

1 **Modelling the Potential Spread of the Red-billed Leiothrix *Leiothrix lutea***
2 **in Italy**

3 Samuele Ramellini^{a, b}, Andrea Simoncini^c, Gentile Francesco Ficetola^{a, d}, Mattia
4 Falaschi^a

5 ^a*Dipartimento di Scienze e Politiche Ambientali, Università degli Studi di Milano, 20133*
6 *Milano, Italy;*

7 ^b*Stazione Romana Osservazione e Protezione Uccelli, 00186 Roma, Italy;*

8 ^c*Dipartimento di Biologia, Università di Pisa, 56126 Pisa, Italy;*

9 ^d*Laboratoire d'Écologie Alpine (LECA), University Grenoble Alpes, CNRS, University*
10 *Savoie Mont Blanc, 38000 Grenoble, France.*

11 Corresponding author: Andrea Simoncini simonciniandre@gmail.com

12 **Modelling the Potential Spread of the Red-billed Leiothrix *Leiothrix lutea* in Italy**

13 **Capsule:** The introduced Red-billed Leiothrix can greatly expand its range in Italy, with
14 many regions being at high risk of invasion due to their high habitat suitability.

15 **Aims:** To assess the environmental variables affecting the distribution of the Red-billed
16 Leiothrix during the invasion process, and to predict the potential distribution of the species
17 in Italy.

18 **Methods:** We retrieved 548 occurrence data from Liguria (Northern Italy), Tuscany and
19 Latium (Central Italy) using the Ornitho.it portal, a citizen science-based resource. We used
20 species distribution models to assess the most important climatic and landscape variables for
21 the presence of the species and to generate a countrywide habitat suitability map.

22 **Results:** Leiothrix distribution was jointly affected by climatic and landscape variables, being
23 related to precipitation seasonality, percentage cover of agricultural areas, and annual
24 precipitation. Habitat suitability for the Leiothrix was highest at intermediate levels of
25 precipitation seasonality, decreased with the amount of agricultural areas, and increased with
26 annual precipitation. The results of species distribution models were highly consistent across
27 regions. The areas with the highest suitability for the species occurred in a strip spanning the
28 northern and western sides of Italy, particularly in regions with a Mediterranean climate.

29 **Conclusion:** Broad areas of Italy have a high risk of invasion by the Red-billed Leiothrix.
30 We provide fine-grained information on the magnitude of habitat suitability over the Italian
31 peninsula.

32 Introduction

33 Invasive alien species (IAS) have major negative impacts on native communities and promote
34 the homogenization of global floras and faunas (Elton 1958, McKinney & Lockwood 1999,
35 Nentwig 2007, Primack & Sher 2018). Moreover, the introduction of IAS influences the
36 economic system of the invaded regions, with often unpredictable outcomes (Pimentel *et al.*
37 2005). Predicting the spread of IAS is pivotal for their control (Elith 2017). This, in turn,
38 requires knowledge of the factors determining the establishment and expansion of introduced
39 species. Still, knowledge of the future spread and the processes that drive it is lacking for
40 many alien bird species (Engler *et al.* 2017).

41 This study focuses on the Red-billed Leiothrix *Leiothrix lutea*, a polytypic species belonging
42 to the family of Babblers (*Passeriformes*, *Timaliidae*) with an Indo-Malayan primary
43 distribution range (Collar *et al.* 2017). This Babbler has been frequently released in nature
44 through the pet trade, one of the main introduction pathways of IAS (Richardson 2010, Pârâu
45 *et al.* 2016). The Leiothrix appears to have species-specific ecological and morphological
46 traits that make it a successful invader across many different regions of the world (Pereira *et al.*
47 2017). It has an important impact on biodiversity and has been classified as one of the
48 seven bird IAS with the strongest effects on native biota (Martin-Albarracin *et al.* 2015),
49 because of competition with native birds and seed dispersion of both native and non-native
50 plant species (Tassin & Rivière 2001). Its presence as a nonindigenous species has been
51 documented in Japan, Hawaii, and Europe (Collar *et al.* 2017). In Europe, the Leiothrix has
52 established populations in Spain, Portugal, France, and Italy (Lever 2005, Brichetti &
53 Fracasso 2010; Pereira *et al.* in press). In Italy, this species is considered a naturalized
54 breeding species (Baccetti *et al.* 2014, Brichetti & Fracasso 2015), and has been recorded
55 mainly in Friuli, Latium, Liguria, Tuscany and the Venetian regions, with scattered data from
56 other regions (Spanò *et al.* 2000, Puglisi *et al.* 2009, Puglisi *et al.* 2011, Ramellini 2017,
57 Pereira *et al.* in press). In this country, the species has been spreading since 1980 (Brichetti &
58 Fracasso 2010) and many reports have been published on its local expansion dynamics (e.g.
59 Verducci 2009, Baghino & Fasano 2017, Ramellini 2017). Knowledge on the factors
60 affecting Leiothrix distribution is limited to the native range, Japan, Spain and Hawaii (Fisher
61 & Baldwin 1947, Amano & Eguchi 2002a, Herrando *et al.* 2010, Collar *et al.* 2017), and fine-
62 scale predictions of its potential expansion are currently restricted to the northeastern Iberian
63 Peninsula (Herrando *et al.* 2010, but see also Pereira *et al.* in press for a coarse-scale analysis).
64 In Italy, no study has provided information on the factors driving Leiothrix distribution, nor
65 has provided information on its potential countrywide invasion.

66 In this study, we aimed to: (i) assess the factors driving Leiothrix distribution in Italy, (ii)
67 identify the areas in Italy that suffer the highest invasion risk, by building species distribution
68 models (SDMs, Elith & Leathwick 2009) with occurrence data from Liguria, Tuscany, and
69 Latium. This knowledge will help to set up appropriate monitoring protocols to prevent
70 further invasions by the Leiothrix in Italy. Given the current knowledge of the habitat
71 preferences of the Leiothrix (e.g. Herrando *et al.* 2010, Collar *et al.* 2017, Ramellini 2017)
72 and of the factors that generally drive species distribution (Bradie & Leung 2017, Bowman *et*

73 *al.* 2017), we hypothesized that: (i) SDMs applied to *Leiothrix* would predict an expansion of
74 the species in Italy, (ii) climatic and vegetation variables (cover of broadleaved forest and
75 shrubs) would have a key role in determining the *Leiothrix* distribution in Italy.

76 **Methods**

77 ***Sources of data***

78 We extracted presence records of *Leiothrix* at the 1-km resolution from the Ornitho portal
79 (www.ornitho.it). This open-access platform collects georeferenced and validated
80 biodiversity data within Italian national borders and its archives are freely searchable by
81 contributors. We did not consider other portals (e.g. eBird and iNaturalist) as they include a
82 very small number of data for the study species, compared to Ornitho. The use of datasets
83 from citizen science projects has gained momentum in ecology during the last decades
84 (Kobori *et al.* 2016, Ellwood *et al.* 2017) and has been successfully employed in invasion
85 biology (e.g. Gallo & Waite 2011, Falaschi *et al.* 2017). The research on the Ornitho portal
86 was performed using the following entries: temporal extent “All the period recorded in the
87 system”, species “Red-billed *Leiothrix*”, spatial extent “Regions of Latium, Tuscany, and
88 Liguria”, i.e. the three regions in Italy where the species is currently widespread. In
89 compliance with the site’s rules, data usage permission was requested via personal
90 communication to the users involved. These data were complemented with our own field
91 records, collected in 2012-2018 in Latium and Liguria. All data were then combined into our
92 final dataset, consisting of 548 georeferenced records, 228 from Liguria, 230 from Tuscany
93 and 90 from Latium. The distribution of records is shown in Figure 1. We assumed that these
94 records represent individuals released in nature from a sufficient amount of time or within
95 already established populations, i.e. we assumed that no records from individuals temporarily
96 recorded in unsuitable habitats existed in our dataset. This assumption is justified by the fact
97 that *Leiothrix* populations in Liguria and Tuscany originated from a single escape of 80
98 individuals from an aviary in 1982 (Besagni 2000). In Latium, populations originated from
99 multiple releases between 1998 and 2003, followed by the rapid establishment and spread of
100 *Leiothrix* naturalized populations (Ramellini 2017).

101 ***Environmental variables***

102 Overall, we considered ten environmental variables, describing landscape (percentage
103 cover of agricultural areas, broadleaved forests, shrubs and bushes, and urban areas;
104 distance from rivers), climatic conditions (total annual precipitation, precipitation
105 seasonality, mean annual temperature, and temperature seasonality), and altitude (Table 2).
106 Moreover, we calculated roads density within the 1-km cell, on the basis of road maps
107 obtained from the Geofabrik OpenStreetMap server (www.geofabrik.de), as it is a major
108 factor determining accessibility and the availability of biodiversity data, particularly in
109 citizen science data (Ficetola *et al.* 2013, Merow *et al.* 2016). All variables were at the 1-
110 km resolution.

111 *Landscape variables*

112 To obtain land-cover information we used the CORINE Land Cover Map of Europe
113 (European Commission *et al.* 1994), which has been successfully used to model invasion
114 risk (e.g. Ficetola *et al.* 2010, Polce *et al.* 2011, Gallien *et al.* 2012). From this map, we
115 extracted four layers, representing the percentage cover of four different land-cover classes
116 at the 1-km resolution: broadleaved forests, shrubs and bushes, agricultural and urban. The
117 *Leiothrix* tends to occupy broadleaved forested areas both in the native and in the invaded
118 range (Herrando *et al.* 2010, Collar *et al.* 2017, Ramellini 2017). Therefore, we expected
119 that the broadleaved variable would contribute significantly to model performance.
120 Coniferous forests are important in the native range (Collar *et al.* 2017), but in the native
121 range coniferous woods have a different species composition and dominant growth forms
122 compared to the invaded range (Blasi *et al.* 2014, Collar *et al.* 2017). Furthermore,
123 coniferous forests have a negligible cover in the study area. Therefore, this variable was
124 not included in our models. We also considered agricultural and urban cover because
125 human-dominated landscapes have multiple impacts on invasive species (Case 1996,
126 Pârâu *et al.* 2016). In the case of the *Leiothrix*, we expected these landscapes to represent
127 unsuitable habitats, given the evidence from other invaded areas (Amano & Eguchi 2002b,
128 Herrando *et al.* 2010, Ramellini 2017).

129 We extracted the distance from rivers from a vectorial map of Italian rivers, downloaded
130 from the ISPRA geoportal (www.sinanet.isprambiente.it). This variable was measured as
131 the distance of the centroid of each cell from the nearest cell containing a river.
132 Other studies found that the presence of rivers is a factor influencing the distribution of the
133 *Leiothrix*, which tends to select nest sites near streams, guided by the greater food
134 availability in freshwater ecosystems (Fisher & Baldwin 1947, Amano & Eguchi 2002a).
135 Nesting near rivers could also influence behavioural trade-offs and possibly increases the
136 fitness of the species (Zhang *et al.* 2016). Moreover, the species could use rivers as
137 pathways for expansion and colonization of new areas (Ramellini 2017).
138 We did not consider variables representing the cover of lakes and wetlands as there is no
139 evidence of *Leiothrix* preference for these environments.

140 *Climatic variables*

141 Climatic variables are fundamental determinants of the distribution and spread of alien
142 species (Guisan *et al.* 2017). We retrieved climatic variables at the 1-km scale (average of
143 the period 1979-2013) from the CHELSA Climate dataset (Karger *et al.* 2017).
144 We considered four climatic variables representing availability and seasonality of water
145 and energy: total annual precipitation, precipitation seasonality, mean annual temperature,
146 and temperature seasonality. Precipitation seasonality and temperature seasonality
147 represent respectively the standard deviation (SD) and the coefficient of variation (CV) of
148 mean monthly values. Precipitation variables are known to be particularly relevant for the
149 species in Japan (Amano & Eguchi 2002a). Before running the analyses, we measured
150 pairwise correlation between variables (Table S1) and we did not consider altitude for

analyses because of its strong correlation with the annual mean temperature ($r = 0.91$). The correlations between the other variables were always < 0.7 (Table S1), suggesting the lack of major collinearity issues (Dormann *et al.* 2012).

Species distribution modelling

We used maximum entropy modelling (Maxent; Phillips *et al.* 2006) to assess relationships between *Leiothrix* distribution and environmental variables. Maxent is among the most widely used methods in species distribution modelling (Gomes *et al.* 2018). It makes use of presence/background data and is, therefore, highly suitable to model citizen science data, with an excellent performance among the SDM approaches (Elith *et al.* 2006, Elith *et al.* 2011, Peterson *et al.* 2011). Engler *et al.* (2017), in a review about SDM in birds, showed that models of this kind help to gain a better insight into the processes underlying the spread of IAS. Furthermore, Maxent is among the models with the highest transferability, i.e. it has excellent performance in predicting suitability outside the calibration areas (Qiao *et al.* 2019).

Model settings

When assessing relationships between species occurrence and environmental variables, we only considered linear and quadratic terms to avoid overfitting (Phillips *et al.* 2006, Herrando *et al.* 2010). Areas that are easily accessible or better surveyed are spatially biased (Phillips *et al.* 2006, Ficetola *et al.* 2013), so that some areas can be overrepresented or underrepresented (Phillips *et al.* 2009, Kramer-Schadt *et al.* 2013). In our analyses, we assumed that areas with a higher density of roads were more frequently sampled and thus overrepresented in our models. We, therefore, included the variable “roads density” as a bias file in all our models, both for the background and the sampled areas (Kramer-Schadt *et al.* 2013). Species distribution models require the selection of background data or pseudo-absences within a buffer zone defined around all the presence-points, representing areas that are actually accessible to the study species (Phillips *et al.* 2009, Godsoe 2010), thus our background points were obtained within a buffer of 100 km from the presence records (Gallien *et al.* 2012). Within the buffer (Figure 1), we excluded points outside Italy and in marine areas.

Modelling workflow and accuracy tests

We followed a modelling workflow aimed at maximizing the robustness of predictions while minimizing the impacts of sampling bias (Nogués-Bravo 2009, Bahn & McGill 2013). We considered occurrences of the *Leiothrix* from Tuscany and Liguria as belonging to a single group of populations as, even if individuals originated from different escape events, populations are currently merged (Figure 1). Therefore, we aggregated data from Liguria and Tuscany, and we considered data from Latium as part of an independent population. We ran separate models for each of the two study populations, using the second population as a test dataset to assess model performance. First, we built SDMs using the Liguria-Tuscany data for training and used the Latium for model validation. Second, we built SDMs using the Latium data for training and used the Liguria-Tuscany data for model validation. The validation in a

different study area is among the most robust tests of model performance (e.g. Nogués-Bravo 2009, Bahn & McGill 2013, Galante *et al.* 2017). To test the overall accuracy of predictions we used the area under the receiver operating characteristic curve (AUC), a frequently employed threshold-independent measure in ecological modelling (Guisan & Zimmermann 2000; for an example of its use with this species see Herrando *et al.* 2010). AUC values range from 0.5 (random output) to 1 (optimal performance). It should be remarked though that the maximum achievable AUC of Maxent models is below 1 (Phillips *et al.* 2006). AUC was run on both the training dataset and the test dataset, to assess the model consistency across areas. For each region we ran three models: one with landscape variables only, one considering climatic variables only, and one considering all the variables. We then used the AUC on the validation dataset to assess the predictive performance of each model.

Full model

In order to obtain a model representing the overall habitat selected by the species in Italy, we ran a model (hereafter full model), considering all the presence records and both climatic and landscape variables. Given the lack of a validation dataset for the full model, the robustness of the model was assessed using a 5-fold cross-validation (Nogués-Bravo 2009). The average model among the cross-validated ones was then projected to the whole Italy, to identify the areas most at risk of invasion outside the study regions. In SDM, extrapolations beyond the range of environmental variables observed in the training area may determine unreliable results. Therefore, we computed multidimensional environmental similarity surfaces and identified areas where SDM extrapolated onto environmental conditions that are outside the ones observed within the training range (Elith *et al.* 2010, Masin *et al.* 2014).

Results

When using Latium as training and Liguria-Tuscany as test dataset, the model including both climate and landscape variables showed the highest performance (Table 1), outperforming models including climate only and landscape only. The model including both climate and landscape was the best one also when calibrated on the Liguria-Tuscany data. Both the model calibrated on the Latium data, and the model calibrated on the Liguria-Tuscany data, showed a good ability to predict the test dataset of the other region, suggesting robustness of the model (Table 1).

Leiothrix potential distribution

By projecting the full model to the whole Italy, we identified two main areas with high suitability for the *Leiothrix*: (i) a band of medium/high suitability stretching from the western corner of Liguria (NW Italy) to the Tyrrhenian side of Calabria (Southern tip of continental Italy) and (ii) in lowland and hilly areas of Northern Italy, immediately South of the Alps (Figure 2). In Sardinia and in portions of Sicily, Calabria, Apulia, and Northern Italy, environmental conditions were mostly outside the range found in the calibration range, thus predictions were not considered for these regions (Figure 2).

227 *Variables contributions and Leiothrix suitability*

228 When we built the full model, precipitation seasonality, percentage of agricultural cover,
229 annual mean temperature, and temperature seasonality were the most important variables in
230 terms of percentage contribution to explain Leiothrix distribution. Distance from the nearest
231 river, broadleaved cover, and percentage cover of urban areas had limited importance (Table
232 2). Leiothrix suitability was highest in areas with low agricultural cover, high annual
233 precipitation, and intermediate precipitation seasonality (Figure 3). Furthermore, suitability
234 was highest in areas with high annual mean temperature (Figure 3b).

235 **Discussion**

236 Our results showed that a further expansion of the Leiothrix in Italy is likely on the northern
237 and western sides of the peninsula, in agreement with our hypothesis that this species has the
238 potential to attain a wider distribution in Italy. We provided indications on the factors that
239 could shape Leiothrix expansion and confirmed the joint importance of climate and landscape
240 variables to understand the distribution of this species (cfr. Bradie & Leung 2017). Some
241 regions where the species is known to occur outside Liguria, Latium, and Tuscany, for
242 instance, the Northeastern area of Piedmont (Grimaldi 1992), were correctly predicted as
243 suitable from the full model.

244 *Climatic variables*

245 Climatic variables were very important to explain the Leiothrix distribution, in agreement
246 with the hypothesis that these factors are key drivers of the spread of invasive birds (Pereira
247 et al. in press, Table 2). Our work suggests that rain regimes in the invaded region can
248 significantly affect the distribution in this species (Table 2). The response curve for annual
249 precipitation showed the highest suitability in areas with precipitation > 1000 mm / year, i.e.
250 values higher than those typical for a Mediterranean climate (Allaby 2015). Such match with
251 high precipitation values is in agreement with observations from Leiothrix invasion in Japan
252 and other areas of Europe (Amano & Eguchi 2002a, Pereira et al. in press) and is not
253 unexpected given that the species is also native of rainy regions of China (Zhang *et al.* 2016).
254 When discussing the factors influencing the Leiothrix invasion in the Hawaiian Islands,
255 Fisher & Baldwin (1947) considered rainfall to be “apparently” not a determining factor.
256 However, it should be remarked that in Hawaii average precipitation are much higher than in
257 Mediterranean regions, and thus they are probably not a limiting factor. As precipitation
258 seasonality influences plant diversity in Mediterranean ecosystems (Clary 2008), the
259 preference of the species for intermediate values of precipitation seasonality might be related
260 to association with particular plant communities. The response curve for annual mean
261 temperature indicated higher suitability at increasing values of temperature, highlighting a
262 preference of the Leiothrix for warmer climates. In our suitability map, the majority of the
263 cells with the highest suitability fell within areas characterized by a Mediterranean climate.
264 The establishment of self-sustaining populations of Leiothrix across other areas with a

Mediterranean climate is well known (Dubois 2007, Herrando *et al.* 2010, Pereira *et al.* in press), suggesting that in its European range the species can occupy niches different from the native ones. This process can be due to niche unfilling of the species (cfr. Petitpierre *et al.* 2012, Strubbe *et al.* 2013), and additional studies are required to evaluate these hypotheses.

Landscape variables

Among the landscape variables, agriculture showed the highest importance in explaining the *Leiothrix* distribution. Suitability decreased in the areas with highest agricultural cover, in accordance with previous studies in Italy and in other invaded areas, where the species tends to occupy rather natural, undisturbed habitats (Amano & Eguchi 2002b, Herrando *et al.* 2010, Ramellini 2017). This is in contrast with the general pattern shown by bird IAS which are often associated to open and disturbed habitats (Case 1996, Duncan *et al.* 2003, see also Pereira *et al.* in press). In our study, distance from the nearest river showed minor importance compared to the other variables. This result could be explained considering that we did not focus on the nesting period, which was the focus of some previous studies underlining the importance of water ecosystems for the species (Zhang *et al.* 2016). Furthermore, our analysis was performed at a rather coarse scale (1-km): it is possible that we did not capture processes occurring at the microhabitat level (e.g. small streams). The cover by broadleaved forests showed a limited importance. This result is not in agreement with our second hypothesis, nor with studies suggesting that forests are a key driver of *Leiothrix* distribution (Herrando *et al.* 2010). This could occur because of the differences between the two areas used to calibrate the models, and because of differences in forest composition that are not captured by broad-scale habitat maps, which are not able to distinguish among typologies of broadleaved forests with different composition or tree density. Advances of remote sensing techniques promise great improvements of our ability to measure habitat at high resolution and could allow to better describe fine-scale habitat variation, thus allowing enhanced understanding of species distribution (Ficetola *et al.* 2014).

Outlook

Our results provide fine-grained, baseline information for the prevention of *Leiothrix* colonization in uninvaded areas. They can also contribute to drawing up management plans for the species both at the local and national levels. Our study further highlights the importance of developing SDMs to assess the invasive potential of IAS. Given the high invasive potential of this Babbler, and the strong known impacts on native species (Martin-Albarracin *et al.* 2015), we suggest its possible inclusion in the list of alien species of European concern (Regulation EU No. 1143/2014). For a proper interpretation of SDMs results and for the definition of future lines of research it is necessary to acknowledge the limitations and assumptions of each modelling technique (Ficetola *et al.* 2010, Araújo & Peterson 2012, Engler *et al.* 2017, Barbet-Massin *et al.* 2018). In our work, we assumed a constant land-use and climate through time as we did not consider historical variations in the environmental conditions. Dynamically modelling the distribution of the species could help in refining our predictions (Brambilla *et al.* 2010). As we did not take into account variations

305 in the species distribution, possible future lines of research could be aimed at defining past
306 patterns of invasion to better understand invasion dynamics and extrapolate further
307 predictions (Ficetola *et al.* 2010). The information we provide could be profitably combined
308 with studies employing connectivity, in order to evaluate the potential spread of the *Leiothrix*
309 while integrating information on landscape connectivity and to identify potential corridors of
310 invasion (e.g. Cowley *et al.* 2015, Falaschi *et al.* 2017). Future work should also be done to
311 refine our knowledge on the environmental conditions that favour the species in the
312 Mediterranean region at a finer spatial scale, e.g. an *in situ* evaluation of population growth
313 rates could help to define the population-persistence niche for this Babbler.

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516 Table 1.

Training region	Test region	Variables	Training AUC	Test AUC
Liguria + Tuscany	Latium	Climate	0.884	0.644
Liguria + Tuscany	Latium	Landscape	0.742	0.534
Liguria + Tuscany	Latium	Climate + landscape	0.900	0.646
Latium	Liguria + Tuscany	Climate	0.929	0.690
Latium	Liguria + Tuscany	Landscape	0.736	0.602
Latium	Liguria + Tuscany	Climate + landscape	0.941	0.704
Liguria + Latium + Tuscany	-	Climate + landscape	-	0.873

517 Performance of models calibrated on the two training regions, using all the data. For the
518 model calibrated with all the data, the test AUC is the average of test AUC in 5 cross-
519 validated models.

520 Table 2.

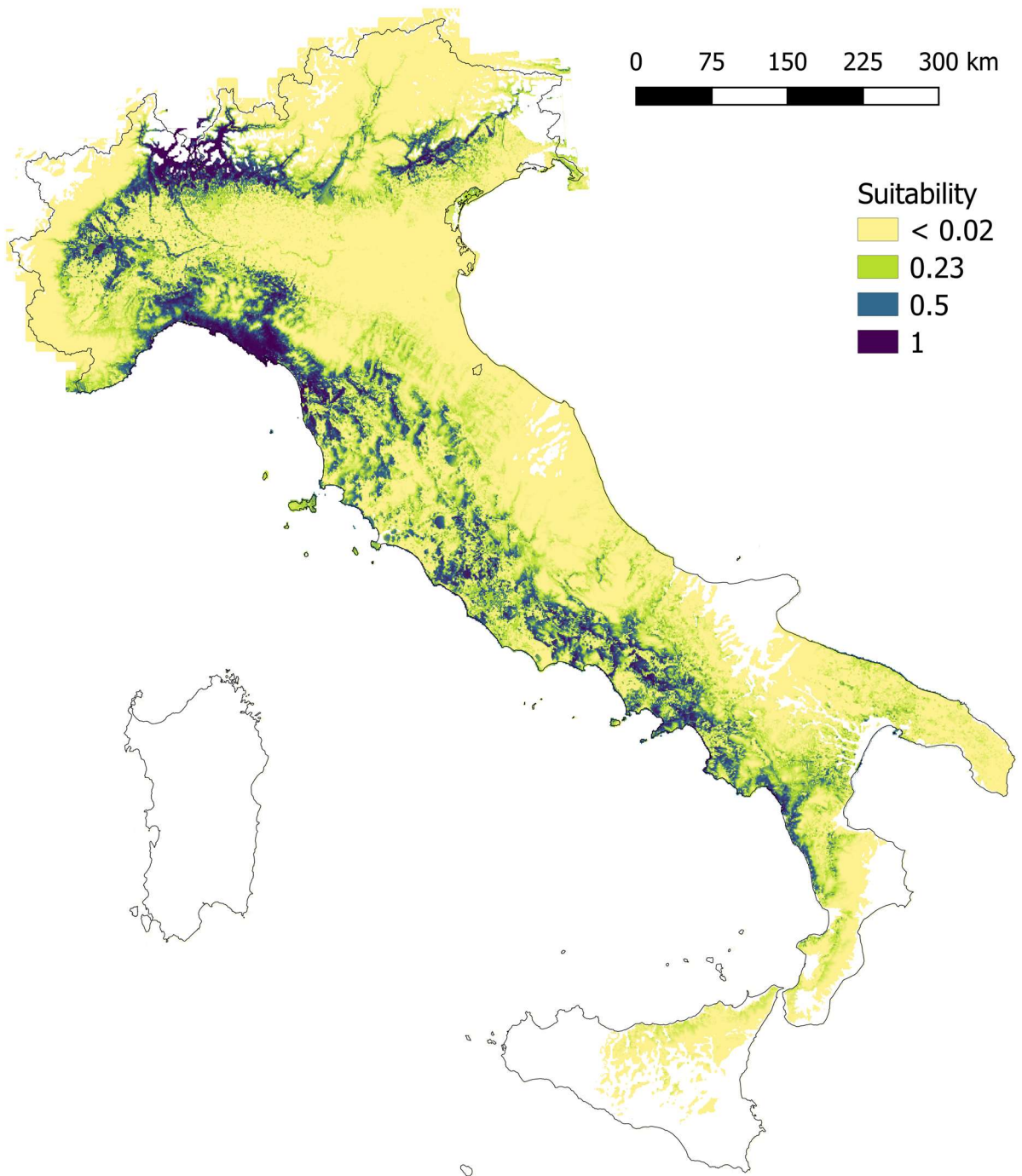
Name	Variable	% Contribution
Bio15	Precipitation seasonality	32.52
Agricultural	Percentage cover of agricultural areas	28.29
Bio1	Annual mean temperature	14.13
Bio4	Temperature seasonality	10.39
Bio12	Annual precipitation	8.43
Heterogeneous	Percentage cover of shrubs and bushes	3.09
Urban	Percentage cover of urban areas	1.98
Broadleaved	Percentage cover of broadleaved forests	1.17
Distance from rivers	Distance from the nearest river	0.0003

521 Environmental variables considered in the species distribution models, and percentage
522 contribution of the variables in the average model.

523 Figure 1. Distribution of the occurrence points used for building species distribution models
524 in Italy. Black lines indicate the region from which the background points were selected.



Figure 2. Habitat suitability map for *Leiothrix lutea* in Italy. Suitability thresholds are set at the minimum training presence threshold (0.02) and at the 10-percentile training of the presence threshold. Barred areas represent regions where the model is extrapolated outside the conditions present in the calibration area.



531 Figure 3. Response curves showing the relationship between environmental variables and
532 suitability (in logistic output) for *Leiothrix lutea*: b-e) climatic variables; a, f, g, i) land-use
533 variables; h) distance from rivers. For each graph, the grey shades represent one standard
534 deviation computed on the basis of a 5-fold cross-validation.

