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Author: Lisandro Benedetti-Cecchi and Luca Rindi

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Table of contents

List of abbreviations and terms

DIC: Deviance Information Criterion

INLA: Integrated Nested Laplace Approximation

Marginal log-Lik.: Marginal Log-Likelihood

MPA: Marine Protected Area

RMSE: Root Mean Square Error

SD: Standard Deviation

SST: Sea Surface Temperature

σ^2_{Region}: variance among regions

σ^2_W: variance of the spatial field

ρ: spatial autocorrelation

Executive summary

The activity focused on developing surveillance maps of the risk of collapse of *Posidonia oceanica* (L.) Delile meadows at the Mediterranean scale. These maps are the result of a statistical model relating the distribution of alive and dead meadows of *P. oceanica* to anthropogenic and climatic stressors. Maps are currently available at the resolution of 1 km^2, allowing zooming within areas of particular interest. The tool will be of considerable practical value for MPA managers, allowing direct visualization of regions at risk of collapse and that require immediate action to prevent an incipient regime shift. A key

step to tailor the model to the specific needs of managers will be to include high resolution data on the distribution of *P. oceanica* and environmental stressors at the scale of individual MPAs. The modeling framework is designed to become integrated in an automated observing system for real-time monitoring of change in the marine coastal environment. Operational capacity of the observing platform will be fostered by the widespread use of automated devices for data acquisition (robots, sensors). The model will self-update as new data become available, providing an early warning system to prevent undesired changes in coastal ecosystems.

1. Introduction

Coastal ecosystems are increasingly exposed to anthropogenic and climate stressors that increase the probability of a catastrophic collapse ("regime shift") (Levin and Mollmann 2014). **Regime shifts are policy relevant phenomena because they directly affect wellbeing, human-livelihoods and ecosystem services, on which society relies** (Rocha et al. 2014). Assessing the risk of regime shift is a key aspect to prevent the collapse of natural systems. The growing development of remote sensing (Hirota et al. 2011) and the consequent availability of large spatial datasets of environmental covariates has opened new opportunities for assessing the probability of collapse of ecosystems at broad spatial scales.

Seagrasses are important components of coastal marine ecosystems and are involved in a wide range of ecosystem services, such as providing protection against wave action, contributing to shoreline stabilization, ameliorating seawater pollution from human-originated bacteria and providing a nursery habitat for commercially important fish and invertebrates (HilleRisLambers et al. 2001, Orth et al. 2006, Waycott et al. 2009). In the Mediterranean Sea, coastal areas are extensively populated by a key primary producer: the endemic seagrasses *Posidonia oceanica* (L.) Delile that can develop meadows extending from the surface to 40-50 m depth. Increasing water turbidity due to coastal urbanization has been recognized as the most important factor driving the collapse of *P. oceanica* and its transition into a degraded state constituted by sediment and dead roots (hereafter dead matte) (Ruiz and Romero 2003, Erftemeijer and Lewis 2006).

We provide surveillance maps for the risk of regime shift in *P. oceanica*, similarly to surveillance maps of disease outbreaks in epidemiology. These maps are the result of a statistical model relating the distribution of alive and dead meadows of *P. oceanica* to multiple climatic and anthropogenic stressors. **Our analysis aims at developing a monitoring platform that allows managers to surveil the status of MPAs and to monitor in real time when the system is likely to shift into a degraded state.**

2. Data collection and modelling

We used a four-step process to compute and map the probability of occurrence of *P. oceanica* and dead matte along the Mediterranean coastline (Fig. 1). First, we obtained

GIS layers for two different data categories: one layer on the distribution of *P. oceanica* and another one for the distribution of dead matte. Second, we merged the two layers and assigned a value of 1 to areas currently colonized by *P. oceanica* and 0 to areas of dead matte (Telesca et al. 2015). Third, we converted the merged map into a 1-km^2 resolution percentage cover of *P. oceanica* and dead matte. Finally, for each 1-km^2 cell, we compiled a set of potentially important environmental drivers of *P. oceanica*: bathymetry, sea surface temperature (SST), current velocity, salinity, water turbidity, oxygen, nutrients (PO_4^- and NO_3^-), and chlorophyll concentrations. For these environmental variables, we calculated: the mean, the variance, the maximum and the range for period encompassing data on *P. oceanica* distribution (1989-2011). In addition to environmental variables, we also extracted several descriptors of human pressures, including: fish farms pressure, fishing pressure, intensity of pollution by maritime transport, marine litter by coastal activity and marine litter linked to marine transport (e.g. currents) (courtesy of the European Topic Centre - University of Malaga). After applying a step-wise selection procedure, bathymetry and other covariates were excluded from the initial set of 38 covariates because weak predictors of the distribution of *P. oceanica* and dead matte and due to problems of multicollinearity

Finally, we used a Bayesian statistical model based on the INLA approach (Integrated Nested Laplace Approximation) to relate the occurrence of *P. oceanica* and dead matte to environmental variables (Lindgren et al. 2011).The model provided two metrics: the probability of occurrence of a given response variable (*P. oceanica* or dead matte) and the exceedance probability, the likelihood of observing a cover of *P. oceanica* or dead matte greater or lower than a given threshold value (% cover). We set the cover threshold probability (π) to <25 % and >50% for *P. oceanica* and dead matte, respectively. Although arbitrary, these thresholds are informative: **high exceedance probability of occurrence of *P. oceanica* below the threshold (25%) suggests high risk of collapse. Similarly, high exceedance probability of dead matte above the threshold (50%) indicates a likely degraded state.** Occurrence and the exceedance probabilities were mapped at the Mediterranean scale and zoomed within the four MPAs of interest to AMARE: Balearic Island, Malta, Torre Guaceto and Sporades.

3. Occurrence and exceedance probabilities for *P. oceanica*

The probability of observing *P. oceanica* was negatively associated with marine

litter and positively associated with SST, O_2 concentration (mean and range) and pollution by maritime transport (Tab.1). The estimated model has a root mean square error (RMSE) of 0.256 and a correlation between predicted and observed validation measures of 0.748, indicating a satisfactory level of accuracy. Exceedance probabilities are moderate to high along the French and Spanish coast and the eastern Mediterranean.

Tab. 1. Bayesian model the occurrence of *P. oceanica* at Mediterranean scale basin. Significant covariates are indicated in bold.

Covariates	**Mean**	**SD**	**Quantiles (95% credible intervals)**	
			2.5%	**97.5%**
Intercept	**-0.8148**	**0.1696**	**-1.1645**	**-0.4893**
SST mean	**0.4173**	**0.1152**	**0.1891**	**0.6418**
O_2 range	**0.2481**	**0.0749**	**0.0997**	**0.3941**
O_2 mean	**0.2079**	**0.0862**	**0.0378**	**0.3764**
Salinity mean	-0.1097	0.0645	-0.2367	0.0170
Fish farm pressure	0.0725	0.0654	-0.0553	0.2012
Pollution by maritime transport	**0.1174**	**0.0391**	**0.0406**	**0.1943**
Marine litter by coastal activity	**-0.3483**	**0.0272**	**-0.4016**	**-0.2950**
σ^2_{Region}	0.179		0.0475	0.4667
σ^2_W	0.887		0.727	1.073
ρ	0.31		0.237	0.394
Validation statistics				
correlation	0.748			
RMSE	0.256			
coverage	1			

Model selection statistics

DIC	13330.53
Marginal log-Lik.	532.05

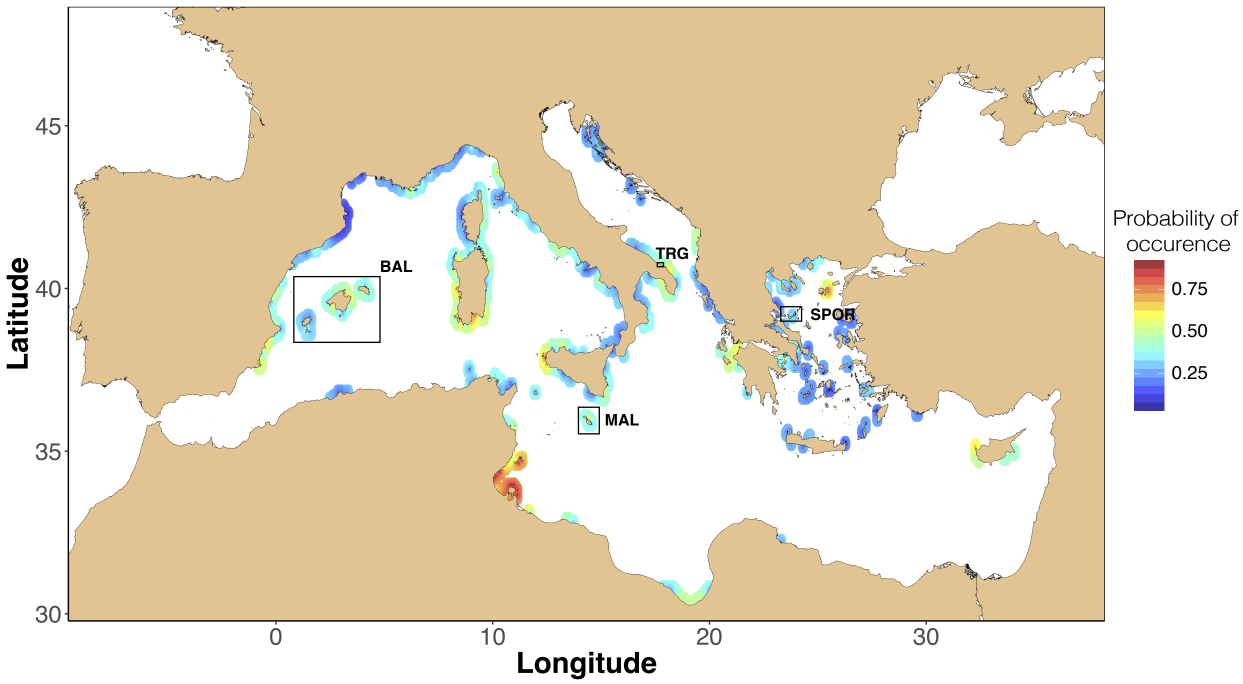

Fig. 2 Occurrence probabilities for *Posidonia oceanica* at the Mediterranean scale. The four MPAs are coded as: BAL: Balearic Island, MAL: Malta, TRG: Torre Guaceto and SPOR: Sporades. Coloured areas have been magnified for visualization.

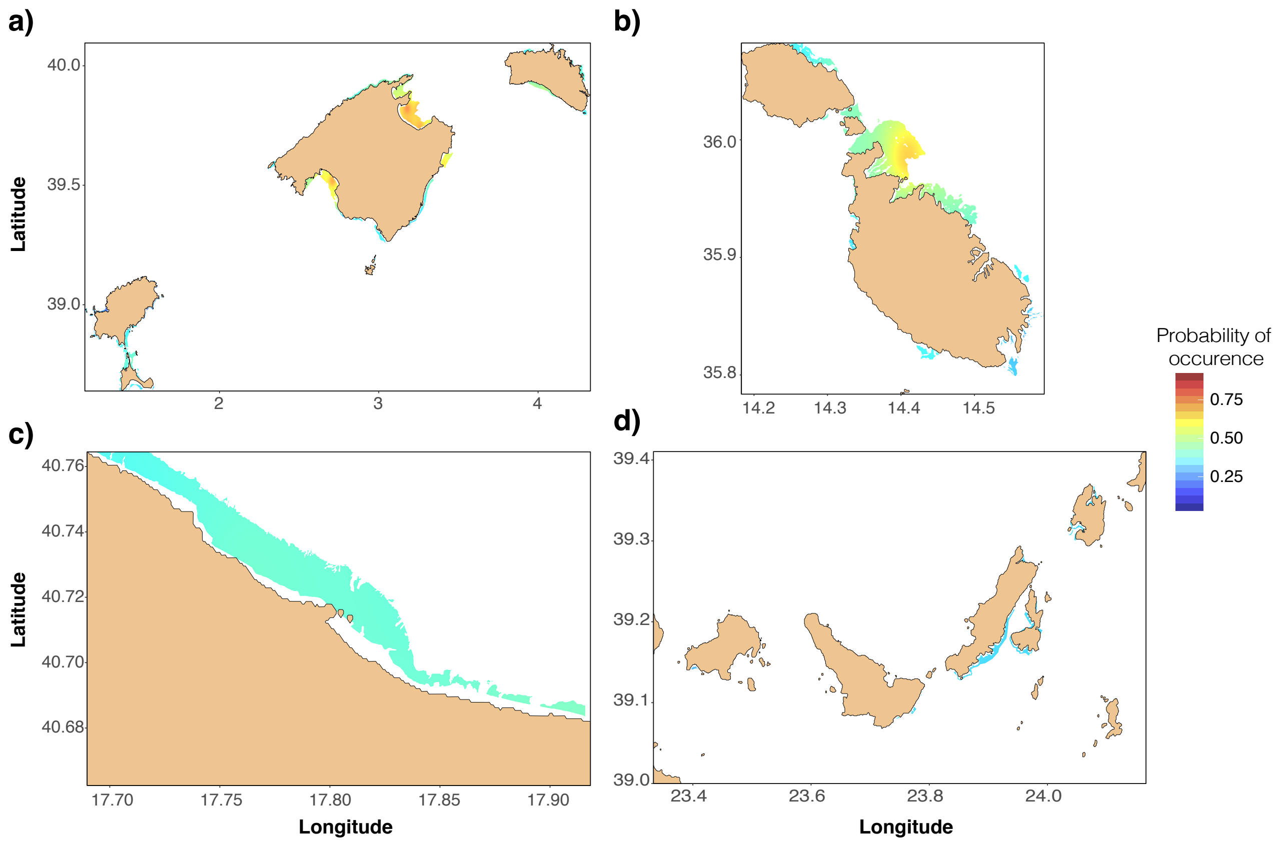

Fig. 3 Occurrence probabilities for *Posidonia oceanica* in the four MPAs. a) Balearic Island, b) Malta, c) Torre Guaceto and 3) Sporades.

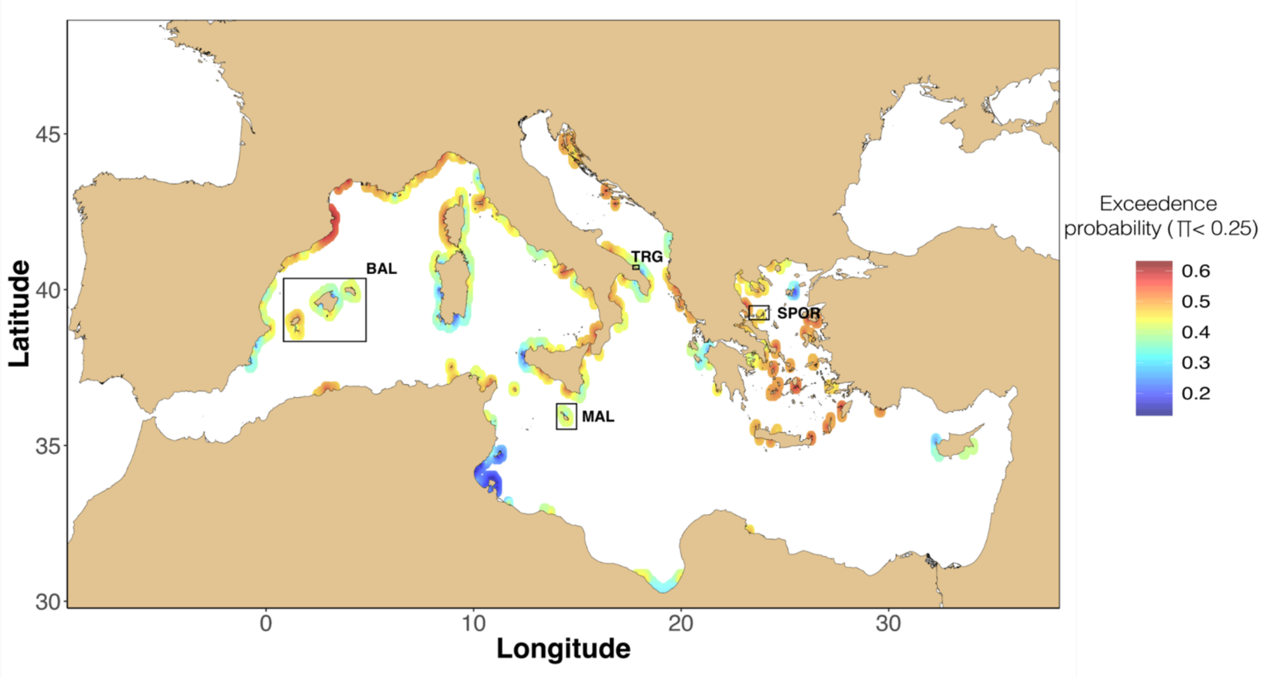

Fig. 4 Exceedance probabilities for *Posidonia oceanica* at the Mediterranean scale. The four MPAs are coded as: BAL: Balearic Island, MAL: Malta, TRG: Torre Guaceto and SPOR: Sporades. Coloured areas have been magnified for visualization.

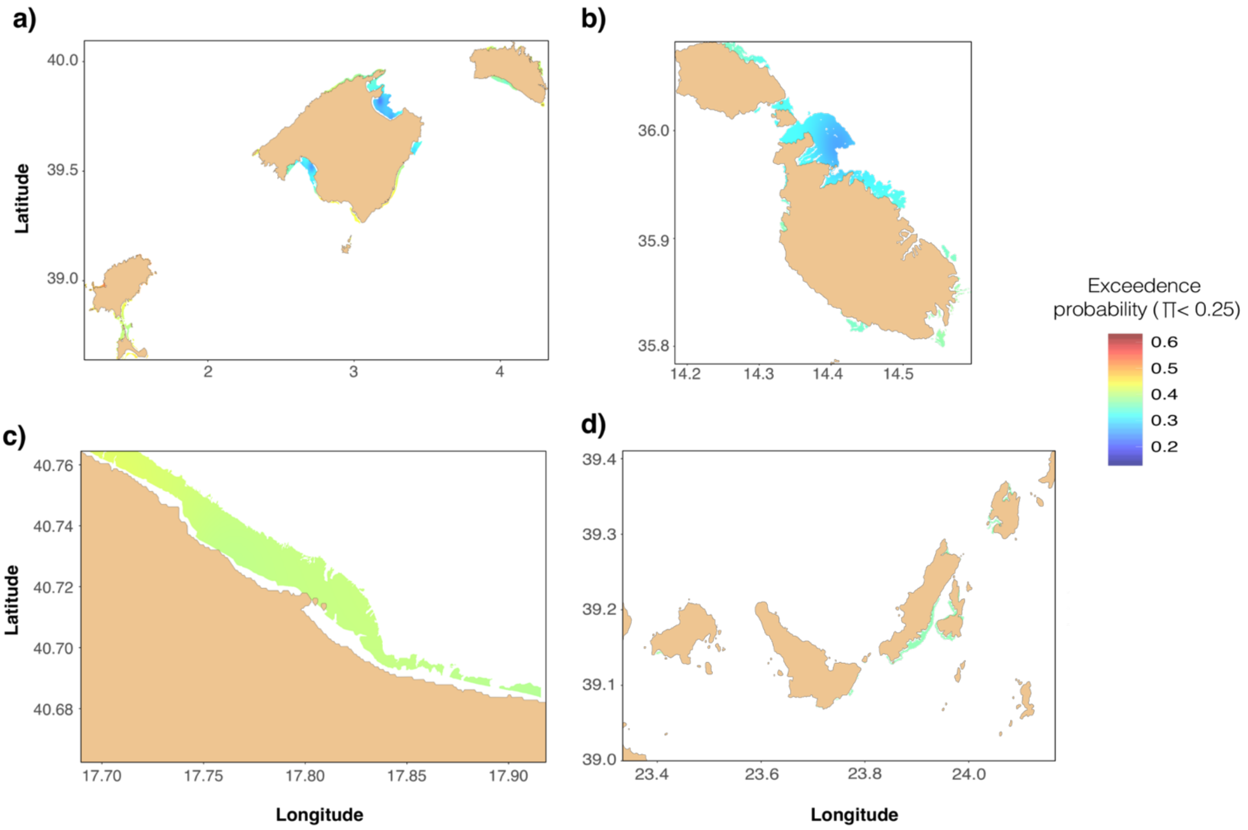

Fig. 5 Exceedance probabilities for *Posidonia oceanica* in the four MPAs. a) Balearic Island, b) Malta, c) Torre Guaceto and 3) Sporades.

4. Occurrence and exceedance probabilities for dead *matte*.

The probability of observing dead matte was negatively associated with SST maxima, salinity variance, PO_4^- range, current velocity range and marine litter linked to marine transport and positively associated with SST, O_2 (mean and range), salinity range and NO_3^- range (Tab. 2). The estimated model had a RMSE of 0.415 and the correlation between predicted and observed validation measures was 0.569. Exceedance probabilities are generally low in the Mediterranean.

Tab. 2. Bayesian model of dead matte occurrence at Mediterranean scale basin. Significant covariates are set in bold.

Covariates	Mean	SD	Quantiles (95% credible intervals)	
			2.5%	97.5%
Intercept	**0.1882**	**0.0167**	**0.1602**	**0.2273**
SST mean	**0.1327**	**0.0453**	**0.0431**	**0.2211**
SST max	**-0.1461**	**0.0616**	**-0.2664**	**-0.0245**
SST range	0.0558	0.0312	-0.0058	0.1167
O_2 mean	**0.1436**	**0.0710**	**0.0045**	**0.2836**
O_2 Max	-0.0744	0.0401	-0.1534	0.0041
O_2 range	**0.0983**	**0.0484**	**0.0036**	**0.1938**
Salinity variance	**-0.0690**	**0.0264**	**-0.1200**	**-0.0166**
Salinity range	**0.0795**	**0.0307**	**0.0185**	**0.1390**
Current velocity range	**-0.0206**	**0.0076**	**-0.0356**	**-0.0057**
Marine litter linked to marine transport	**-0.0261**	**0.0035**	**-0.0330**	**-0.0192**
Marine litter by coastal activity	0.0116	0.0091	-0.0066	0.0292
Pollution	-0.0012	0.0063	-0.0135	0.0111
Fish farm influence	-0.0103	0.0066	-0.0233	0.0026
NO^-_3 variance	-0.0316	0.0164	-0.0638	0.0007
NO^-_3 range	**0.0496**	**0.0204**	**0.0093**	**0.0893**
PO^-_4 variance	0.0644	0.0366	-0.0075	0.1363
PO^-_4 range	**-0.0918**	**0.0386**	**-0.1676**	**-0.0162**
σ^2_{Region}	0.327		0.3	0.361
σ^2_W	0.017		0.0135	0.0213
ρ	0.133		0.101	0.178

Validation statistics	
Correlation	0.569
RMSE	0.415
Coverage	1

Model selection statistics	
DIC	-1562.83
Marginal log-Lik.	438.05

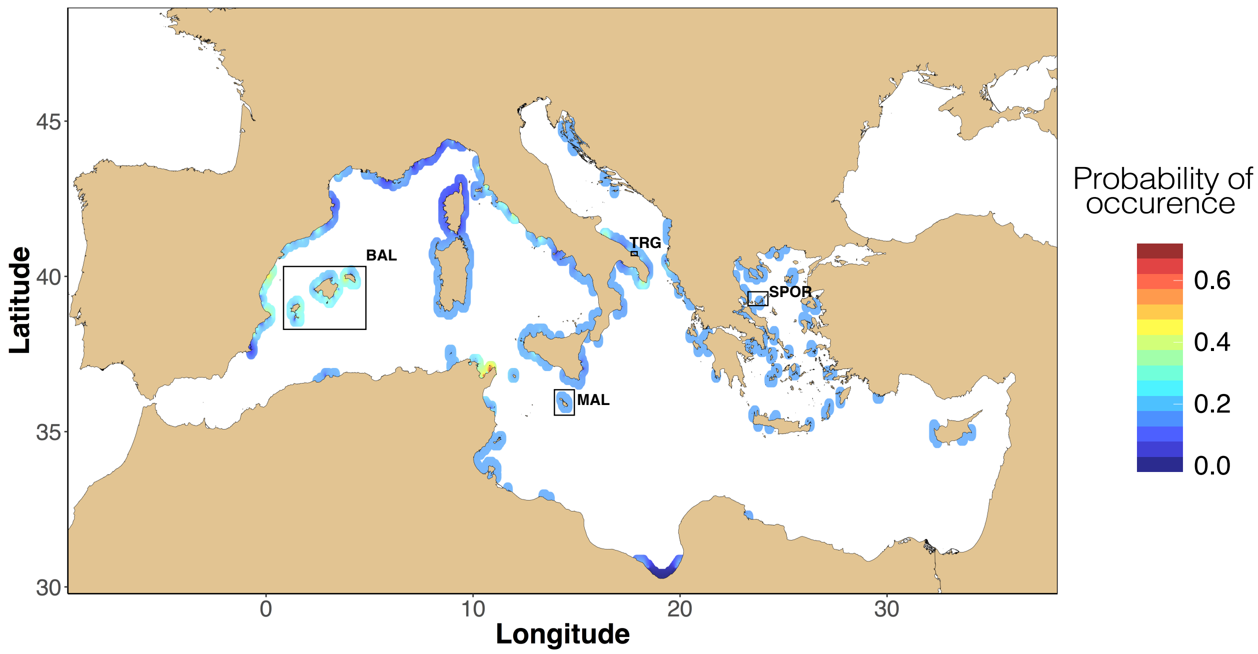

Fig. 6. Occurrence probability for dead matte at the Mediterranean scale. The four MPAs are coded as: BAL: Balearic Island, MAL: Malta, TRG: Torre Guaceto and SPOR: Sporades. Coloured areas have been magnified for visualization.

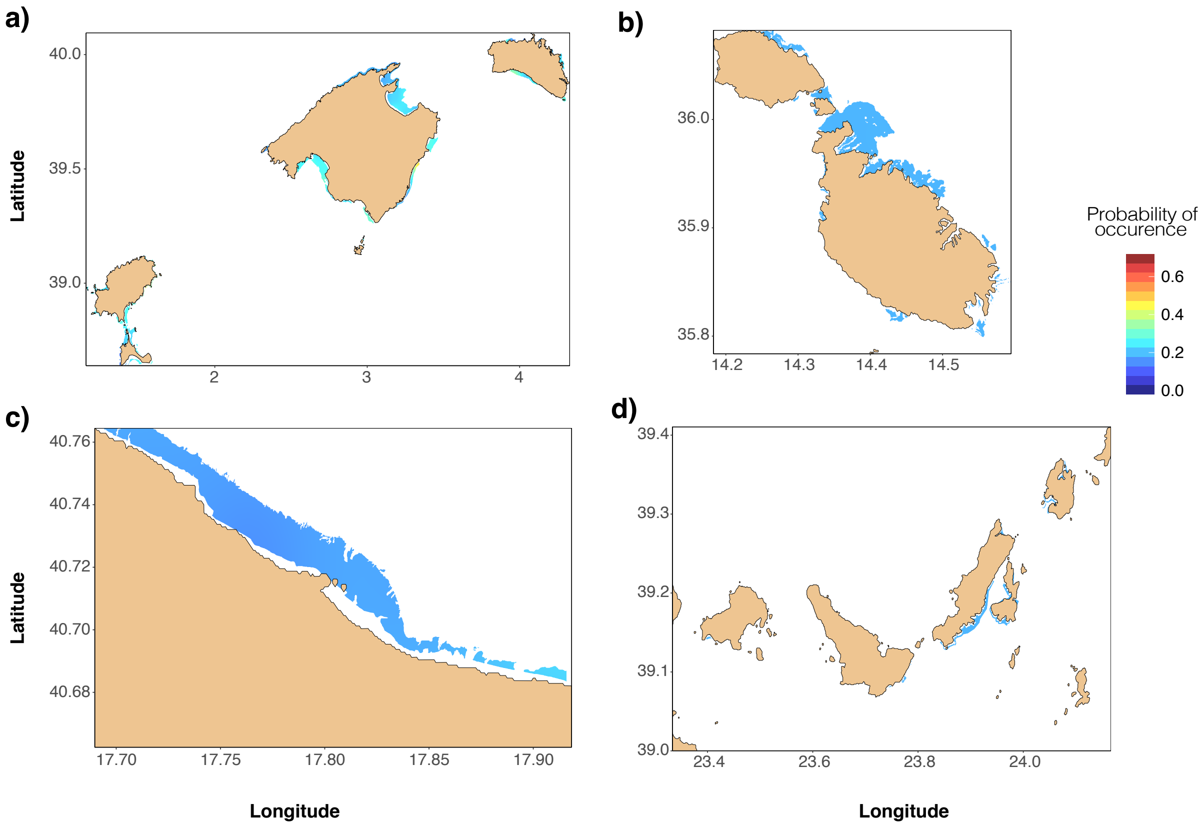

Fig. 7 Occurrence probability for dead matte in the four MPAs. a) Balearic Island, b) Malta, c) Torre Guaceto and 3) Sporades.

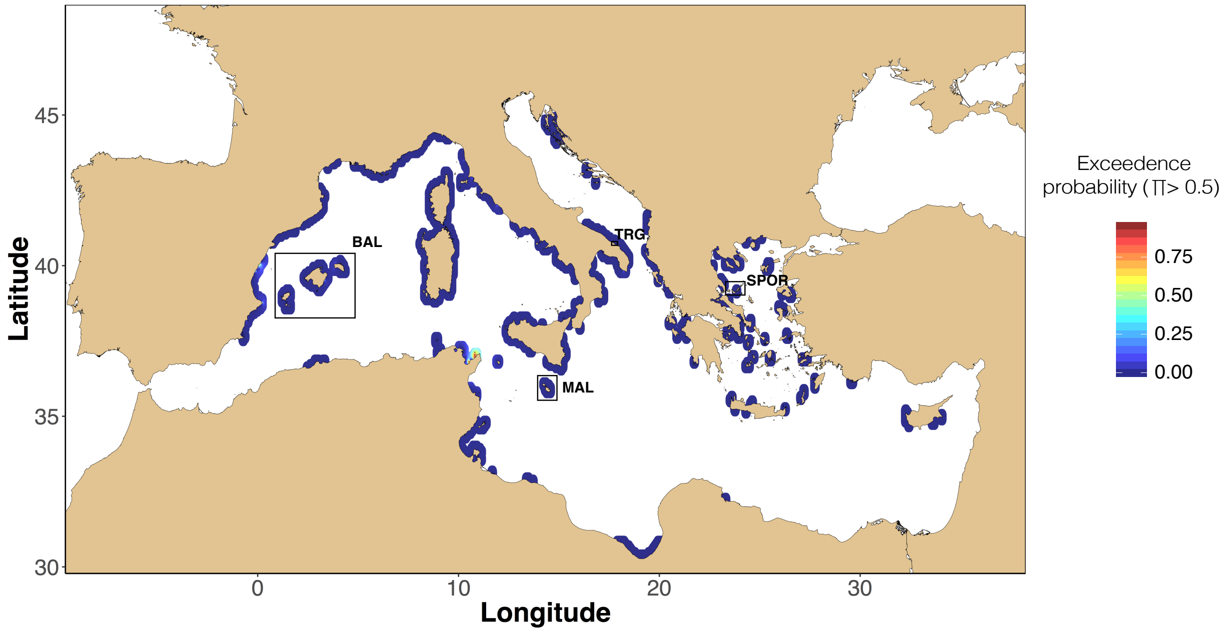

Fig. 8. Exceedance probability for dead matte at the Mediterranean scale. The four MPAs are coded as: BAL: Balearic Island, MAL: Malta, TRG: Torre Guaceto and SPOR: Sporades. Coloured areas have been magnified for visualization.

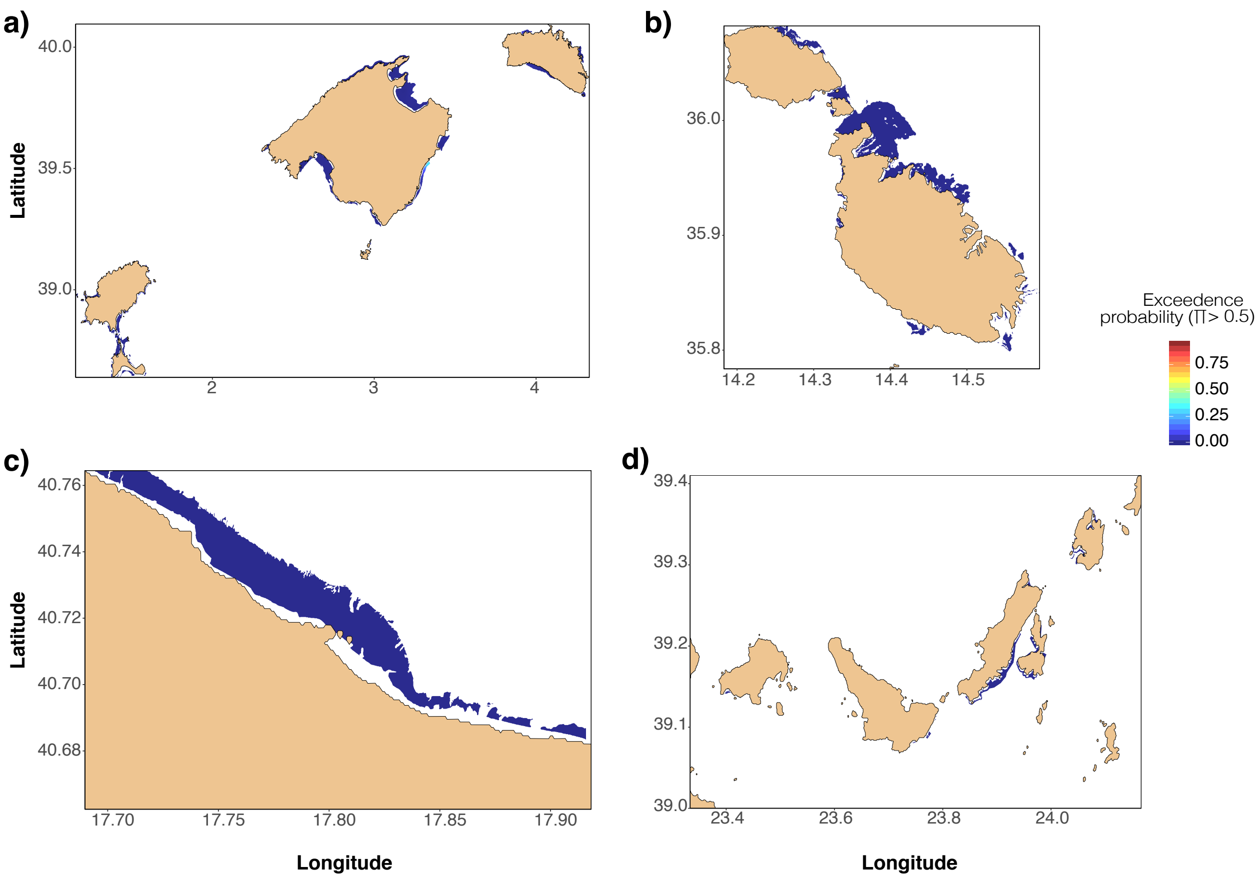

Fig. 9 Exceedance probability for dead matte in the four MPAs. a) Balearic Island, b) Malta, c) Torre Guaceto and 3) Sporades.

5. Concluding remarks and future directions

Our analysis provides insights into the climatic and anthropogenic pressures potentially driving the degradation of *P. oceanica* and the identification of areas where *P. oceanica* is likely to collapse into dead matte. **The positive association of *P. oceanica* with O_2 concentration reinforces the notion that oxygenation is a key feature of well-preserved shallow marine environments, but also highlights the potential impacts that global trends of declining oxygen may have on marine coastal ecosystems (Schmidtko et al. 2017, Breitburg et al. 2018)**. The positive association between *P. oceanica* and mean SST reflects the abundance of this primary producer in southern areas of the Mediterranean (along the Tunisian coast; Fig. 2). **This pattern suggests that warming of the Mediterranean Sea may not pose an immediate threat to *P. oceanica* at norther latitudes**. Instead, caution must be payed when considering the positive association between *P. oceanica* and intensity in maritime transport. This relation highlights that *P. oceanica* occurs in areas exposed to intense maritime transport, which may cause further contraction of *P. oceanica* in the near future. Dead matte was positively associated with SST and O_2 (mean and range), salinity range and NO_3^- range. Some of these covariates were also positively associated with the occurrence of *P. oceanica*, emphasizing the overlap in the distribution of the two states in some regions. The patterns may also indicate the potential for dead matte to further expand in areas where *P. oceanica* is currently in a good state. The negative association of *P. oceanica* with marine litter originating from the coast suggests that this pressure does not pose an immediate threat to seagrass meadows. Similarly, the negative relation between marine litter from the sea and dead matte suggests no causal relation between this pressure and the decline of *P.* oceanica. However, given the increasing amount of marine litter in the sea, we recommend sustained monitoring of this pressure and its potential effects on *P. oceanica*.

Although our analysis has identified significant associations between *P. oceanica* and environmental variables, there is scope to increase the performance of the model by improving the quality of the data. **Increasing resolution of data on the distribution of *P. oceanica,* dead matte and potentially important environmental drivers will allow a better characterization of the status and risk of collapse of *P. oceanica* within individual MPAs**. Most available data is qualitative (presence/absence) and this limits the ability to identify thresholds and tipping points. **Increased availability of quantitative data on *P. oceanica* (cover, number of shoots) will allow better identification of tipping points**. Similarly, quantitative data on the distribution of dead matte (cover, extent) will improve understanding of where *P. oceanica* has collapsed. **Perturbation experiments will be key to assess the resilience of *P. oceanica* and to unambiguously identify critical thresholds in abundance beyond which the system switches into dead matte**. Experimentally probed critical thresholds can then be used to provide more objective estimates of exceedance probabilities. The lower accuracy of the model for dead matte compared to the one for *P. oceanica* (correlation between estimation and validation data of 0.56 and 0.75, respectively) reflects the limited availability of information on the distribution of dead matte in the original dataset (Telesca et al. 2015). Thus, **increasing data availability is expected to improve the**

performance of these probabilistic models in general.

Our modeling framework is designed to become integrated in an automated observing system for real-time monitoring of change in the marine coastal environment. Operational capacity of the observing platform will be fostered by the widespread use of automated devices for data acquisition (robots, sensors). The models will self-update as new data become available, providing an early warning system to prevent further degradation of coastal ecosystems. **This framework can be extended to surveillance of other important ecosystems, such as macroalgal forests (*Cystoseira* spp.) or coralligenous assemblages, both within MPAs and at the scale of the entire Mediterranean.**

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