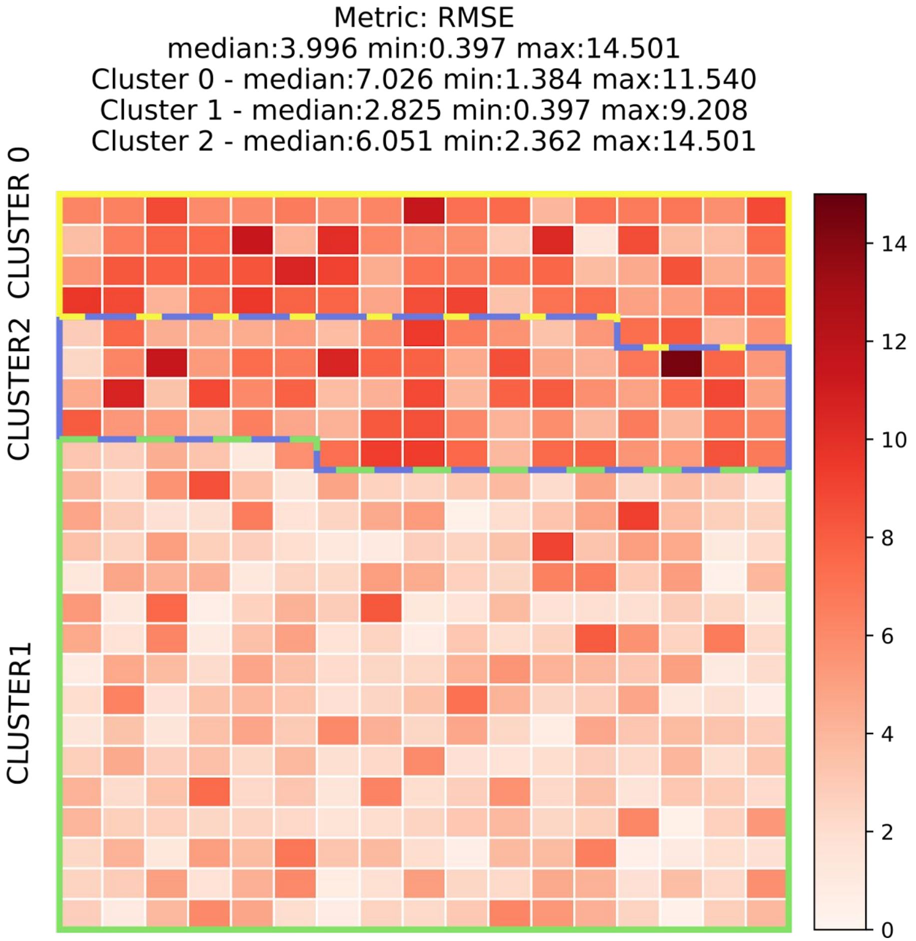


3. Results

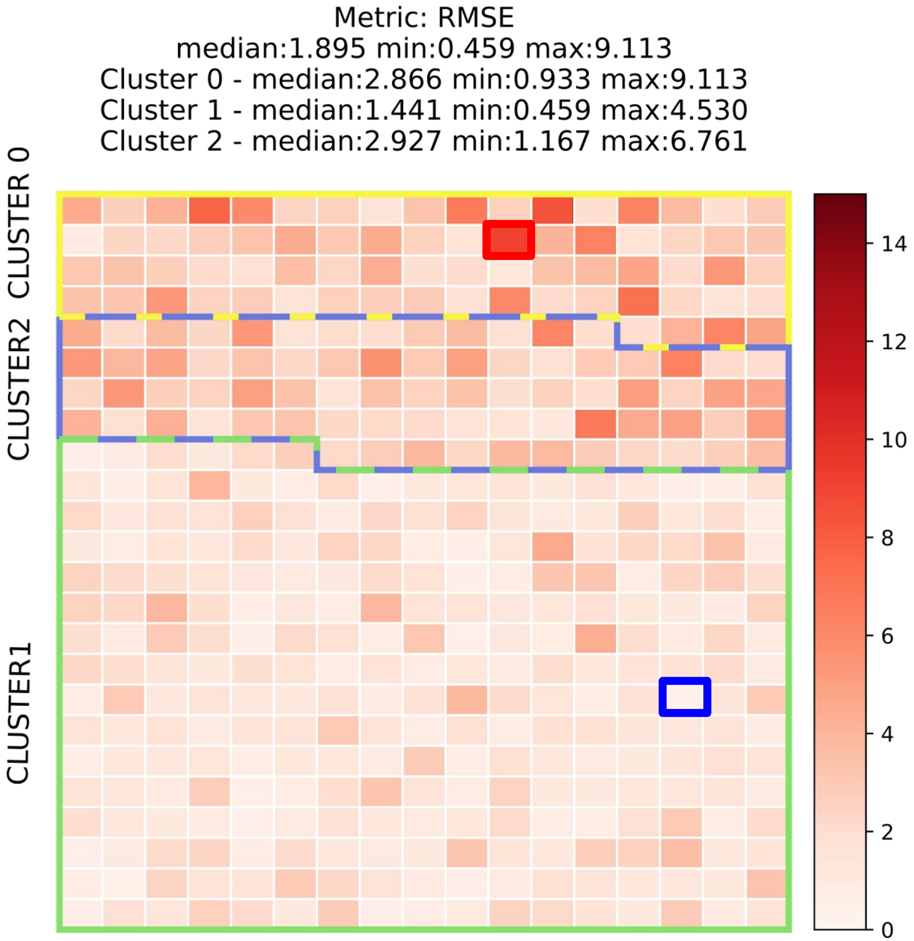
3.1. Calibration Results

Mixed
Validation Dataset

RMSE



ORIGINAL MODEL



NEW MODEL

Worst

Best

3. Results

3.1. Calibration Results

Mixed
Validation Dataset

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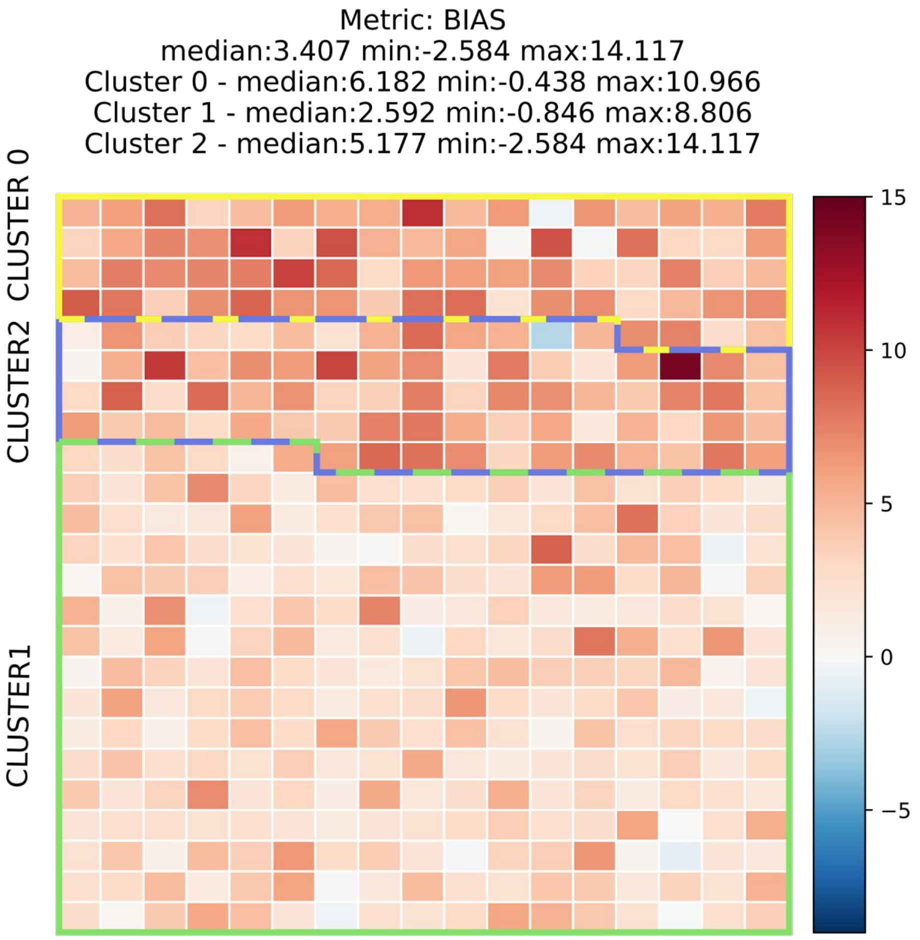
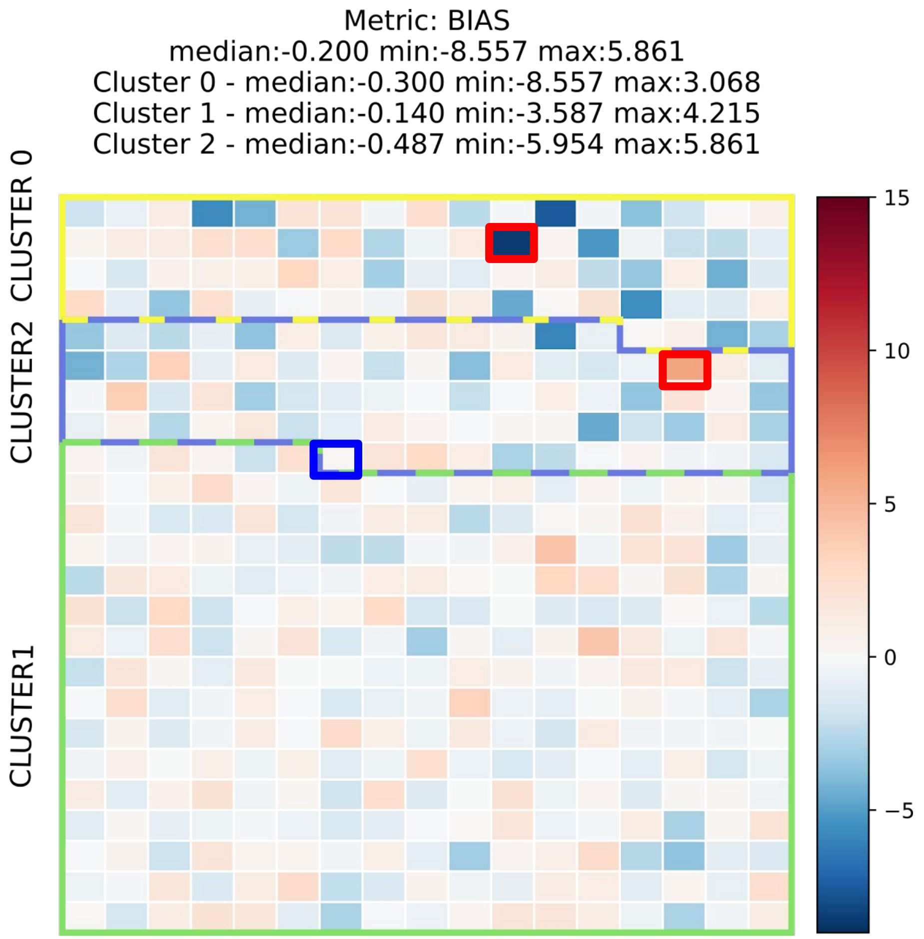
Worst

Best

BIAS



ORIGINAL MODEL



NEW MODEL

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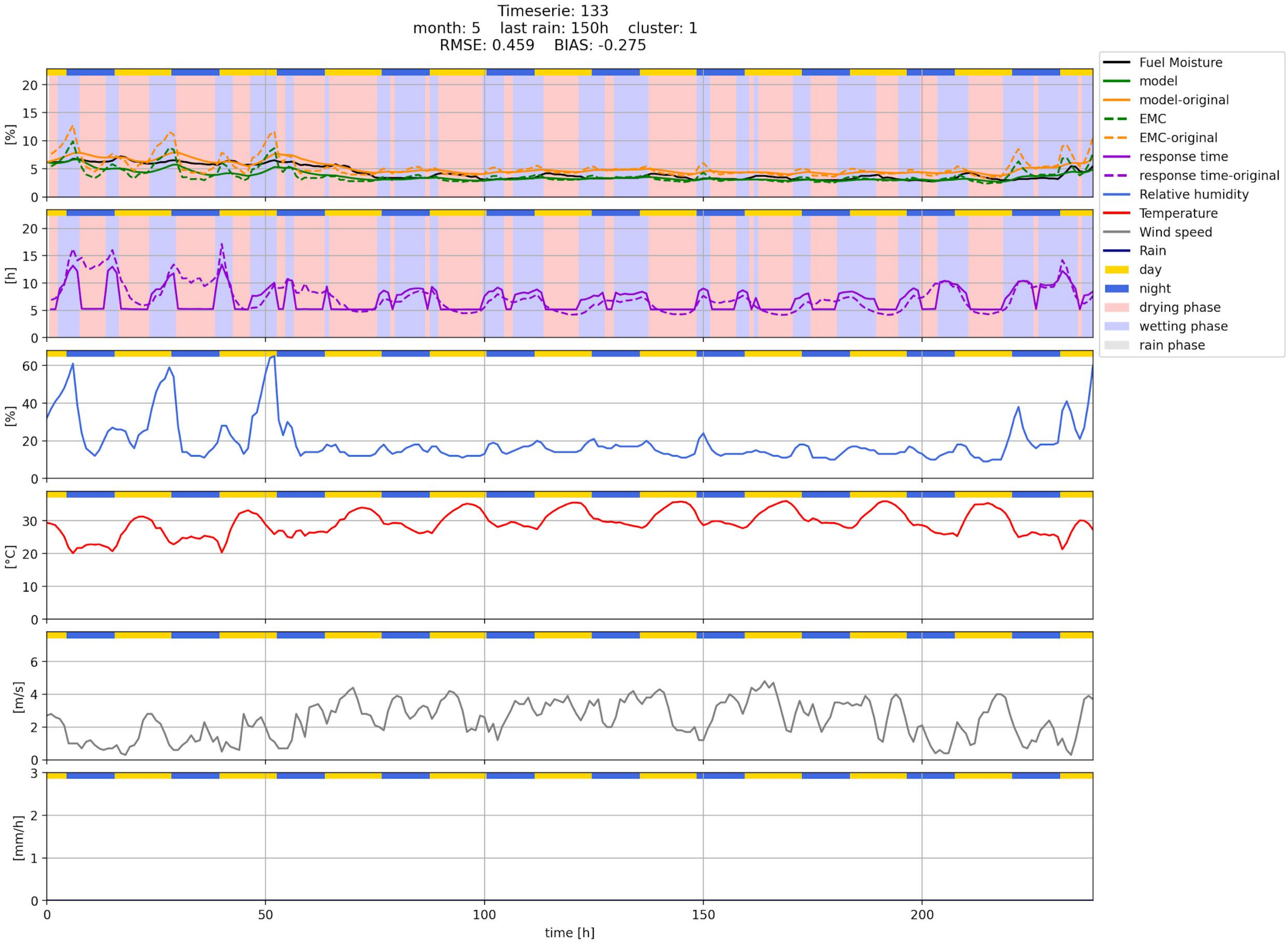
3. Results

3.1. Calibration Results

Mixed
Validation Dataset

Best time-serie
Metric: RMSE



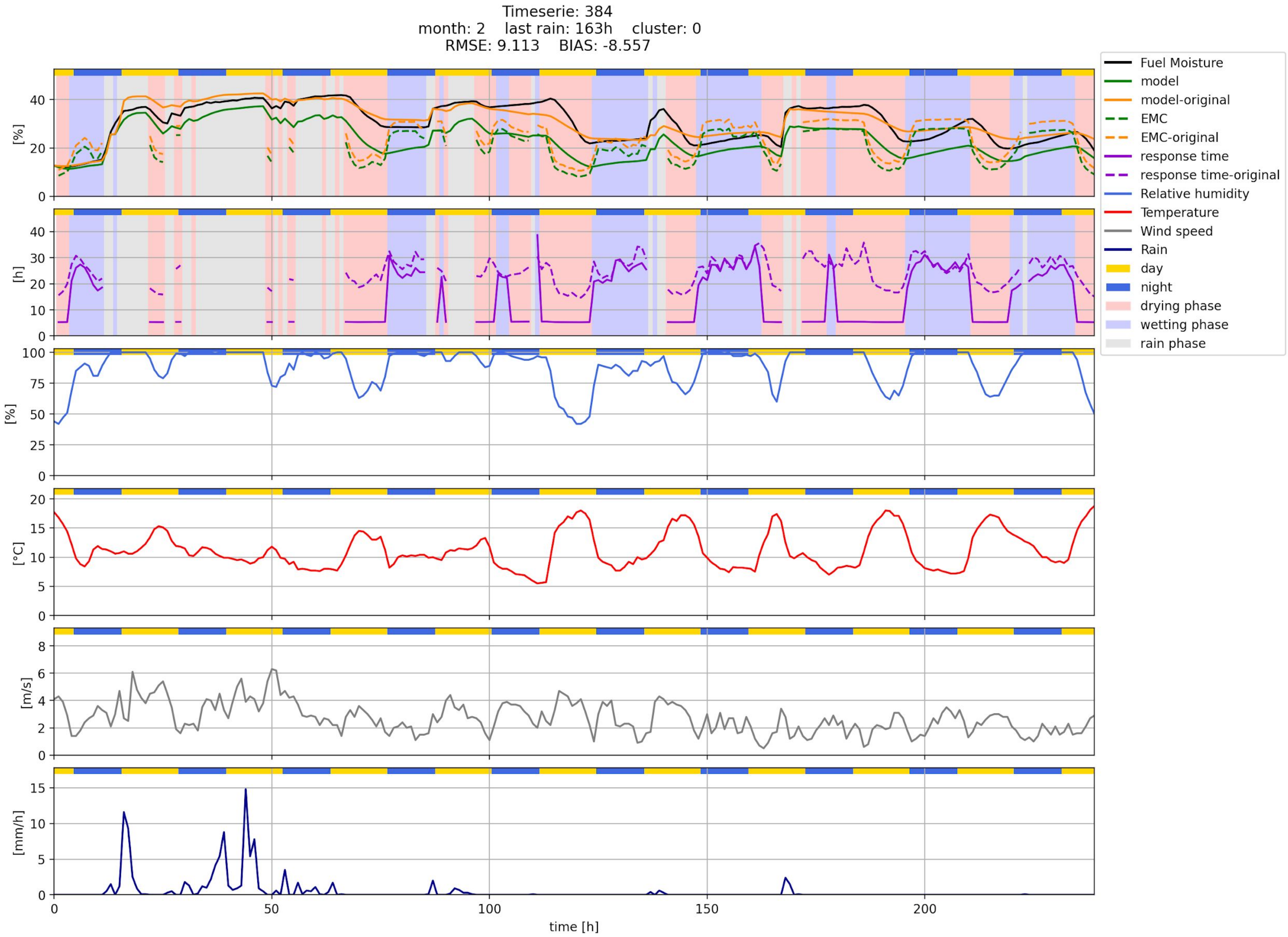
3. Results

3.1. Calibration Results

Mixed
Validation Dataset

Worst time-serie
Metric: RMSE

Worst time-serie
underestimation
Metric: BIAS

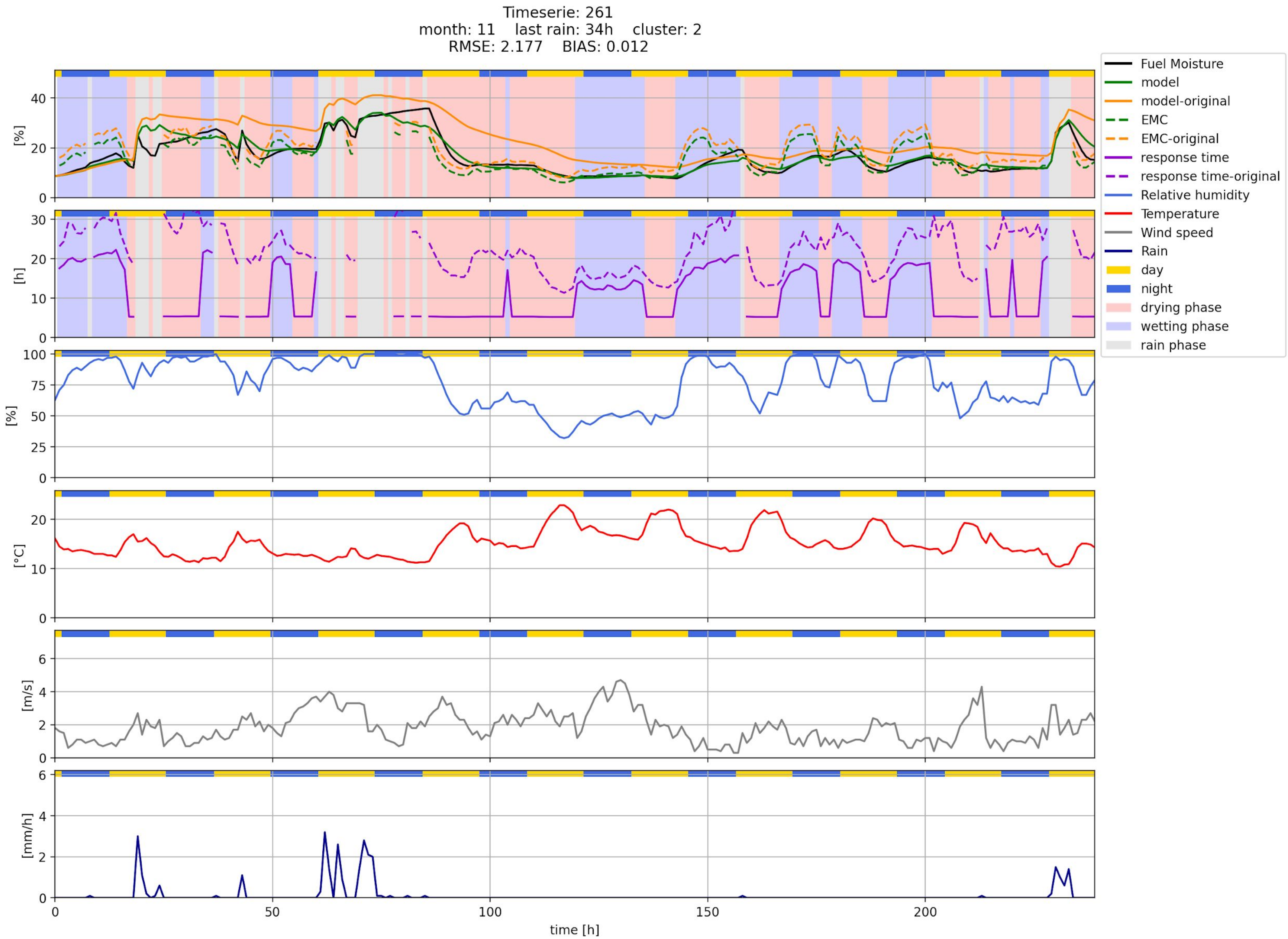


3. Results

3.1. Calibration Results

Mixed
Validation Dataset

Best time-serie
Metric: BIAS

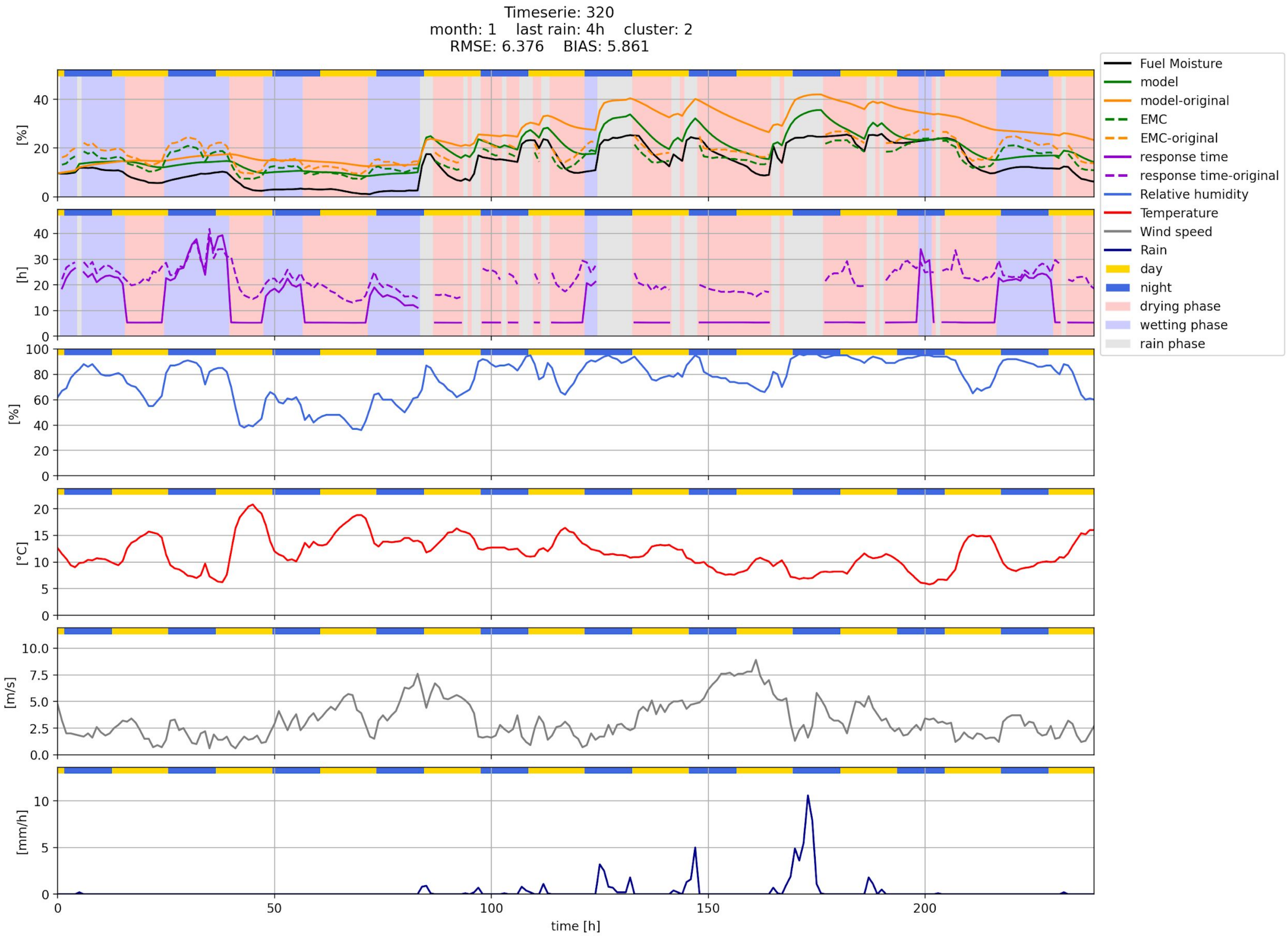


3. Results

3.1. Calibration Results

Mixed
Validation Dataset

Worst time-serie
overestimation
Metric: BIAS



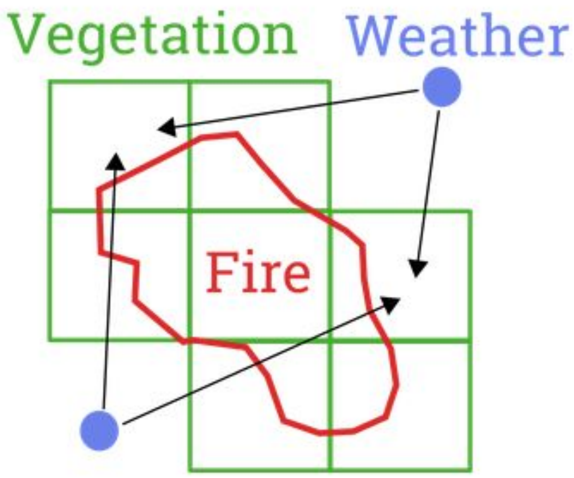
3. Results

3.2. FFMC Model for Wildfire Danger Assessment

To evaluate FFMC model performance on wildfire danger assessment, we computed the FFMC model results for **87783 wildfires occurred in Italy from 2007 to 2021** (source: Italian Civil Protection Department, wildfire data for research purposes).

For each wildfire event, we collected:

- the 3-hours outputs of COSMO Numerical Weather Prediction model [8] of all the grid points within 7 km from the wildfire centroid, for 10 days before the event;



- the vegetation types interested by the wildfire event, from CORINE 2018 Land Cover Map, aggregated in 4 classes: grasslands, broadleaves, shrubs, conifers.

	Grasslands	Broadleaves	Shrubs	Conifers
T0	12 h	120 h	24 h	48 h
Saturation	40%	60%	40%	50%

Different fuel parameters used for the different classes considered

[8] Consortium for Small-scale Modeling - COSMO. url: https : //www .cosmo-model.org/ (accessed: 24.11.2022).

3. Results

3.2. FFMC Model for Wildfire Danger Assessment

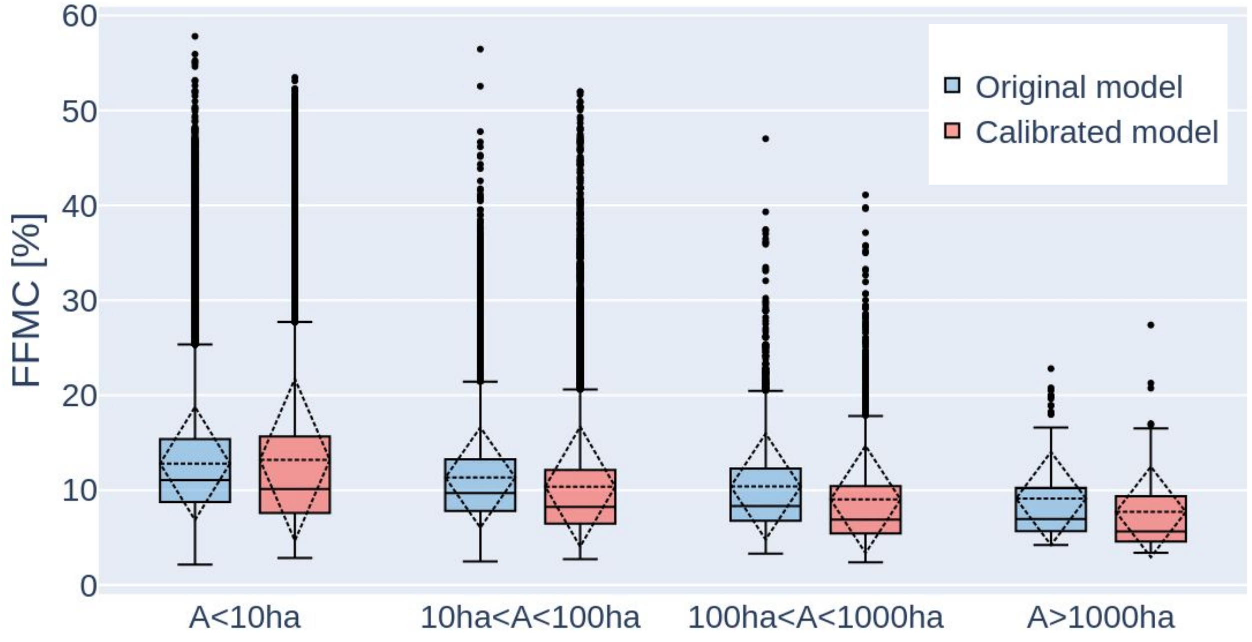
The model run in an ensemble approach: each weather output is used for each fuel type considered.
The time step considered is **3 hours**, as the weather outputs.

→ 10 days are considered before the wildfire event in order to avoid transitory behavior.

Then, the FFMC outputs of the day of the fire are aggregated in the **daily mean 50th percentile.**

The same procedure has been done for the original FFMC model of RISICO.

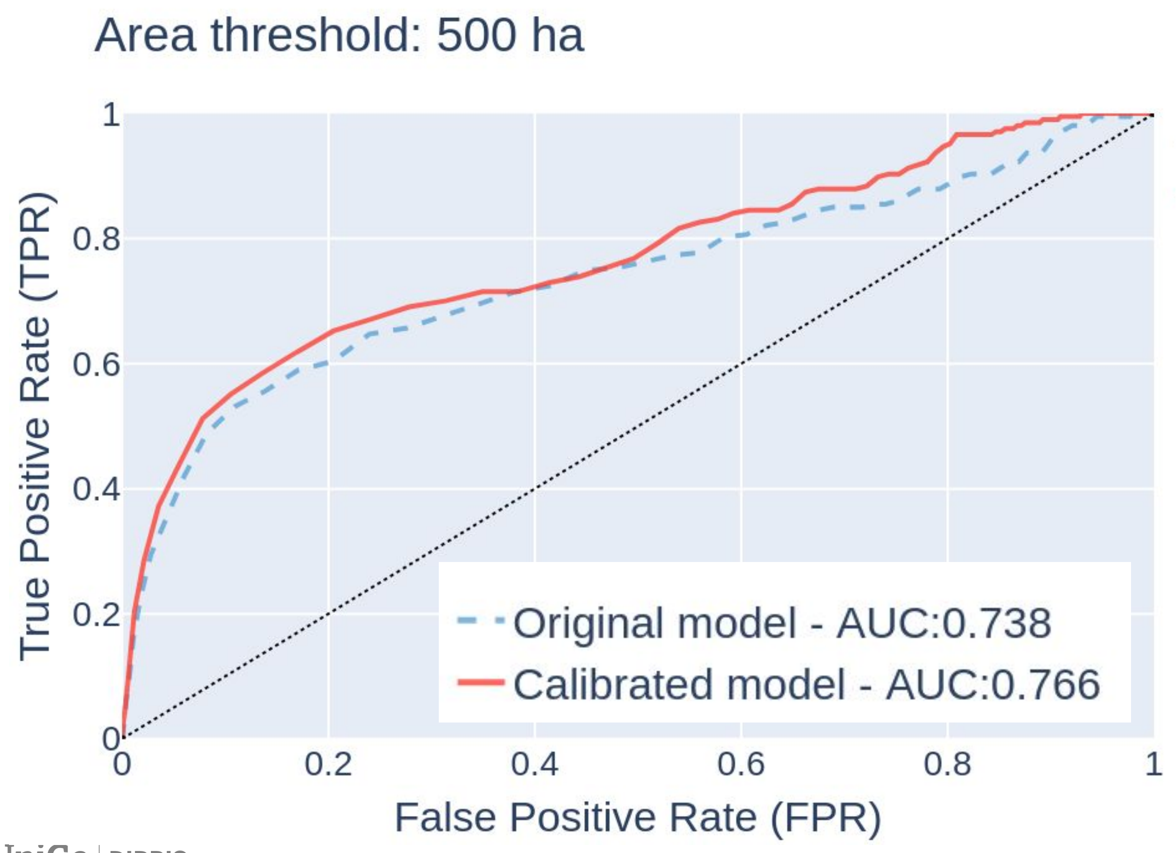
The calibrated model shows a better performance for very large wildfire, identifying for them lower values of FFMC with respect to the original model.



3. Results

3.2. FFMC Model for Wildfire Danger Assessment

To assess the ability of the model to discriminate very large wildfires, we computed the Receiver Operating Characteristics (ROC) curve for wildfire larger than **500 ha,** where different threshold values of FFMC from 0% to 60% are used as threshold to classify a large wildfire (with values below this threshold).



The calibrated model shows a better performance in discriminate very large wildfire, with an increase in the Area Under the Curve (AUC) value.

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