

1Humidity and low pH boost occurrence of Onygenales fungi in soil at 2global scale

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25Abstract

26Soils are important reservoirs for potential human pathogens and opportunistic fungi such as
27the dermatophyte or dimorphic fungi in the order Onygenales. In soils, these taxa are
28decomposers but many of them have the potential to cause respiratory and skin diseases in
29humans and, in some cases, systemic infections. Even so, the factors that determine the
30biogeography and ecology of order Onygenales remain largely undocumented. To address
31this knowledge gap, we surveyed members of Onygenales from topsoil fungal communities
32at 235 sites across six continents and provided a first global atlas. We retrieved 4.3% of the
33total fungal sequences (~420 Onygenales) across nine biomes ranging from deserts to tropical
34forests. This work advances our knowledge on the ecology and global distribution of order
35Onygenales and suggests the hypothesis that wet and acid soils support the larger proportions
36of these fungi, while their richness is constrained by aridity.

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39**Keywords:** Aridity, Fungi, Onygenales, soil-borne pathogens, soil communities

40Introduction

41 The Fungal Kingdom is one of the most diverse groups of organisms in our planet
42(Hawksworth and Lücking 2017; Wu et al. 2019; Hyde et al. 2020). Many of these taxa are
43fundamental for supporting nutrient cycling, plant-soil mutualistic relationships and organic
44matter decomposition. However, others such as the opportunistic dimorphic fungi have the
45potential to cause important human diseases (Garcia-Solache and Casadevall 2010; Rodrigues
46et al. 2020; Casadevall 2020). Many of the most aggressive dimorphic fungal are
47Ascomycetes of the order Onygenales (Eurotiomycetes), which includes the spherule-forming
48Coccidioides spp. and yeast-forming fungi of the genera *Histoplasma*, *Paracoccidioides*, and
49*Blastomyces*. The same order also includes dermatophytes, the most common true pathogenic
50fungi causing superficial severe skin infections (e.g. *Trichophyton* spp.), as well as a number
51of non-pathogens.

52 Order Onygenales is also known to include emerging human pathogens due to
53increasing rates of immunosuppression from autoimmune disorders (Schwartz et al. 2019);
54moreover, unlike most fungal pathogens, may infect immunocompetent hosts, causing
55systemic mycoses with high case-fatality rates (Taylor 2014). This fungal order emerged
56around 150 million years ago (MYA) (Sharpton et al. 2009) and generally lives in animal
57burrows and as soil decomposers (Kollath et al. 2020) but, under certain environmental
58circumstances, they can also grow on human hosts (Van Dyke et al. 2019). They may enter in
59contact with humans through dust and air particles from soils surrounding our cities. Thus,
60learning more about the biogeography and ecology of order Onygenales can help us to
61develop new hypotheses to link their potential pathogenesis with human health.

62 Recently, species distribution models (SDM), which associate occurrence records
63with environmental variables that are expected to affect the species probability of persistence,
64have been increasingly applied to soil-dwelling fungi (Hao et al. 2020) and Onygenales in
65particular (Ocampo-Chavira et al. 2020) to estimate the environmental conditions that are
66most suitable for this particular group of fungi. However, despite these sound advances, our
67knowledge remain limited to local and regional scale (e.g. Ocampo-Chavira et al. 2020,
68Yamauchi et al. 2021) and we are lacking a systematic and comprehensive assessment of the
69global patterns and environmental factors associated with these important organisms in
70natural biomes at global scale.

71 To address this knowledge gap, we performed a global soil survey conducted in 235
72natural ecosystems on six continents (Supplementary Figure S1). This database includes a

73wide variety of bioclimatic regions (arid, temperate, tropical, continental and polar), covering
74~73% of the environmental conditions found on Earth (Supporting Information; Egidi et al.
752019). To characterize Onygenales fungi in our survey, we used the ITS amplicon
76sequencing that, albeit encompassing a few limitations in terms of absolute quantification of
77the fungal ITS gene due to the hypervariable target region and primer choice (Nilsson et al.
782019), it is nowadays a predominant method to characterize diversity and structure of fungal
79communities in environmental samples (e.g. Alteio et al. 2021; Baldrian et al. 2021). We also
80generated the first global atlas for the current distribution of these fungi and used a suite of
81machine learning and statistical analysis to (i) identify the most dominant Onygenales taxa,
82and (ii) describe how their global distribution is influenced by climate and other important
83environmental factors. Besides, in this study, we do not make any claim on the pathogenesis
84associated with Onygenales, and focus on exploring the biogeography and ecology of these
85important soil-borne organisms aiming to provide the basic knowledge to develop future
86hypotheses on the linkages between these taxa and human health.

87

88**Materials and Methods**

89*Global survey*

90Study sites and soil sampling

91We used data from a global field survey (Egidi et al. 2019; Delgado-Baquerizo et al. 2020) to
92identify the distribution and ecological drivers of Onygenales taxa in soils from natural
93ecosystems worldwide. Briefly, bulk soils (top 7.5 cm) were collected from 235 ecosystems
94located in 18 countries from six continents (Supplementary Figure 1; Supplementary Table
95S1) and covered nine biomes (temperate, tropical and dry forests, cold, temperate, tropical
96and arid grasslands, shrubland and boreal) between 2003 and 2015. Locations were selected
97to provide a solid representation for most environmental conditions (for example, climate,
98soil, and vegetation types) found on Earth. Each location include composite soil samples
99from 5-10 soil cores. Composite samples were then sieved on arrival at the laboratory (2 mm
100mesh). Then, a portion of soil was immediately frozen at -20°C for molecular analyses, and
101the rest of the soil was air-dried and stored for a month before physicochemical analyses.

102Environmental factors

103Our field global survey included 13 environmental variables, which were obtained either in
104the field or from satellites and databases: Aridity Index; precipitation seasonality (PSEA);
105mean annual temperature (MAT); mean diurnal temperature range (MDR); elevation; net

106primary productivity (NDVI) index, 2003–2015 period; soil properties (texture [% of clay +
107silt], soil pH, total C, N and P concentrations and C: N ratio). Elevation and climatic
108variables, which include MAT, temperature and precipitation seasonality, were collected
109from the Worldclim database (<https://www.worldclim.org>; ~1 km resolution) (Hijmans et al.
1102005). The aridity index (Food and Agriculture Organization, 1989) (AI, the ratio of
111precipitation to potential evapotranspiration) of each site was calculated using data
112interpolations provided by WorldClim (Zomer et al. 2006). To facilitate the interpretation of
113our results, we used $1 - AI$ as our surrogate of aridity (Delgado-Baquerizo et al. 2013). Soil
114properties (texture (% of clay + silt), pH and total organic C) were determined from topsoil
115(top 7.5 cm) samples collected from each location using standardized protocols (Maestre et
116al. 2012). To avoid biases associated with having multiple laboratories analyzing soils from
117different sites, all the samples were analyzed at the Universidad Rey Juan Carlos (Spain). Soil
118pH was measured with a pH meter in a 1:2.5 mass: volume soil and water suspension. The
119concentration of soil total organic carbon (C) was determined using a wet chemistry method
120(Anderson et al. 1993). Continent and ecosystems type were also included in the modelling.

121

122*Bioinformatics*

123The bioinformatics processing data is detailed in Egidi et al. 2019. Briefly, fungal diversity
124was determined by sequencing the Internal Transcribed Spacer (ITS) region 2 (Blaalid et al.
1252013) with primers FITS7 (GTGARTCATCGAATCTTTG)/ITS4
126(TCCTCCGCTTATTGATATGC) (Ihrmark et al. 2012) on an Illumina MiSeq platform ($2 \times$
127300 PE), and both positive and negative controls were included. All reads were quality
128filtered and dereplicated with the USEARCH pipeline, and low-quality bases were end-
129trimmed before merging. All the merged reads had an expected error < 0.5 ; the quality-
130filtered reads were clustered into operational taxonomic units (OTUs) of the length of 180 bp,
131at 100% similarity thresholds using UNOISE (Edgar 2016a). OTU identification was
132obtained against the UNITE fungal database (V7.2) (Abarenkov et al. 2016) using the
133SINTAX algorithm with a $\geq 80\%$ probability threshold (Edgar 2016b). A ZymoBIOMICSTM
134Microbial Community DNA Standard has been used as positive control. After checking the
135distribution of sample sequencing depth (4,449–144,175, median: 46,481 reads), the OTU
136abundance table were rarefied without replacement to 4,449 sequences per sample. We
137examined whether the sampling effort was adequate to capture the fungal community
138richness by generating species accumulation plot using the ‘specaccum’ function in the R

139package ‘vegan’ (v. 2.3-4; Oksanen et al., 2013), resulting in mostly saturated accumulation
140curve (Supplementary Figure S2) which is indicative of a satisfactory representation of the
141most common Onygenales members these communities harbor. As the main purpose was to
142focus on Onygenales (Eurotiomycetes), ITS sequences belonging to this order were filtered
143and used for downstream analysis. Each Onygenales OTU sequence ($n = 417$) was then
144searched against the GenBank repository using the BLAST function and ITS_RefSeq_Fungi
145database.

146

147Statistical analyses

148Random forest

149We used the Random Forest (RF) model as described in (Delgado-Baquerizo et al. 2018) to
150identify the major significant environmental predictors explaining the variation of
151Onygenales according to environmental variables. The most common vegetation type (i.e.
152forest) in our database was included in our RF analysis as categorical variables with two
153levels: 1 (forest) and 0 (other ecosystem types). We also use the total fungal and bacterial
154richness, namely the total number of OTUs across the sampled sites, to test if changes in
155microbial composition influence Onygenales proportion (Delgado-Baquerizo, 2019). The
156importance of each predictor variable is determined by evaluating the decrease in prediction
157accuracy, i.e., increase in the mean square error between observations and OOB (out-of-bag)
158predictions, when the data for that predictor is randomly permuted. RF was implemented
159using the '*randomForest*' package V.4.6-14 in the R environment. In addition, to exclude
160possible confounding effects due to spatial autocorrelation of environmental variables, we
161repeated the correlation analysis between the main environmental variables and Onygenales
162richness (number of OTUs) and relative abundance, while controlling for space (e.g. latitude
163and longitude).

164

165Correlation analyses

166We then conducted a Spearman correlation analyses to evaluate the associations between the
16713 environmental variables and the relative abundance and richness (i.e. number of OTUs) of
168Onygenales families and genera using the ‘ppcor’ package (Kim et al. 2015). Spearman rank
169correlations measure the strength and direction of association between two ranked variables.
170They do not require normality of data, and linearity is not a strict assumption of these

171analyses. We used a false discovery rate approach to determine adjusted *P* values for all the
172correlations to control for spurious (false positives) correlations.

173

174*Distribution of richness of Onygenales fungi globally*

175A Random Forest regression analysis (Lahouar & Slama, 2015) was implemented to predict
176the distribution of richness of Onygenales fungi globally. We used the variables as follows:
177forest cover (land cover type from the MCD12Q1 V6 product for 2016 derived from the
178International Geosphere–Biosphere Programme classification; Loveland et al. 1999), net
179primary productivity (Normalized difference vegetation index; NDVI), soil C, pH, aridity,
180mean annual temperature, mean annual precipitation, mean diurnal range, precipitation
181seasonality, temperature seasonality and elevation and richness (number of Onygenales
182OTUs) data from 235 ecosystems with a range of richness between 1 and 24. The random
183forest model was constructed by finding the set of covariate combinations that most robustly
184predict the training samples. In particular, 999 numbers of trees and 999 replicates were used.
185To assess the accuracy of the predictions calculated from the random forest-based model, we
186calculated how much the parameter space of the predictors differed from the original dataset.
187We used the Mahalanobis distance of any multidimensional point of the dimensions given by
188the exogenous variables to the centre of the known distribution that we had previously
189calculated and the distance of any multidimensional point to the convex hull formed by the
190235 ecosystem locations that were used in the model. We then used outlier identification to
191mask our results and provide more reliable predictions at the 0.9 quantile of the chi-squared
192distribution with eleven degrees of freedom to which each location belongs (Mallavan et al.
1932010). The modelling approach was then validated by returning predicted values (x-axis)
194versus observed values (y-axis), following Piñeiro et al. (2008).

195

196**Results and Discussion**

197 Using amplicon sequencing targeting the internal transcribed spacer (ITS) region, we
198identified 417 fungal OTUs belonging to the order Onygenales out of the 24,391 fungal
199OTUs found in our global survey. Using the number of reads as proxy to estimate the relative
200abundance of each Onygenales sequence in a given sample (Giner et al. 2016; Weiss et al.
2012017), we found that these taxa represented between 0.1 and 14% of all the ITS sequences
202across the study samples, contributing to ca. 4.5% of the total reads identified as fungi
203(Figure 1a). Our results suggest that these organisms are likely a small but significant

204component of soils in natural ecosystems worldwide. Besides, albeit in our global survey we
205reached a satisfactory representation of Onygenales members (Supplementary Figure S2), the
206diversity of taxa identified in this study may be constrained by the fungal taxa amplified with
207the primer pair used here and we are potentially underestimating the distribution of some
208lineages that are poorly amplified with commonly used ITS primers. Therefore, we envisage
209that future studies, including under-sampled regions of the world and ad hoc sequencing
210methodologies, will allow to better characterizing the Onygenales members of the global soil
211mycobiome.

212 On average, the sequences of Onygenales surveyed were dominated by Onygenaceae
213and Gymnoascaceae families, the first including the most dangerous dimorphic fungal species
214(Muñoz et al. 2018). A few genera were prevalent (Figure 1b; Supplementary Figure S3;
215Supplementary Table 2 for a complete list), which include the opportunistic genus
216*Chrysosporium*, known to cause skin as well as pulmonary infections (Gopal et al. 2020), and
217*Auxarthron*, *Spiromastix*, and *Gymnoascus*. Together, these OTUs accounted for almost a
218quarter (ca. 25%) of the retrieved ITS sequences classified as Onygenales. Many species of
219this group are considered to be of low pathogenic potential (Rizzo et al. 2014). In particular,
220*Spiromastix* and *Gymnoascus* include biotechnologically important extreme-resistant fungi,
221showing a high salinity and temperature tolerance (Zhou et al. 2016). Less frequent were
222dermatophytes such as *Microsporum* spp. Conversely, strains of *Emergomyces* and
223*Coccidioides* spp. that are accounted as the major contributors to the infections against
224patients with HIV/AIDS, and the Coccidioidomycosis (or ‘Valley Fever’) (Schwartz et al.
2252018; McCotter et al. 2018; Gorris et al. 2021) that cause the majority of reported cases in the
226United States, were retrieved at the lowest percentage.

227 We then used the Random Forest (RF) machine learning approach to identify the most
228important predictors of the distribution of these organisms worldwide. As the complexity of
229diverse soils communities is known to be crucial in regulating humans and plants pathogens
230(Samaddar et al. 2021), we first explored whether total microbial (bacterial and fungal)
231diversity influenced the Onygenales proportion. We found that both fungal and bacterial
232assemblages had significant, albeit weak, positive association with soil Onygenales (Figure
2332a,c), suggesting that the establishment and survival of these organisms might depend on
234even relatively small changes in soil communities.

235 Recently, it has been proposed that wet environments contribute to the ongoing
236expansion of the occurrence of currently known fungal pathogens in some areas of the Earth
237(Friedman and Schwartz 2019). Strikingly, we found that aridity, together with pH, were the

238most important environmental predictors of the distribution of Onygenales worldwide (Figure
2392a; Supplementary Figure S4). Significant associations ($P < 0.05$) were also obtained when
240controlling for spatial autocorrelation (i.e., using latitude and longitude as controlling matrix).
241Similar results were observed using non-parametric correlation analyses. We found that the
242increases in aridity had an overall negative effect on both richness (i.e. number of OTUs) and
243relative abundance when we focused on all Onygenales taxa, whereas no significant effects
244were detected at finer taxonomic levels with the exception of *Spiromastix* spp. (Figure 2b,c;
245Supplementary Figure S5). It is well known that some onygenalean fungi such as
246*Coccidioides* species are endemic to arid and semi-arid regions of North America, growing in
247sandy alkaline soils, rich in organic matter and salts; yet, they can also spread in nearly any
248type of desert soil, including those with low pH levels, tolerating soil temperatures ranging
249from -6.5 to 60.5 °C (Kollath et al., 2016). However, Onygenales may actually display
250different ecological preferences according to the phylogeny and can be classified as
251soil/oligotrophic, soil/keratinophilic, dung/agricultural, skin/nail, hair/feather, insect/pollen,
252halophilic/osmophilic, systemic and plant associated (Kandemir et al., 2020). It has been
253proposed a clear link between the capacity to tolerate or even prefer extreme environmental
254parameters and the emergence of opportunistic pathogenicity in the fungal Kingdom
255(Gostinčar et al., 2018). The evidences of our study suggest that wet and acid soils may
256support the spreading of "generalists", more competitive Onygenales taxa that are widely
257spread; conversely, dry and alkaline conditions favor the growth of "specialists" Onygenales
258such as *Coccidioides* spp. more restricted in specific regions, taking advantage over other
259microorganisms that cannot tolerate the extremes (del Rocío Reyes-Montes et al., 2016).

260 We also found that mean annual temperature (MAT) is positively associated with the
261richness of multiple taxa in the Ascosphaeraceae family as well as members of *Auxarthron*
262genus (Figure 2b). Yet, *Histoplasma*, a genus including members that has the potential to
263cause the serious human disease Histoplasmosis (Armstrong et al. 2018; Oladele et al. 2018),
264was found positively associated with MAT, even if it was recovered in low abundance in our
265dataset. It has been recently proposed that a gradual adaptation to increasing temperature
266caused by climate change could lead to an increase of fungi that can cause disease (Nnadi et
267al. 2021). In addition, climate change can bring major changes to the epidemiology of
268infectious diseases (Oaks et al. 1992; Patz et al. 1996), increasing the geographic range of
269pathogenic species or their vectors (De Crecy et al. 2009; Casadevall 2020).

270 Based on our global survey, we then generated the first global atlas that depicts the
271current distribution of the richness onygenalean fungi globally (Figure 3). Our results showed

272that these fungi may have a global spread, even in those localities where they have been
273never reported (e.g. Russia, and Alaska) (Chaturvedi et al. 2020). In addition, in accordance
274with results of our multivariate analyses, we identified humid regions in the Northern
275Hemisphere, particularly sites in East Europe, as important hotspots of Onygenales
276distribution.

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279**Conclusions**

280 Taken together, our results based on a global survey provide a baseline understanding
281of dominant soil-borne Onygenales taxa identity, their occurrence and main environmental
282factors that drive their distribution in soils of natural ecosystems, highlighting that wet and
283acid soils are expected to support globally the largest proportions of these organisms. This
284evidence is the first contribution to understand the distribution and habitat preference of this
285systematic group that has potential human health implications. As anthropogenic activities
286continue to affect soil biodiversity in many ways, potentially influencing the balance and
287distribution of potential soil-borne human pathogens (Babič et al., 2020; Ferrareso et al.
2882020), the risk of exposure and infections may increase in the future. Therefore,
289understanding the ecology, distribution, and diversity of Onygenales taxa, including potential
290pathogens, in natural environments where they occur may serve as a scientific basis to
291identify potential areas of risk. In addition, future work is necessary to identify the fine-scale
292distribution of these organisms in specific localities.

293

294**Data statement**

295The metadata associated with the global field survey are publicly available in Figshare
296(<https://doi.org/10.6084/m9.figshare.11484747>). Richness information that was used to
297implement the predictive model are publicly available in Figshare
298(https://figshare.com/articles/dataset/Untitled_Item/14776239).

299

300**Authors' contributions**

301C.C. developed the original idea of the analyses presented in the manuscript. M.D.-B. and
302B.K.S. put together the original global database. Statistical analyses, environmental
303modelling were done by C.C. Map was generated by E.G. The manuscript was written by

304C.C. with contributions from L.S., E.G., B.K.S., and M.D.-B. All authors have read and
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318

319**Competing Interests**

320The authors declare no competing financial interests.

321

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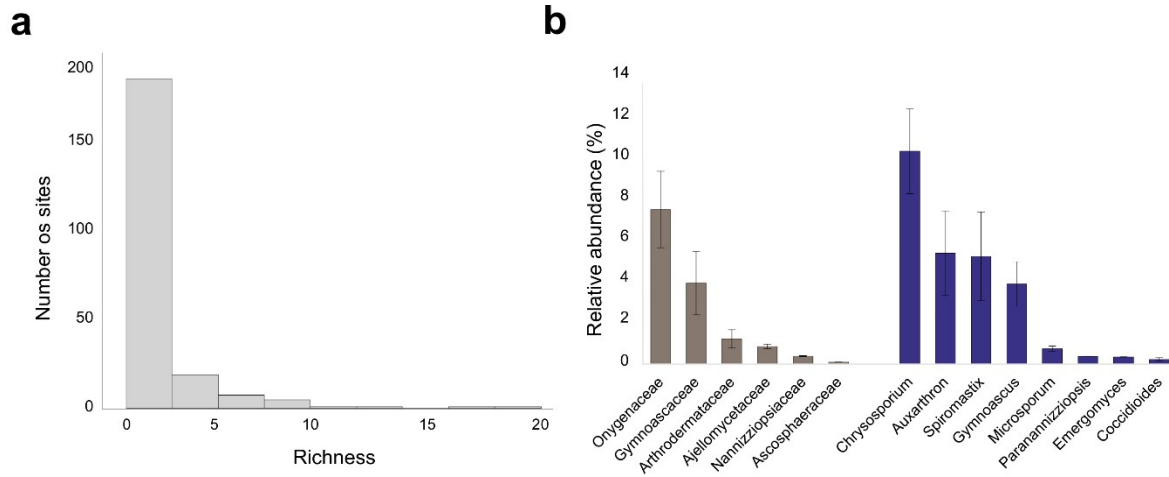
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517**Figures**

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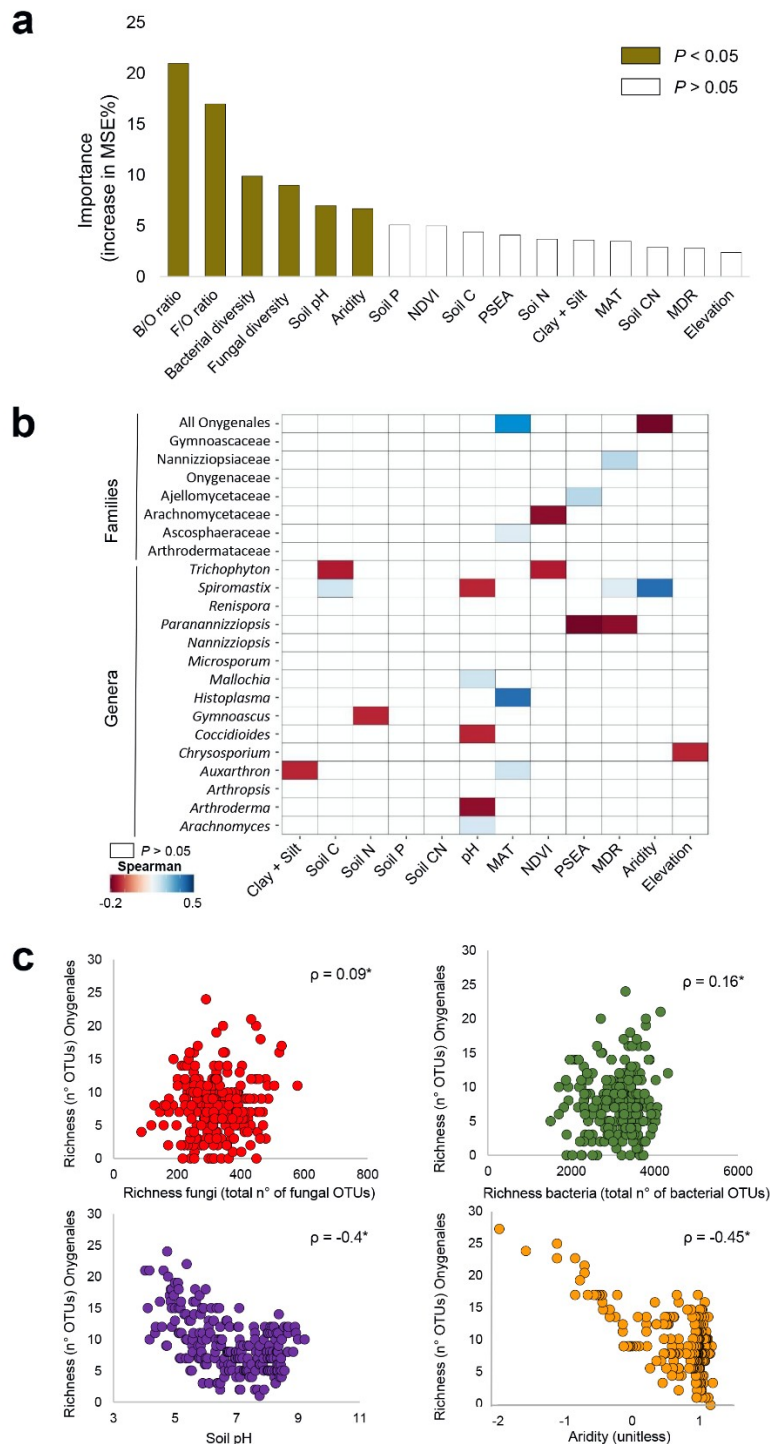
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521**Figure 1. Relative abundance and identity of Onygenales worldwide. a)** Distribution of
522the richness of total Onygenales across the 235 ecosystems surveyed. **b)** Relative abundance
523(percentage of all ITS sequences; mean \pm standard error) of the most common Onygenales
524identified at family and genus level across all sites.

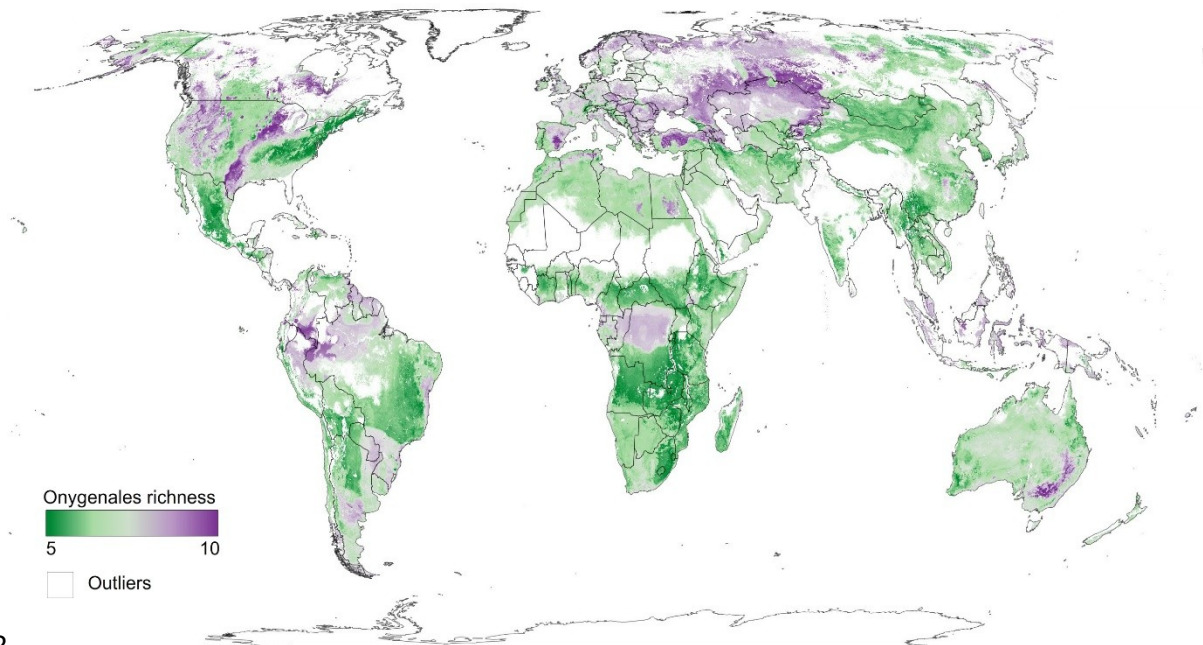
525The standard error is calculated by dividing the standard deviation by the square root of
526number of measurements (number of taxa in a given family or genus) that make up the mean.
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529 **Figure 2. Environmental factors associated with Onygenales richness (i.e. number of**
 530 **OTUs).** **a)** Random forest (RF) analyses identifying the importance of potential predictors of
 531 Onygenales richness. RF Importance = Increase in % mean square error. Coloured and white
 532 columns represent $P < 0.05$ and $P > 0.05$, respectively. MAT, mean annual temperature;
 533 MDR, mean diurnal temperature range; PSEA, temperature precipitation seasonality; NDVI,
 534 normalized difference vegetation index. B/O = bacteria to Onygenales ratio; F/O = fungi to
 535 Onygenales ratio. **b)** Spearman correlations between environmental factors and Onygenales
 536 richness ($n = 235$). Correlations with a false discovery rate adjusted $P > 0.05$ are excluded
 537 (plotted in white). **c)** Selected examples showing the relationship between environmental
 538 factors and Onygenales richness. Spearman correlation coefficients are shown in the upper
 539 part of each panel. *, $P < 0.05$.

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543 **Figure 3. Predicted global distribution of Onygenales richness (i.e. number of OTUs)**
544 **fungi in soil.** The model performance with $R = 0.89$ and $P < 0.001$ in the validation of the
545 modeling approach returning predicted values versus ground values. Outliers are calculated
546 from the 0.9 quantile of the chi-square distribution with eleven degrees of freedom to mask
547 areas of low reliability and provide more reliable predictions (see Materials and Methods).