Supplementary Material

S1. ST-DBSCAN procedures

This spatial-temporal density-based clustering algorithm requires three inputs: the spatial window (ϵ_1), the temporal window (ϵ_2), the tail window, and the minimum number of neighbors for a node (*Minpts*) in a cluster. If the distance to other points falls within the two distance windows (ϵ_1 and ϵ_2), the neighbors are considered candidates for the same cluster. If, after this partition, the cluster density is higher than the minimum number of neighbors ($Minpts$), a new cluster is created Birant and Kut [1], Lemos et al. [2], Rus et al. [3].In our analysis, we considered an ad hoc group for the noisy points. In our analysis, the spatial and temporal windows correspond to realistic movements. The first choice is based on the fact that movements between urban markets are mostly by truck and that markets operate on a weekly basis.

To identify the "best partition", we initially estimated a set of possible numbers of clusters by analyzing the D and Hubert indexes for different partitions, depending on the three parameters. Secondly, we conducted a sensitivity analysis by varying the spatial (between 20 and 300 km), temporal (between 2 and 20 days) and density values. The best partition was then chosen based on constraints that less than 50% of the total points in a cluster should be core nodes, and that at most 10% of the total points should be outliers.

Table S1: For each possible pair of clusters, we count the number of common administrative units, together with the extent of each cluster

Nodes		Regional Level (R)			Provincial Level (P)			Communal Level (C)		
i	j	R_i	R_j	Common	P_i	P_j	Common	C_i	C_j	Common
0	1	7	9	7	11	29	9	14	57	3
0	2	7	9	7	11	30	8	14	63	3
0	3	7	1	1	11	2	1	14	4	0
0	4	7	2	1	11	4	1	14	4	0
0	5	7	3	3	11	5	2	14	5	2
0	6	7	4	4	11	5	1	14	6	0
1	2	9	9	9	29	30	21	57	63	17
1	3	9	1	1	29	2	1	57	4	1
1	4	9	2	2	29	4	3	57	4	1
1	5	9	3	3	29	5	2	57	5	1
1	6	9	4	4	29	5	2	57	6	1
2	3	9	1	1	30	2	2	63	4	2
2	4	9	2	2	30	4	3	63	4	0
2	5	9	3	3	30	5	3	63	5	2
2	6	9	4	4	30	5	3	63	6	0
3	4	1	2	0	2	4	0	4	4	0
3	5	1	3	0	2	5	0	4	5	0
3	6	1	4	0	2	5	0	4	6	0
4	5	2	3	1	4	5	0	4	5	0
4	6	2	4	1	4	5	0	4	6	0
5	6	3	4	3	5	5	2	5	6	0

Table S2: Model validation performance metrics by region. The mean absolute error (MAE), its median (Med MAE), bias, coefficient of determination (R^2), and correlation coefficient (r) are calculated for each region across n observed communes.

Region	n	MAE	Med MAE	Bias	R^2	r
Béni Mellal-Khénifra	21	2.73	2.66	-1.22	0.141	0.540
Casablanca-Settat	14	2.76	1.87	2.04	-0.224	0.396
Drâa-Tafilalet	2	1.96	1.96	1.96	0.553	1.000
Fès-Meknès	36	2.59	1.82	-0.38	-0.178	0.276
Marrakech-Safi	10	2.01	2.14	1.32	0.092	0.621
Oriental	14	2.80	2.39	1.28	-0.382	0.174
Rabat-Salé-Kénitra	12	2.91	2.84	-2.22	-0.499	0.440
Souss-Massa	5	3.65	2.77	3.36	-7.564	-0.863
Tanger-Tétouan-Al Hoceima	11	5.47	5.03	5.14	-3.923	-0.340

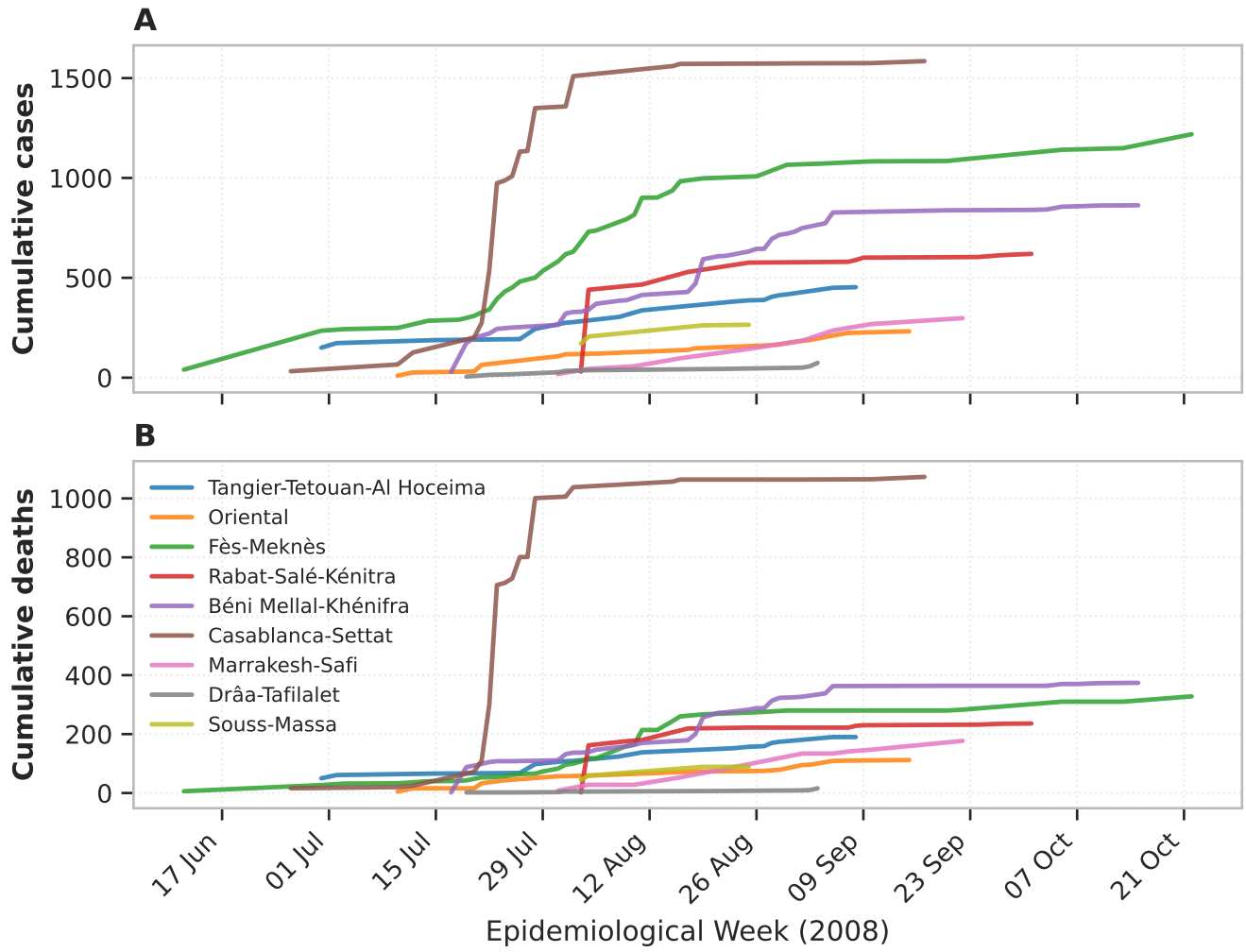

Figure S1: Regional and commune-level outbreak coverage in Morocco (2008). Regions are ordered vertically by the chronological onset of their first reported outbreak (as seen in Panel B)

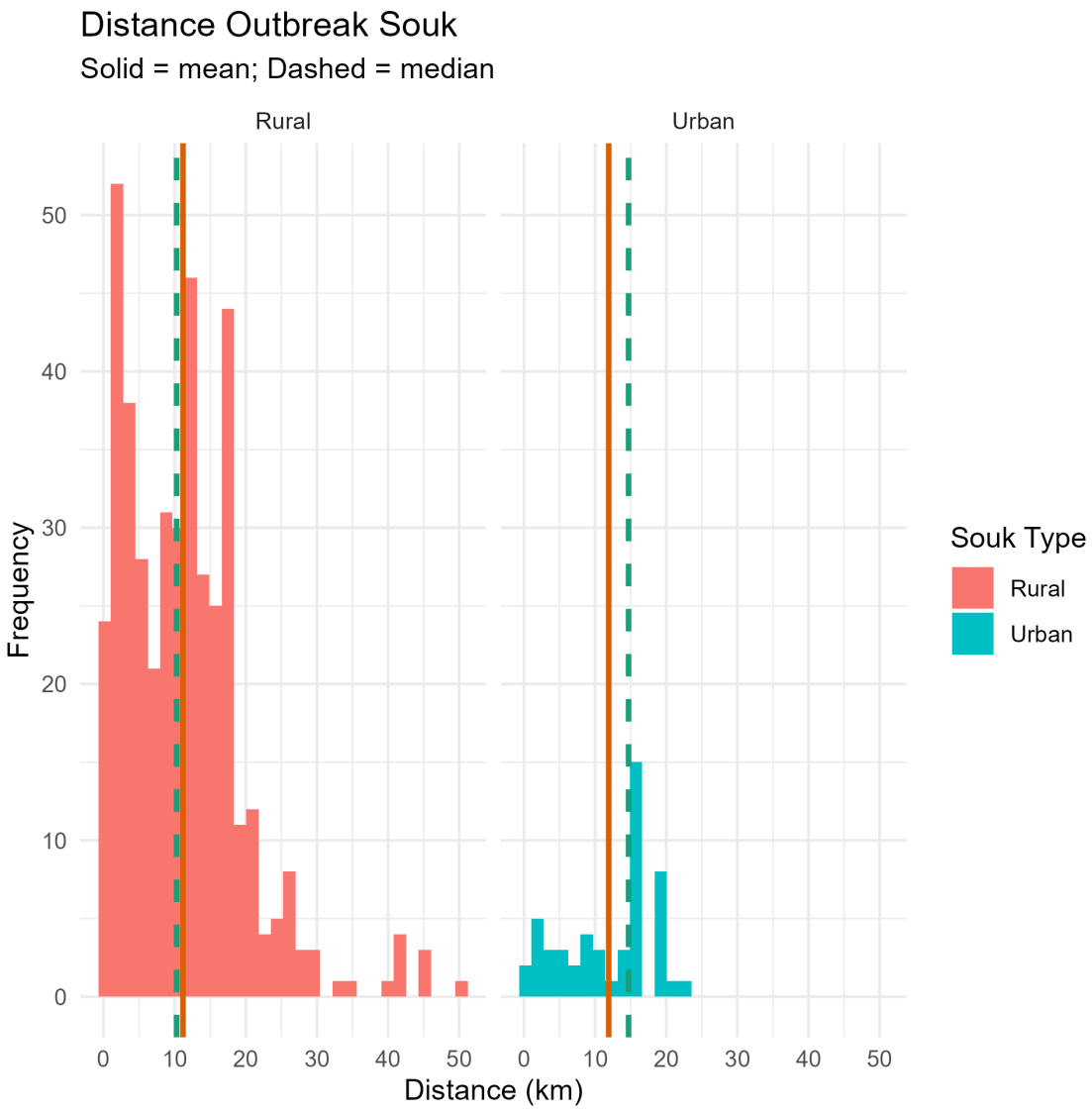

Figure S2: Distribution of outbreak locations with closest market either rural (red) or urban (blue) market.

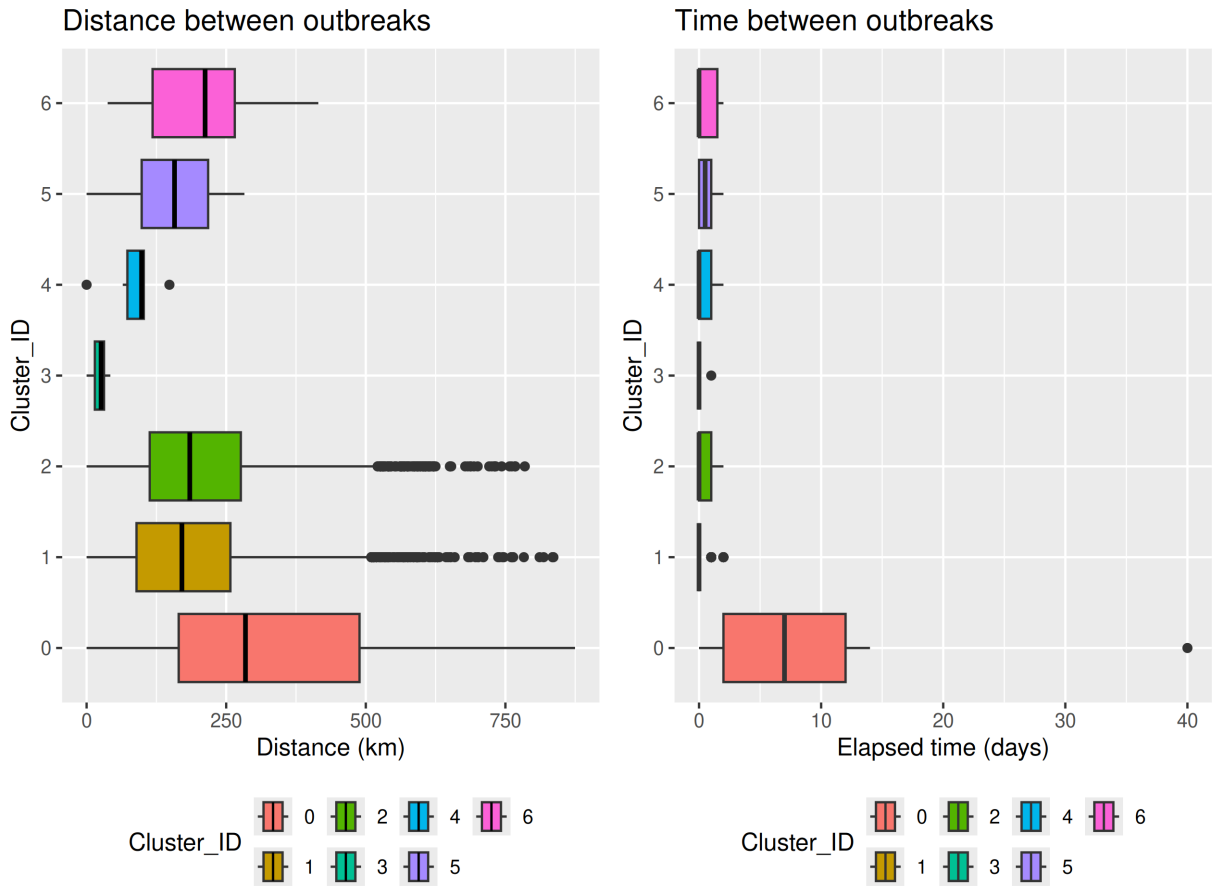

Figure S3: Distribution of the distance (in km) between outbreaks (on the left) and of time elapsed (in days) between outbreaks (on the right) by clusters.

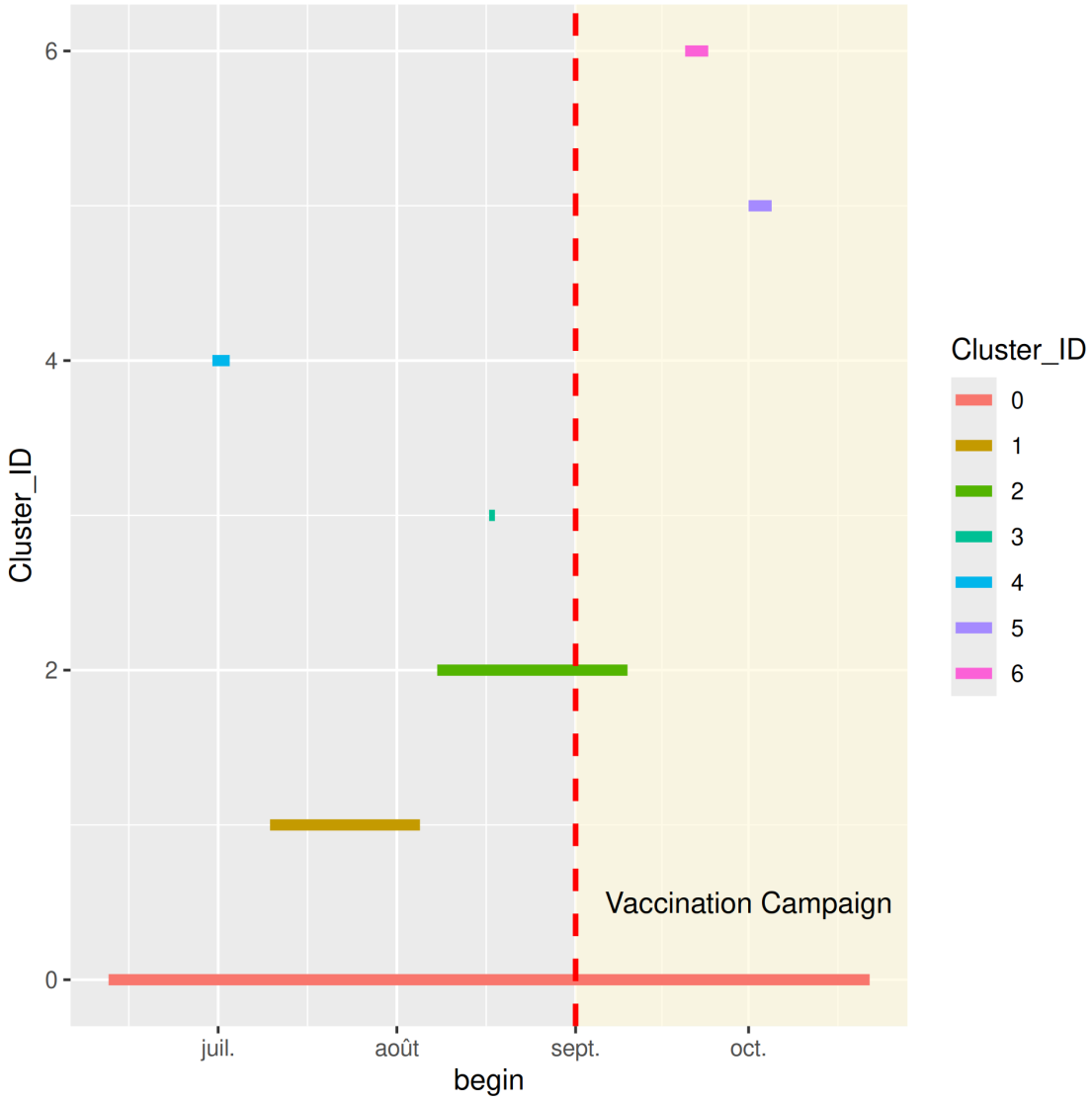

Figure S4: Time interval of outbreaks declaration. Each line corresponds to a specific cluster and the ends of segment the date of the first and last declaration (in days since the beginning.

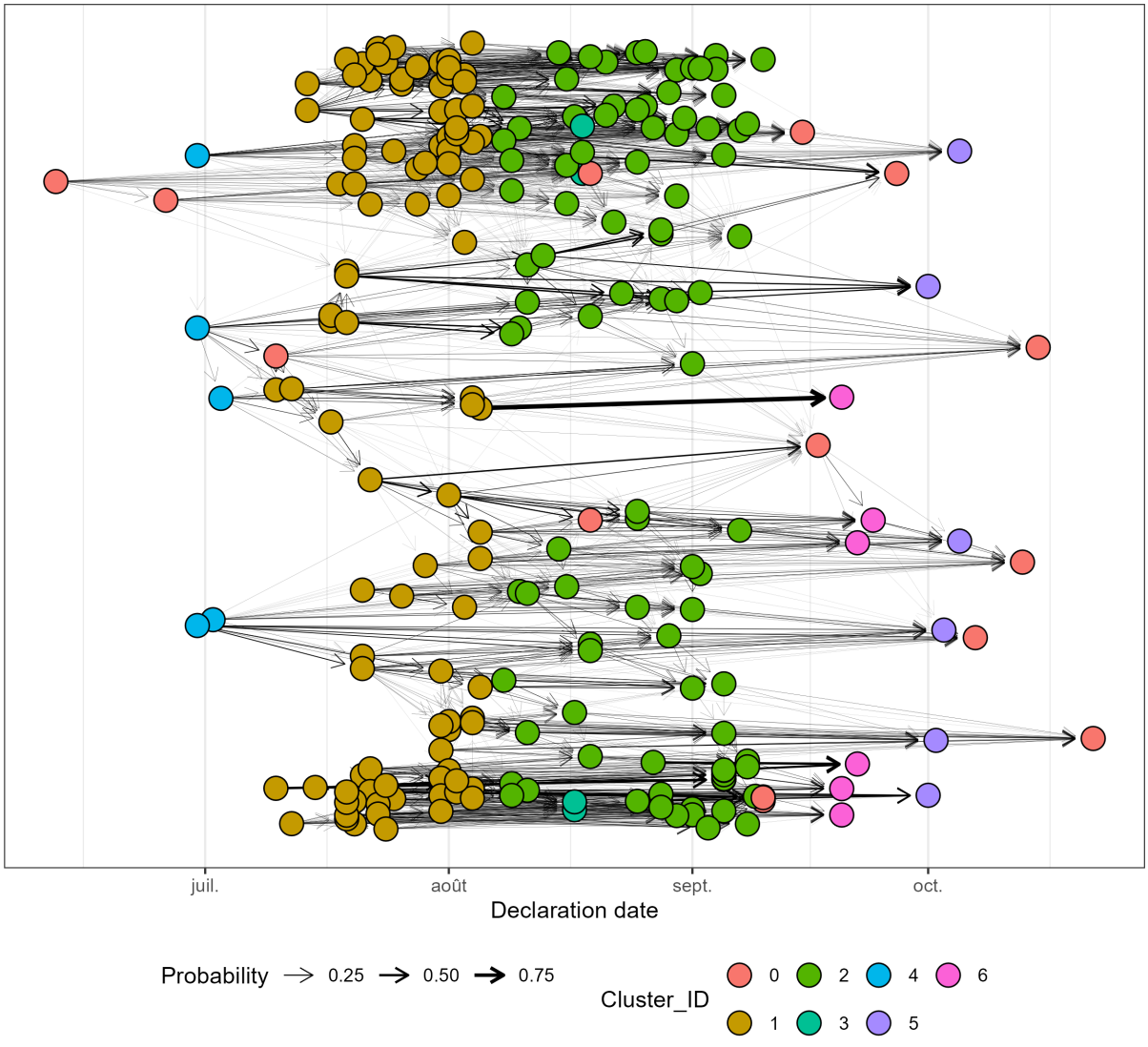

Figure S5: The resulting transmission trees. Nodes are colored based on the cluster they belong to.

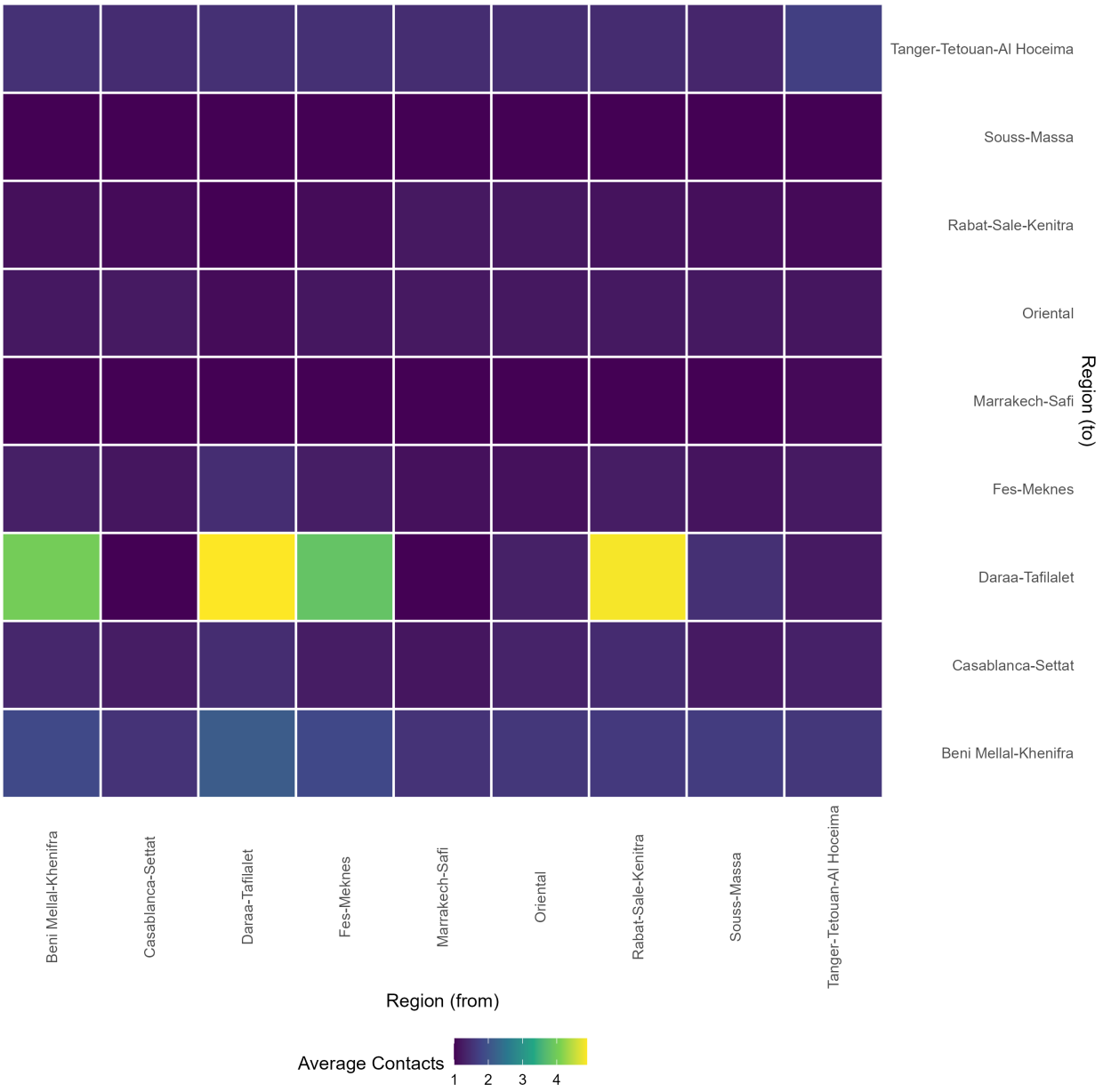

Figure S6: Heatmap representing the number of contacts between regions.



Figure S7: Heatmap representing the number of contacts between communes.



Figure S8: Posterior pairplot of calibrated parameters. Histogram-based pairwise posterior summaries for the calibrated model parameters in the selected scenario. The diagonal panels show the marginal posterior distributions for each parameter, and the off-diagonal panels show pairwise joint structure and dependence between parameters. The overlaid marker indicates the posterior median vector.

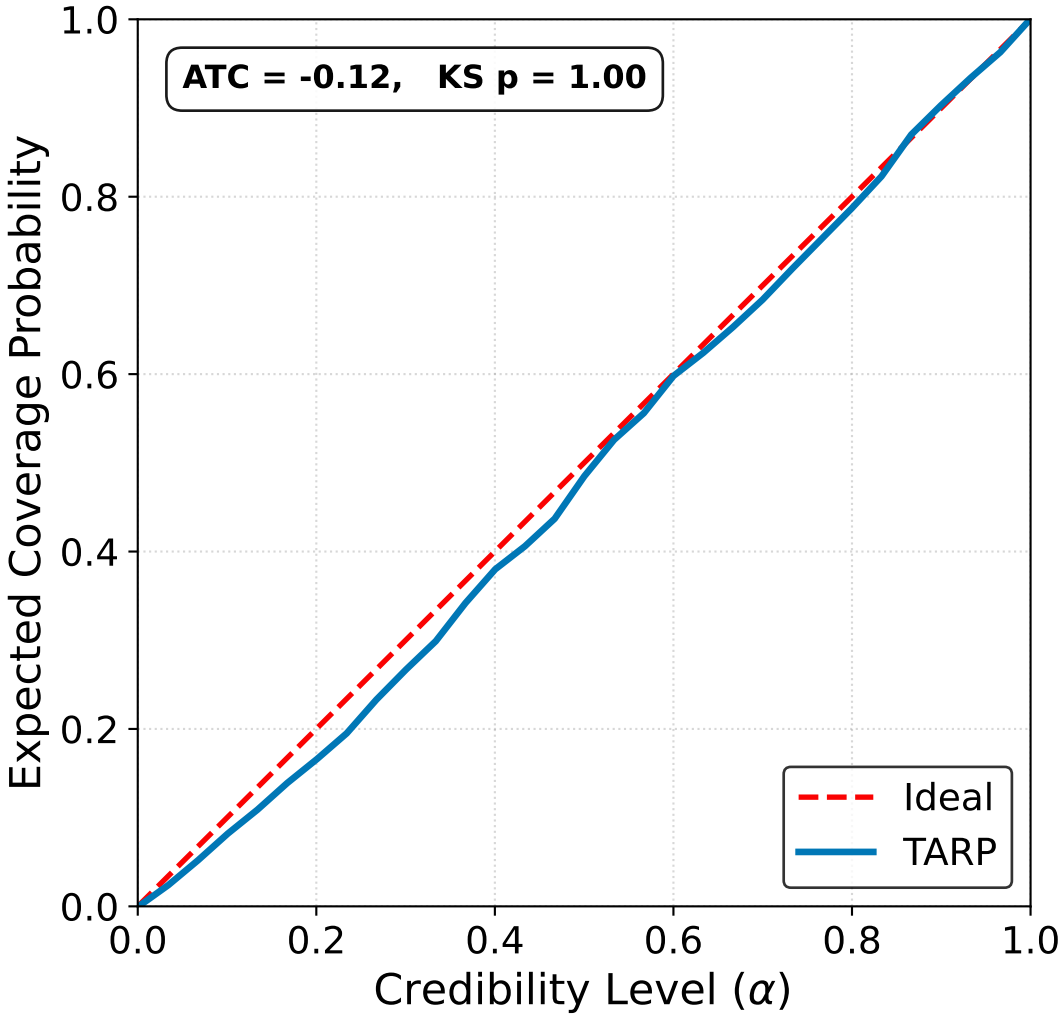

Figure S9: TARP diagnostic. Empirical coverage probability ECP(α) (solid line) is plotted against nominal coverage α for α on a dense grid, with the diagonal ECP(α) = α shown as reference (dashed). Results computed from $N = 1000$ prior-predictive replicates with $M = 2000$ posterior samples per replicate, using standardized Euclidean distance (parameters scaled by prior standard deviations) and reference points $r^{(i)} = \theta^{(i)}$. The Area-To-Curve is ATC $= -0.120$ and the global Kolmogorov–Smirnov test yields $p \simeq 1.0$, indicating close agreement with ideal joint calibration and a negligible tendency toward slight under-confidence.

References

[1] D. Birant, A. Kut, ST-DBSCAN: An algorithm for clustering spatial–temporal data, Data & Knowledge Engineering 60 (2007) 208–221. doi:10.1016/j.datak.2006.01.013.

[2] P. Lemos, A. Coogan, Y. Hezaveh, L. Perreault-Levasseur, Sampling-Based Accuracy Testing of Posterior Estimators for General Inference, arXiv preprint, 2023. doi:10.48550/arXiv.2302.03026. arXiv:2302.03026.

[3] A. M. M. Rus, Z. A. Othman, A. A. Bakar, S. Zainudin, A Hierarchical ST-DBSCAN with Three Neighborhood Boundary Clustering Algorithm for Clustering Spatio–temporal Data, International Journal of Advanced Computer Science and Applications 13 (2022). doi:10.14569/IJACSA.2022.0131274.