**Mayfield and Dempsey Appendix A-Supplemental Methods**

***Coral health index (CHI)-details.*** The CHI is described in detail in prior works (see main text for references.) but has been redescribed here for convenience. It involves averaging four metrics of coral performance as follows. First, a “heat map score” (HMS) is first calculated across the 10 univariate response variables (RNA/DNA ratio, Symbiodiniaceae GCP, four host coral gene mRNAs, & four endosymbiont RNAs [Table 2]); this is akin to summing all response variables that fell outside the normal range for a healthy coral. For instance, if two thermal stress biomarkers fell outside the normal reference range (Table 2), the biopsy would receive an HMS of 2. The second parameter used in the calculation of the CHI is the “color metric,” which is the average of the inverse-standardized color score (since high color scores are indicative of healthy corals, & we aimed for the color metric to scale to where high values are reflective of stressed corals), the inverse-standardized Symbiodiniaceae GCP, and the standardized tissue necrosis score (the percentage of the colony with either completely bleached or necrotic tissue). The variability index is the third parameter used in the calculation of the CHI; this is simply the standard deviation across the standardized means of all continuous response variables used in calculation of the HMS. As higher variation is indicative of loss of control of homeostasis, higher variability index values reflect corals of compromised health. Finally, the Mahalanobis distance is calculated to serve as the multivariate counterpart to the variability index, indicating the degree of multivariate deviation from normal behavior; high Mahalanobis distances are strong evidence for physiological stress.

The HMS, color metric, variability index, and Mahalanobis distance were each standardized across all samples individually, averaged for each individual, and then standardized again across all pocilloporid coral samples. The resulting values were then multiplied by -1 since the CHI scales to where low values are for stressed corals and high values are for resilient ones. These values were next converted to normal quantile scores, then range-scale-adjusted to where they spanned 0 to 1. Finally, these values were multiplied by 5 to yield the final CHI scores. In the example shown in Table 2, the respective *z*-scores of the HMS, color metric, variability index, and Mahalanobis distance are 1.2, 0.2, 3.5, and not estimable (the Mahalanobis distance cannot be calculated with missing data, & not all response variables were measured for this sample.), respectively. The three values would be averaged (1.6), assessed against the respective means of all other samples, and once again standardized: -2.5. This value would then be converted to a normal quantile score (-1.7), range-scaled from 0 to 1 (0.16), and then multiplied by 5 to yield a CHI of 0.8, which is evidence for extreme physiological stress.

**Mayfield and Dempsey Appendix B-Supplemental Tables**

**Table A1.** Predictive models of the coral health index (CHI) as either continuous or binned into five levels.Onlymodels with misclassification rates (MR)≤10% or validation (Val) R2>0.8 (for continuous CHI) were considered to be useful for managers. See Table 1 and Appendix C for the environmental (ENV) and ecological (ECO) parameters. The MR was averaged across 10 runs since upwards of 200 tours were featured in the neural networks (NN). The NN structure, most important environmental factor (EF), and model script name are only shown for those with MR≤10% or Val R2>0.7. HL=hidden layer.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Model name** | **#EF in model** | **Superior model type**  (# models tested) | **Superior model MR (%)** | **NN structure/important EF/script name** |
| **CHI as 5 levels:** 0, 1, 2, 3, or 4-5 | | |  |  |
| 12 ENV+8 simple ECO | 20 | NN GUI-HL1 (n=100) | 57 |  |
| 12 ENV+all ECO | 88 | NN GUI-HL1 (n=100) | 62 |  |
| 16 ENV+all ECO | 92 | NN GUI-HL1 (n=100) | >50 |  |
| 17 ENV+5 PHYS+73 ECO | 95 | NN GUI-HL1 (n=600) | 10 | Gaussian(1)-boost(11)/max. colony length/neural of CHI (norm quant)-binned 95 EF HL1 MR=10% |
| **Continuous CHI:** 0 to 5 | |  | **Val R2** |  |
| 16 ENV+all ECOa | 92 | NN GUI-HL1 (n=500) | 0.55 |  |
| 17ENV+all ECOa | 93 | NN GUI-HL1 (n=100) | 0.56 |  |
| 93 EFb | 93 | NN GUI-HL1 (n=100) | 0.67 |  |
| 93 EFb | 93 | NN GUI-HL2 (n=300) | all failed |  |
| 95 EFb | 95 | NN GUI-HL1 (n=100) | 0.72 | tanH(4)-linear(2)-Gaussian(5)-boost(7)/sum(coral genera) |
| 111 EFa | 111 | NN GUI-HL1 (n=200) | 0.76 | tanH(9)-linear(3)-Gaussian(8)-boost(3)/generic diversity |

aCHI as normal quantile (norm quant) scores. bCHI as cumulative probabilities.

**Table A2.** Predictive models of coral resilience with a categorical Y: resilient vs. sick/weak.The environmental (ENV) and ecological (ECO) parameters are as in Table 1. The misclassification rate (MR) was averaged across 10 runs of each neural network (NN). The NN structure, most important environmental factor (EF), and script name are only shown for those with MR<20%. HL=hidden layer.

| **Model name**  (#EF in model) | **Superior model type** | **#models tested** | **Superior model MR** (%) | **NN structure/important EF/script name** |
| --- | --- | --- | --- | --- |
| ENV only (n=17) | NN GUI-HL1 | 700 | 32 |  |
| ENV only (n=17) | NN GUI-HL2 | 2,300 | 22 |  |
| 12 ENV+6 simple ECO (n=18) | NN GUI-HL1 | 500 | 27.5 |  |
| 12 ENV+6 simple ECO (n=18) | NN GUI-HL1 | 200 | 23.7 |  |
| 23 predictors | NN GUI-HL1 | 300 | 8.7 | Gaussian(1)-boost(17)/coral cover-binned/ neural of healthy vs. sick 23 EF HL1 MR=9%a |
| 22 predictors (23 EF minus Symbiodiniaceae assemblage) | NN GUI-HL1 | 300 | 11 | Gaussian(1)-boost(10)/max. length/neural of healthy vs. sick 22 EF HL1 MR=11%b |
| 23 predictors | NN GUI-HL2 | 500 | 23 |  |
| All benthic+all ECO minus 4 (n=93) | NN GUI-HL1 | 600 | 17 | Gaussian(1)-boost(2)/ max. colony length/neural of healthy vs. sick 93 EF HL1 MR=17% |
| All benthic+all ECO minus 4 (n=93) | NN GUI-HL2 | 1,000 | 19.5 | tanH(4)-linear(1)-Gaussian(3)-tanH2(1)-linear2(5)-Gaussian2(2) |
| 95 predictors | NN GUI-HL1 | 100 | 20.5 |  |
| All ENV+all ECO (minus island; n=96) | NN GUI-HL1 | 1,000 | 10.5 | Gaussian(1)-boost(4)/depth & PAR/neural of healthy vs. sick 96 EF HL1 MR=10.5% |
| All ENV+all ECO (n=97) | NN GUI-HL1 | 300 | 11 | Gaussian(1)-boost(11)/generic diversity/  neural of healthy vs. sick 97 EF HL1 MR=11% |
| All ENV+all ECO (n=97) | NN GUI-HL2 | 2,000 | 21 |  |
| Most ENV+all ECO+ multivariate (n=103) | NN GUI-HL1 | 500 | 0/35c |  |

aSee Figure 3. bSeeFigure 5. cUsed validation (0% MR) and field test samples (35% MR) to reduce chance of over-fitting.

**Table A3.** Torch analysis of coral resilience (resilient vs. sick/weak). The 329-image data table was split into 75% training/25% validation data. All models were run with 20 epochs. Despite the rich information contained in images of the coral colonies (taken with an Olympus TG2 underwater camera with *in situ* white balancing), no Torch model approached the accuracies obtained from the boosted neural networks (Table A2). The images used can be found on [coralreefdiagnostics.com](http://coralreefdiagnostics.com/) under the Palau section.

| **Model name**  (#EF in model) | **Image model** | **Tabular model** | **Learning rate** | **Superior model accuracy** (%) |
| --- | --- | --- | --- | --- |
| Images only (n=1) | LeNet5 | Multilayer perceptron | 0.001 | 60 |
| Images only (n=1) | LeNet5 | FTTransformer | 0.001 | 59 |
| Images only (n=1) | LeNet5 | Multilayer perceptron | 0.01 | 56 |
| Images only (n=1) | LeNet5 | FTTransformer | 0.01 | 59 |
| Images only (n=1) | LeNet5 | Multilayer perceptron | 0.1 | 63 |
| Images only (n=1) | LeNet5 | FTTransformer | 0.1 | 63 |
| Images only (n=1) | LeNet5 | Multilayer perceptron | 1 | 63 |
| Images only (n=1) | LeNet5 | FTTransformer | 1 | 57 |
| Images only (n=1) | CustomConv2D | Multilayer perceptron | 0.001 | 59 |
| Images only (n=1) | CustomConv2D | FTTransformer | 0.001 | 43 |
| Images only (n=1) | CustomConv2D | Multilayer perceptron | 0.01 | 64 |
| Images only (n=1) | CustomConv2D | FTTransformer | 0.01 | 63 |
| Images only (n=1) | CustomConv2D | Multilayer perceptron | 0.1 | 61 |
| Images only (n=1) | CustomConv2D | FTTransformer | 0.1 | 50 |
| Images only (n=1) | GoogLeNet | Multilayer perceptron | 0.001 | 60 |
| Images only (n=1) | GoogLeNet | FTTransformer | 0.001 | 42 |
| Images only (n=1) | GoogLeNet | Multilayer perceptron | 0.01 | 54 |
| Images only (n=1) | GoogLeNet | FTTransformer | 0.01 | 63 |
| Images only (n=1) | GoogLeNet | Multilayer perceptron | 0.1 | 43 |
| Images only (n=1) | GoogLeNet | FTTransformer | 0.1 | 63 |
| Images only (n=1) | EfficientNet\_B1 | Multilayer perceptron | 0.001 | 59 |
| Images only (n=1) | EfficientNet\_B1 | FTTransformer | 0.001 | 60 |
| Images only (n=1) | EfficientNet\_B1 | Multilayer perceptron | 0.01 | 48 |
| Images only (n=1) | EfficientNet\_B1 | FTTransformer | 0.01 | 48 |
| Images only (n=1) | EfficientNet\_B1 | Multilayer perceptron | 0.1 | 62 |
| Images only (n=1) | EfficientNet\_B1 | FTTransformer | 0.1 | 63 |
| Image+19 predictors (n=20) | LeNet5 | Multilayer perceptron | 0.001 | 60 |
| Image+19 predictors (n=20) | LeNet5 | Multilayer perceptron | 0.01 | 70 |
| Image+19 predictors (n=20) | LeNet5 | Multilayer perceptron | 0.1 | 64 |
| Image+99 predictors (n=100) | LeNet5 | Multilayer perceptron | 0.001 | 61 |
| Image+99 predictors (n=100) | LeNet5 | Multilayer perceptron | 0.01 | 65 |
| Image+99 predictors (n=100) | LeNet5 | Multilayer perceptron | 0.1 | 69 |
| Image+99 predictors (n=100) | LeNet5 | Multilayer perceptron | 1 | 71 |