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REWEIGHTING WATER QUALITY INDICATORS TO BE MORE REPRESENTATIVE OF RIVERS NATIONALLY

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Prepared for Ministry for the Environment

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EXECUTIVE SUMMARY

Land, Air, Water Aotearoa (LAWA) leverages a database of water quality and ecological health indicators measured at over 1000 sites around Aotearoa New Zealand. Water quality and macroinvertebrate data (attribute indicators) are collected at these sites and analysed to provide a national-scale picture of the health of rivers and streams. A challenge with the current method of presenting a national summary of river water quality and ecological health, based on attribute indicators from monitored sites, is that these sites are not representative of rivers nationally. For example, high-elevation small streams are under-represented in the sites that are monitored currently. This is an issue because we may have a skewed picture of water quality at a national scale, which tends towards more (or less) healthy rivers.

The bias in representativeness of monitoring sites has been addressed previously via model-based approaches to estimating attribute scores for all reaches in New Zealand. Here, we take an alternative approach that explored six options for reweighting the number of reaches each LAWA site represents in the national network. The goal was to find the nearest (in either geographic distance or environmental distance) monitoring site that was environmentally / physiochemically similar to each of the non-monitored reaches and assign the associated monitoring site attribute score to the reach, namely for water quality attributes *E. coli*, ammoniacal nitrogen, dissolved reactive phosphorus, water clarity and macroinvertebrate community index. We then recalculated the proportion of reaches in each of the attribute bands (A, B, C, D, E) and compared these reweighted results to the unweighted LAWA results.

Five of the six methods relied on placing reaches and monitoring sites into discrete categories (e.g. based on land cover, geology, etc.). As these classification systems increased in complexity, there were a number of reaches that could not be associated with a monitoring site, which restricted the representativeness of the methods. The sixth method did not rely on categorising reaches, rather it measured the distance between reaches and monitoring sites in multivariate environmental space. Using this method, the majority of reaches (over 98%) could be associated with a monitoring site. Overall, the six methods used to reweight LAWA attribute indicators resulted in relatively minor changes to LAWA indicator scores (typically less than a 10% change in the number of sites in each attribute band for each of the indicators).

Our results suggest either, i) the LAWA monitoring network does a relatively good job of representing the wider catalogue of rivers, or ii) the classification methods tested here do not adequately match up monitoring sites to reaches. We therefore do not recommend a reweighting approach. If reweighting is to occur, we recommend using a method that operates in continuous environmental space, rather than one that is based on placing sites into predefined classes (e.g. based on land cover). A modelling-based approach of predicting reach indicator values is likely the best solution. Importantly, the large amount of data required for such modelling exists, the models have been shown to perform well and the models do not require reaches to be classified into discrete groups.

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1. INTRODUCTION

Land, Air, Water Aotearoa (LAWA) leverages a database of water quality and ecological health indicators to report on the state and trends of these at individual sites and at a national scale. Data is derived from monitoring of over 1000 sites around Aotearoa New Zealand, with this network maintained by regional councils and the National Institute of Water and Atmospheric Research (NIWA). Water quality and macroinvertebrate data (attribute indicators) are collected at these sites and analysed to provide a national-scale picture of the health of rivers and streams. A key LAWA response variable is the ‘state’ of attribute indicators, which are described in terms of attribute bands (A, B, C, D or E), with ‘A’ being indicative of ‘good’ health and ‘D / E’ being indicative of poor ecological health.

A challenge with the current method of presenting a national summary of river water quality and ecological health, based on attribute indicators from all the monitored sites, is that these sites are disproportionately located in coastal locations, in large rivers, and often in catchments dominated by urban or agricultural land use (Unwin et al. 2014). These sites were primarily chosen to meet the needs of regional councils and local communities, and they were not selected with the goal of generating a national picture of water quality. Therefore, when extrapolating findings from the monitoring sites to the national scale, there are biases in the relative representation of different systems; for example, streams in ‘pasture’-dominated catchments are over-represented in the database (Figure 1).

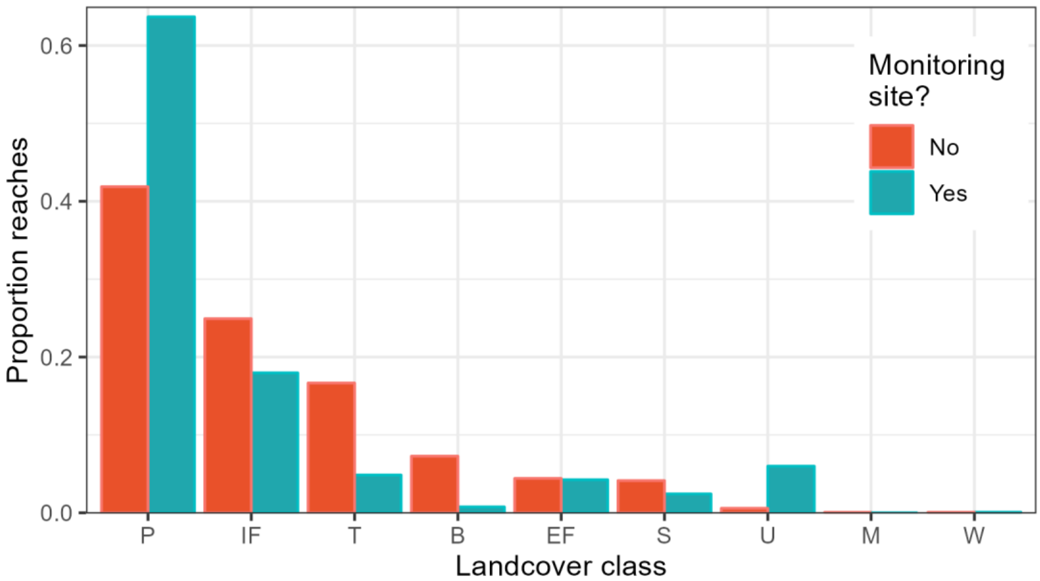

Figure 1. Distribution of reach land cover for LAWA monitoring sites (Yes) and all reaches across Aotearoa (No) based on REC land cover classes. ‘P’ = pasture, ‘IF’ = indigenous forest, ‘T’ = Tussock, ‘B’ = bare ground, ‘EF’ = exotic forest, ‘S’ = scrub, ‘U’ = urban, ‘M’ = miscellaneous, and ‘W’ = Wetland.

Previous attempts have been made to address the bias in the representativeness of monitoring sites via model-based (random forest) approaches to estimating attribute scores for all reaches in Aotearoa (Whitehead et al. 2022). Here, however, we took an alternative approach and explored multiple options for reweighting the number of reaches represented in each of the A, B, C, D and E bands for water quality indicators, dissolved reactive phosphorus (DRP), ammoniacal nitrogen (NH4N), *Escherichia coli* (*E. coli*), and water clarity (Clarity), as well as the macroinvertebrate community index (MCI).

The reweighting methods were based on classifying all reaches across the country into a subcategory (e.g. based on River Environment Classification (REC) catchment land use) and finding the nearest LAWA monitoring site within the same subcategory (details below). We then assigned the LAWA monitoring site attribute score (e.g. 'B') to the given reach. The overall aim was to assign all reaches in the country an attribute score for each of the indicators. This was achieved by:

i) starting with the REC database of river reaches for all of Aotearoa
ii) assigning the attribute band (A, B, C, D, E) of the 'nearest' monitoring site to each REC reach
iii) calculating the proportion of sites in each attribute band for each attribute indicator using the entire REC network
iv) comparing the new reweighted distribution of attribute band scores to those of LAWA monitoring sites.

How the 'nearest' monitoring site for any given REC reach was determined depended on the method used. We explored six possible methods that grouped reaches depending on physiochemical, habitat and land use variables. At the same time, we also considered the geographic distance between REC reaches and monitoring sites.

The goals of this report were twofold:

i) Describe the methods used to reweight LAWA attribute indictors and present the associated summary figures based on a variety of reweighting methods.
ii) Generate a database indicating which LAWA monitoring site is associated with each of the REC reaches for every method used.

2. INPUT DATASETS AND METRIC REWEIGHTING METHODOLOGY

2.1. Input datasets

Reweighting the LAWA attribute indicators required a combination of data sources. These data sources included:

i) LAWA state estimates – we used the latest version of publicly available data (available at https://www.lawa.org.nz/download-data/). This dataset has state attribute band (A, B, C, D, E) scores for water quality indicators (e.g. *E. coli*, DRP, Clarity, NH4N and MCI). The 2022 dataset included between 1017 and 1042 monitoring sites, depending on the indicator.

ii) FENZ database – in particular, the 'river predictors' dataset containing measures of 31 physiochemical / environmental predictor variables for each of the reaches in the REC database. Also, the 'river classification' dataset, which contains multiple classification systems based on environmental factors (Leathwick et al. 2010).

iii) REC database, which contains key classification variables including 'climate', 'source-of-flow', 'geology' and 'land cover'. The variables are used to classify each of the reaches in the REC database.

iv) LAWA site code look-up table – a table giving the REC 'nzreach' code associated with each of the LAWA monitoring sites.

2.2. Associating monitoring sites with river reaches

We used six different methods to associate REC reaches with monitoring sites. The goal was to find the nearest (in either geographic distance or environmental distance) monitoring site that was environmentally / physiochemically similar to each of the non-monitored reaches. Prior to reweighting, we removed all first-order streams from the databases, as very few have monitoring sites, and thus characteristics of these small streams are poorly represented. We then calculated the middle point of all reaches and used this as the 'reach location' for any spatial distance calculations. Each attribute indicator was not always measured at every LAWA monitoring site; therefore, prior to reweighting each attribute indicator, the list of LAWA monitoring sites was limited to only those where the given attribute indicator had been measured. This prevented reaches being erroneously associated with monitoring sites where the given indicator was not measured.

2.2.1. Method 1: FENZ_20

Here, each REC reach was associated with the nearest (in Euclidean distance – "as the crow flies") LAWA monitoring site, which was in the same FENZ_20 class. The FENZ_20 classification groups the reaches into one of 20 classes based on environmental factors. The underlying classification was determined via Generalised Dissimilarity Modelling (GDM) analyses carried out on fish and macroinvertebrate communities (Leathwick et al. 2008). A limitation of using the FENZ database is that a proportion of REC reaches, which are disproportionately larger rivers, do not have a FENZ classification. This results in a relatively high proportion of LAWA monitoring sites not being associated with a FENZ class (Table 1; Appendix 1).

Table 1 Proportion of reaches in each of FENZ_20 subclasses for LAWA monitoring sites, and all reaches. See Leathwick et al. (2008) for detailed FENZ class descriptions.

FENZ class	Broad class description	LAWA monitoring sites (%)	REC reaches (%)
A	Low-elevation rivers and streams	18.60	16.20
B	Low-elevation rivers and streams	0.15	0.25
C	Low-elevation rivers and streams	59.10	43.20
D	Low-elevation rivers and streams	0.80	3.73
E	Low-elevation rivers and streams	0.51	0.20
F	Low-elevation rivers and streams	0.00	0.02
G	Mid-elevation rivers and streams	3.94	9.96
H	Mid-elevation rivers and streams	0.34	7.18
I	Mid-elevation rivers and streams	0.73	0.95
J	Mid-elevation rivers and streams	0.00	4.67
K	Mid-elevation rivers and streams	0.00	0.20
L	Mid-elevation rivers and streams	0.00	0.38
M	Glacial rivers	0.00	0.05
N	High-elevation streams – non-glacial	0.73	2.85
O	High-elevation streams – non-glacial	0.00	0.65
P	High-elevation streams – non-glacial	0.00	0.56
Q	High-elevation streams – non-glacial	0.00	0.17
R	High-elevation streams – non-glacial	0.00	0.01
S	High-elevation streams – glacial	0.00	0.54
T	High-elevation streams – glacial	0.00	0.22
NA		16.40	0.01

2.2.2. Method 2: FENZ_ENV_DIST

Here, each REC reach was associated with the nearest monitoring site in multivariate environmental space using the 31 physiochemical / environmental predictors in the FENZ 'predictor' database. Variables in this database include measures of reach slope, flow, riparian condition and rainfall, among others. See the FENZ user manual for a full description of all variables (Leathwick et al. 2010).

Distances in environmental space were calculated using the 'dist()' function in the 'stats' v4.2.3 package using the computational software R (R Core Team 2020). The distance between two sites was calculated as:

$$\sqrt{\sum_i (x_i - y_i)^2}$$

where, x_i is a vector of environmental values (i) associated with site x, and y_i is a vector of environmental values (i) associated with site y (Borg and Groenen 2005).

2.2.3. Methods 3-6: REC_CL, REC_CSOFG, REC_CSOFGL, REC_CSOFGLNP

Here, similar to Method 1, each reach was associated with the nearest (in Euclidean distance – "as the crow flies") LAWA monitoring site, but also within each of the four different REC classifications.

Method 3 (REC_CL) was based on a combination of climate (C) and land cover (L; Table 2) classes and consisted of 50 possible subcategories, e.g. cool-dry / indigenous forest.

Table 2 Proportion of reaches in each of REC landcover subclasses for LAWA monitoring sites, and all REC reaches (excluding first-order streams).

Landcover class	Class description	LAWA monitoring sites (%)	REC reaches (%)
B	Bare ground	0.76	7.27
EF	Exotic forest	4.25	4.42
IF	Indigenous forest	18.00	24.90
P	Pastoral	63.70	41.90
S	Scrub	2.43	4.13
T	Tussock	4.85	16.70
U	Urban	5.99	0.58
W	Wetlands	0.08	0.07
M	Miscellaneous	0.00	0.06

Method 4 (REC_CSOFG) was based on a combination of climate (C), source-of-flow (SOF) and geology (G) classes and consisted of 126 possible subcategories, e.g. lake / hard sedimentary.

Method 5 (REC_CSOFGL) was based on climate (C), source-of-flow (SOF), geology (G), and land cover (L) classes and consisted of 558 possible subcategories, e.g. lake / hard sedimentary / indigenous forest.

Method 6 (REC_CSOFGLNP) was based on climate (C), source-of-flow (SOF), geology (G), land cover (L) and network position (NP) classes and consisted of 1135 possible subcategories, e.g. lake / hard sedimentary / indigenous forest / middle-order.

See the 'River Environment Classification user guide' (Snelder et al. 2010) for details of the subcategories within each of the REC classes. Briefly, however, climate is made up of six subcategories, which describe broadscale climate regions, e.g. cool-dry, warm-wet. Source-of-flow is made up of eight subcategories, e.g. glacial-mountain, lake, spring. Geology is made up of seven subcategories and broadly describes the rock types present in the catchment of each reach, e.g. hard sedimentary, soft sedimentary, volcanic basic. Land cover is made up of eight subcategories and describes land cover at the local scale, e.g. indigenous forest, bare ground, urban (Fraser and Snelder 2021). Finally, network position, made up of three subcategories, describes where in the catchment a reach is located, e.g. low-order, middle-order or high-order.

2.3. Reweighting methodology

Once each reach was associated with a monitoring site based on the six methods described above, the percentage of reaches associated with each attribute band (A, B, C, D, E) was calculated for each of the attribute indicators (*E. coli*, DRP, NH4N, Clarity and MCI). This reweighting was done using the length (km) of reaches, rather than the number of reaches. The distribution of reaches in each of the attribute bands was then compared to the unweighted LAWA results and also to results where indicator scores were predicted for the entire country via random forest models (Whitehead et al. 2022).

2.4. Missing classification categories

As the number of unique subcategories with a method increased (e.g. in the REC_CL method there were 50 subcategories, whereas in the REC_CSOFGLNP method there were over 1100), it became increasingly likely that there were no (0) LAWA monitoring sites in some of the subcategories; therefore, some reaches could not be associated with a monitoring site. For example, using the REC_CL method, 44 (0.00016%) of REC reaches are in the CD/M category, but there are no (0) LAWA sites in the CD/M category. Therefore, by reweighting the attribute scores, we can say that they are more representative of the national river network, but they are not representative of the *entire* network (Figure 2). Additionally, the spatial distribution of missing reaches was not random (Appendix 1), meaning there are likely biases in terms of which reaches could and could not be given an indicator score.

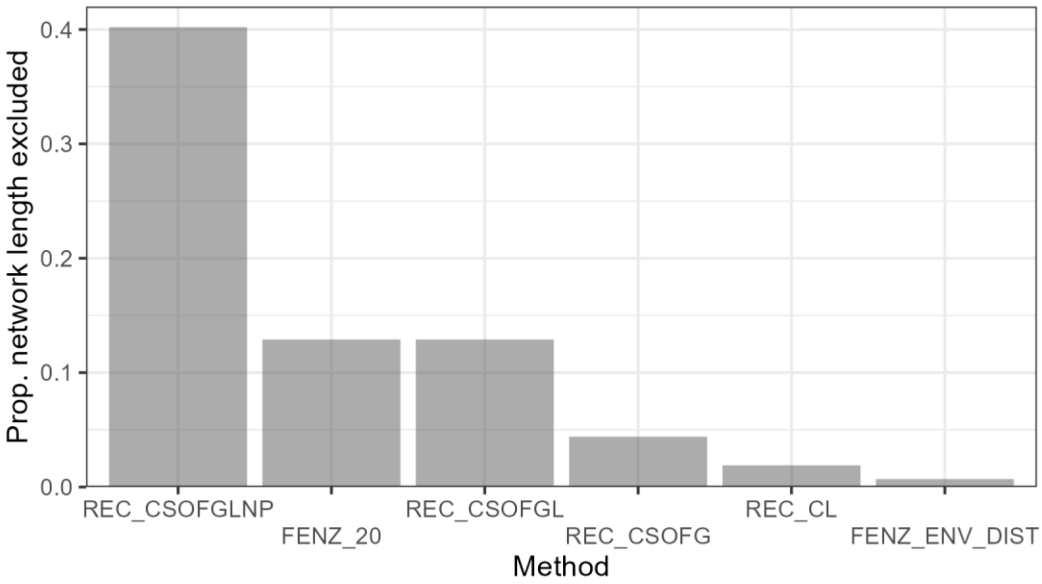

Figure 2. Proportion of total network length not used in reweighting for each of the six reweighting methods used.

2.5. Software

All analyses were carried out using the statistical computing software R v4.2.3 (R Core Team 2020). We used the *tidyverse* v2.0.0 (Wickham et al. 2019) metapackage for data manipulation, the *sf* v1.0.12 (Pebesma 2018) package for spatial analysis, and the *future* v1.32.0 package for parallelisation (Bengtsson 2021).

3. RESULTS OF METRIC REWEIGHTING

3.1. Database

Having attributed the nearest monitoring site to each of the REC reaches, a database was generated (Table 3). The database can be filtered based on the reweighting method used and the indicator of interest. The database is available as a .csv file.

Table 3 Example section of the database associating each REC reach to a LAWA monitoring site. 'nzreach' is the REC reach label, 'method' is the six classification methods we used, 'indicator' is the water quality indicator and 'near_mon_nzreach' is the REC label of the nearest monitoring reach.

nzreach	method	indicator	near_mon_nzreach
1000007	FENZ_20	MCI	1002906
1000007	FENZ_20	ECOLI	1004083
1000007	FENZ_20	DRP	1004083
1000007	FENZ_20	NH4N	1004083
1000007	FENZ_20	CLARITY	1004083
1000007	FENZ_ENV_DIST	MCI	309480
1000007	FENZ_ENV_DIST	ECOLI	1042286
1000007	FENZ_ENV_DIST	DRP	1042286

3.2. Reweighted metrics

Here, we present results for each of the six methods used to reweight the attribute state scores. Reweighted stacked bar plots are given for each of the five indicators (Clarity, NH4H, DRP, *E. coli*, MCI). Reweighted scores (by reach length) are compared to unweighted results and predictions from random forest models (Whitehead et al. 2022).

Reweighting the LAWA attributes using the FENZ_20 level classification resulted in relatively small changes to the distribution of state scores. The percentage of sites in attribute bands A or B increased slightly for NH4N, *E. coli* and DRP but decreased for Clarity and MCI (Figure 3). Using the FENZ_ENV_DIST classification, the percentage of sites in attribute bands A or B increased slightly for NH4N, *E. coli* and MCI but decreased for Clarity and DRP (Figure 4). Using the REC_CL classification, the percentage of sites in attribute bands A or B increased slightly for all the indicators except Clarity (Figure 5). Using the REC_CSOFG classification, the percentage of sites in attribute bands A or B increased slightly for all the indicators (Figure 6). Using the REC_CSOFGL classification, the percentage of sites in attribute bands A or B increased slightly for all the indicators except Clarity and MCI (Figure 7). Using the

REC_CSOFGLNP classification, the percentage of sites in attribute bands A or B increased slightly for all the indicators except NH4H (Figure 8). For many of the methods and indicators, the modelled results show a greater increase in the number of sites in the 'A' and 'B' bands compared to the weighted methods; this is likely due to first-order streams being excluded from our reweighting analysis, while they were included in the modelled results; therefore, this likely artificially increases the observed differences between the two methods.

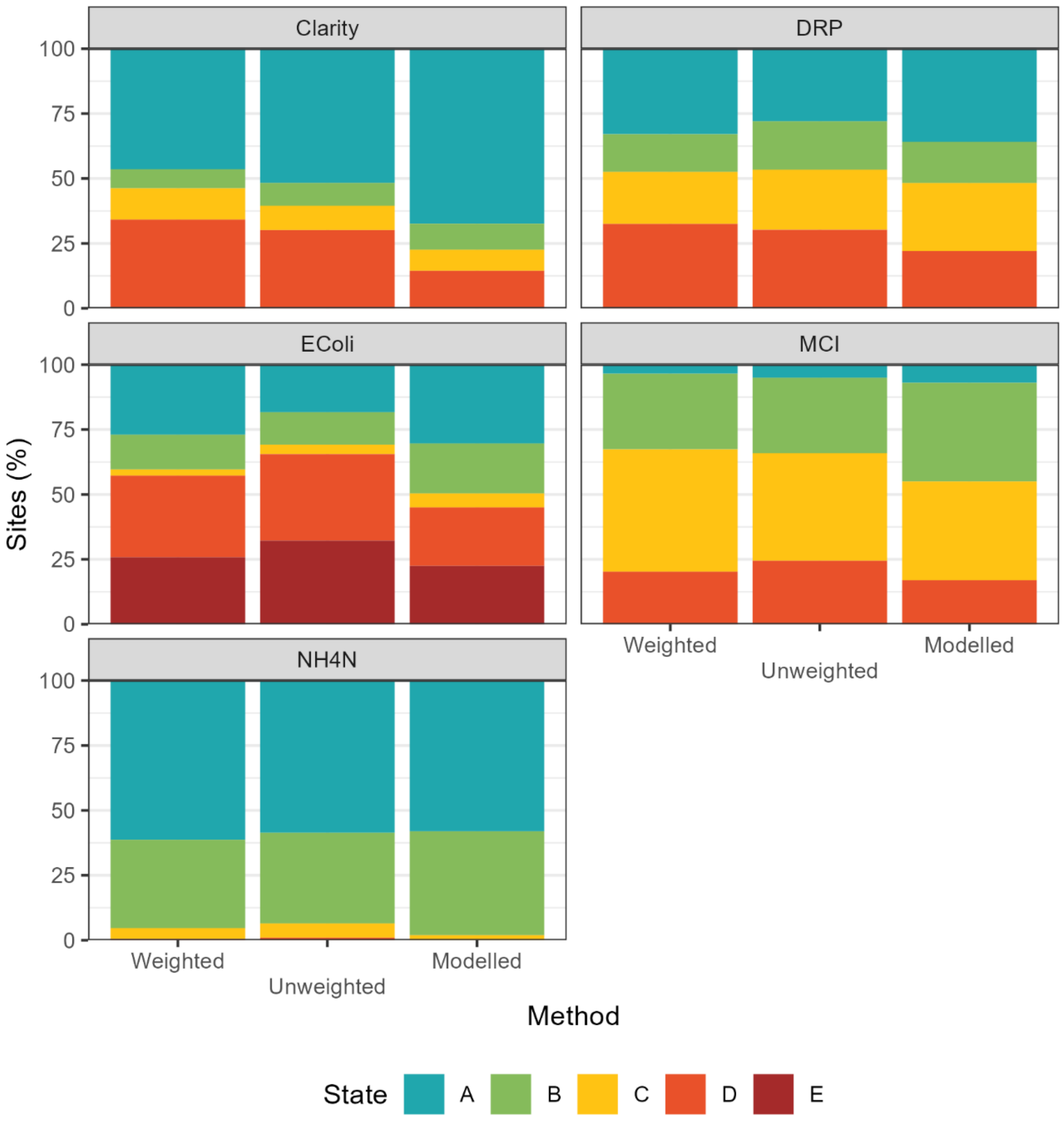

Figure 3. Unweighted and weighted LAWA attribute state scores, reweighted based on the FENZ__20 classes. Note only the attribute *E. coli* has an 'E' band (the scale is A-D for the rest), 'modelled' is from the random forest model results of Whitehead et al. (2022), 'unweighted' are the raw LAWA results and 'weighted' is the FENZ_20 result.

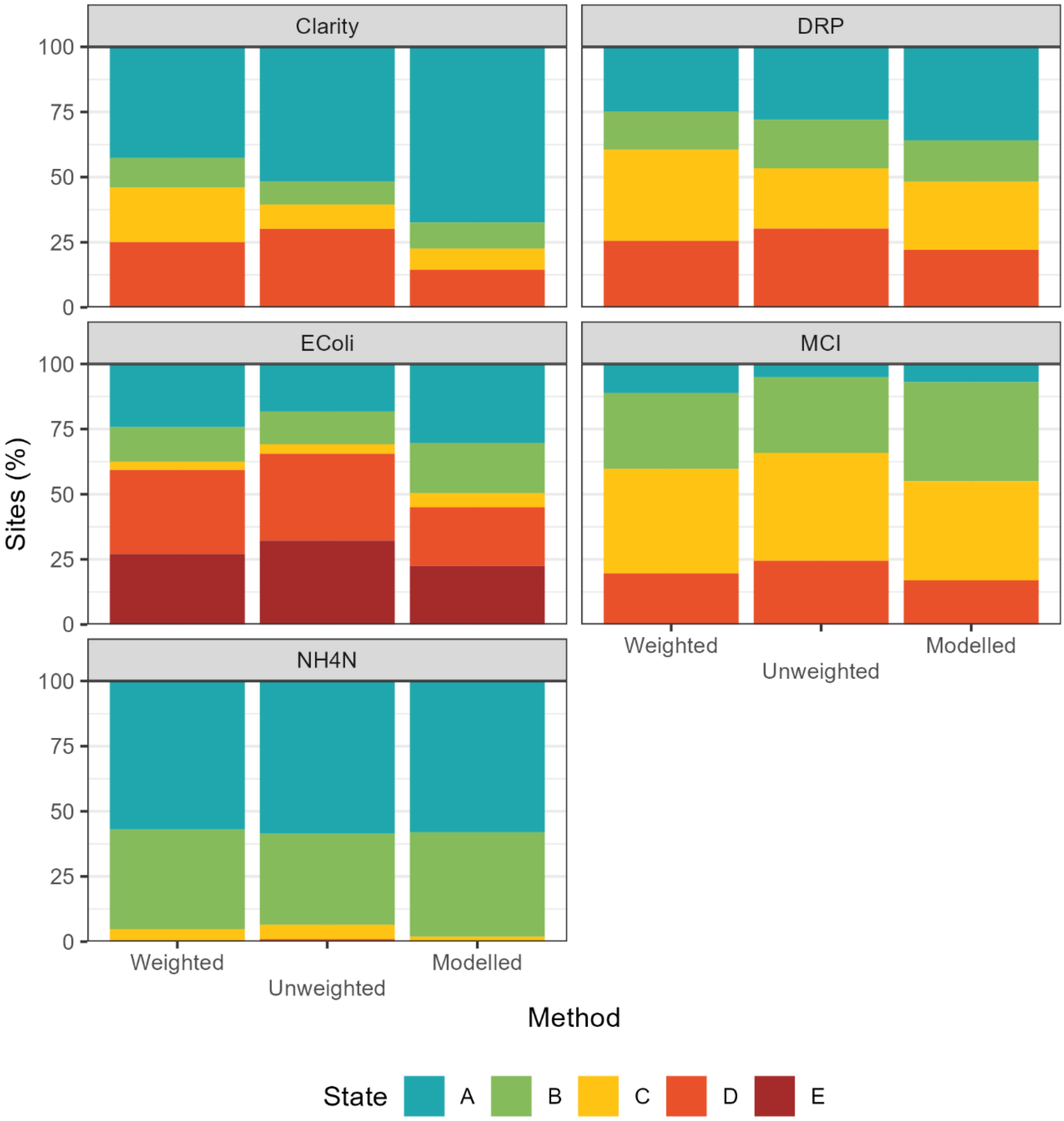

Figure 4. Unweighted and weighted LAWA attribute state scores, reweighted based on the FENZ__ENV_DIST method. Unweighted and weighted LAWA attribute state scores, reweighted based on the FENZ__ENV_DIST classes. Note only the attribute *E. coli* has an 'E' band (the scale is A-D for the rest), 'modelled' is from the random forest model results of Whitehead et al. (2022), 'unweighted' are the raw LAWA results and 'weighted' is the FENZ__ENV_DIST result.

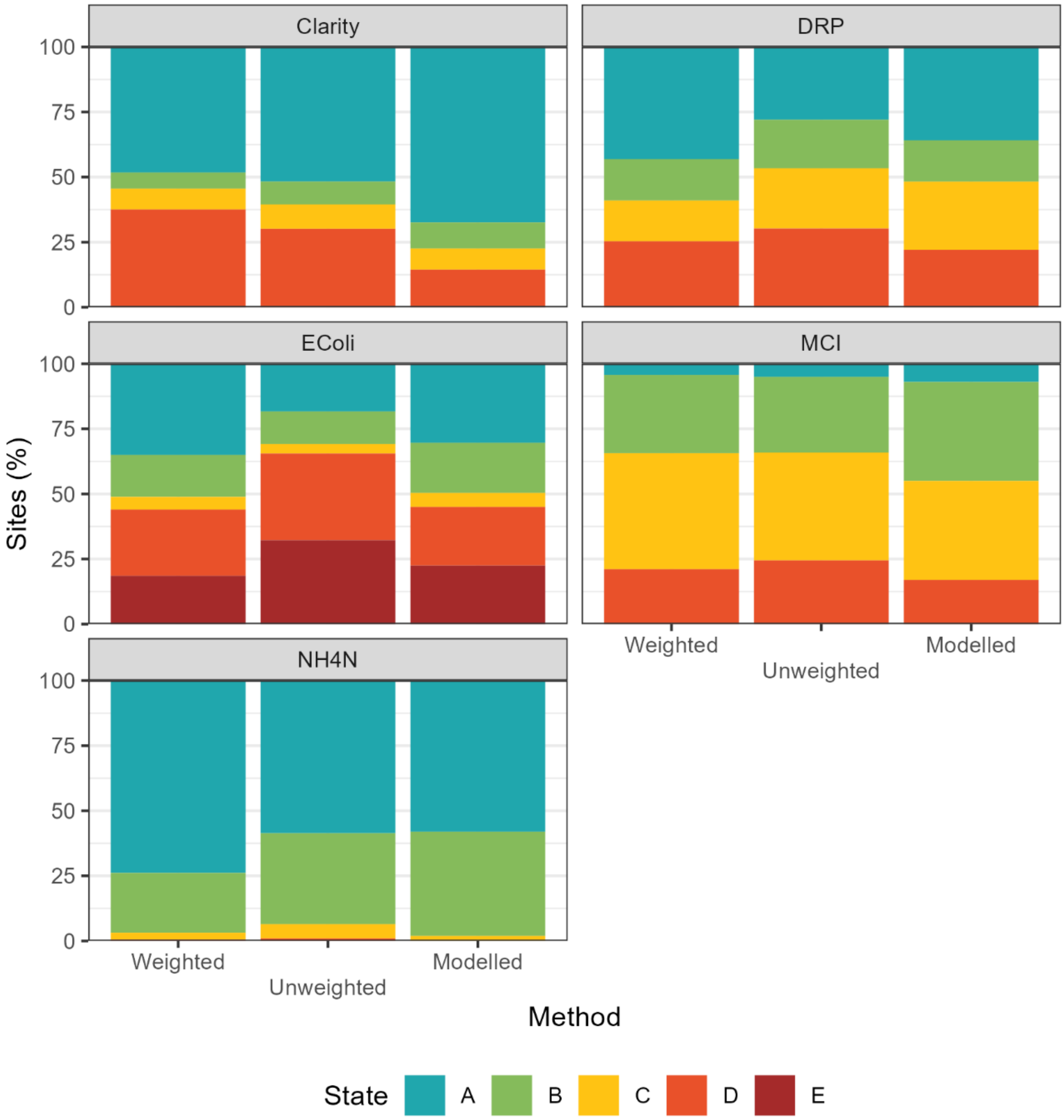

Figure 5. Unweighted and weighted LAWA attribute state scores, reweighted based on the REC_CL method. Unweighted and weighted LAWA attribute state scores, reweighted based on the REC_CL classes. Note only the attribute *E. coli* has an 'E' band (the scale is A-D for the rest), 'modelled' is from the random forest model results of Whitehead et al. (2022), 'unweighted' are the raw LAWA results and 'weighted' is the REC_CL result.

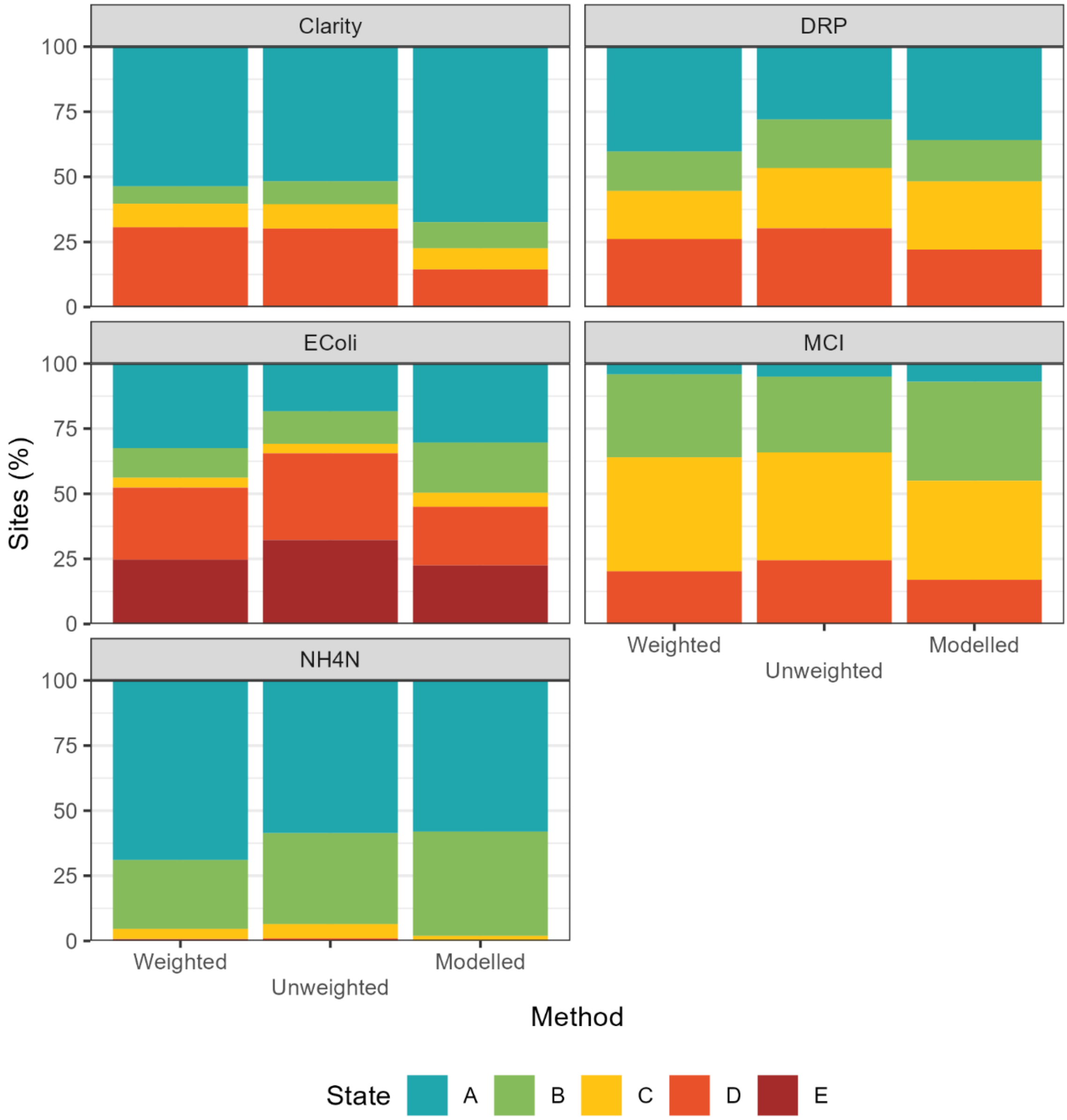

Figure 6. Unweighted and weighted LAWA attribute state scores, reweighted based on the REC_CSOFG method. Unweighted and weighted LAWA attribute state scores, reweighted based on the REC_CSOFG classes. Note only the attribute *E. coli* has an 'E' band (the scale is A-D for the rest), 'modelled' is from the random forest model results of Whitehead et al. (2022), 'unweighted' are the raw LAWA results and 'weighted' is the REC_CSOFG result.

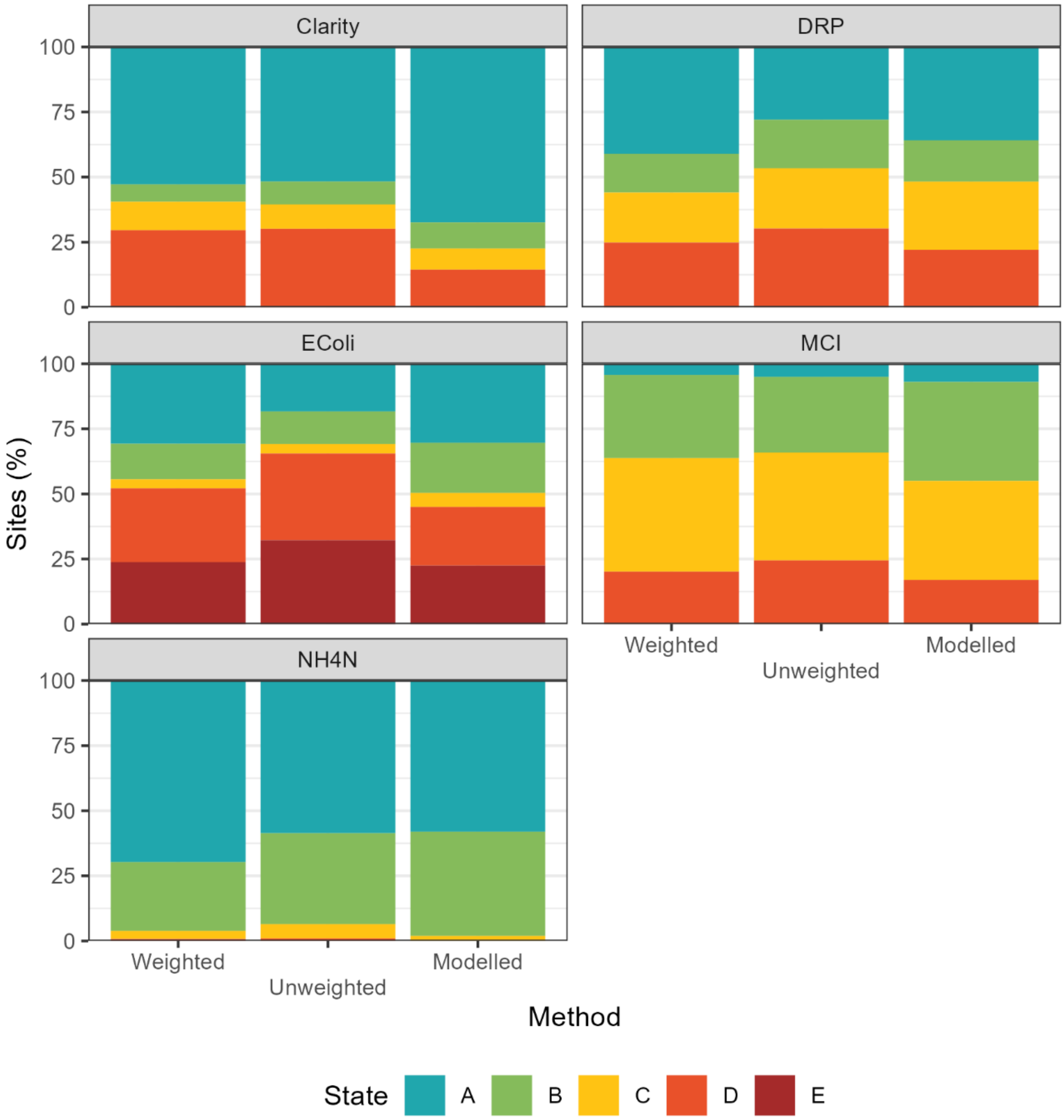

Figure 7. Unweighted and weighted LAWA attribute state scores, reweighted based on the REC_CSOFGL method. Unweighted and weighted LAWA attribute state scores, reweighted based on the REC_CSOFGL classes. Note only the attribute *E. coli* has an 'E' band (the scale is A-D for the rest), 'modelled' is from the random forest model results of Whitehead et al. (2022), 'unweighted' are the raw LAWA results and 'weighted' is the REC_CSOFGL result.

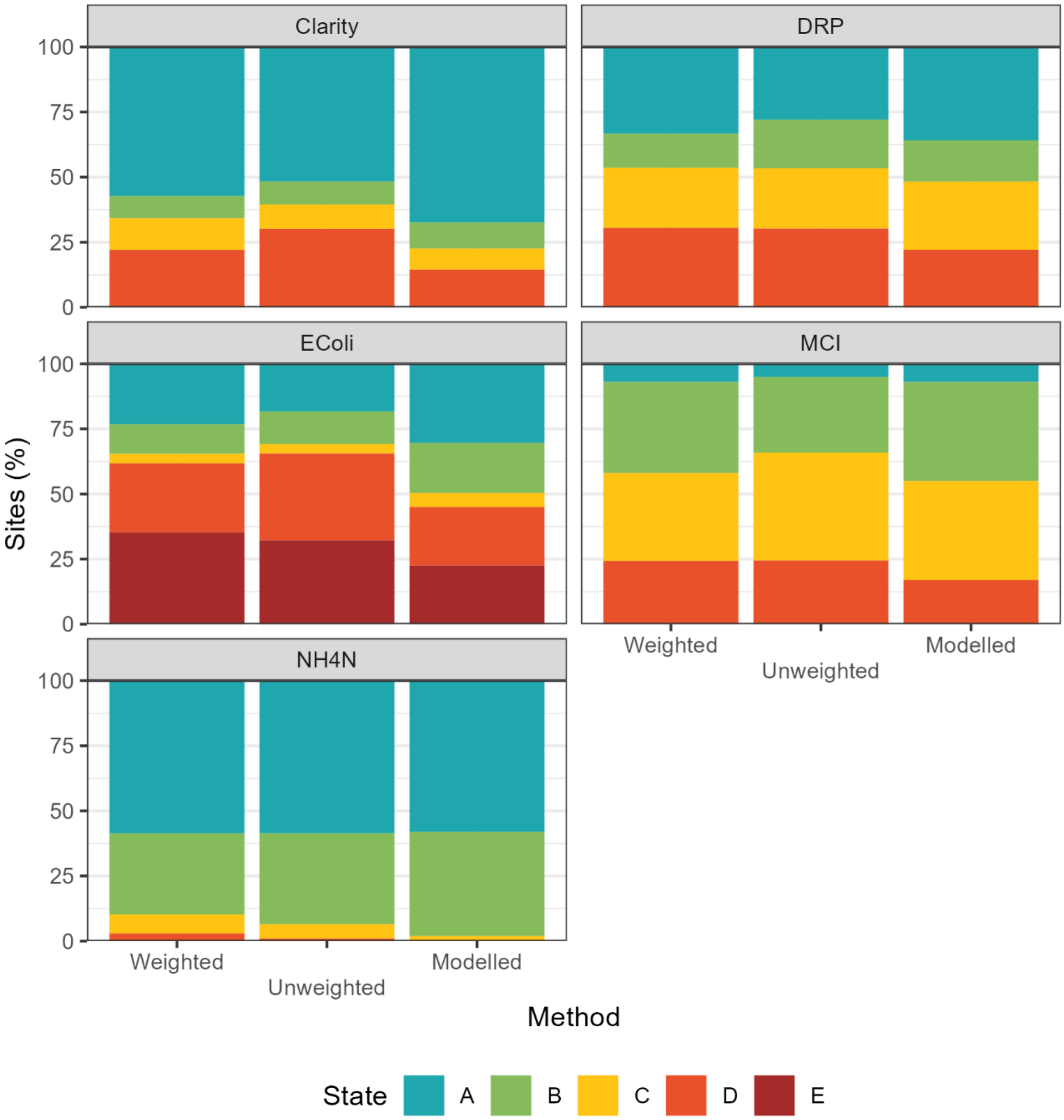

Figure 8. Unweighted and weighted LAWA attribute state scores, reweighted based on the REC_CSOFGLNP method. Unweighted and weighted LAWA attribute state scores, reweighted based on the REC_CSOFGLNP classes. Note only the attribute *E. coli* has an 'E' band (the scale is A-D for the rest), 'modelled' is from the random forest model results of Whitehead et al. (2022), 'unweighted' are the raw LAWA results and 'weighted' is the REC_CSOFGLNP result.

3.3. Distance of reaches to monitoring sites

The geographic distance ("as the crow flies") of reaches to the nearest monitoring site was relatively similar for the six reweighting methods used. The FENZ_20 method had the lowest median distance (15.5 km), whereas the FENZ_ENV_DIST method had the highest median distance (118 km). A smaller distance is preferred because as a reach and a monitoring site get further apart, they are increasingly likely to vary in ways not captured in the REC or FENZ classifications used here.

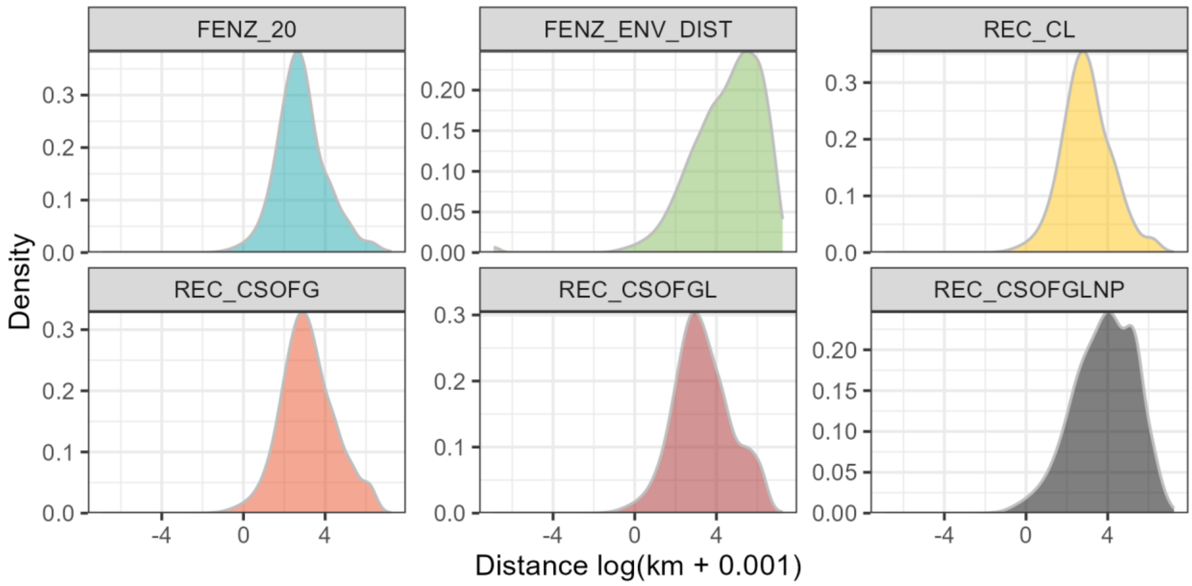

Figure 9. Geographic distance of reaches to their associated monitoring sites, for each of the six reweighting methods used. Note the distances displayed on a log axis.

4. SUMMARY

Overall, the six methods used to reweight LAWA state indicators DRP, NH4N, MCI, Clarity and *E. coli* resulted in relatively similar changes to LAWA indicator scores, with a broad trend of a small increase in the proportion of sites in the A and B band for all indicators except Clarity. Given the current monitoring network under-represents sites that are more likely to have low levels of human impact, the observed results are as expected, although we perhaps anticipated a greater increase in the number of sites in the A and B categories. These results suggest i) the LAWA monitoring network already adequately represents the wider catalogue of rivers, or ii) the classification methods tested here do not effectively match monitoring sites with reaches. Overall, the relatively small changes in the proportion of sites in each of the attribute bands seen in the results here, and those modelled by Whitehead et al. (2022), indicate that with the input data available, LAWA is presenting a reasonable national picture of water quality across Aotearoa.

Here, we presented the results of reweighting the 'state' attribute; however, an additional component of the water quality picture is the 'trend' attribute. Extrapolating the trend for all sites across Aotearoa, either through modelling or a reweighting approach, will likely be less accurate than extrapolating state estimates because there are fewer sites where there are trend estimates, and this will be increasingly true for the longer trend periods (e.g. 15-year trends). Similarly, if state and trend are combined into a single metric, there will be a large number of sites with either state or trend missing, and thus the dataset used to extrapolate information for the whole country will be smaller still. Ultimately, if there is a desire to extrapolate a combined state / trend metric across Aotearoa, the modelling-based approach is likely the best option, as there are formal model evaluation tools available that can be used to quantify the accuracy of model results (e.g. using training data and root mean square deviation).

None of the methods evaluated make constraints on the maximum distance a reach must be from a monitoring site to be attributed to it. Adding a maximum distance could be beneficial, as sites at opposite ends of the country could be grouped together despite having differences that are not captured in the REC or FENZ database. Conversely, if a maximum distance is set too small, it may not be possible to find a similar site within that range, resulting in a large number of unclassified sites. Another consideration is that as the number of subcategories associated with a method increases, it becomes more likely that there may be no (0) monitoring sites in some of the subcategories. Therefore, with all but the simplest (e.g. just using REC land cover) methods, there will be a number of reaches that cannot have an associated monitoring site. This results in the undesirable effect of having to exclude reaches from the reweighting, which in turn weakens the intended national-scale inferences. This issue was particularly apparent for the most complex method (REC_

CSOFGLNP), where over 40% of reaches could not be associated with a monitoring site (Figure 2; Appendix 1).

Here, we used pre-existing REC and FENZ categories to associate monitoring sites with reaches. In the future, it could be worth exploring custom categorisation methodologies based on more recent physiochemical and land use data and building custom classifications. A method that operates in continuous space is preferable; for example, the ENV_DIST method does not have the classification issue outlined above. Ultimately, a model-based approach (such as the random forest regression approach as implemented by Whitehead et al. 2022) to predict reach indicator values is likely the best solution. Significantly, the large amount of data required for such models already exists, and moreover, the models have been shown to perform relatively well and do not require reaches to be pre-classified into groups.

Ultimately, while there are certainly biases in the distribution of monitoring sites (for example across land use classes), the relatively small deviation in results between raw LAWA monitoring sites, national reweighted results and national modelled results (e.g. https://www.stats.govt.nz/indicators/river-water-quality-phosphorus) suggests that the council river monitoring site network does a reasonably good job of representing the national water quality picture, at least for second-order and above reaches.

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Appendix 1. Reaches not associated with monitoring sites

For each of the six reweighting methods used, a proportion of subclasses contained no (0) monitoring sites. Therefore, reaches in these subclasses could not be used to reweight attribute scores. The number of subclasses that did not contain a monitoring site increased with the complexity of the reweighting method, i.e. REC_CL had relatively few unused reaches (less than 5%; Figure A1.1), whereas REC_CSOFGLNP had many (over 40%; Figure A1.2.).

Figure A1.1. Map illustrating reaches that belonged to a REC_CL class that did not contain a monitoring site and could therefore not be used when reweighting indicator scores.

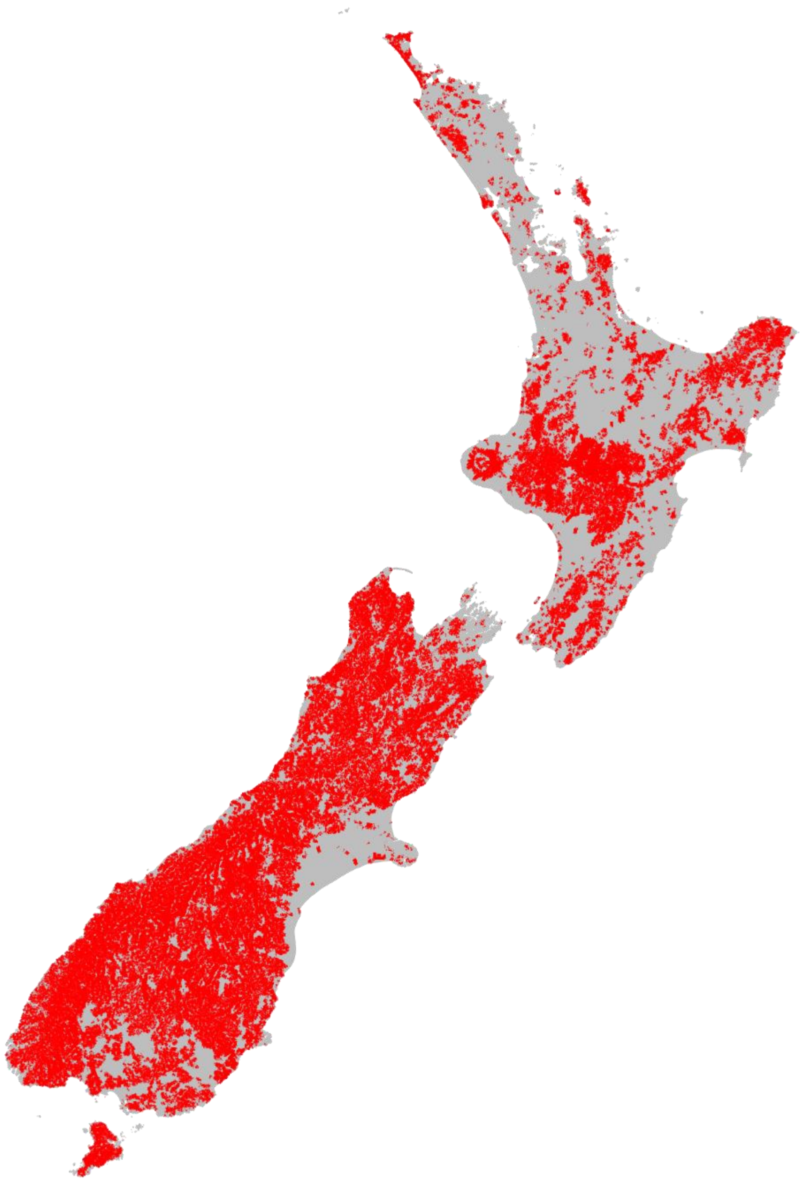

Figure A1.2. Map illustrating reaches that belonged to a REC_CSOFGLNP class that did not contain a monitoring site and could therefore not be used when reweighting indicator scores.

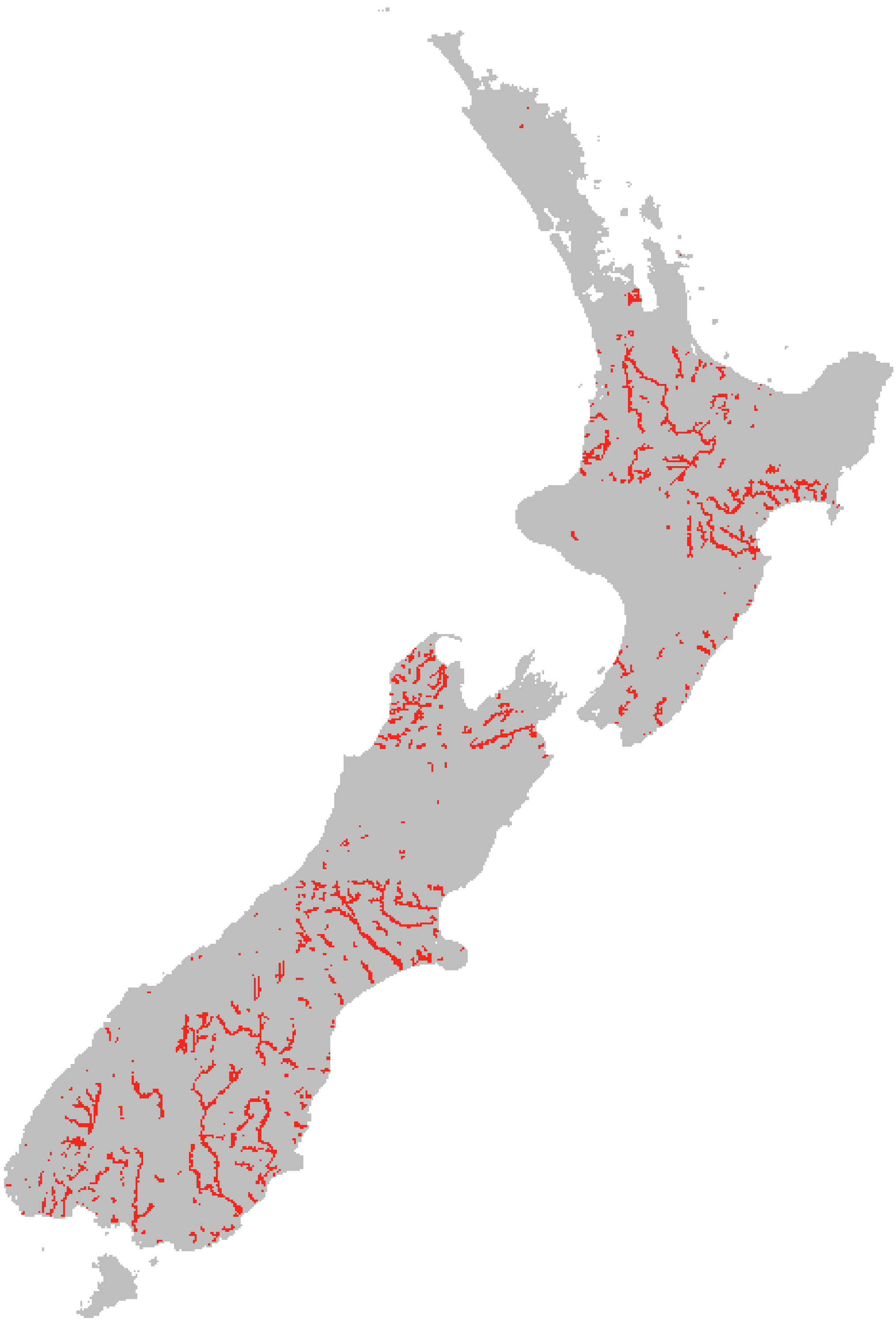

Figure A1.3. Map illustrating REC reaches that did not have a FENZ_20 classification.