Stratified Active Learning for Spatiotemporal Generalisation in Large-Scale Bioacoustic Monitoring

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Abstract

Active learning optimises machine learning model training through the data-efficient selection of informative samples for annotation and training. In the context of biodiversity monitoring using passive acoustic monitoring, active learning offers a promising strategy to reduce the fundamental data and annotation bottleneck and improve global training efficiency. However, the generalisability of model performance across ecologically relevant strata (e.g. sites, season etc) is often overlooked. As passive acoustic monitoring is extended to larger scales and finer resolutions, inter-strata spatiotemporal variability also increases. We introduce and investigate the concept of *stratified active learning* to achieve reliable and generalisable model performance across deployment conditions. We compare between implicit cluster-based diversification methods and explicit stratification, demonstrating that cross-strata generalisation is a function of stratum divergence, not sampling balance. Additionally, mutual information as well as exclusion analysis show that spatiotemporal context can explain a substantial proportion of species label variance and inform sampling decisions.

Keywords: Active Learning, Audio Classification, Bioacoustics, Stratification

1. Introduction

Passive acoustic monitoring (PAM) provides biodiversity insights at previously infeasible scales and resolutions [1, 2]. The affordability of acoustic recording devices (ARDs) combined with recent improvements such as

network-connected data streaming vastly improve the scalability of monitoring but also the quantity of raw data collected [3]. Recent gains in computational bioacoustics [4] are fundamentally data-driven, with the quality of inference dependent on the quality and quantity of labelled data. However, as the quantity of raw acoustic data increases exponentally the availability of data labels remains a severe bottleneck, due to the requirement for skilled annotators.

Further, as biodiversity monitoring expands to larger spatial and temporal scales, the ecological and acoustic heterogeneity across recording sites increases. Monitoring stations may be deployed across diverse habitats and regions where differences in species composition and background noise, such as wind, rain, insect activity and anthropogenic sounds, introduce significant spatial variation. Different habitats also affect sound attenuation [5, 6] and model detectability [7]. The detectability of certain species also changes with seasonal and environmental factors [8] and also variation due to regional dialects [9]. There is also potential variability between recording devices [10] which makes generalisable performance across locations more challenging. Temporal variability further arises from daily vocalisation patterns (e.g. dawn chorus), seasonal dynamics driven by phenology and migration, and long-term changes dues to microphone degradation or shifting climate and habitat conditions. Models for species recognition are expected to produce reliable predictions across this full range of conditions, requiring that training data is representative of the underlying variability across deployment conditions.

Active learning is the machine learning technique of dynamically selecting informative samples for annotation and model training. By allocating annotation resources to high-priority samples, active learning aims to achieve higher model performance with fewer annotated samples (training efficiency). Active learning, based on uncertainty sampling, has been demonstrated to improve global training efficiency (peak performance per sample) [11] as well as per species training efficiency [12, 13].

Sample diversification is an important aspect of active learning. To maximise the information gain, samples must have high entropy/uncertainty (i.e. not already predictable) *and* diversity. Diversification minimises redundant information. For practical purposes, active learning is typically applied over batches. Larger batch sizes reduce adaptivity and increase the risk of includ-

ing redundant samples [14, 15]. Methods such as batched active learning, where the batch size refers to the number of samples selected for annotation per iteration, implicitly promote sample diversity across batches by iteratively updating the modeled probability distribution given a reduction in entropy. However, this does not account for intra-batch diversity and so various hybrid approaches exist to improve intra-batch diversity [16]. Diversification alone is not effective as samples should be both informative (high-entropy) and non-redundant (not currently represented in the batch) [17]. Hybrid sampling approaches that attempt to select both informative but diverse samples have demonstrated improved performance compared to pure diversification methods [13].

Clustering is generally applied to improve the diversity of sample selection by sub-sampling clusters within an embedding space (i.e. based on acoustic features). High-quality embeddings capture relevant variability without explicitly using spatial or temporal information. Stratified sampling, by explicitly selecting samples from defined strata such as sites, seasons, or years, is a common way to ensure training data captures ecological variability across space and time (Figure 1). Stratification can be considered a form of explicit diversification, in contrast to traditional active learning diversification methods which implicitly account for variability.

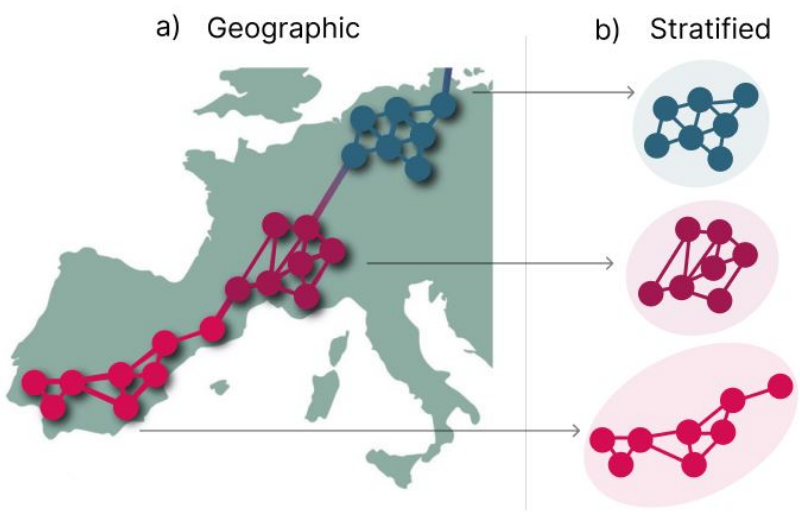

Figure 1: Demonstration of stratified sampling (b) based on geographic location (a).

2. Contributions

This paper makes the following contributions:

- We demonstrate that model performance, using traditional transfer learning and active learning, does not generalise across monitoring sites.
- We develop a framework for evaluating model and sampling performance across spatial and temporal strata.
- We empiricially compare implicit and explicit active learning diversification methods on relevant multi-site long-term datasets and propose the method of *stratified active learning*.
- We analyse stratum-level divergence, investigating methods to identify mutual information between strata.

In the following, we formalise our machine learning framework, before proposing the modifications of *stratified active learning*. We empricially evaluate this using public bioacoustic datasets of birds and anurans. Datasets are publicly available via their respective authors. All code notebooks are open-source and publicly available. Here, we focus on the application of acoustic monitoring but the contributions of this work are relevant across monitoring modalities.

3. Method

To summarise the method, we compare the performance evenness across strata using implicit cluster-based and explicit stratification-based diversification within an active learning framework. Performance is assessed using the aggregated F1 score per stratum with evenness quantified using the Pielou Evenness Index [18] and coefficient of variation, providing a framework for comparing model generalisability across ecological gradients. Additionally, we analyse stratum-level divergence using the Jensen-Shannon divergence and quantify the mutual information between strata with both label and predictive distributions.

3.1. Model

As input we use a set of embeddings pre-generated by a neural network (in our case, BirdNet [19] penultimate layer) $\mathcal{X} = \{x_1, x_2, ..., x_N\}$ where $x_n \in \mathbb{R}^{N \times 1024}$ is the embedding of a single acoustic obseration and 1024 is the feature dimension. A simple classifier model $f_\theta(x_n)$ is defined as single linear layer $f_\theta(x_n) : \mathbb{R}^{1024} \rightarrow \mathbb{R}^{|c|}$ with an output dimension corresponding to the number of classes c using a standard transfer learning configuration. The efficacy of transfer learning, especially in the context of biodiversity monitoring application, has been demonstrated in various studies [20, 21, 12, 13]. The model generates a multi-label prediction, hence sigmoid activation is applied to the model logits $\hat{y}_n = \sigma(f_\theta(x_n))$. Only the classification head is fine-tuned. The model and training hyperparameters are fixed across this study to isolate sampling effects, consistent with previous works [12, 13].

3.2. Sampling for Active Learning

Given samples across large spatial and temporal scales we want to compare if hybrid uncertainty sampling implicitly provides generalisable performance across strata or if explicit stratification improves performance. We use a standard uncertainty sampling approach, where the samples with the highest uncertainty are selected for annotation. Binary entropy is selected for uncertainty quantification and is a standard method for multi-label data hence this method is fixed across all sampling and diversification methods:

$$H(\hat{\mathbf{p}}_c) = -\sum_{i=1}^{c} \hat{p}_i \log_2 \hat{p}_i + (1 - \hat{p}_i) \log_2 (1 - \hat{p}_i) \tag{1}$$

Per sample entropy is aggregated using the maximum across classes $H_n = \arg\max H(\hat{\mathbf{p}}_c)$ per sample. Per-stratum binary entropy (without diversification) is reported as entropy sampling and is the baseline sampling method for comparison.

3.3. Diversification

We evaluate three sampling methods: 1) binary entropy without diversification (equation 1), 2) cluster-entropy diversification and 3) stratification-entropy diversification. Clustering (Cluster-Entropy) using pre-generated BirdNet embeddings provide a content-based representation, allowing similar samples to be grouped. By sampling from clusters based on uncertainty, active learning can select informative examples while ensuring diversity across

the embedding space, thereby reducing redundancy in the labeled set. Unlike stratification, where samples are explicitly categorised by site and date (year or month), cluster-based diversification is not provided with spatiotemporal information but may implicitly represent spatial and temporal information through their correlation with acoustic variability (e.g. species composition and environmental noise).

Cluster-Entropy Diversification Based on a similar approach cluster-margin [15], cluster-entropy is a hybrid uncertainty sampling and diversification approach. A subset of sample embeddings (20%) are used to compute Hierarchical Agglometerive Clusters (HAC) using Ward linkage criteria for a precomputed set of clusters $\mathcal{C}_{cluster} = \{c_1, c_2, ..., c_k\}$ (depending on the desired sampling batch size $k = 20$) where each cluster c contains sample embeddings. All training embeddings are assigned to cluster means by Euclidean distance. Binary entropy is then computed for all clustered embeddings and the highest uncertainty samples from each cluster are selected:

$$S_k = \underset{\mathbf{x}_n \in \mathcal{C}^{(k)}_{\text{cluster/strata}}}{\arg\max} \quad H_n \tag{2}$$

Stratified-Entropy Diversification Samples are categorised by t strata varying by the number of sites (spatial) or time periods (temporal). Binary entropy is used to compute the uncertainty of samples $\mathcal{C}_{strata} = \{c_1, c_2, ..., c_t\}$. Similarly, the samples with the highest binary entropy uncertainty per stratum are selected (equation 2).

For stratified-entropy spatial (sites) and temporal (yearly, monthly) stratification are compared separately. The number of strata depends on the number of locations or time-periods present in the dataset. Therefore we apply posthoc random subsampling to selected samples so that the sampling batch size is consistent between approaches.

Hyperparameters. An iterative batched active learning process of up to 500 cumulative samples (25 epochs) were computed with 20 samples per batch for all sampling approaches. A mini-batch size of 20 was used with an Adam optimiser and learning rate scheduler (ReduceLROnPlateau) starting at 0.01, limited at a minimum of 0.0001.

3.4. Datasets

Datasets were selected which cover varied spatial and temporal scales as well as having necessary metadata regarding recording sites and dates. **AnuraSet** [22] is a multilabel bioacoustic dataset from South America containing vocalisation of 42 anura species. The dataset spans four recording sites and three years (2019 - 2021). This dataset reflect a multi-site national monitoring application. The World Annotated Bird Acoustic Dataset **(WABAD - Europe)** [23] is the most comprehensive multi-label bioacoustic dataset currently available. Recordings span 26 sites across Europe and seven years (2016 - 2023) reflecting a large-scale transnational monitoring study.

Challenges and Limitations. These datasets reflect samples collected from complex and real-world passive acoustic monitoring. These are challenging datasets given class imbalance and uneven sampling across strata (sites and time periods). These challenges reflect the real-world challenges of passive acoustic monitoring at scale. There are limitations when making comparison to raw field recordings. Sampling bias and over-representation of positive samples inflates the performance of non-diversification based sampling. These dataset do not reflect the true sparsity of positive samples. Evaluation of sampling strategies given a dataset with existing sampling biases is a point of caution. However, relative performance differences are still applicable.

3.5. Evaluation

The F1 (macro averaged by class) is the primary model performance metric computed on the test set. Macro (non-weighted average) metric were selected because they more accurately represent performance for underrepresented species. Performance is calculated per stratum. A fixed threshold of 0.5 is used for all F1 evaluation.

An important and often overlooked aspect of evaluation is the generalisability of model performance, especially across spatial and temporal scales with significant variability. Intra and inter-strata evenness of performance metrics are evaluated using the Pielou Evenness Index $J^{'}$ [18] (also called the Shannon Equitability Index), which computes the sum of per stratum entropy over the maximum entropy:

$$J' = \frac{H'}{H'_{\max}} = \frac{-\sum_{i=1}^{n} p_i \log(p_i)}{\log(n)} \tag{3}$$

The Pielou Index ranges from 0 to 1 with a higher value indicating better evenness. Additionally, the coefficient of variation (CV), equation (4), is reported which measures the relative dispersion of performance across strata where lower values indicate better evenness:

$$CV = \frac{\sigma}{\mu} \tag{4}$$

Here we are defining performance evenness across strata as a proxy for generalisability. True generalisability also implies robustness beyond observed strata. Evenness can also be considered as an indicator of fairness across sub-populations.

3.6. Divergence and Mutual Information

Jensen-Shannon (JS) Divergence is used to measure distributional differences between strata by computing the pair-wise JS-divergence. The JS-divergence of the true label distributions and predicted class distributions (categorical distributions) are computed, estimating the true distributional differences between strata and the differences captured by the model respectively.

The mutual information quantifies the amount of information that knowing one variable (e.g. stratum S) reveals about the other (e.g. prediction or label Y). The normalised mutual information is used to compare the proportion of uncertainty explained by strata information:

$$NMI(Y:S) = \frac{I(Y:S)}{H(Y)} = \frac{H(Y) - H(Y|S)}{H(Y)} \tag{5}$$

In this case Y is a categorical distribution across classes, either the true distribution (label) or predictive distribution. These divergence/similarity measures are used to explore potential explanations for the performance evaluation outcomes.

3.7. Exclusion Analysis

Exclusion analysis provides a direct evaluation of model generalisability across strata. By withholding samples from all but one stratum we evaluate the generalisability of the model across all strata and assess how well the model transfers to unseen but ecologically relevant conditions. Here the relative F1 (macro averaged) performance is reported for each stratum which

is the relative difference between the first and last (25th) epoch. This analysis is paired with JS-divergence measurements between strata to measure the distribution divergence (predicted performance divergence) across strata.

3.8. Weighted Sampling

We explore weighted stratification using the pair-wise JS-divergence between strata. Strata with low divergence mutually benefit from sampling. Hence, strata with low divergence can be sampled less, potential reducing redundancy while retaining model performance.

4. Results and Discussion

4.1. Spatial Stratification

First we show results using AnuraSet before extending to the larger WABAD. AnuraSet (Spatial) is evaluated across four sites (INCT20955, INCT4, INCT41, INCT17) using binary entropy sampling without any diversification as a baseline. This achieves a Pielou Index of 0.931 and coeficient of variation of 0.411. When evaluating per stratum performance, clear correlation between the number of samples selected and the model performance is observed (Figure 2). Note that in this case, per-stratum F1-macro (test) is only evaluative, no stratification of training samples is applied. The orange bars represent the average entropy per-stratum.

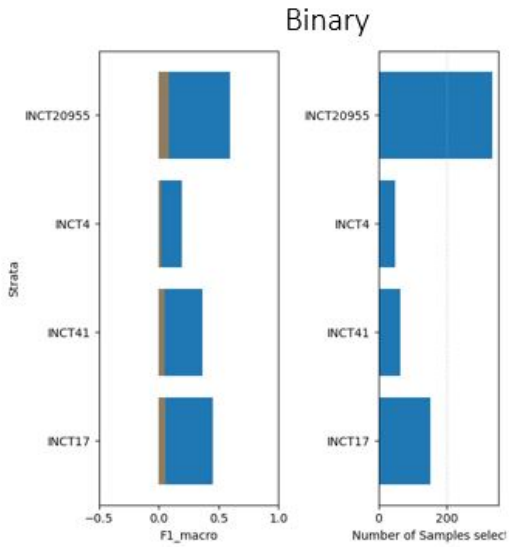

Figure 2: Comparison of model performance using AnuraSet with spatial stratification (sites) and entropy sampling without diversification. Orange bars represent average per-stratum entropy.

Comparing diversification methods we observed improved generalisability across strata using stratified sampling (Figure 3) achieving a Pielou Index of 0.992 and coefficient of variation of 0.142. Cluster-based diversification achieved a Pielou Index of 0.985 and a coefficient of variation of 0.203 also improving on only entropy sampling.

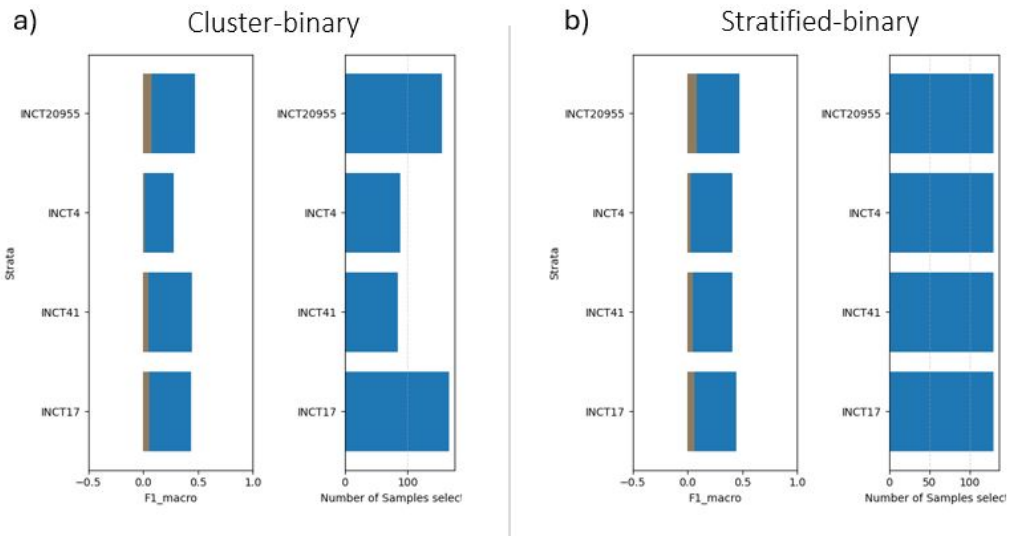

Figure 3: Comparison of cluster-entropy and stratified-entropy diversification using AnuraSet with spatial (site) stratification.

This result suggests that balanced sampling across relevant strata can improve the generalisability of model performance. While it is true that diverse and representative data is a necessary component of model generalisability, a fundamental assumption when applying active learning is that samples are not uniformly informative. Therefore, model generalisability depends not just on sampling uniformly across strata, but also how informative those samples are. Ideally, samples are both representative and informative. Existing uncertainty quantification methods such as binary entropy provide a means to predict sample information gain and therefore inform sampling decisions.

Exclusion analysis of sample selection from a single site (INCT20955) demonstrates lower model performance (Figure 4a)) for strata with higher divergence as expected (Figure 4b).

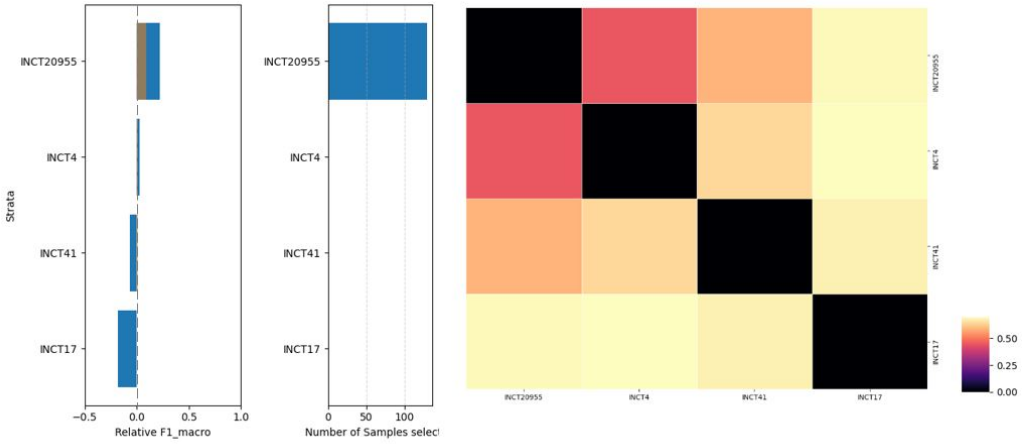

Figure 4: Exclusion analysis with sampling from a single site (INCT20955) showing a) per stratum performance and b) JS-divergence of predictive distribution between sites.

Mutual information. Additionally, mutual information quantifies the amount of information provided about the label given knowledge about the stratum (e.g. site, year). High mutual information indicates that the strata is informative of species composition (label distribution) or predicted labels (predictive distribution). For AnuraSet (spatial) the mutual information between the strata and species true label distribution is 40.3% of the total entropy. This suggests that spatial location explains a substantial portion of label variability and that species composition varies meaningfully across sites. After training, the mutual information of the predictive distribution with respect to the strata reaches 34.9%, approaching the upper-bound of 40.3%. These results demonstrate that spatial context accounts for a substantial proportion of species label variance. In this work we investigate spatiotemporal context from a sampling perspective, however these results also suggest that explicit encoding of spatial information (embedding) may benefit overall performance.

4.2. Temporal Stratification

AnuraSet (temporal) is evaluated across three years of data (2019 - 2021). Using entropy and cluster-entropy sampling it is observed that 2021 is undersampled yet the performance is even across all years (Figure 5). **Stratification with balanced sampling introduces redundant samples, resulting in lower performance evenness**. This result would suggest that 2021

contains little relevant variation compared to other years. However, the JS-divergence analysis of the temporally stratified label distributions contradict this: 2021 has the highest divergence compared to other years. Inconsistencies in generalisation and divergence between years are due to **mismatched temporal coverage**, with 2021 only representing January. This leads to an artificial alignment with 2020 data, improving generalisation, while also exaggerating divergence when a full-year distribution and partial-year distribution are compared. The JS-divergence Figure 6 demonstrates high-resolution (monthly) divergence.

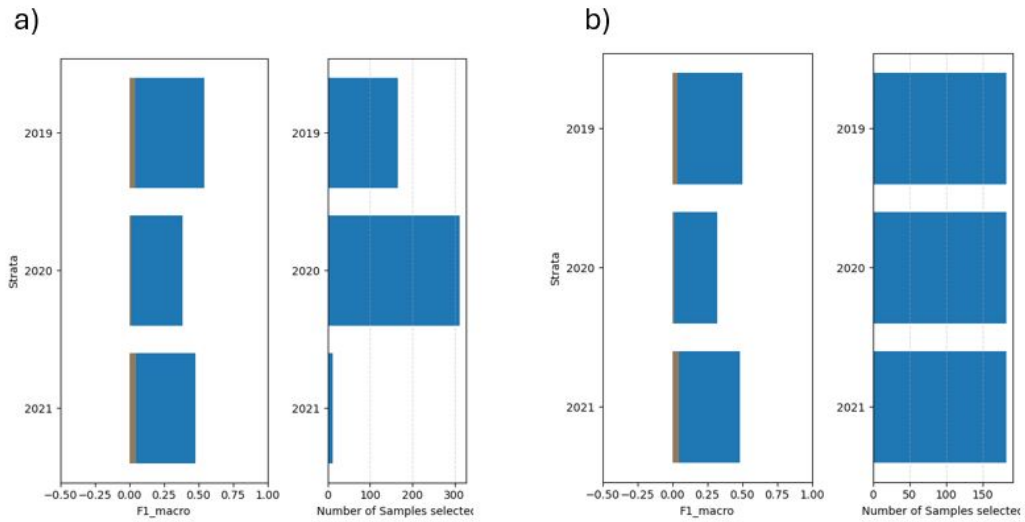

Figure 5: Comparison of a) cluster-entropy and b) stratified-entropy diversification using AnuraSet with temporal (year) stratification.

The mutual information between years and species labels is 6.18% (5.22% excluding 2021), with a predictive mutual information of 3.85% (3.36% excluding 2021). This suggests that only a small proportion of species variation is explained by year and that year as a stratification variable captures little ecologically relevant signal. This is likely due to the temporal resolution being too coarse with little variation in species composition from year-to-year. Figure 6, the monthly JS-divergence, suggests that there is ecologically relevant information at higher-resolutions, demonstrated by consecutive months with low divergence. The monthly strata provides a label distribution mutual information of 24.6% and predictive mutual information of 15.3%, also

suggesting that more relevant information has been captured at higher resolutions.

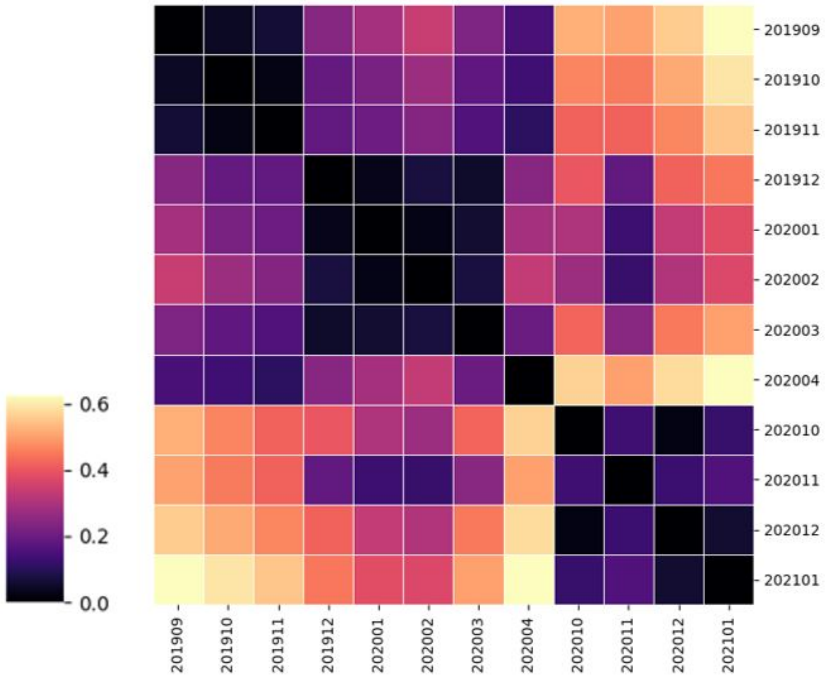

Figure 6: JS-divergence of per-month label distributions (AnuraSet)

These results demonstrate that per-strata model performance is a function of cross-strata divergence but also highlights the need for caution when making direct stratum-to-stratum comparisons on imbalanced and inconsistently sampled strata.

Next we investigate how divergence information can be used to inform sampling decisions. When comparing per-stratum performance using custom date ranges {A, B, C} corresponding to {201909 to 201911, 201912 to 202004, 202010 to 202101} based on divergence from figure 6. This results in an improved evenness with a Pielou Index of 0.996 and coefficient of variation of 0.090. Additionally, the mutual information between predictive distributions also increases from 3.85% to 16.0%.

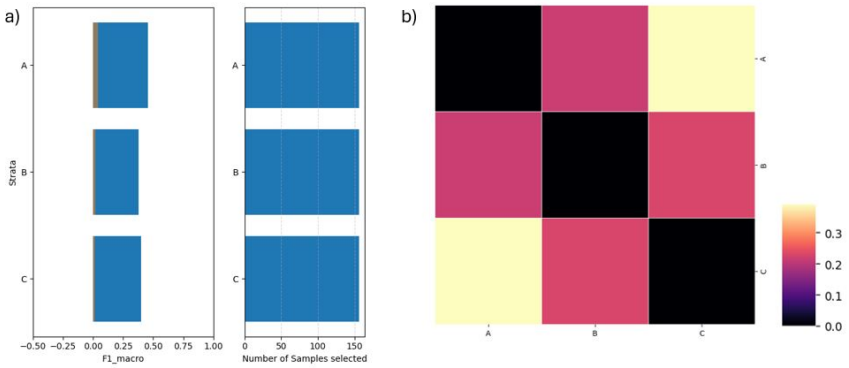

Figure 7: Comparison of a) per stratum performance and b) JS-divergence of predictive distribution between date ranges.

4.3. Scalability

Extending this evaluation to WABAD-Europe data across 26 locations and 7 years (2016-2023) highlight the variability in model performance across spatially and temporally diverse recordings. Balanced stratified sampling results in a minor improvement to performance evenness with a Pielou Index of 0.974 and coefficient of variation of 0.424 compared to cluster-entropy of 0.972 and 0.428 respectively. Both methods improve upon entropy sampling which achieved a Pielou Evenness of 0.964 and coefficient of variation of 0.476. Uneven sampling for stratified-entropy (Figure 8b), is due to posthoc subsampling required for balanced batchsizes.

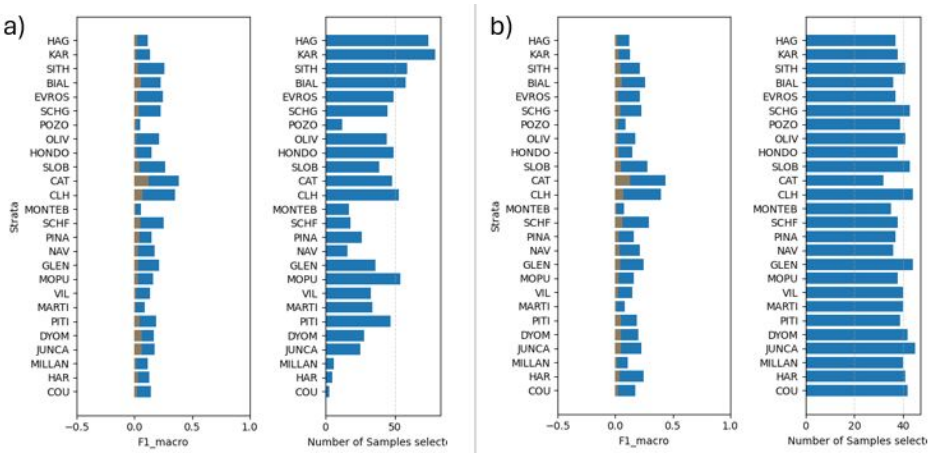

Figure 8: Comparable performance between a) cluster-entropy diversification and b) stratification.

Weighted Stratified Sampling. We have demonstrated that divergence is predictive of cross-strata generalisation. Additionally, our results suggest that even sampling across strata does not benefit performance evenness and can introduce redundancy. Comparing weighted stratification (Figure 9), a minor improvement in performance evenness is demonstrated with a coefficient of variation of 0.395 and Pielou index of 0.976 compared to without weighting with scores of 0.424 and 0.974 respectively.

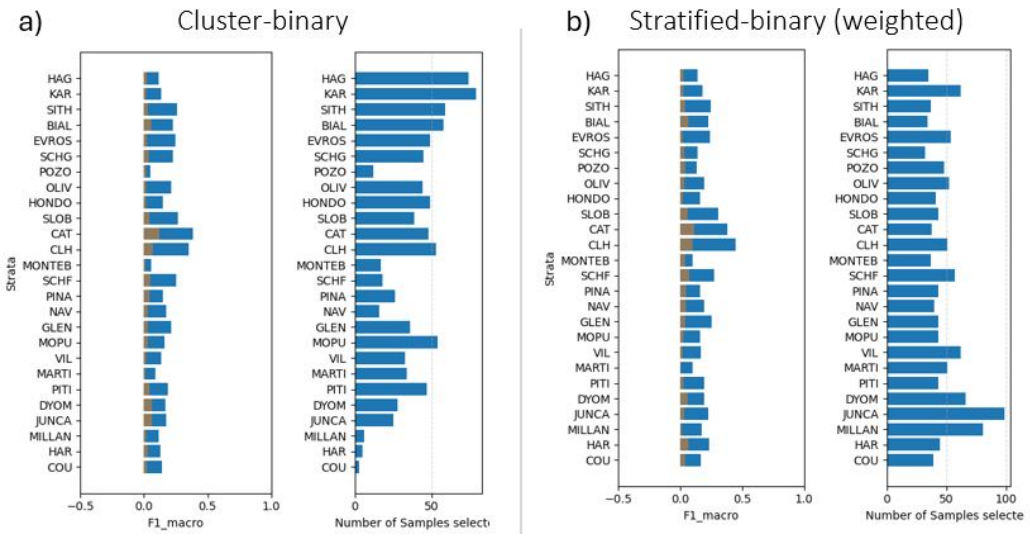

Figure 9: Minor improvement in performance evenness between a) cluster-entropy diversification and b) stratified-entropy (weighted).

Comparing temporal stratification on WABAD-Europe highlights the same issue of imbalanced and inconsistent representation. Temporal stratification fails to improve performance evenness. This is again due to inconsistent month-level coverage and more specific to the WABAD dataset, the aggregation of recordings from many independent studies.

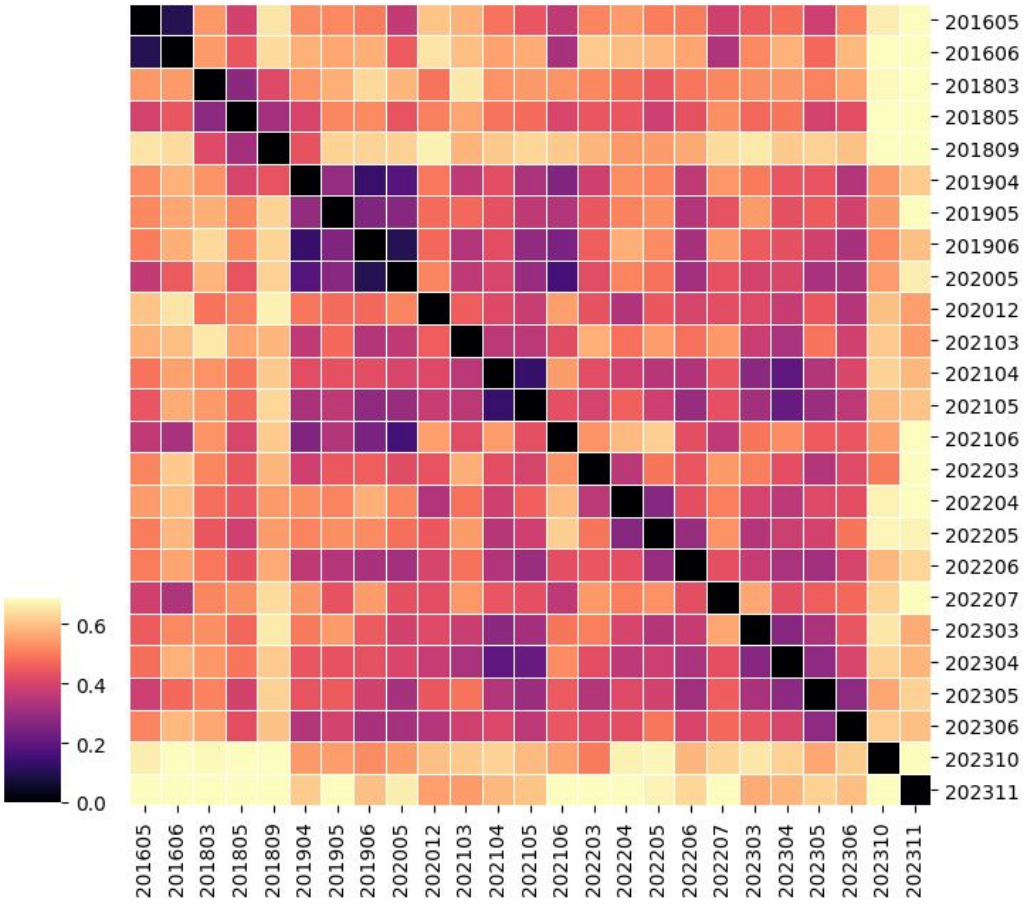

Figure 10: JS-divergence of per-month label distributions (WABAD-Europe)

Scaling to the larger WABAD-Europe dataset show that both cluster and stratification-based diversification yield only modest performance evenness gains and overall generalisability remains low. This is likely compounded by data imbalance and the datasets construction from many independent studies which introduce inconsistencies in spatial and temporal coverage.

4.4. Conclusions

Model performance is not even across ecologically relevant gradients and global performance metrics should not be assumed to be reflect performance across all strata. Our results demonstrate the stratified active learning can improve the evenness of model performance across ecologically relevant

strata. The benefit of stratification depends on the relevance of the stratification axis and the divergence between strata. Even sampling across strata does not guarantee improved generalisation, potentially introducing redundancy particularly for strata with low divergence. Both implicit cluster-based and explicit stratification-based diversification improved generalisability. Surprisingly, stratification by coarse site-level metadata improved generalisability more than clustering. This suggests that the embeddings alone do not capture all relevant ecological variation. These findings provide practical guidance for biodiversity monitoring and highlight the potential of divergence-informed sampling. This study also reveals current limitations of stratification:

- Stratification is only beneficial when the axis of stratification captures relevant ecological or acoustic variation.
- Stratified sampling should ideally be performed across well-defined intervals. However, the available datasets often suffer from incomplete coverage and insufficient samples within daily, monthly or seasonal bins, limiting the reliability of temporal comparison.
- Divergence is a useful measure of variability between strata but can be biased by non-relevant variation such as low sampling or insufficient sample coverage.

We investigate cross-strata generalisability from a sampling perspective using a standard active learning process which is well-understood to promote efficient use annotator time. Future work could extend this evaluation to alternative approaches such as evenness-based regularisation of learning. Spatiotemporal metadata could also be integrated (encoded) into existing cluster-based diversification methods. Additionally, we focus on spatial (site) and temporal (annual and month) stratification, but alternative resolutions and other ecologically relevant axes such as habitat, elevation and forest cover remain unexplored and could yield further improvements.

CRediT Authorship Contribution Statement

Ben McEwen: conceptualisation, implementation, writing. **Corentin Bernard**: data preparation, implementation and review. **Dan Stowell**: conceptualisation and review.

Acknowledgements

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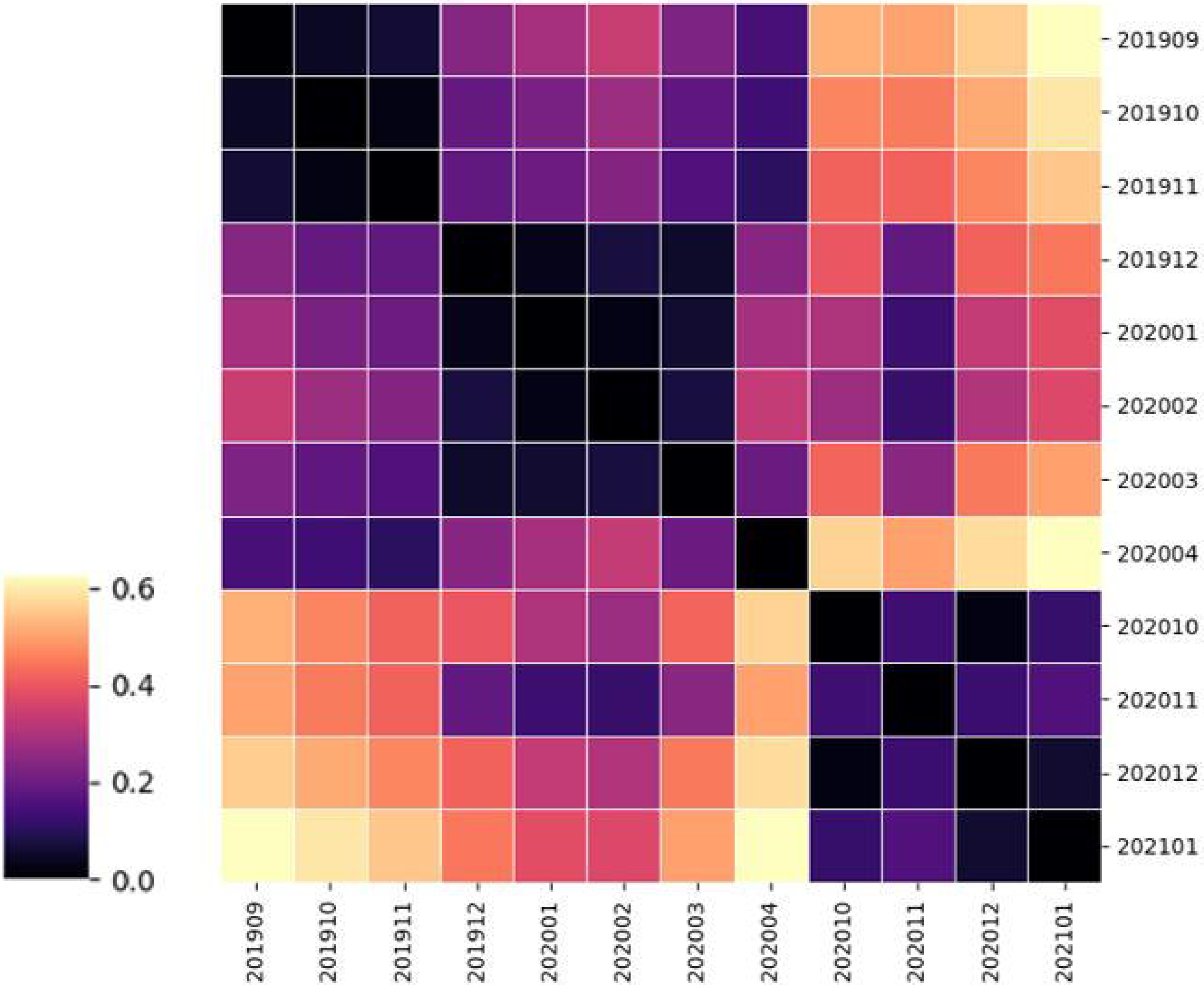
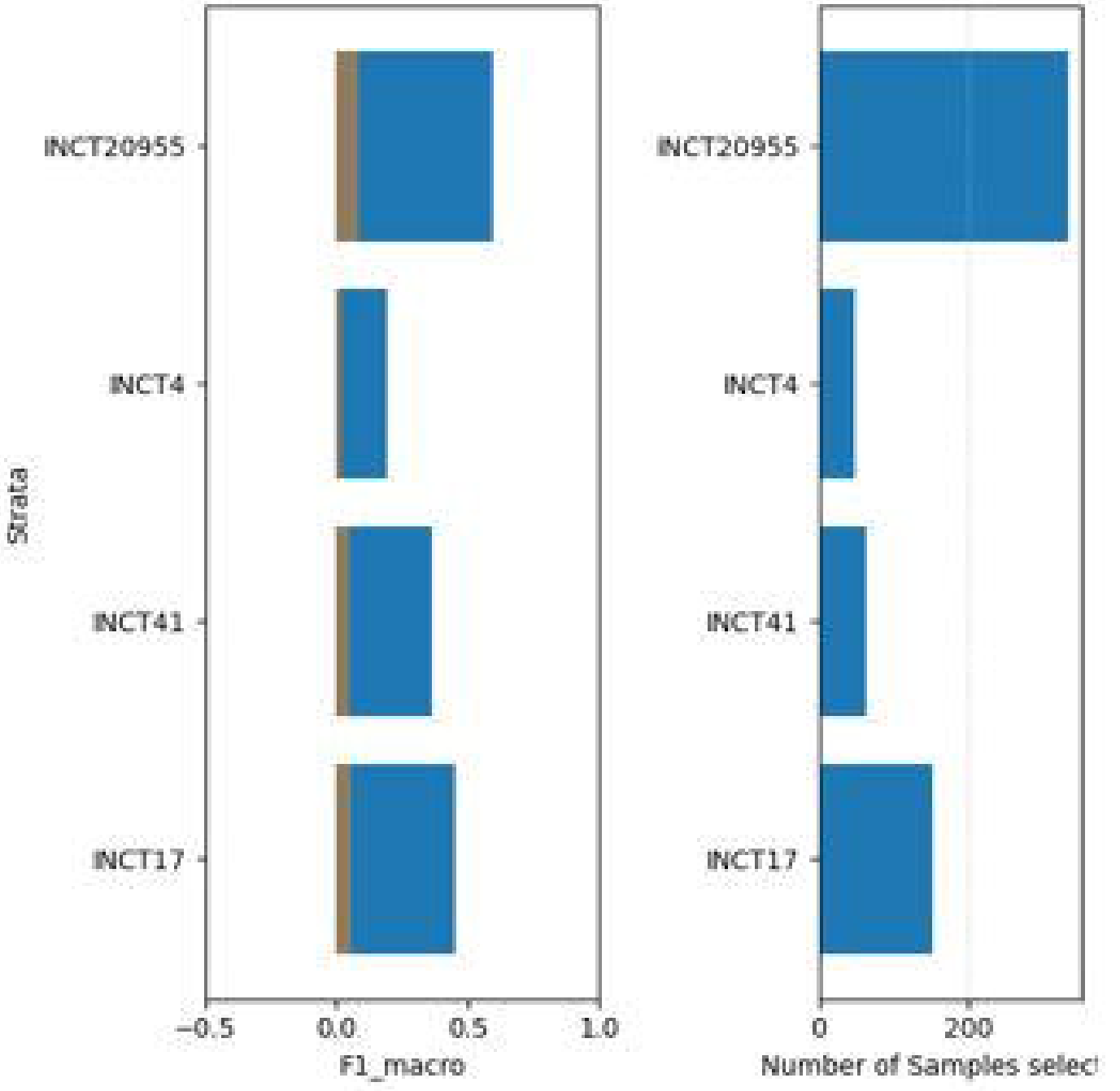
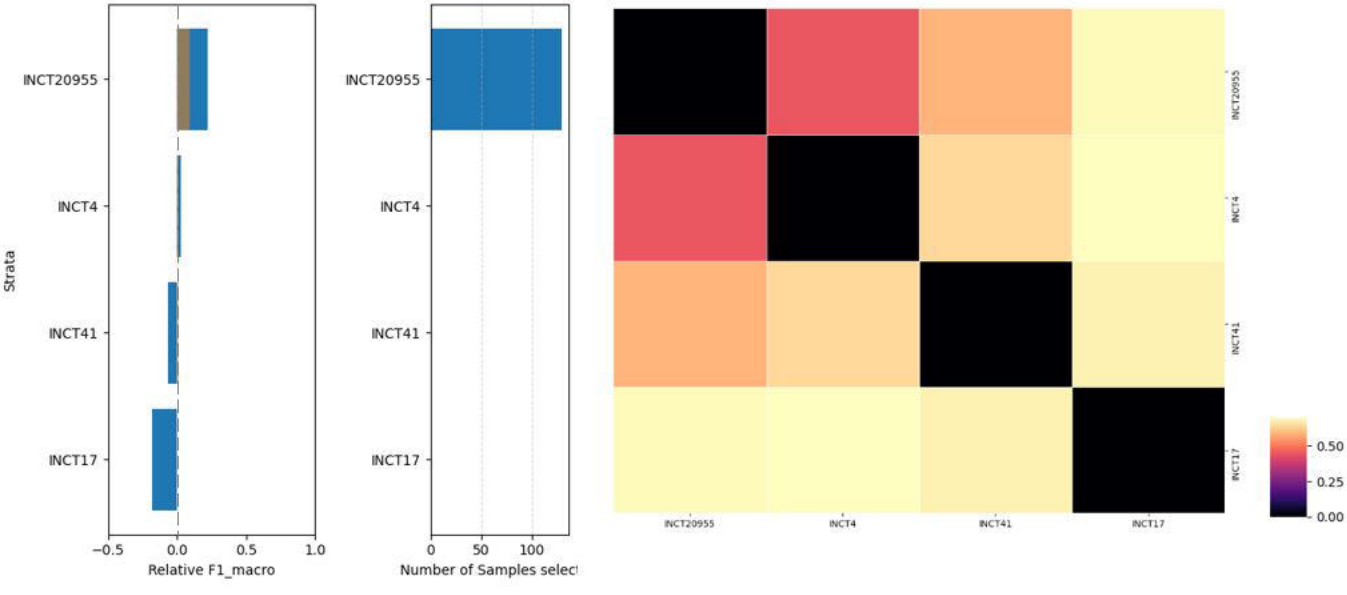
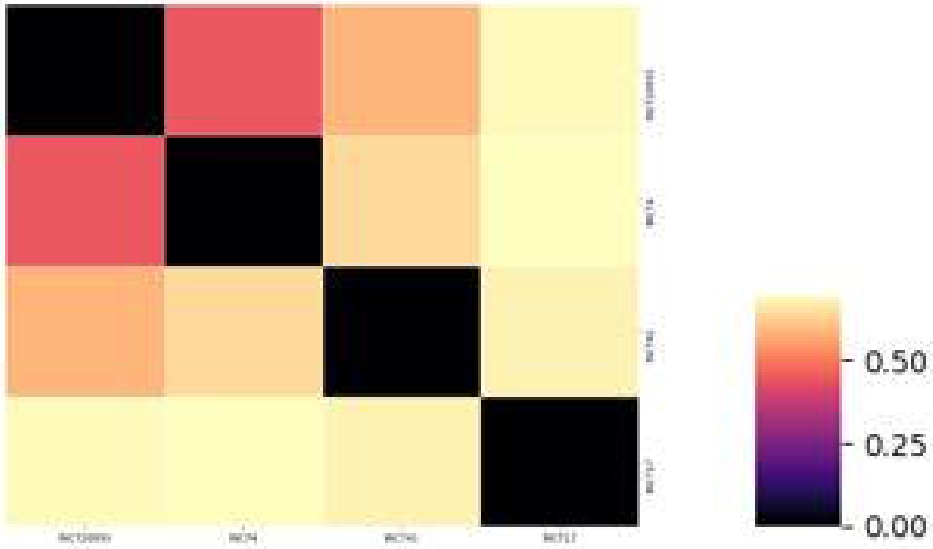

201909
201910
201911
201912
202001
202002
202003
202004
202010
202011
202012
202101
0.6
0.4
0.2
0.0

Binary


INCT20955
INCT4
INCT41
INCT17
Strata
−0.5
0.0
0.5
1.0
F1_macro
INCT20955
INCT4
INCT41
INCT17
0
200
Number of Samples selec


Strata
INCT20955
INCT4
INCT41
INCT17
−0.5
0.0
0.5
1.0
Relative F1_macro
0
50
100
Number of Samples select
0.50
0.25
0.00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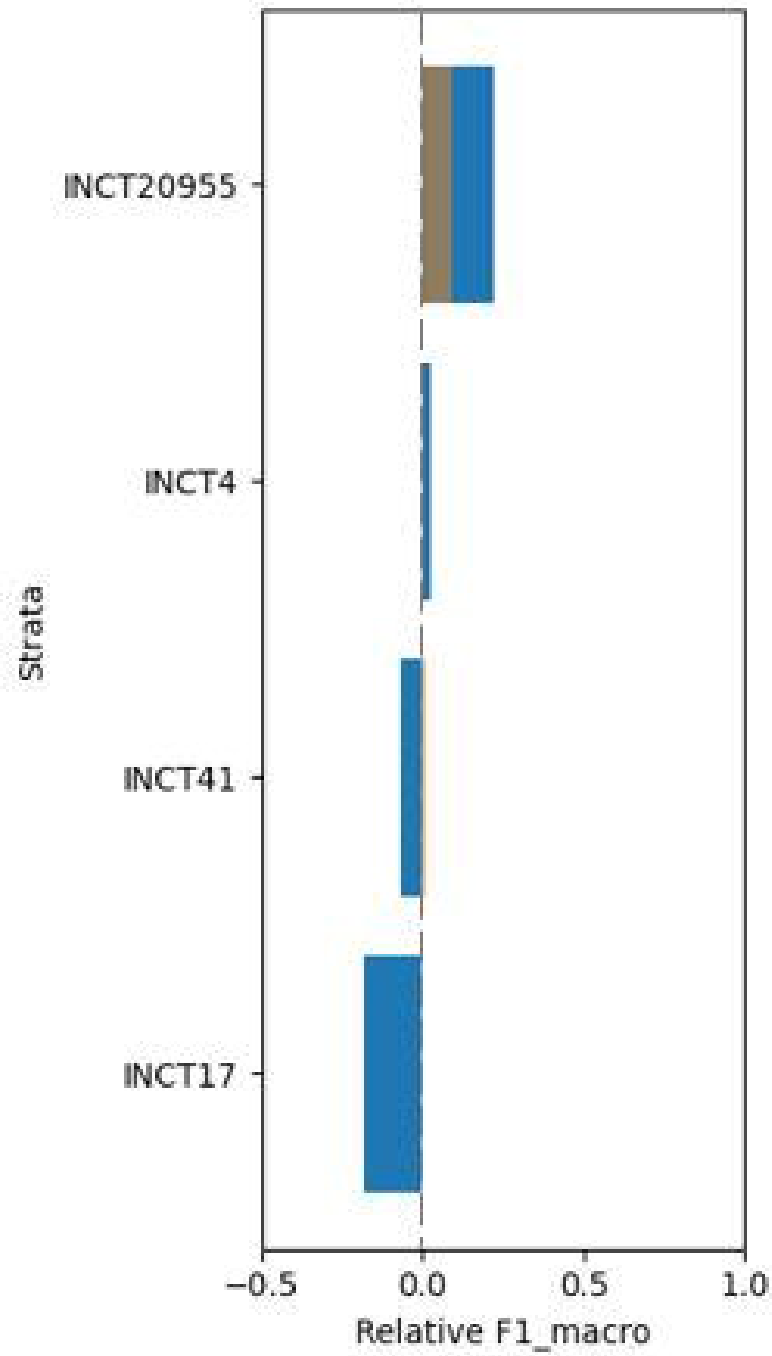
0.25
0.00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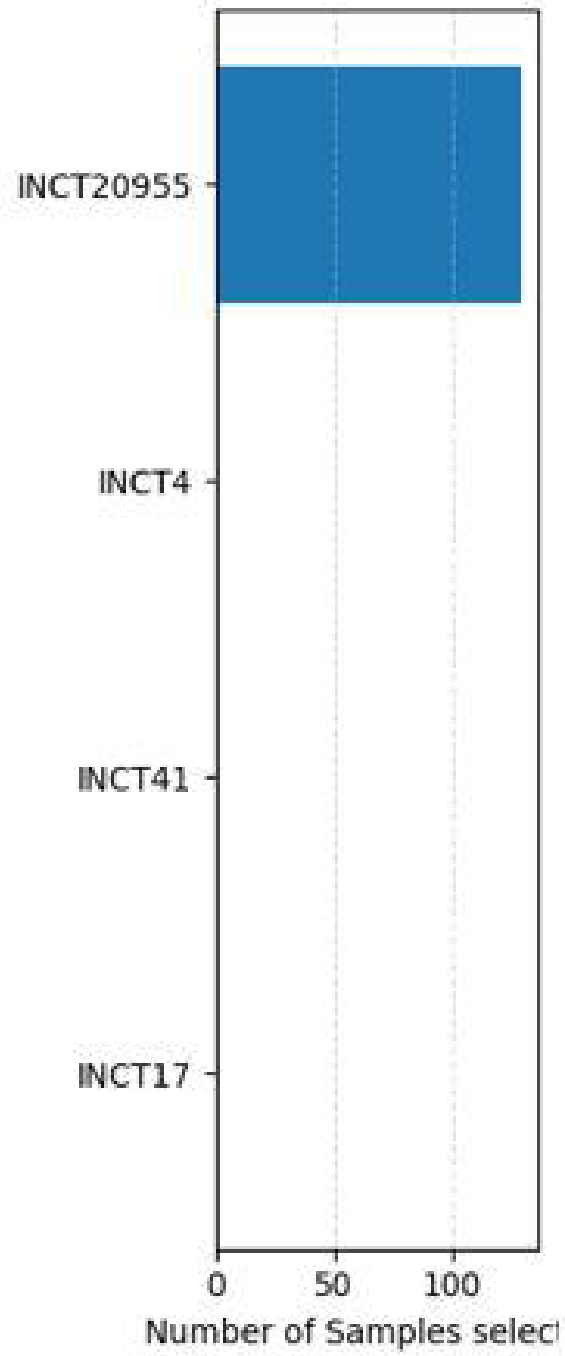
INCT4
INCT41
INCT17
Strata
−0.5
0.0
0.5
1.0
Relative F1_macro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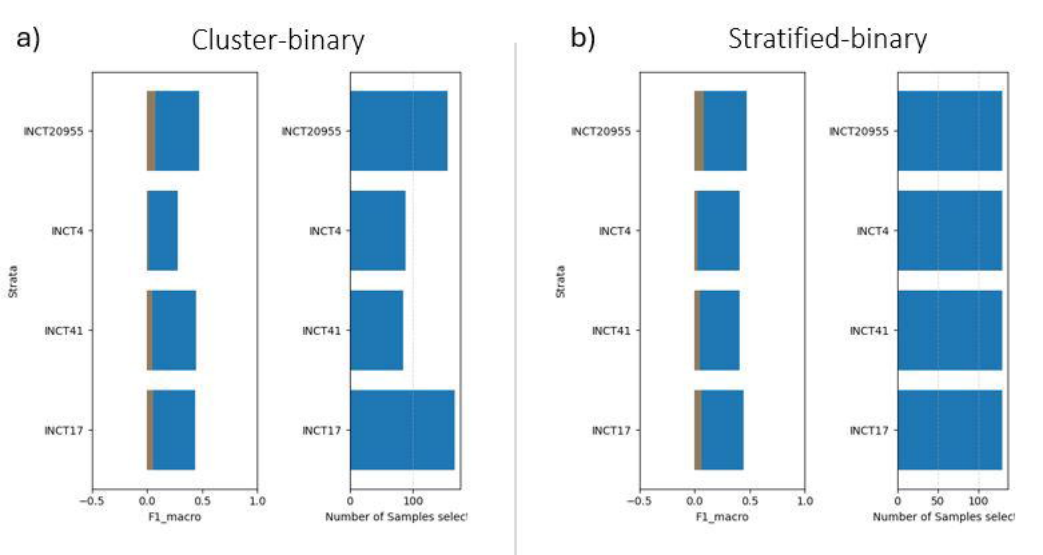
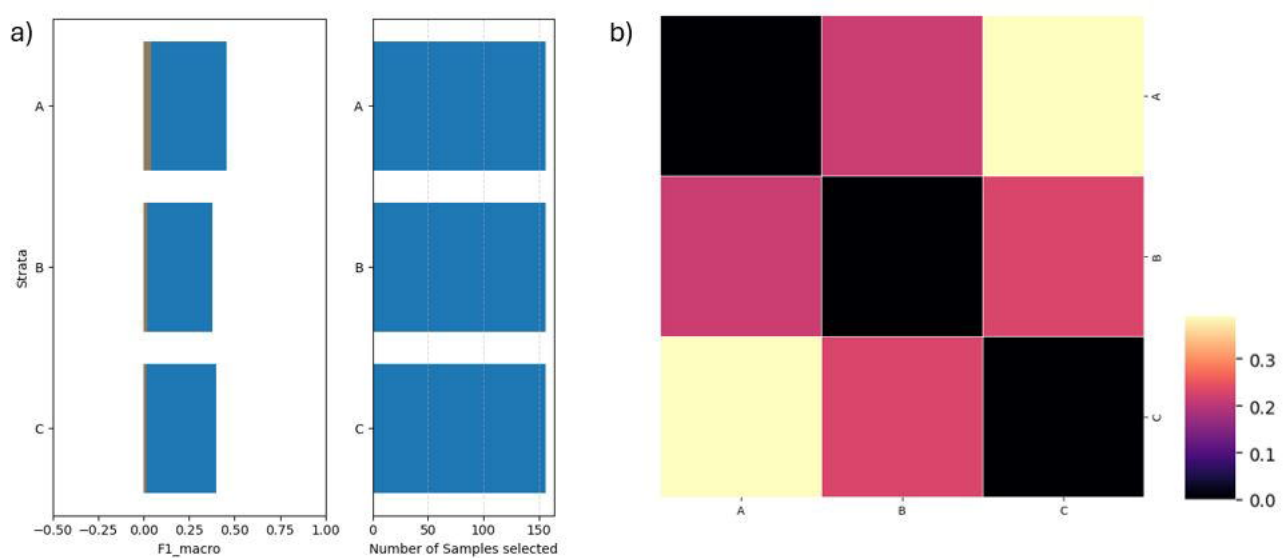
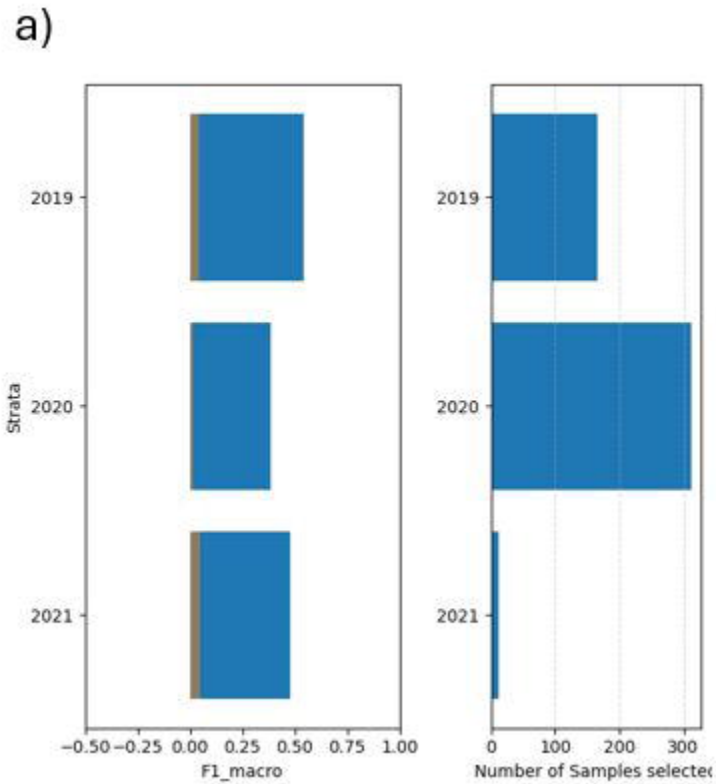
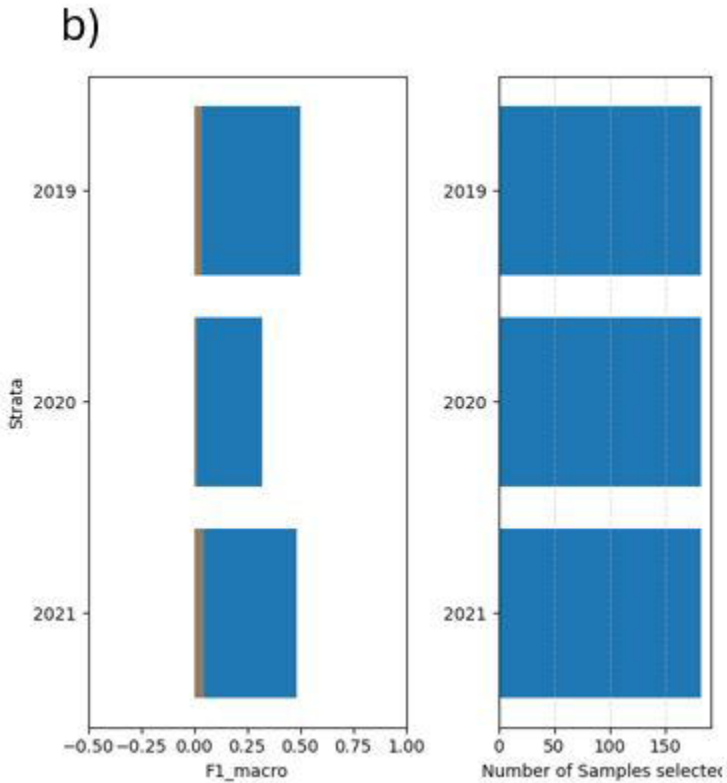
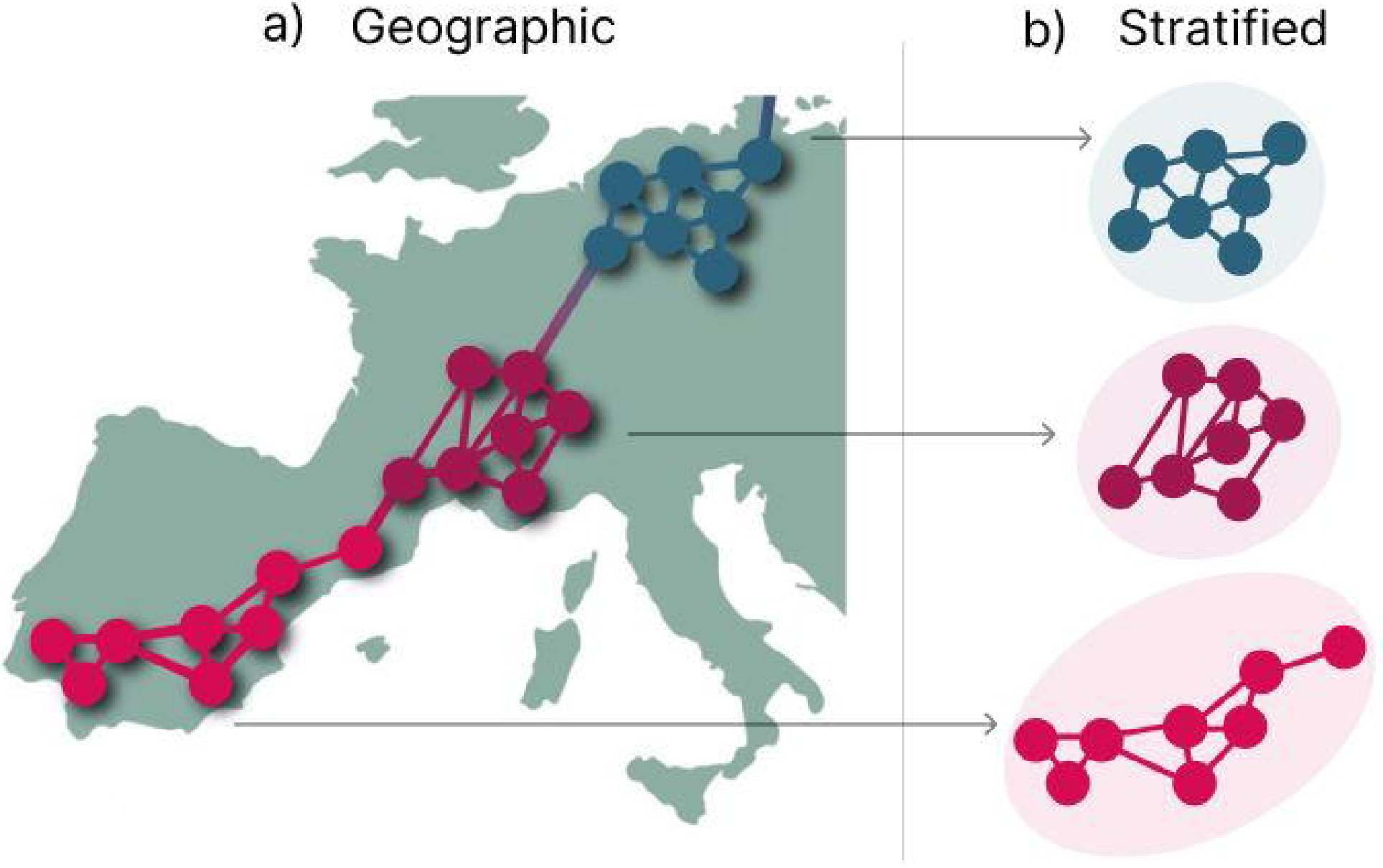
INCT4
INCT41
INCT17
0
50
100
Number of Samples selec

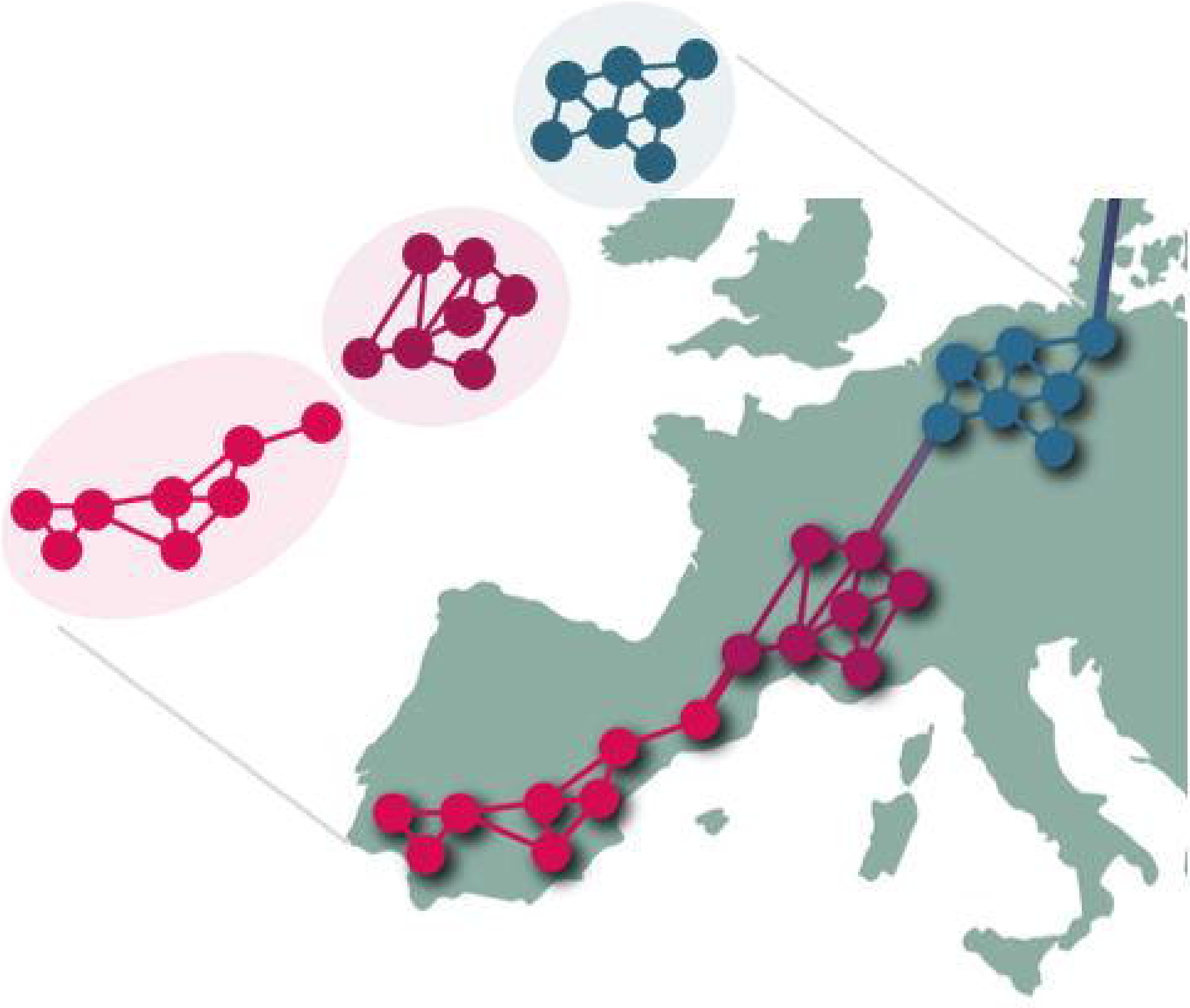

a)
Cluster-binary
b)
Stratified-binary
Strata
INCT20955
INCT4
INCT41
INCT17
−0.5
0.0
0.5
1.0
F1_macro
0
50
100
Number of Samples selec

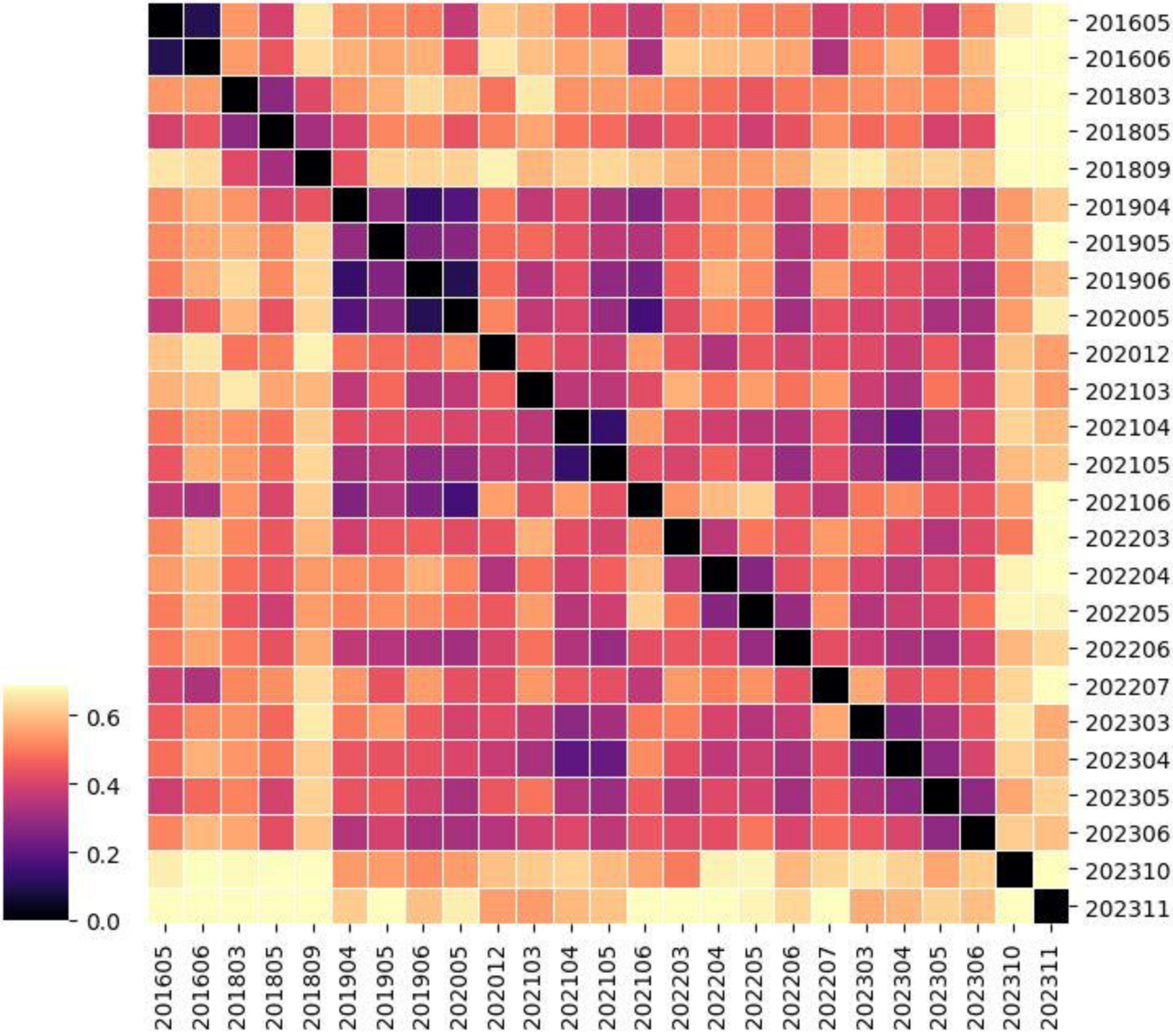

a)
Strata
A
B
C
−0.50 −0.25 0.00 0.25 0.50 0.75 1.00
F1_macro
0 50 100 150
Number of Samples selected
b)
A
B
C
0.3
0.2
0.1
0.0


a)
Strata
2019
2020
2021
−0.50 −0.25 0.00 0.25 0.50 0.75 1.00
F1_macro
0 100 200 300
Number of Samples selecte


b)
Strata
2019
2020
2021
−0.50 −0.25 0.00 0.25 0.50 0.75 1.00
F1_macro
0 50 100 150
Number of Samples selecte


a) Geographic
b) Stratified




201605
201606
201803
201805
201809
201904
201905
201906
202005
202012
202103
202104
202105
202106
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202205
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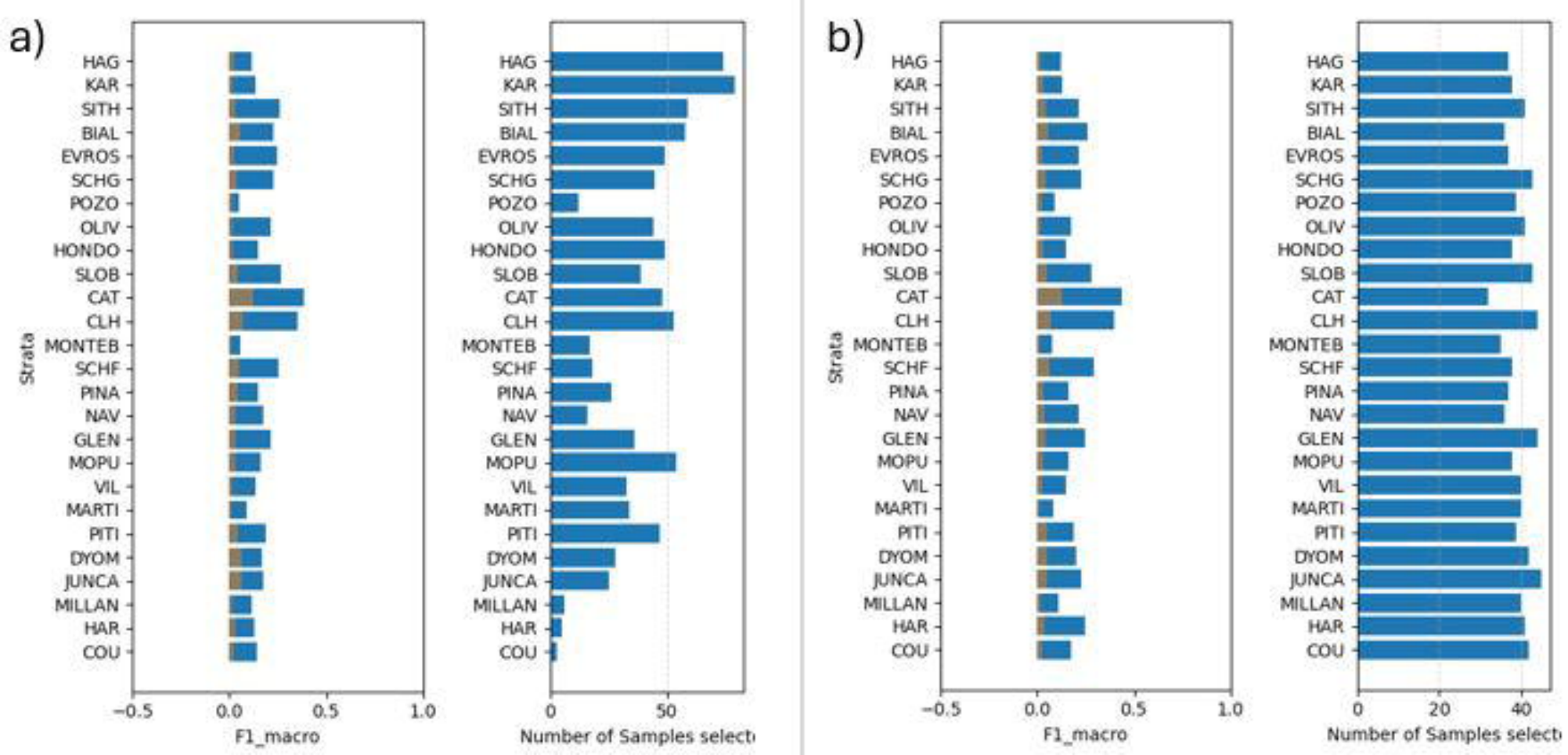
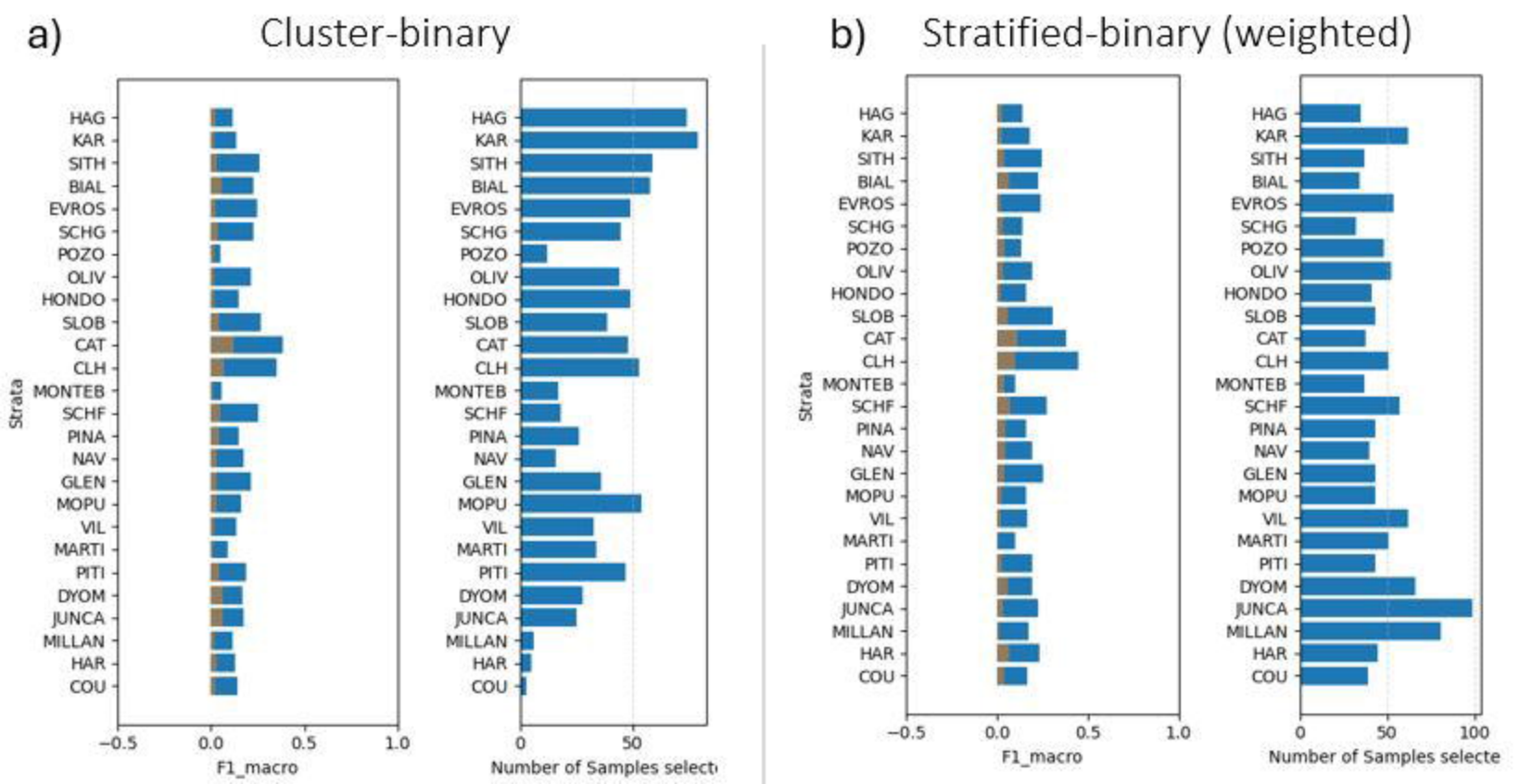
202207
202303
202304
202305
202306
202310
202311
0.6
0.4
0.2
0.0


a)
b)
Strata
HAG
KAR
SITH
BIAL
EVROS
SCHG
POZO
OLIV
HONDO
SLOB
CAT
CLH
MONTEB
SCHF
PINA
NAV
GLEN
MOPU
VIL
MARTI
PITI
DYOM
JUNCA
MILLAN
HAR
COU
−0.5
0.0
0.5
1.0
F1_macro
0
50
20
40
Number of Samples select


a)
Cluster-binary
b)
Stratified-binary (weighted)
Strata
HAG
KAR
SITH
BIAL
EVROS
SCHG
POZO
OLIV
HONDO
SLOB
CAT
CLH
MONTEB
SCHF
PINA
NAV
GLEN
MOPU
VIL
MARTI
PITI
DYOM
JUNCA
MILLAN
HAR
COU
−0.5
0.0
0.5
1.0
F1_macro
0
50
100
Number of Samples selecte