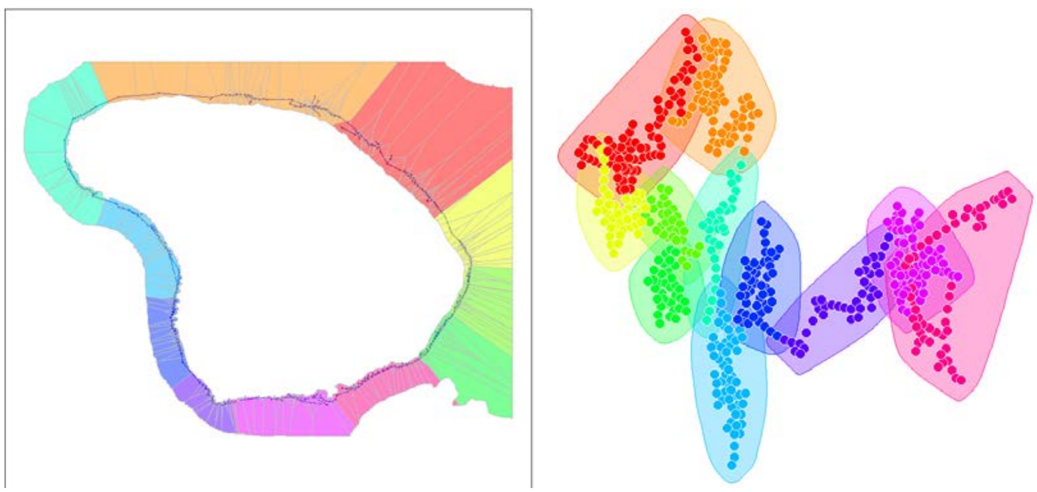
Downscaling Ecological Trends from the Spatially Randomized Datasets of the National Coral Reef Monitoring Program

Thomas A. Oliver, Hannah Barkley, Courtney Couch, Tye Kindinger, Ivor Williams



U.S. DEPARTMENT OF COMMERCE
National Oceanic and Atmospheric Administration
National Marine Fisheries Service
Pacific Islands Fisheries Science Center

NOAA Technical Memorandum NMFS-PIFSC-106
https://doi.org/10.25923/2fef-8r42

July 2020

Downscaling Ecological Trends from the Spatially Randomized Datasets of the National Coral Reef Monitoring Program

Thomas A. Oliver[1], Hannah Barkley[2], Courtney Couch[2], Tye Kindinger[2], Ivor Williams[1]

[1] Pacific Islands Fisheries Science Center
National Marine Fisheries Service
1845 Wasp Boulevard
Honolulu, HI 96818

[2] Joint Institute for Marine and Atmospheric Research
University of Hawaii
1000 Pope Road
Honolulu, Hawaii 96822

NOAA Technical Memorandum NMFS-PIFSC-106

July 2020

U.S. Department of Commerce
Wilbur L. Ross, Jr., Secretary

National Oceanic and Atmospheric Administration
Neil A. Jacobs, Ph.D., Acting NOAA Administrator

National Marine Fisheries Service
Chris Oliver, Assistant Administrator for Fisheries

Recommended citation

Oliver TA, Barkley H, Couch C, Kindinger T, Williams I. 2020. Downscaling ecological trends from the spatially randomized datasets of the National Coral Reef Monitoring Program. NOAA Tech Memo. NOAA-TM-NMFS-PIFSC-106, 59 p. doi:10.25923/2fef-8r42

Copies of this report are available from

Science Operations Division
Pacific Islands Fisheries Science Center
National Marine Fisheries Service
National Oceanic and Atmospheric Administration
1845 Wasp Boulevard, Building #176
Honolulu, Hawaii 96818

Or online at

https://repository.library.noaa.gov/

Cover: Minimum spanning tree of clustered coral reef benthic cover data, Lana‘i, 2005–2015.

Table of Contents

List of Tables

List of Figures

Executive Summary

For coral reef managers to cost-effectively maintain and improve reef resilience, they need to understand temporal changes in the reef ecosystem at spatial scales fine enough to capture distinctions in the ecological processes affecting reefs. (Anthony et al. 2015). This monitoring challenge is relatively simple with fixed plot data, but in regionally-focused monitoring programs with spatially randomized sampling it can be very challenging to infer trends over any scale except that for which the survey was explicitly designed (e.g., region, island, sector; Smith et al. 2011). While useful for tracking regional/island scale responses, many ecological drivers and responses that may shed light on patterns of resilience occur at smaller spatial scales than those addressed in regional monitoring designs (McClanahan et al. 2012).

For the National Coral Reef Monitoring Program (NCRMP), the problem is particularly acute. Constraining NCRMP's ecological reporting within the traditional design poses three fundamental problems: (1) NCRMP random sampling programs are designed to be summarized across **large spatial areas**, and it is difficult to assess temporal patterns at any scale different from the explicit, *a priori* design scale (i.e., region/island/sector, Smith et al. 2011; Brainard et al. 2014). (2) Our defined sampling sectors were designed by expert opinion about likely patterns in reef ecology, not from benthic data explicitly; therefore, existing sectors may be **ecologically heterogeneous**. (3) As the traditional analysis has no built-in mechanism to account for methodological variation, we **rarely compare distinct methods** measuring the same parameters, and thereby limit the temporal range over which we attribute trends.

To address these linked issues, we present a statistical technique based on *contiguous clustering* and *mixed model analysis* to downscale the NCRMP Pacific Reef Assessment and Monitoring Program data and apply it to a case study in the main Hawaiian Islands (Barrett 2011; Bates et al. 2015).

Our goals in this analysis are to (1) identify spatial sectors that are smaller than our current survey design scale while retaining robust, responsible statistical sampling, (2) ensure that our sectors are as ecologically homogenous as possible, and (3) extend our temporal coverage and sampling density by responsibly comparing similar metrics across multiple methods within the coherent statistical framework of a mixed-effects model.

Specifically, we identify clusters based on NCRMP benthic cover data from four different survey methods, and then use mixed model analysis to assess both the optimal number of spatial sectors and the significance of long-term temporal change in hard coral cover in each newly created sector. Interesting patterns in Hawaiian percent cover data are revealed with significant long-term trends that are obscured at the island level: 13 out of 63 sectors show long-term decline, and only 4 out of 63 show an increase in coral cover.

Introduction

A Fundamental Monitoring Challenge for Resilience-Based-Management

As reef managers increasingly focus on implementing resilience-based management, fine scale data on reef ecological processes are more important than ever (Mcleod et al. 2019). For coral reef managers to cost-effectively maintain and improve reef resilience, they need to understand temporal changes in the reef ecosystem at spatial scales fine enough to capture distinctions in the ecological processes affecting reefs. (Anthony et al. 2015).

This monitoring challenge is relatively simple with fixed plot data, but in regionally-focused monitoring programs with spatially randomized sampling it can be very challenging to infer trends over any scale except that for which the survey was explicitly designed (e.g., region, island, sector; Smith et al. 2011). In addition, coral reefs and the drivers of reef ecological processes are notoriously patchy in space (Hamylton 2013). While broad-scale monitoring data are useful for tracking regional/island scale responses, many ecological drivers and responses that may shed light on patterns of resilience occur at smaller spatial scales than those addressed in regional monitoring designs (McClanahan et al. 2012). By reporting the 'mean' results of large, heterogeneous sectors, such monitoring programs run the risk of obscuring underlying ecological distinctions that may be key to the success of resilience-based management (Mcleod et al. 2019).

For the National Coral Reef Monitoring Program (NCRMP), this challenge is particularly acute. Pacific NCRMP has an enormous sampling domain, spanning 49 islands spread across 6,000 kilometers of ocean. In designing a program to efficiently sample this space, NCRMP's designers explicitly committed to geographically comprehensive sampling, as they feared selected fixed sites would fail to be adequately representative (Brainard et al. 2014). When faced with real-world budgets and sampling logistics, this "wide-but-thin" strategy leads to relatively large reporting sectors and builds an explicit tension between geographic comprehensiveness and fine spatial reporting.

Constraining ecological reporting within the traditional NCRMP design poses three fundamental problems: (1) NCRMP random sampling programs are designed to be summarized across **large spatial areas**, and it is difficult to assess temporal patterns at any scale different from the explicit, *a priori* design scale (i.e., region/island/sector, Smith et al. 2011; Brainard et al. 2014). (2) Our defined sampling sectors were designed by expert opinion about likely patterns in reef ecology, not from benthic data explicitly; therefore, existing sectors may be **ecologically heterogeneous**. (3) As the traditional analysis has no built-in mechanism to account for methodological variation, we **rarely compare distinct methods** measuring the same parameters, and thereby limit the temporal range over which we attribute trends.

A Proposed Solution

The solution we propose here is a version of statistical downscaling, which is less focused on the efficient allocation of sampling effort, like that provided by statistical survey design principles (e.g., Smith et al. 2011), and more on finding the optimal balance between statistical robustness and a fine spatial scale of reporting in an existent dataset (e.g., Benestad et al. 2008).

While a common endeavor in the field of climate modeling and meteorology (Benestad et al. 2008), statistical downscaling is increasingly applied to ecological data (Wu et al. 2006; Azaele et al. 2012; Keil and Jetz 2014; Pourmokhtarian et al. 2016). Both ecological and climate modeling utilize a broad range of statistical techniques ranging from Empirical Orthogonal Functions (EOF), linear models, heirarchical mixed models, and a range of clustering techniques (Benestad et al. 2008).

Here we apply *spatially contiguous clustering* and *mixed model analysis* to downscale the NCRMP Pacific Reef Assessment and Monitoring Program data and apply it to a case study in the main Hawaiian Islands (Barrett 2011; Bates et al. 2015). Our goals in this analysis are to (1) identify spatial sectors that are smaller than our current survey design scale while retaining robust, responsible statistical sampling, (2) ensure that our sectors are as ecologically homogenous as possible, and (3) extend our temporal coverage and sampling density by responsibly comparing similar metrics across multiple methods within the coherent statistical framework of a mixed-effects model.

The contiguous clustering method we apply links neighboring sampling points in a graph representation, estimates similarity between linked points, and calculates a minimum spanning tree to find natural divisions between groups of neighbors (Assunção et al. 2006). We then apply mixed model analysis (Zuur et al. 2009) to the resulting groups to both define the optimal balance between fine spatial resolution and statistical robustness and to analyze the resulting grouped data.

Methods

We detail the methods using the benthic data from the main Hawaiian Islands as a case study, but the methods are easily generalizable to other data types and other geographies. Throughout this methodological description, we will refer to our code-base, developed in R, available upon request of the authors (R Developement Core Team 2015).

A. Methodological Walk-through

The method we present here consists of four major sections: (1) data compilation, (2) hierarchical contiguous clustering, (3) assessment of appropriate cluster level, (4) mixed model assessment of trends.

1. Data Compilation

First, we summarize relevant data across methodologies and metrics. A key step in this process is to thoughtfully, with an understanding of the respective methods, compile data into an analyzable dataset detailed below.

1A. Acquire and Compile Datasets, Linking Parameters across Methods.

In the MHI case, we use 4 datasets of proportional benthic cover: Benthic Towed Diver Survey (TDS; 2005−2016), Line Point Intercept Surveys (LPI; 2006−2015), and photo-quadrat surveys analyzed using both Coral Point Count with Excel Extensions (CPCE; 2010−2013) and CoralNet (CN; 20015−2016). Across these distinct methods, we identified 6 benthic percent cover categories that could be responsibly compared: *Hard Coral Cover*, *Soft Coral Cover*, *Crustose Coralline Algal Cover*, *Total Algal Cover (lumping Turf/Macro)*, *Sand/Sediment*, and all *Other* characterized benthos. Thereby we generated a set of 6,840 points of characterized benthos, spanning 7 islands and 11 years, 2005 through 2016 (Table 1).

It is important to strike the appropriate balance between including datasets that will increase the spatial and temporal scope of one's analysis, and limiting the analysis to those datasets that can be responsibly compared without greatly reducing the ecological utility of the combined dataset due to either the paucity or coarseness of the retained measures. Broader inclusion across methods will likely mean a coarser description of benthic status as one's analysis will be limited by the coarsest of the available methods, such as TDS. In this methodological demonstration, we skewed toward inclusion and chose to provide wide temporal coverage and hence can only describe ecologically coarse categories of benthic cover (Table 1; Figure 1).

1B. Divide Compiled Dataset into Cluster Set and Analysis Set

We divide the data into (1) the *Cluster Set*, i.e., the data we will use to define contiguous, small, homogenous, statistically robust clusters, and (2) the *Analysis Set*, i.e., the data we will analyze for temporal trends using the spatial grouping of the generated clusters.

Here, the *Cluster Set* consists of all spatial points sampled from 2005–2015, excluding any data after the coral bleaching event of 2015, to reduce temporal heterogeneity within the clusters. The *Analysis Set*, however, consists of all data, including the bleaching impacted periods.

Table 1. Descriptive Summary of Datasets by Method.

Benthic Cover Assessment Method	Description	Years Available	Total Surveyed Sites
Towed Diver Benthic Survey (TDS)	Coarse benthic description from ~200 m segments of reef.	2005, 2006, 2008, 2010, 2016	5,210
Line Point Intercept (LPI)	Small set of fixed site data transects, with cover assessed a specific points (by diver).	2006, 2008, 2010, 2014, 2015	186
Photo-quadrats – Annotated using Coral Point Count Excel Extensions (CPCE)	Spatially random sites, with 30 photos per site. Human annotation at randomized points on photo using CPCE software.	2010, 2012, 2013	792
Photo-quadrats – Annotated using CoralNet	Spatially random sites, with 30 photos per site. Human annotation at randomized points on photo using CoralNet software.	2015, 2016	652

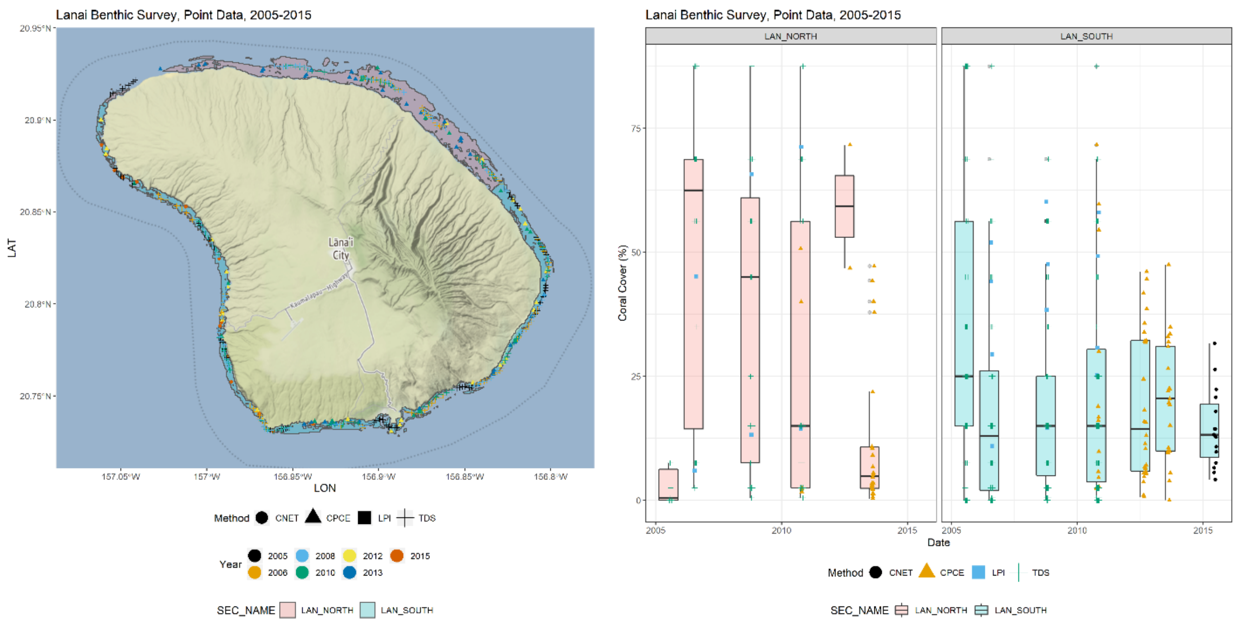


Figure 1: Baseline data example—Lana'i. Map of existing survey data Lana'i, (left). Sector scale percentage hard coral cover, by year and collection method (right).

2. *Hierarchical Contiguous Clustering*

For each island, we ran a set of methods to generate hierarchical contiguous clusters that are both spatially contiguous and as ecologically homogenous as possible.

To perform the clustering, we first convert points to polygons using Voronoi tessellation (2A), define a neighbor-joining network and assign branch lengths based on ecological distance across six benthic cover categories (2B), and then prune the network into a minimum-spanning tree (2C) to set up for evaluating the quality of defined clusters (Section 3).

2A. Points to Polygons: Voronoi Tessellation.

One of the major challenges presented by the contiguous clustering of point data is determining which data are "contiguous" to which. There are multiple approaches one could use to translate point data into data covering spatial areas, including gridding or multiple versions of interpolation (e.g., kriging). As each of those methods require an *a priori* assessment of the proper spatial scale over which to judge heterogeneity (i.e., grid size), we instead opted to convert our point data into polygon data using Voronoi tessellation.

Voronoi tessellation translates a set of points into the respective polygons that describe a nearest-neighbor "watershed" around each point, returning a polygon that represents the area in which the corresponding point is the geographically closest data point available. Points are spatially contiguous if their respective Voronoi polygons share an edge.

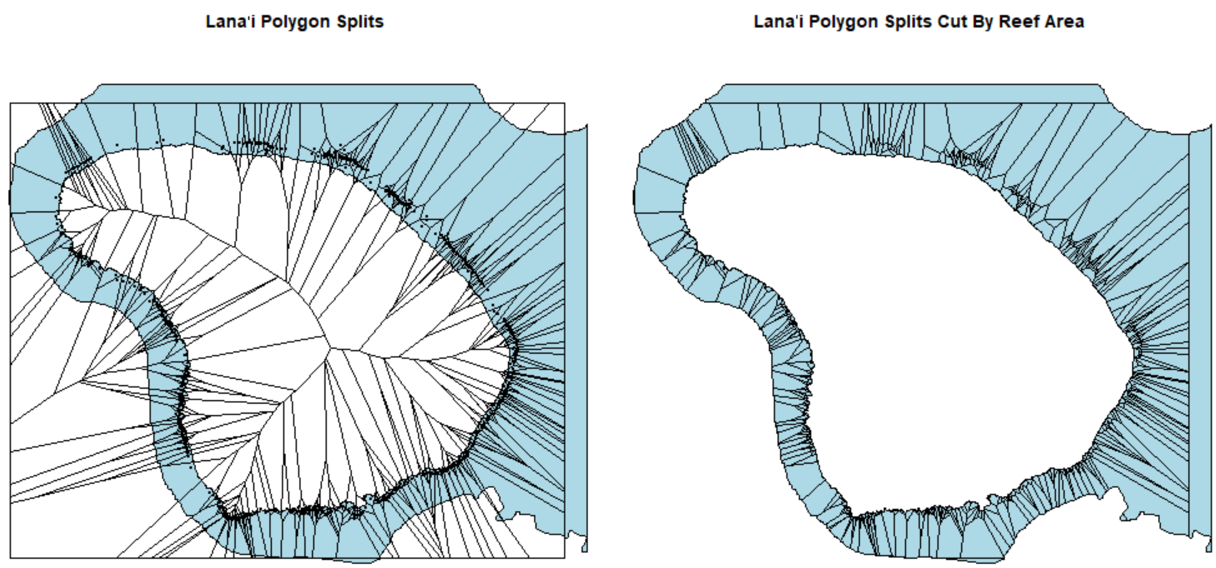


Figure 2: Voronoi tessellation. (A) Tessellation of benthic points cut by rectangular bounding box. (B) Tessellated polygons cut with bathymetry (0–100 fathoms).

However, in the real coral reef ecosystem, geographically proximate points may or may not be ecologically contiguous because land or deep water can easily come between them. Therefore, we cut the polygons generated by Voronoi tessellation with another polygon describing possible coral reef habitat. This clipping polygon is bounded by the coastline and the 100 fathom boundary, and its intersection with the Voronoi polygons returns polygons clipped to generate more ecologically reasonable proxies for neighboring points (Figure 2, Figure 3).

All analyses in this section were performed in R, using the packages *sp*, for generating SpatialPointsDataFrames, and *deldir*, for generating the Voronoi tessellation (Pebesma and Bivand 2005; Turner 2016).

Figure 3: Voronoi tessellation, Lana'i.

2B. Polygons to "Neighbor List" Network

We reformat the polygon structure into a network representation, with the nodes in the network representing each polygon, edges in the network connecting neighboring polygons, and edge weight (length) representing ecological distance as calculated by a multi-variate dissimilarity between the benthic composition of neighboring polygons (Figure 3, Figure 4).

Using the function *poly2nb* in the *spdep* package in R, we first generate a "neighbor list", a network representation of all polygon neighbor relationships, i.e., a network of the Voronoi polygons that share edges (Bivand et al. 2005). Then we scale the relationships in this network by ecological dissimilarity, essentially adding branch lengths that correspond to how different one polygon's benthic composition is from its neighbors. In our analytical code, we provide a range of distance/dissimilarity options available in the R package *vegan*, and the *spdep* functions *nbcosts* and *nb2listw* to generate the dissimilarity measures and apply them to the neighbor list, respectively (Dixon 2003).

The code is written to allow the user to choose a dissimilarity metric from among Euclidean distance, Bray-Curtis dissimilarity, Gower dissimilarity, and two different metrics of compositional dissimilarity. In this methodological example, we used the simple Euclidean distance among scaled metrics of percent cover as a robust default, but some sectors may be sensitive to this choice of dissimilarity metric.

2C. "Neighbor List" Network to Minimum Spanning Tree

Using neighbor network with edge weights proportional to ecological similarity, we can algorithmically identify the *minimum spanning tree* that represents the shortest possible path through the neighbor network, which connects all vertices. This minimum spanning tree stands as a single representation of hierarchical sets of observable contiguous clusters, that is, groups of polygons that are very ecologically similar, separated by their more ecologically distinct neighbors with longer branch lengths. By identifying the longest branch lengths in the minimum spanning tree, we can successively split the tree into more, increasingly similar subgroups (Figure 4, Figure 5), which are not only ecologically similar but also spatially contiguous.

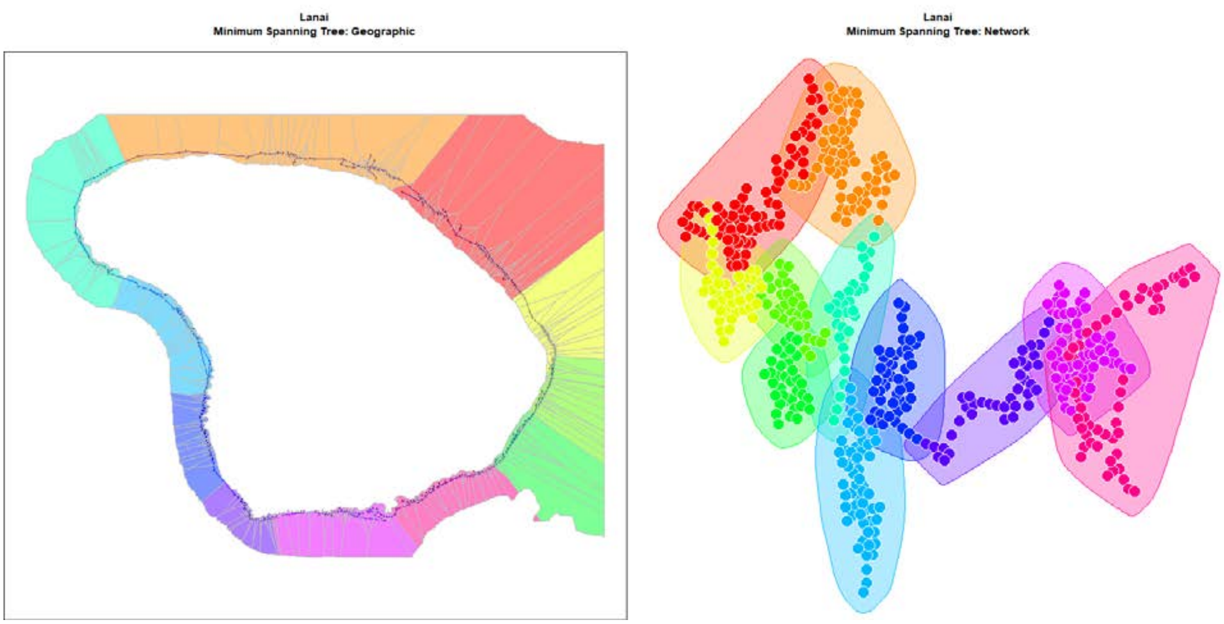


Figure 4: Contiguous clusters from 'cuts' in a minimum spanning tree Lana'i. Spatially contiguous clusters around Lana'i (left) resulting from: Minimum spanning tree of benthic ecological dissimilarity, with 10 'cut' branches, returning 11 contiguous clusters (right).

3. Select the Appropriate Number of Clusters

With the generation of a minimum spanning tree, we have a data structure that represents a hierarchically nested set of clusters, but we do not yet know the appropriate number of clusters. To assess the appropriate number of clusters to generate, we will primarily balance the number/size of sectors against the statistical performance of the cluster set, as our other goals are inherently dealt with in the methodological approach.

For clarity, we return to our stated goals: clusters that are (1) small but statistically robust, (2) ecologically homogeneous, and (3) responsibly mix disparate methods. Given any level of clustering, the *contiguous clustering* method described above maintains ecological homogeneity of clusters, and *hierarchical mixed modelling* can account both for distinct survey methods and stratification in the sampling design (e.g., depth strata). With homogeneity and mixed methods inherently dealt with, the balance between small size and statistical robustness will determine our level of clustering.

We also define a *minimum cluster standard* by sample size (in our case, $N \geq 30$ points) and split the dataset into clusters by "cutting" the longest uncut branch in the minimum spanning tree that generates large enough clusters to include 30 sampling points. The choice of this minimum standard could arguably be pressed in one of two directions. One could expand this minimum to require that any identified cluster meet a larger set of characteristics of statistical quality, including random spatial distribution, balance across time and strata, etc. Alternatively, we could reduce this standard to allow for "sacrificial" clusters i.e., to identify areas that are poorly sampled, and exclude these data from the analysis of more robust spatial clusters at the stage of mixed model analysis.

The cluster set is split into 2 clusters, then 3, then 4, and so on. For each level of clustering generated, we then evaluate the features and statistical performance of four quality metrics: (1) model performance for a temporal hierarchical mixed model (model AIC for assessing long-term temporal trends), (2) mean cluster spatial statistical power (detectable effect size in a spatial t-test), (3) cluster sample size (N, mean number of samples per cluster), and (4) cluster spatial size (mean geographical distance among cluster centroids in km; Figure 5).

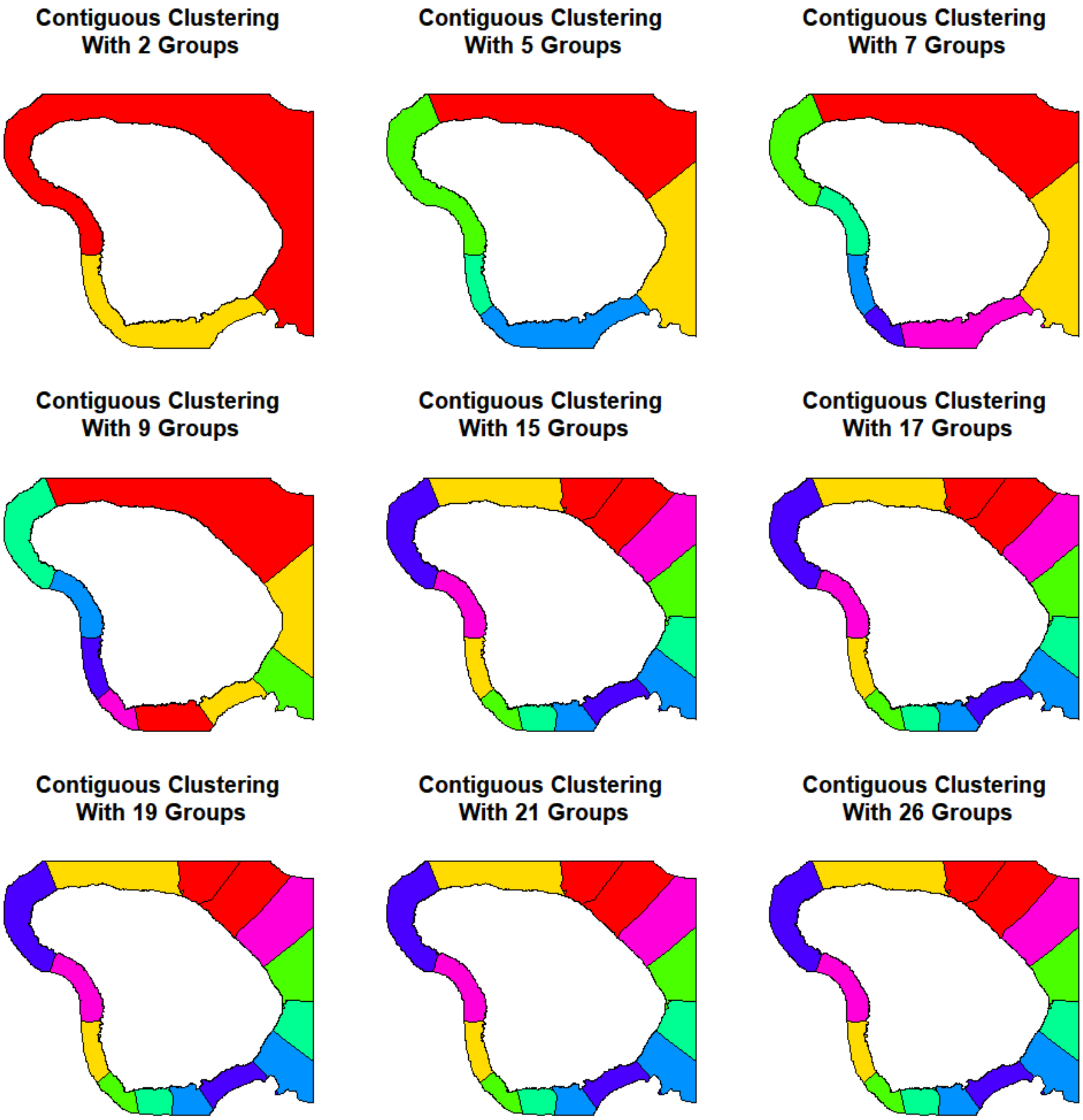


Figure 5: Successive grouping of spatial clusters Lana'i.

The mixed model performance measure (quality metric #1, AIC; Figure 6A, C) has the greatest impact on our choice of cluster level, but the other metrics are useful for context. Following the patterns shown in Figure 6, we can follow the logic that leads us to a chosen level of clustering.

Figure 6A shows the balance between two measures of statistical performance. We rely most on the AIC of a hierarchical mixed model defined using *lmer* in the *lme4* package. The Gaussian fixed effects model is defined with Coral Cover as a function of Cluster Identity, Date, and their interaction (i.e., Coral_Cover ~ Cluster + Date + Cluster × Date), using random effects for Depth Strata and Method. We evaluate and plot each models' Akaike Information Criterion for each level of clustering.

We also calculate a measure of spatial statistical power for each cluster, i.e., the percentage effect size at which we have an 80% chance of detecting significant shift in the mean between clusters at a significance level $p = 0.05$ using a one-sample T Test. We then plot the mean and standard error of that metric.

Figure 6A and C show that AIC improves rapidly when moving from 1 cut to 3 (i.e., 2 to 4 clusters), while effect size is unchanged. Both AIC and effect size get worse in moving from 3 cuts to 8 (4 to 9 clusters), but we reach the best AIC at 10 cuts (11 clusters).

We can see in Figure 6B that as the number of clusters increases, clusters get smaller both in size and in number of points sampled. This linear trend provides little in the way of inflection points with which we can define a non-arbitrary optimum but is useful for guiding intuition.

Figure 6D plots the distance between a given cluster-level's position and the ideal in terms of downscaled sector size and sample size (N) measured from the points shown in Figure 6B (i.e., the ideal would be tiny clusters with high N, marked by "*" in Figure 6B). Assuming an equal weight between the span of spatial cluster size and the span of cluster sample size (N) across the dataset, this plot can highlight tradeoffs. For example, in the Lana‘i case shown, the chosen cluster level (10, green circle) is already trading off raw number of samples per cluster to get to smaller clusters.

Overall, Figure 6 suggests that either 3 or 10 cuts would be a reasonable choice, but 10 is arguably better, while more than 10 erodes performance on all metrics up until 14, where the algorithm apparently failed to find branches to cut that meet our minimum standard of a minimum N of 30 per cluster.

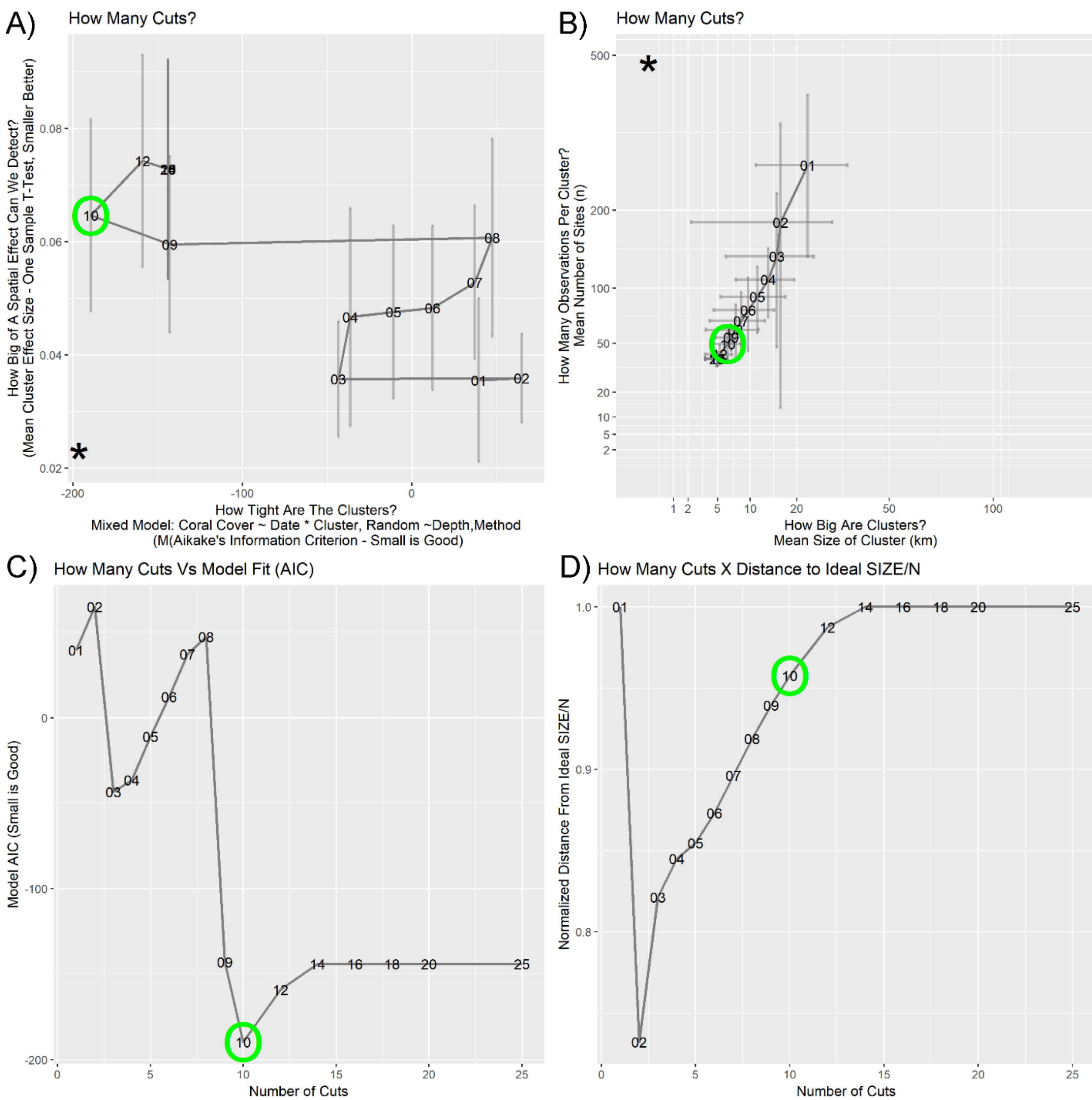


Figure 6: Identifying the appropriate level of clustering. (A) Temporal model performance (AIC) vs. spatial statistical power (effect size), (B) cluster size vs. cluster sampling, (C) univariate plot of mixed model AIC, (D) scaled distance to 'ideal' size/sampling balance. Green circles indicate selected clustering level, * indicates ideal balance between desirable characteristics.

4. Mixed Model Analysis of Trends

Given a chosen level of clustering and the spatial polygons, we can define spatial sectors with which to run our analysis (i.e., Figure 4A) and apply hierarchical mixed models to evaluate long-term trends.

Hierarchical mixed models provide many tools to allow us to responsibly address the kinds of issues that will arise when treating data outside the strict framework in which they were designed. However, these methods are not magic, and moving forward with a skeptical eye toward deviations likely to generate spurious conclusions is critical.

B. Strategies to Statistically Address Known Issues

1. Non-Random Spatial Sampling

By using (new) smaller sectors our existing dataset may not be defensible as spatially random. This is especially risky when a new sector spans a boundary between two design sectors, as each design sector is likely to have different sampling allocations, and therefore non-uniform sampling effort.

We can assess the empirical importance of this theoretical issue by statistically testing for spatial non-randomness in our sampled datasets and assessing if non-homogeneous sampling is a major hurdle.

To demonstrate this test, we applied a metric of spatial randomness that assesses patterns of clustering vs. over-dispersion in relation to a random (Poisson) process. Specifically, using the *spatstat* package in R (Baddeley and Turner 2005), we applied the variance−stabilized Ripley's K-function (a.k.a. Besag's transformation) to data at Lanaʻi grouped according to our traditional design sectors and to the same data grouped with the recommended 11 downscaled clusters (Bivand et al. 2013).

2. Data That Violate Assumptions: Non-normality, Over-Dispersion, Zero-Inflation

In any statistical modeling exercise, it is important to specify the underlying distribution from which your sample is drawn to ensure robust model fit and to avoid error. In our traditional statistical sampling design, we frequently apply Gaussian assumptions to fit our data as a robust default (Smith et al. 2011). However, with the proliferation of statistical tools associated with the software package R, it is increasingly simple to both test for normality and model non-normal data using mixed model analyses. Specifically, the package *DHARMa* allows for easy tests of non-normality of errors, zero-inflation, and over-dispersion, and with each deviation from assumptions we can modify a mixed model to account for these issues using the packages *lme4*, *nlme*, or *glmmTMB* (Bates et al. 2015; Brooks et al. 2017; Hartig 2018; Pinheiro et al. 2018).

3. Spatial Non-Independence: Autocorrelation

In addition to spatial non-randomness, means of data sampled too closely together risk violating the assumption of independent samples and can tend to both skew results and over-state statistical power. Autocorrelation is an issue in both space and time; however, space is the larger concern as our sampling events are generally at least a year apart, and therefore less likely to violate the assumption of temporal independence.

There are multiple means of managing spatial autocorrelation in existing data. One method would be to calculate stratified means over a grid, with a grid scale larger than that of expected (or calculated) autocorrelation. In the case of Hawaiian reef data, the Hawai'i Monitoring and Reporting Collaborative (HIMARC) project has shown auto-correlated patterns in the benthos up to approximately 250 m (Mary Donovan, HIMARC, pers. comm.). In this case, we would apply a grid of 300m or larger.

The mixed model package *nlme* allows the user to specify autocorrelation structures that will account for the potential violation of the assumption of independence in the model, down weighting closely-packed sampling and correcting the calculation of model power.

4. Unbalanced Sampling across Time, Methods and Stratification Variables

Whether in traditional design sampling or in the novel method proposed, the user needs to be skeptical about the effects of unbalanced sampling across time periods, stratification variables (i.e., depth), and distinct methods (if applicable). Sectors with strong correlations between time, method, and strata can generate spurious results. While there is no "silver bullet" to apply in this case, the user should apply minimum standards of temporal coverage within sectors and be wary of results that appear driven by shifts in stratification or methods that may outstrip the mixed model framework's ability to account for them. We can reasonably choose to set these more stringent minimum quality thresholds either at the clustering stage or at the mixed model analysis stage (see discussion of "sacrificial clusters" in Section 2C above)

C. Demonstrative Model Applied Here

In the demonstrative model, we have not strictly controlled for all of the issues raised above, and therefore all results should be interpreted as a "proof of concept," not a well-supported presentation of ecological trends.

Similar to the models with which we evaluated cluster-level AIC, we apply a simple, long-term linear slope analysis to the hard coral cover in each defined sector, accounting for method and depth-strata as random effects. Again, we use hierarchical mixed models defined with *lmer* in the *lme4* package. The Gaussian fixed effects model is defined as CoralCover ~ ClusterID*Date, using random effects for depth strata and method (Bates et al. 2015).

By using the package *emmeans*, we can determine a slope estimate of hard coral cover change over the 11 years of the survey by evaluating the estimated marginal means of the interaction between date and clusterID (Lenth et al. 2019). We record as significant and display the slope of all clustered sectors in which both lower and upper confidence limits share a sign, i.e., do not span zero. Cluster by cluster results are shown below in the results section.

Results

We repeated the above analysis for each of the main Hawaiian Islands (except Kahoʻolawe). In each island, at least one sector showed significant long-term trends, very few of which were apparent from the sector-scale comparison. Again, these results stand to demonstrate the potential of the proposed method, have not met the standard of thorough statistical vetting, and should not be interpreted as robust trends.

Regional Pattern: Significant Smaller-Scale differences, Skew toward Decline.

From a regional perspective, we segmented the data into 63 spatial sectors across 7 islands. Of those 63 sectors, 13 (20.6%) showed significant long-term trends of declining coral cover over the 11-year span of analysis, 4 (6.3%) showed significant increasing trends, and the remaining 46 (73.0%) showed no significant trend. Among sectors showing a significant trend, declining sectors are significantly more common than increasing sectors (13:4 sectors; 76%:24% of sectors; binomial glm: $z = 2.06$, $p = 0.0393$).

Lanaʻi: Trend Results

We divided Lanaʻi into 11 sectors, with 1 (#1 NE) showing a significant long-term decline, and two others (#5 and #9–SE, SW) showing significant long-term increases (Figure 7). For the island-wide baseline, see Figure 1.

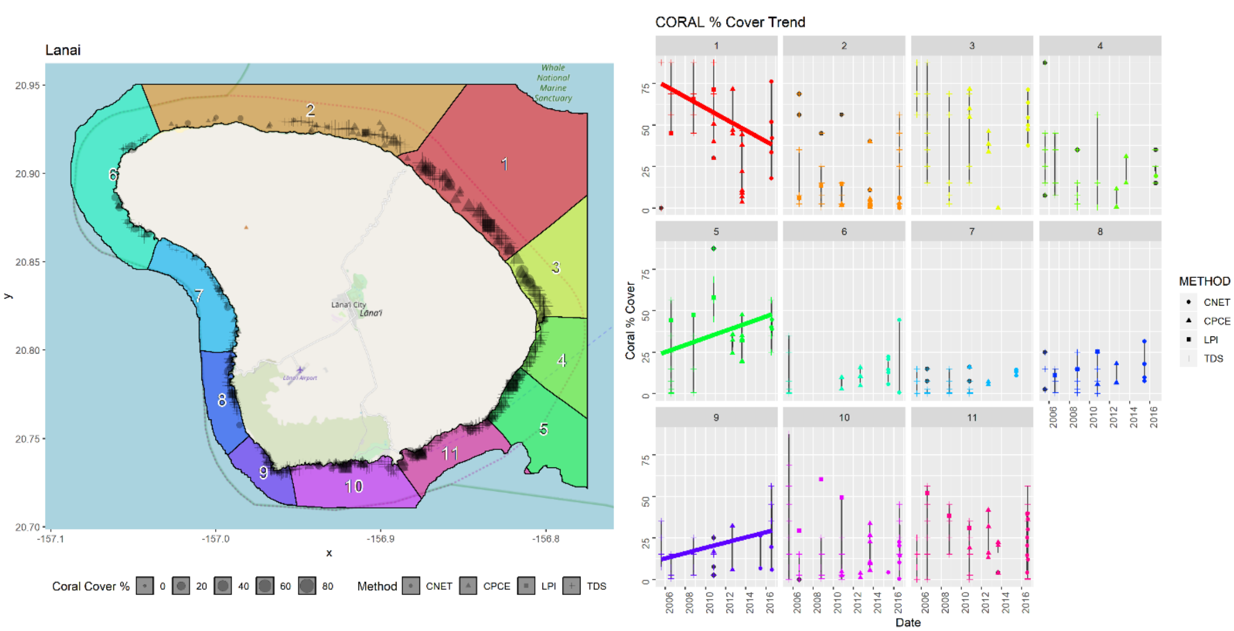


Figure 7: Clustered survey data, Lanaʻi.

Design vs. Down Sampling: Assessment of Spatially Random Sampling, Lanaʻi

To gauge uncertainties about imposing spatially non-random sampling through downscaling, we applied Ripley's K (variance stabilized), a metric of spatial homogeneity to our data from Lanaʻi. These data were grouped both by the two traditional design sectors there and by the 11 recommended downscaled sectors. Empirically testing the issue shows that the data grouped by downscaled sectors do not present greater non-random spatial patterns by the K-function than the traditional sectors, at least in this case (Figure 8). While the traditional, larger sectors (red) show rapid and persistent patterns of spatial clumping, the smaller sectors (green) appear to show lower deviation from the random null model (blue).

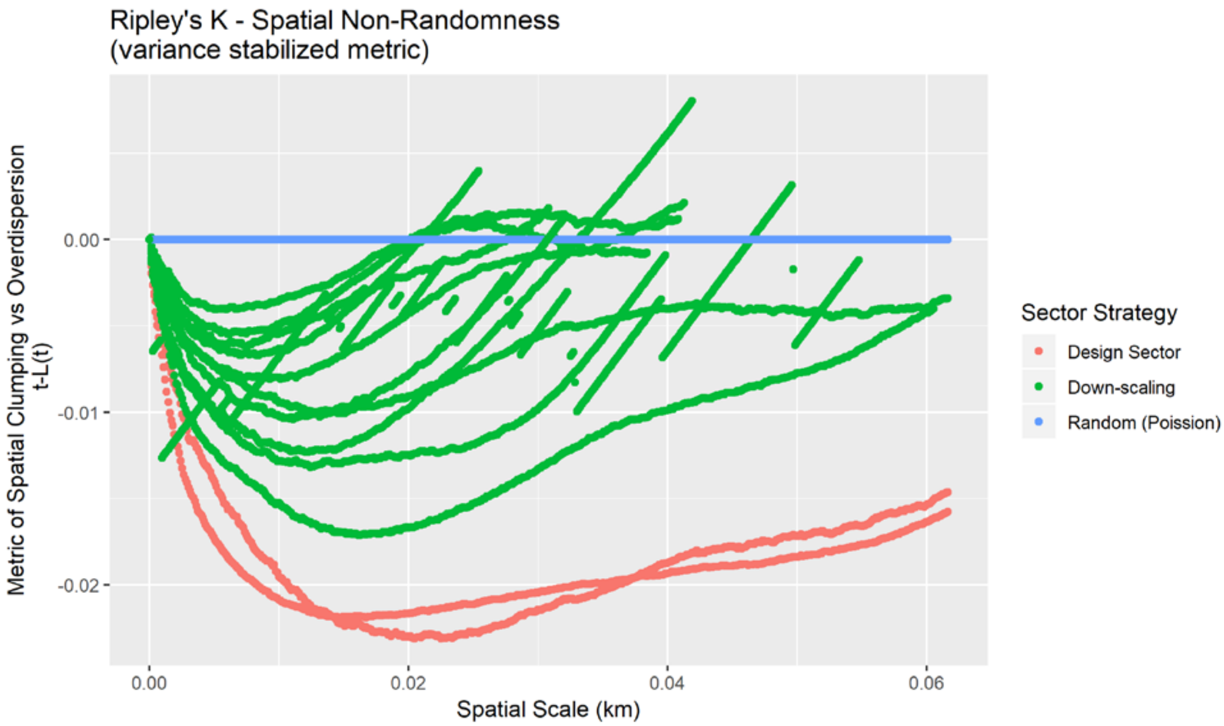


Figure 8: Spatial non-randomness of sampling data grouped by traditional design sectors (red), downscaled sectors (green), or random null model (blue).

Hawai‘i Island: Trend Results

Baseline, sector-scale data from Hawai‘i show temporal coverage from 2006–2016, with no apparent sector-level trends (Figure 9).

We divided Hawai‘i into 10 sectors; 1 (#5—Hamakua coast) shows a significant long-term increase. However, in 2016 only TDS data were available and there is some potential for methodological artefact that should be further explored. Two sectors (#4—Kona and #10—SE) show significant long-term decreases, but #10 was only sampled in 2006 and 2008, so we may question the biological robustness of this statistical result. However, sector #4 (Kona) is well sampled and shows a significant decline from a mean of 39.9% (±2.1% se) in 2010 to 26.2% (±1.2% se) in 2016, for a 34% reduction in cover over 7 years.

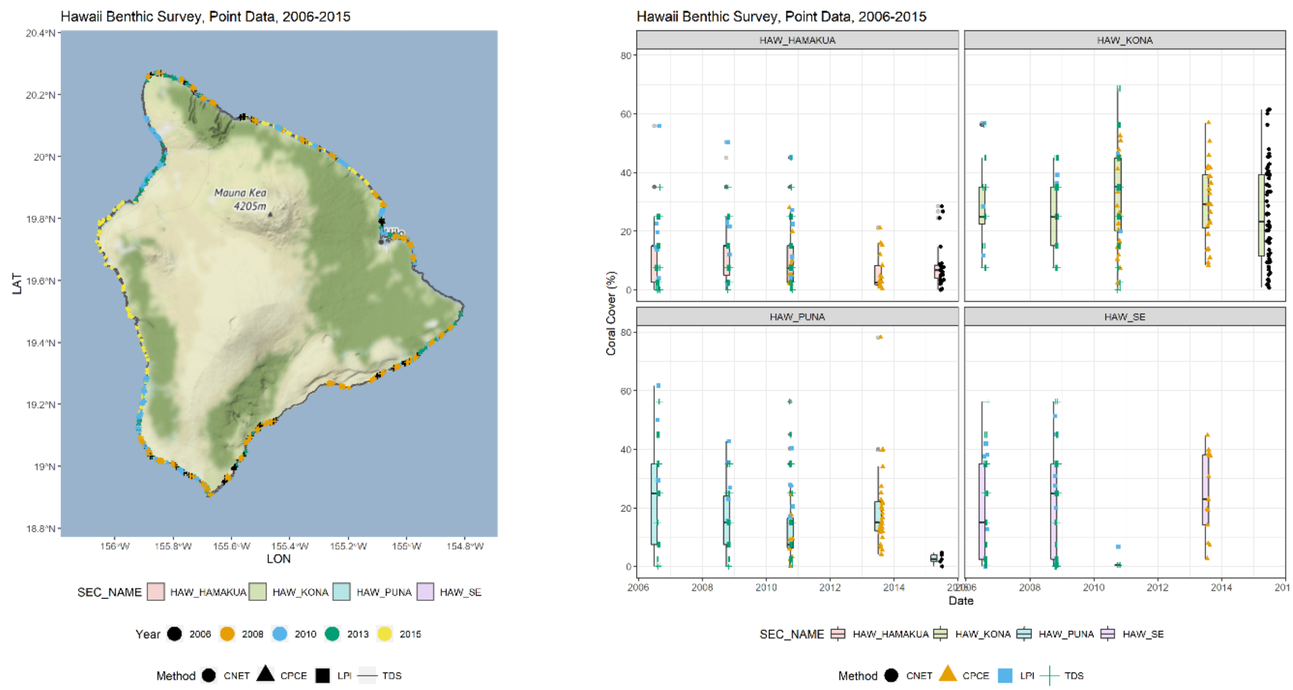


Figure 9: Baseline benthic data, sector-scale, Hawai‘i.

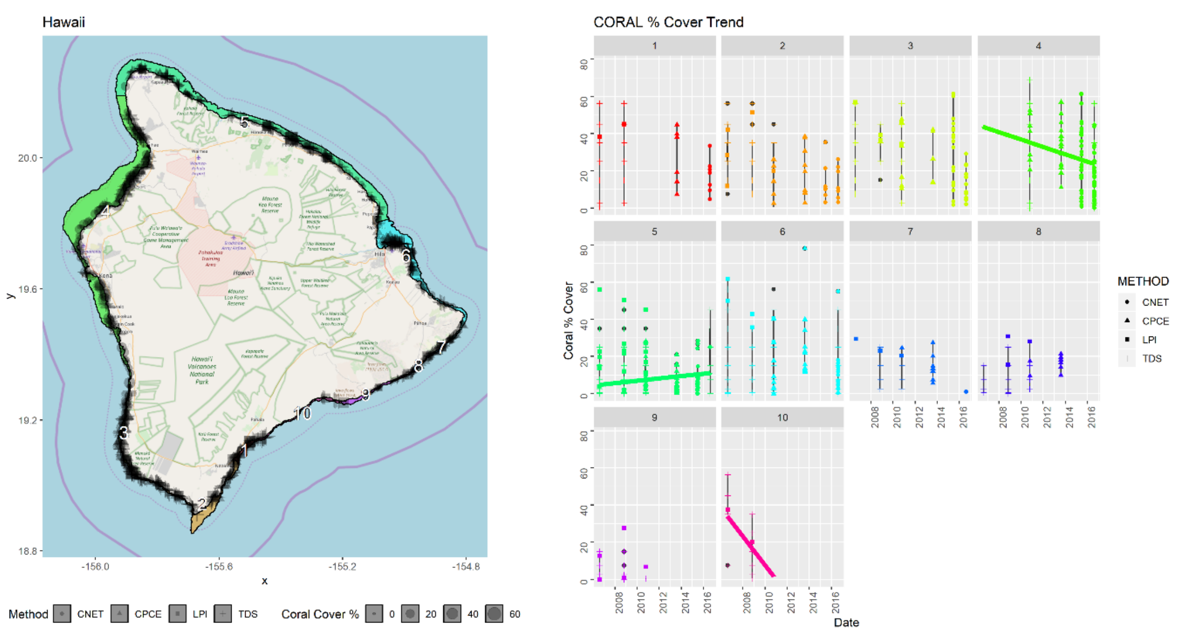


Figure 10: Clustered survey data, Hawai‘i Island.

Maui: Trend Results

Baseline, sector-scale data from Maui show an island divided into seven sub-island sectors in our NCRMP design, a relatively high number (Figure 11). Unique in our main Hawaiian Islands design, these seven roughly map into similar sectors as the eight we identified through downscaling.

We divided Maui into 8 sectors, none of which shows increasing coral cover. Three sectors (#1—N. Kahului, #6—Hana and #8—S. Maui) show significant long-term decreases, but #8 is lightly sampled so we may question the biological robustness of this statistical result. There are no data from Sector #6 after 2013, and only light sampling that year. However, N. Kahului, sector #1, is well sampled and shows a significant decline (Figure 12). Each of these patterns is also apparent in the traditional NCRMP sector-level data (Figure 11).

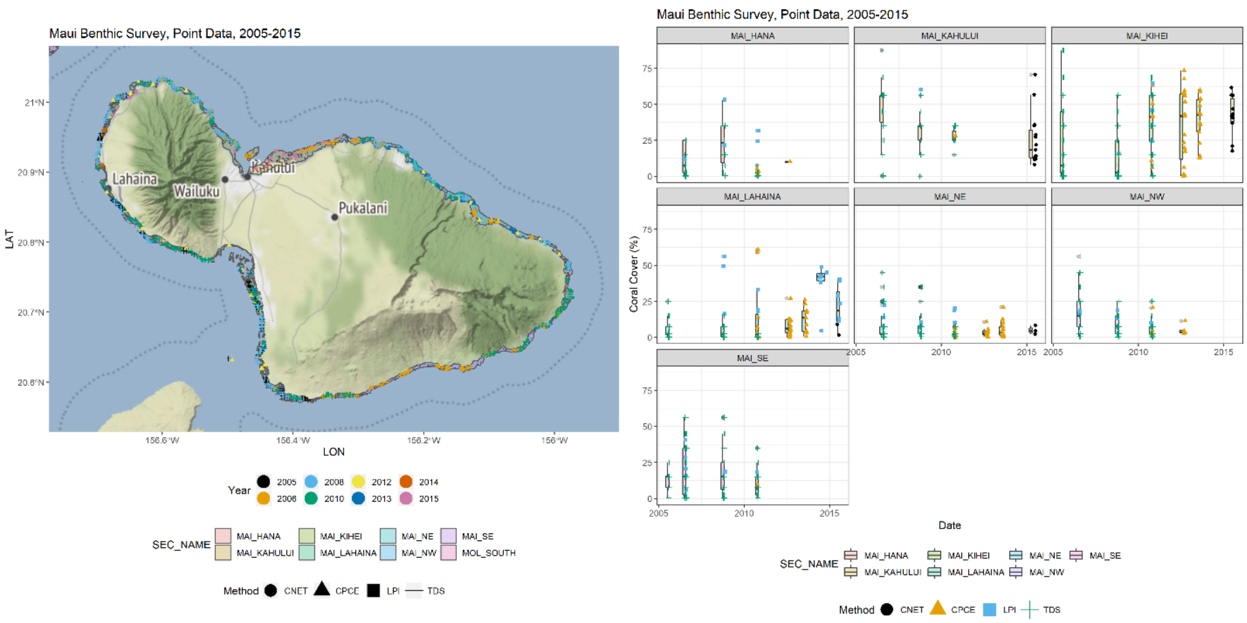


Figure 11: Baseline benthic data, sector-scale, Maui.

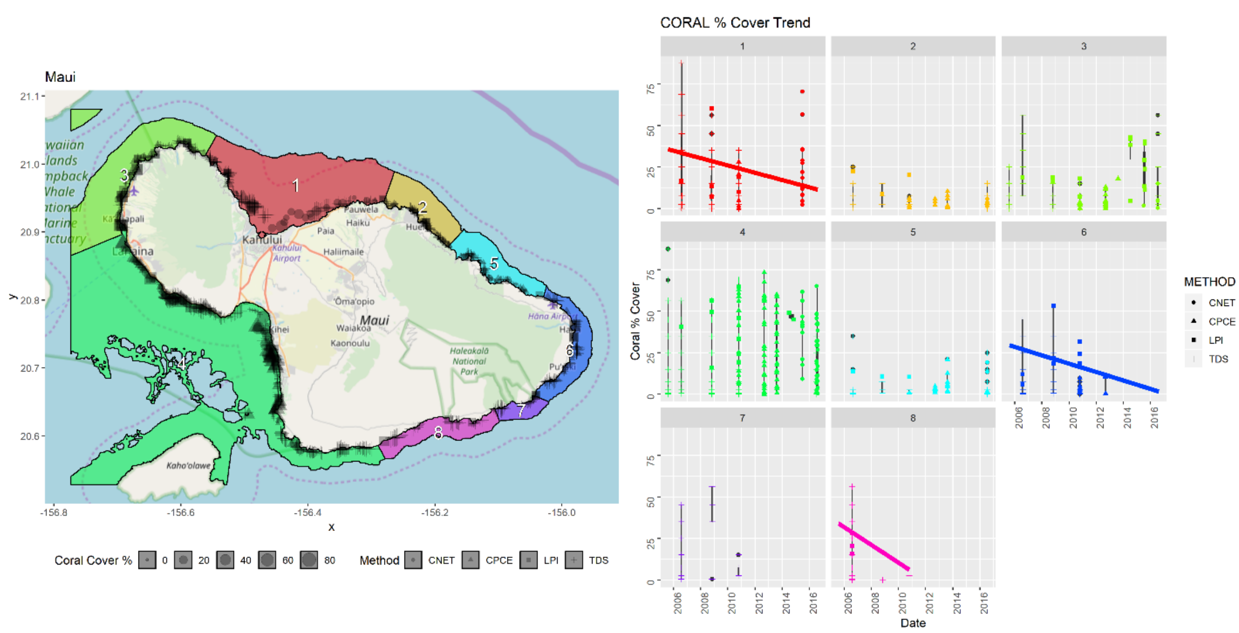


Figure 12: Clustered survey data, Maui.

Moloka‘i: Trend Results

Baseline, sector-scale data from Moloka‘i show temporal coverage from 2006–2016, with low means in 2006 and 2008 and high in 2010, due to spatially restricted sampling. (Figure 13).

We divided Moloka‘i into 9 sectors, with no sector showing increasing coral cover. Two sectors show significant long-term decreases (#5 and #6—both SE, an area associated with sediment flow) (Figure 14).

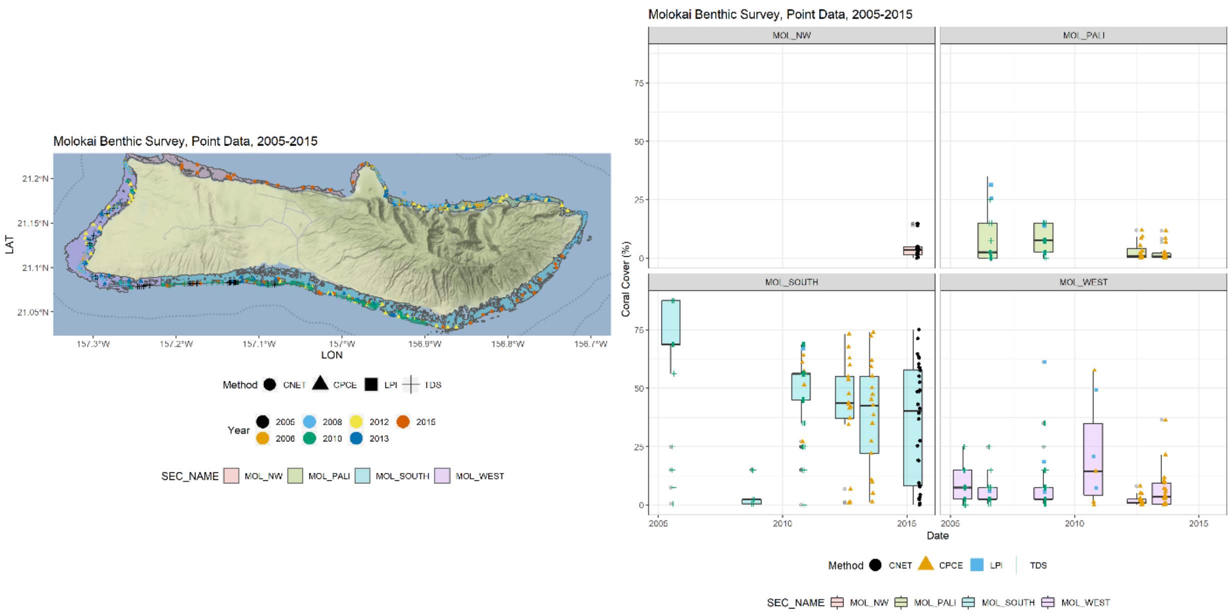


Figure 13: Baseline benthic cover survey data, Moloka‘i.

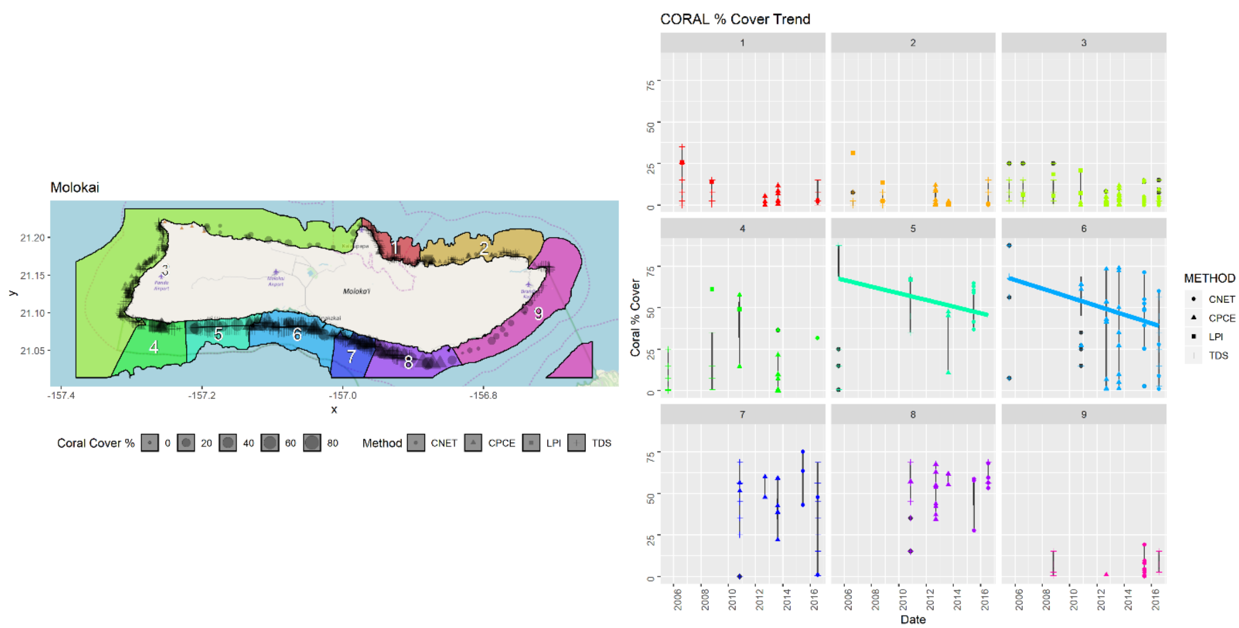


Figure 14: Clustered survey data, Moloka‘i.

O‘ahu: Trend Results

Baseline, island-scale data from O‘ahu show temporal coverage from 2006–2016 with no apparent trends. (Figure 15).

We divided O‘ahu into 9 sectors, with one sector (#1—Windward) showing increasing coral cover. Three sectors (#3—S. O‘ahu, #7—Kaena Pt, and #8—Mokulē‘ia) show significant long-term decreases (Figure 16).

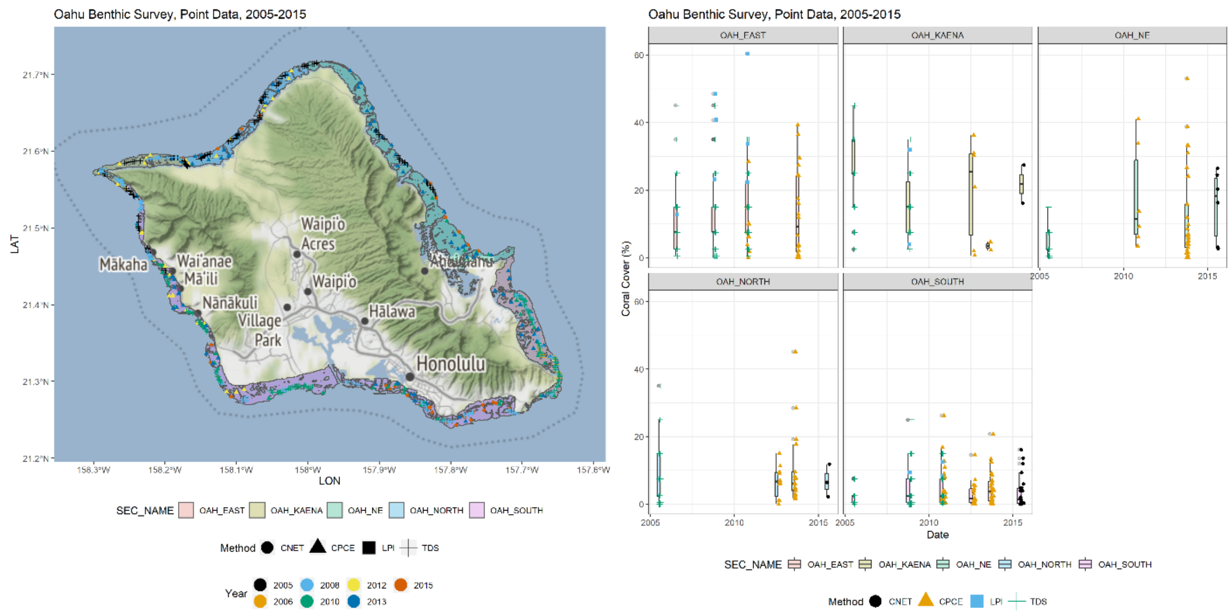


Figure 15: Baseline benthic cover survey data, O‘ahu.

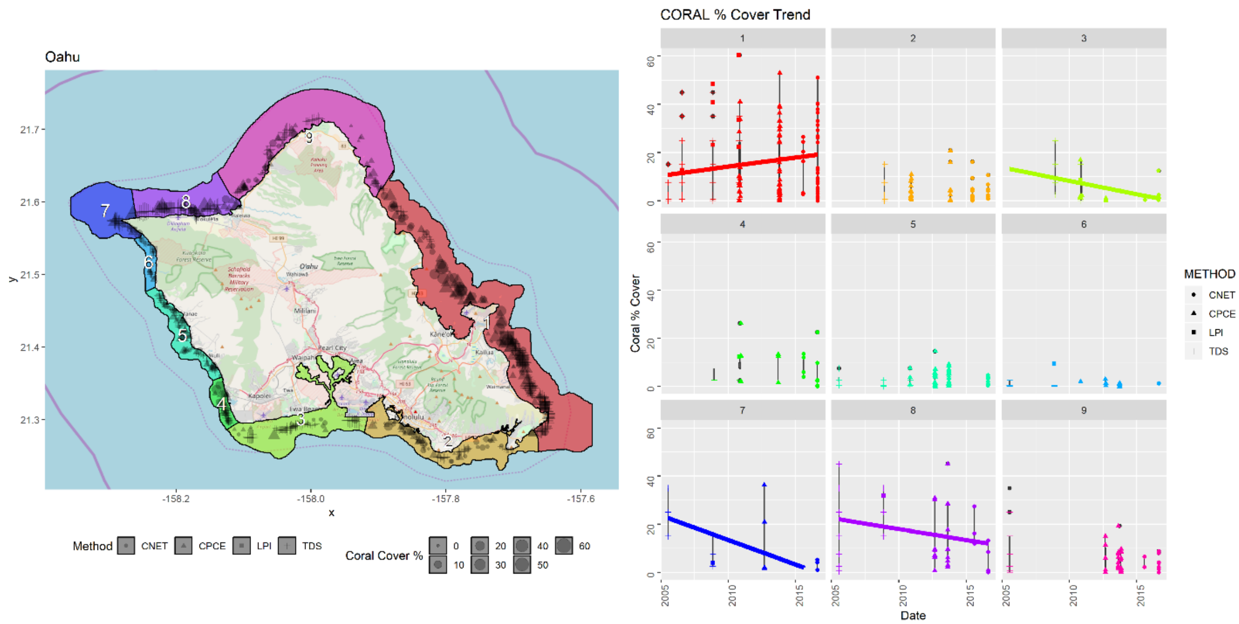


Figure 16: Clustered survey data, O‘ahu.

Kaua‘i: Trend Results

Baseline, sector-scale data from Kaua‘i show temporal coverage from 2006–2016, with one apparent decline in the spatially broad KAU_NAPALI sector. (Figure 17). We divided Kaua‘i into 10 sectors, with no sectors showing increased coral cover. One sector (#3—Miloli‘i) shows a significant long-term decrease. Sector #3 overlaps with KAU_NAPALI, but localizes the decline in a much more spatially constrained area than does the original sector (KAU_NAPALI; Figure 18).

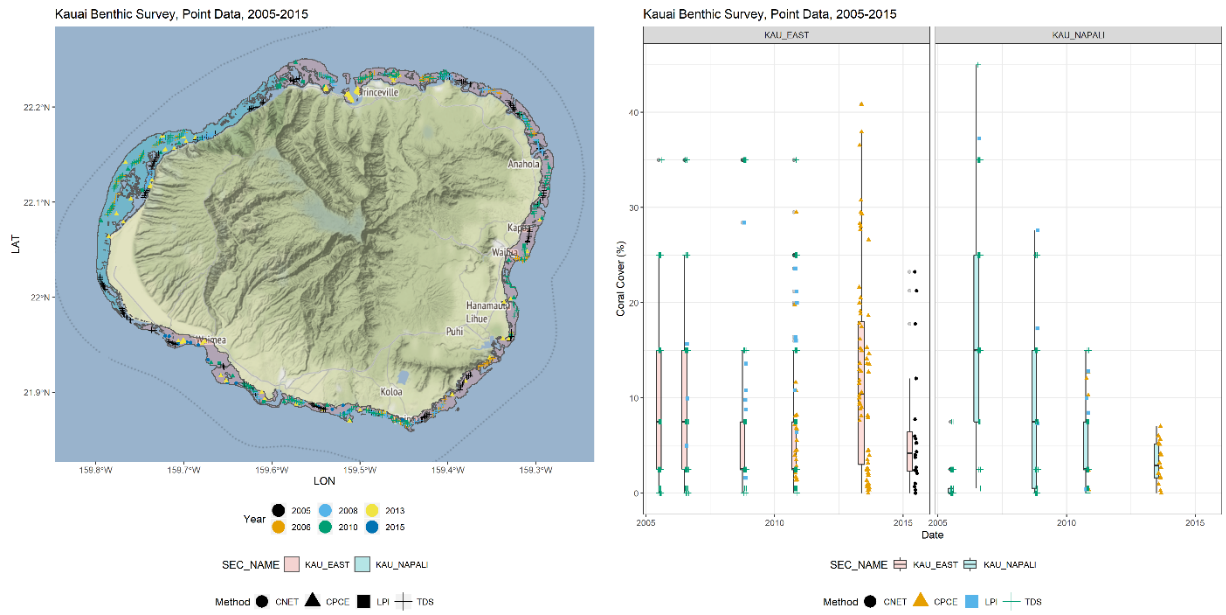


Figure 17: Baseline benthic cover survey data, Kaua‘i.

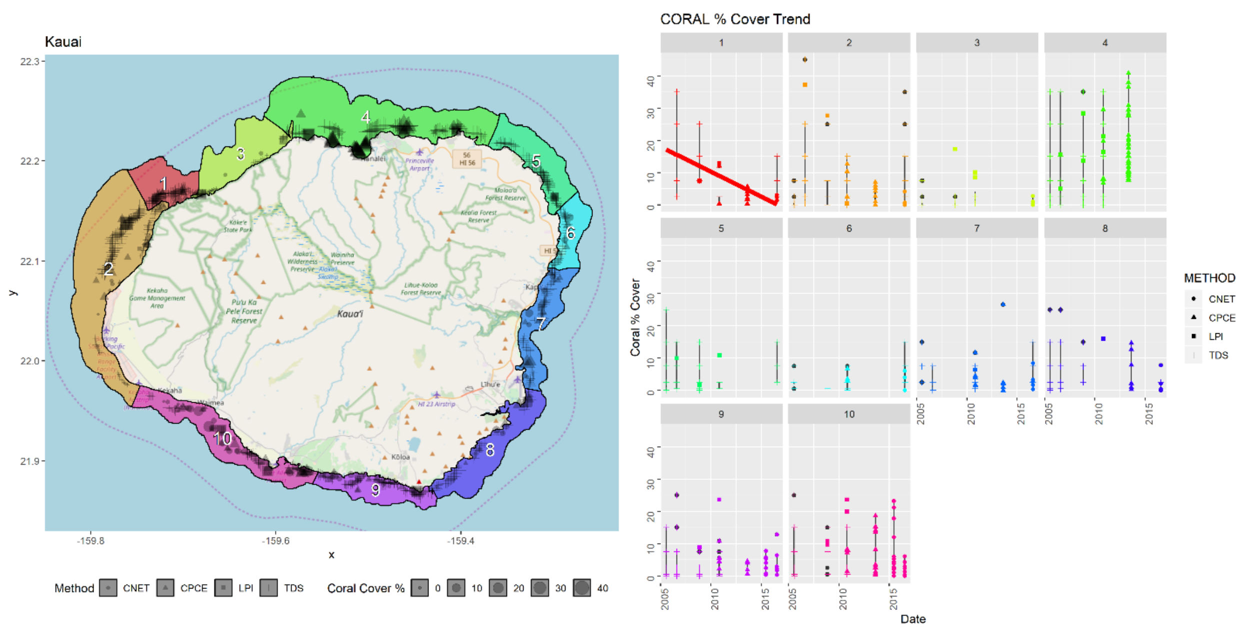


Figure 18: Clustered survey data, Kaua‘i.

Niʻihau: Trend Results

Baseline, sector-scale data from Niʻihau show temporal coverage from 2006–2016, with no apparent trends. (Figure 19). We divided Niʻihau into 6 sectors, with no sectors showing increased coral cover. One sector (#1—NE) shows a significant long-term decrease (Figure 20).

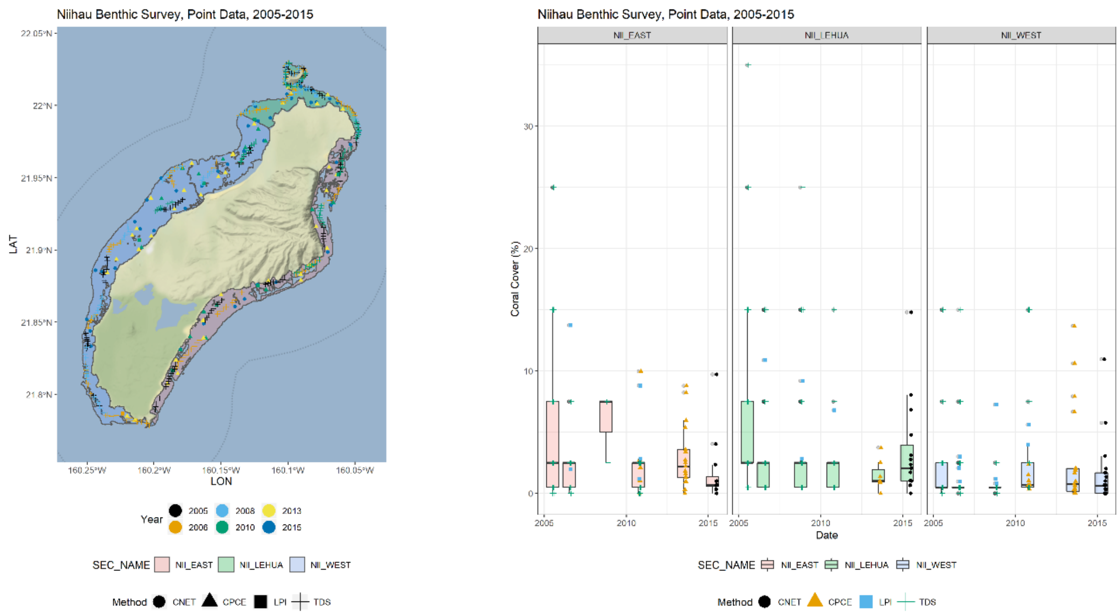


Figure 19: Baseline benthic cover survey data, Niʻihau.

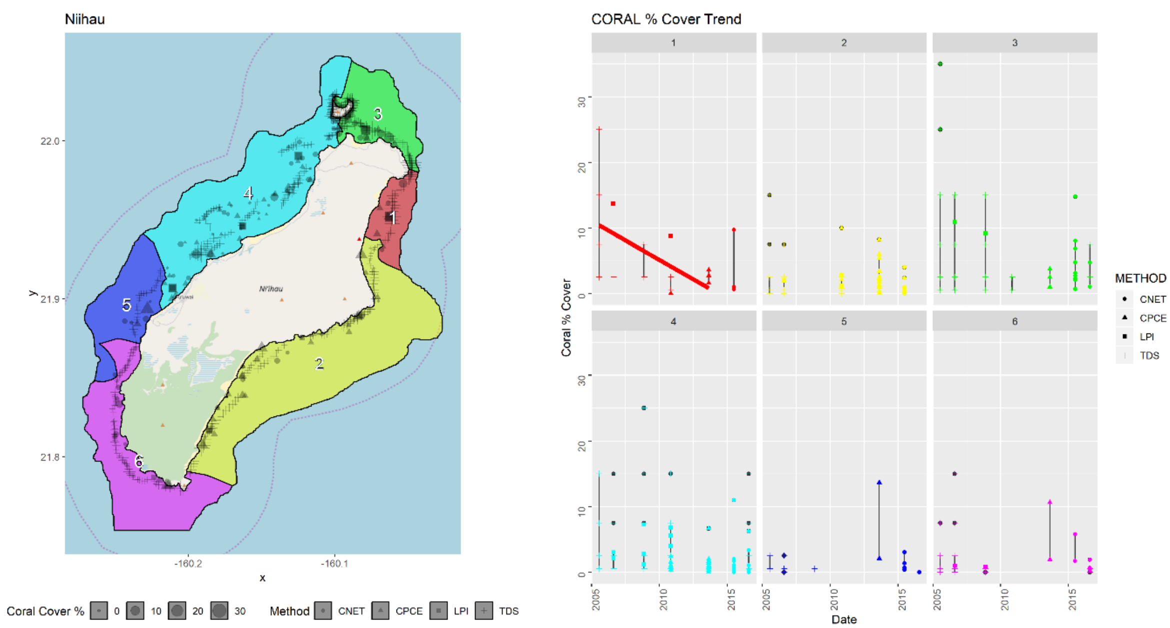


Figure 20: Clustered survey data, Niʻihau.

Discussion

Highlighting Finer Scale Trends

The downscaling methodology presented shows potential for re-clustering existing data into ecologically meaningful clusters at a fine spatial scale that remains statistically robust.

In six of the seven examples we explored in the main Hawaiian Islands, the downscaled sector subsets revealed statistically significant sector-level trends that were obscured in the traditional design's sector-level focus. The seventh, Maui, is the rare island in which our sector design roughly matches our "statistically optimal" sizing followed in our downscaling methodology. Given the spatial variation in both ecological drivers and population responses, this heterogeneity in trends should not surprise us. However, as the distinction among "places faring poorly" and "places faring well" can greatly inform inference about the drivers of resilience, our results highlight the importance of this methodological pursuit (Anthony et al. 2015).

In addition to revealing long-term trends, we also show that among all sectors indicating a significant trend, there is a significant skew toward coral cover decline around the islands during the period 2005–2016. The 13 sectors exhibiting significant linear decline make up over 20% of the 63 sectors state-wide, and over 75% of those 17 sectors showing any significant, long-term trend.

Spatial Sectors for Broader Inference across Data Sets

The identified sectors not only provide a framework for analyzing our benthic data, as shown with our mixed model exploration, but they also provide a footprint over which to "cut" datasets of potenial drivers or correlates to reef ecological processes which can be used to explore possible causes and effects of the observed benthic patterns. Specifically, we will attempt to correlate patterns of water quality, thermal stress, etc., as well as patterns in the fish communities at these spatial scales which are more likely to reveal ecological dynamics.

Other Downscaling Options to Explore

Other protocols for downscaling our datasets present both promise and limits that may complement the method outlined here. Future work will explore patterns of gridding and interpolation across multiple spatial scales, with an evaluation that allows the data to highlight optimal or interesting scales. By using these complementary methods in a portfolio of analyses, we can maximize our robust conclusions and minimize potential for errors in downscaling these data.

Potential Confounds & Caveats

While the method shows promise, its use also presents potential pitfalls for robust inference of temporal trends. In this kind of downscaling exercise, we must be clear with ourselves and our intended audience that we are using survey data at a scale finer than that the survey effort was designed to address. Any such effort will present risks and problems and will require a skeptical eye when viewing results.

Despite the many potential sources of error presented in our methods section, arguably, the biggest are having adequate, random, and well-balanced representation across space, time, and stratified variables within a sector. Specifically, when applying this methodology, it is important to take care of (1) non-random sampling in downscaled sectors, (2) balanced sampling across survey years, and (3) the limitations of mixed model random effects to control for both variation among methods and stratification. In the methods section, we detailed our strategies for managing each of these issues and empirically demonstrate a technique to test for non-random sampling. We will further explore best practices to control for these potential sources of error as we move to operationalize these methods and present more robust trends.

Portfolio of Tools Needed for Resilience-Based Management

In light of our critical need to generate robust information at the spatial scales over which resilience-supporting processes are occurring, this portfolio of techniques presents the promise to make the most of our existing datasets. Additionally, it provides a strong foundation for revisiting our statistical designs to supply the science necessary to adaptively support resilience-based management into the future.

Acknowledgements

We would like to acknowledge NOAA's Coral Reef Conservation Program (CRCP) for funding this analysis and both CRCP and NOAA's Ocean Acidification Program for funding of the National Coral Reef Monitoring Program over the years. We also would like to acknowledge the dozens of hardworking biologists who collect NCRMP's data that are not mentioned as authors of this report; without them these quality data would not exist.

Literature Cited

Anthony KRN, Marshall PA, Abdulla A, Beeden R, Bergh C, Black R, Eakin CM, Game ET, Gooch M, Graham NAJ, et al. 2015. Operationalizing resilience for adaptive coral reef management under global environmental change. Glob Chang Biol. 21:48–61. doi:10.1111/gcb.12700.

Assunção RM, Neves MC, Câmara G, Da Costa Freitas C. 2006. Efficient regionalization techniques for socio-economic geographical units using minimum spanning trees. Int J Geogr Inf Sci. doi:10.1080/13658810600665111.

Azaele S, Cornell SJ, Kunin WE. 2012. Downscaling species occupancy from coarse spatial scales. Ecol Appl. doi:10.1890/11-0536.1.

Baddeley A, Turner R. 2005. spatstat: An R package for analyzing spatial point patterns. J Stat Softw.

Barrett TM. 2011. Voronoi tessellation methods to delineate harvest units for spatial forest planning. Can J For Res. doi:10.1139/x96-214.

Bates D, Mächler M, Bolker B, Walker S. 2015. Fitting Linear Mixed-Effects Models Using lme4. J Stat Softw. doi:10.18637/jss.v067.i01.

Benestad RE, Hanssen-Bauer I, Chen D. 2008. Empirical-statistical downscaling.

Bivand R, Bernat A, Carvalho M, Chun Y, Dormann CF, Dray S, Halbersma R, Lewin-Koh N, Ma J, Millo G. 2005. The spdep package. Compr R Arch Netw.

Bivand RS, Pebesma E, Gómez-Rubio V, Bivand RS, Pebesma E, Gómez-Rubio V. 2013. Spatial Point Pattern Analysis. In: Applied Spatial Data Analysis with R.

Brainard R, Caldow C, Eakin CM, Gittings SR, Gledhill D, Hill R, Jeffrey C, Karazsia J, Kosaki R, Loper C, et al. 2014. National Coral Reef Monitoring Plan.

Brooks ME, Kristensen K, van Benthem KJ, Magnusson A, Berg CW, Nielsen A, Skaug HJ, Mächler M, Bolker BM. 2017. glmmTMB balances speed and flexibility among packages for zero-inflated generalized linear mixed modeling. R J.

Dixon P. 2003. VEGAN, a package of R functions for community ecology. J Veg Sci. doi:10.1111/j.1654-1103.2003.tb02228.x.

Hamylton S. 2013. Five practical uses of spatial autocorrelation for studies of coral reef ecology. Mar Ecol Prog Ser. doi:10.3354/meps10267.

Hartig F. 2018. DHARMa: Residual Diagnostics for Hierarchical (Multi-Level / Mixed) Regression Models. R Packag version 020. doi:10.1016/j.diagmicrobio.2015.06.021.

Keil P, Jetz W. 2014. Downscaling the environmental associations and spatial patterns of species richness. Ecol Appl. doi:10.1890/13-0805.1.

Lenth R, Singmann H, Love J, Buerkner P, Herve M. 2019. emmeans: Estimated marginal means, aka least-squares means. R Packag Version 134. doi:10.1080/00031305.1980.10483031>.License.

McClanahan TR, Donner SD, Maynard JA, MacNeil MA, Graham NAJ, Maina J, Baker AC, Alemu I. JB, Beger M, Campbell SJ, et al. 2012. Prioritizing Key Resilience Indicators to Support Coral Reef Management in a Changing Climate. PLoS One. 7. doi:10.1371/journal.pone.0042884.

Mcleod E, Anthony KRN, Mumby PJ, Maynard J, Beeden R, Graham NAJ, Heron SF, Hoegh-Guldberg O, Jupiter S, MacGowan P, et al. 2019. The future of resilience-based management in coral reef ecosystems. J Environ Manage. doi:10.1016/j.jenvman.2018.11.034.

Pebesma E, Bivand RS. 2005. S Classes and Methods for Spatial Data : the sp Package. Econ Geogr.

Pinheiro J, Bates D, DebRoy S, Sarkar D, Heisterkamp S, Willigen B Van. 2018. nlme: Linear and Nonlinear Mixed Effects Models. R package version 3.1-137. Retrieved from https//cran.r-project.org/package=nlme.

Pourmokhtarian A, Driscoll CT, Campbell JL, Hayhoe K, Stoner AMK. 2016. The effects of climate downscaling technique and observational data set on modeled ecological responses. Ecol Appl. doi:10.1890/15-0745.

R Developement Core Team. 2015. R: A Language and Environment for Statistical Computing. R Found Stat Comput. doi:10.1007/978-3-540-74686-7.

Smith SG, Ault JS, Bohnsack JA, Harper DE, Luo J, McClellan DB. 2011. Multispecies survey design for assessing reef-fish stocks, spatially explicit management performance, and ecosystem condition. Fish Res. doi:10.1016/j.fishres.2011.01.012.

Turner R. 2016. deldir: Delaunay triangulation and dirichlet (voronoi) tessellation. R Packag version 01-15. doi:10.1007/BF02105652.

Wu J, Jones KB, Li H, Loucks OL. 2006. Scaling and uncertainty analysis in ecology: Methods and applications.

Zuur AF, Ieno EN, Walker NJ, Saveliev AA, Smith GM, Ebooks Corporation. 2009. Mixed Effects Models and Extensions in Ecology with R - Mixed Effects Modelling for Nested Data.

Appendix A: Clustering Process Plots By Island

Hawai‘i Island: Clustering Process Plots

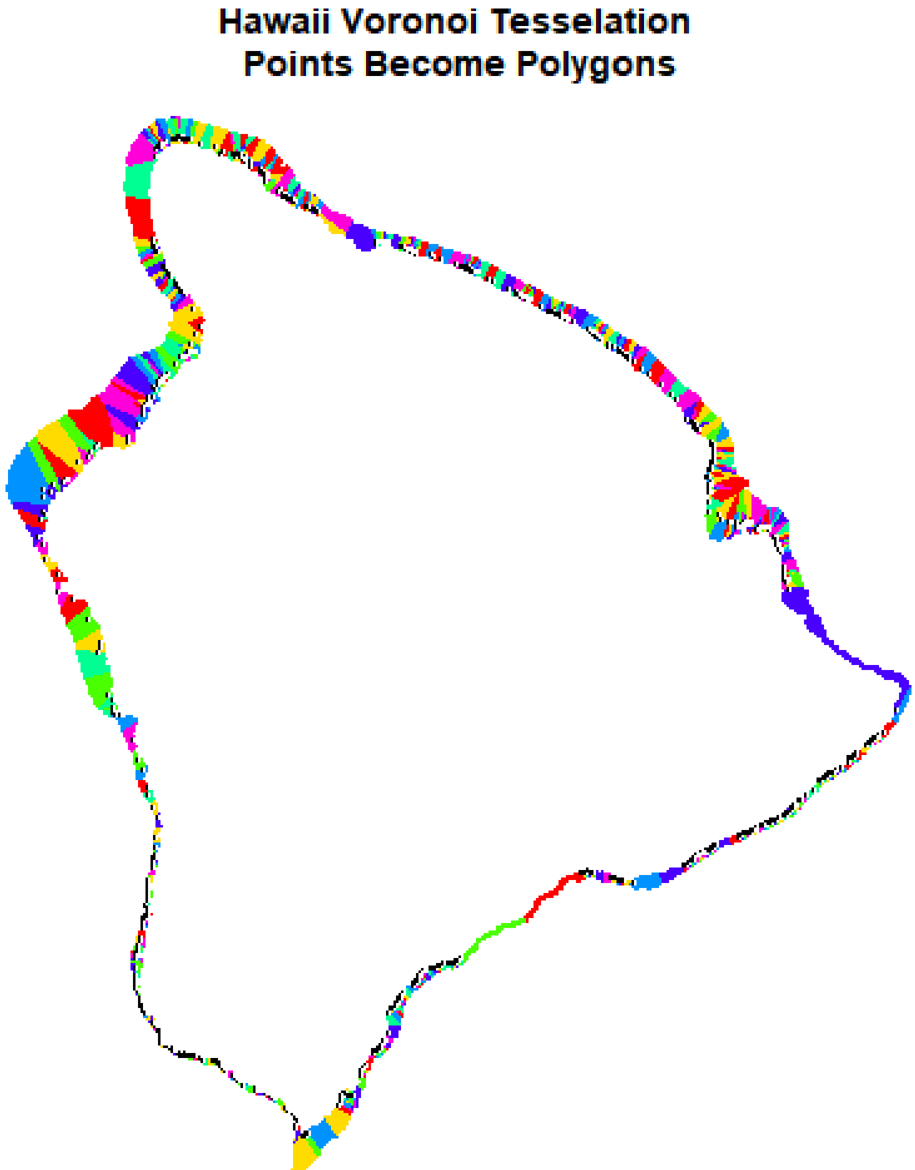


Figure A 1: Voronoi tessellation visualization, Hawai‘i Island.

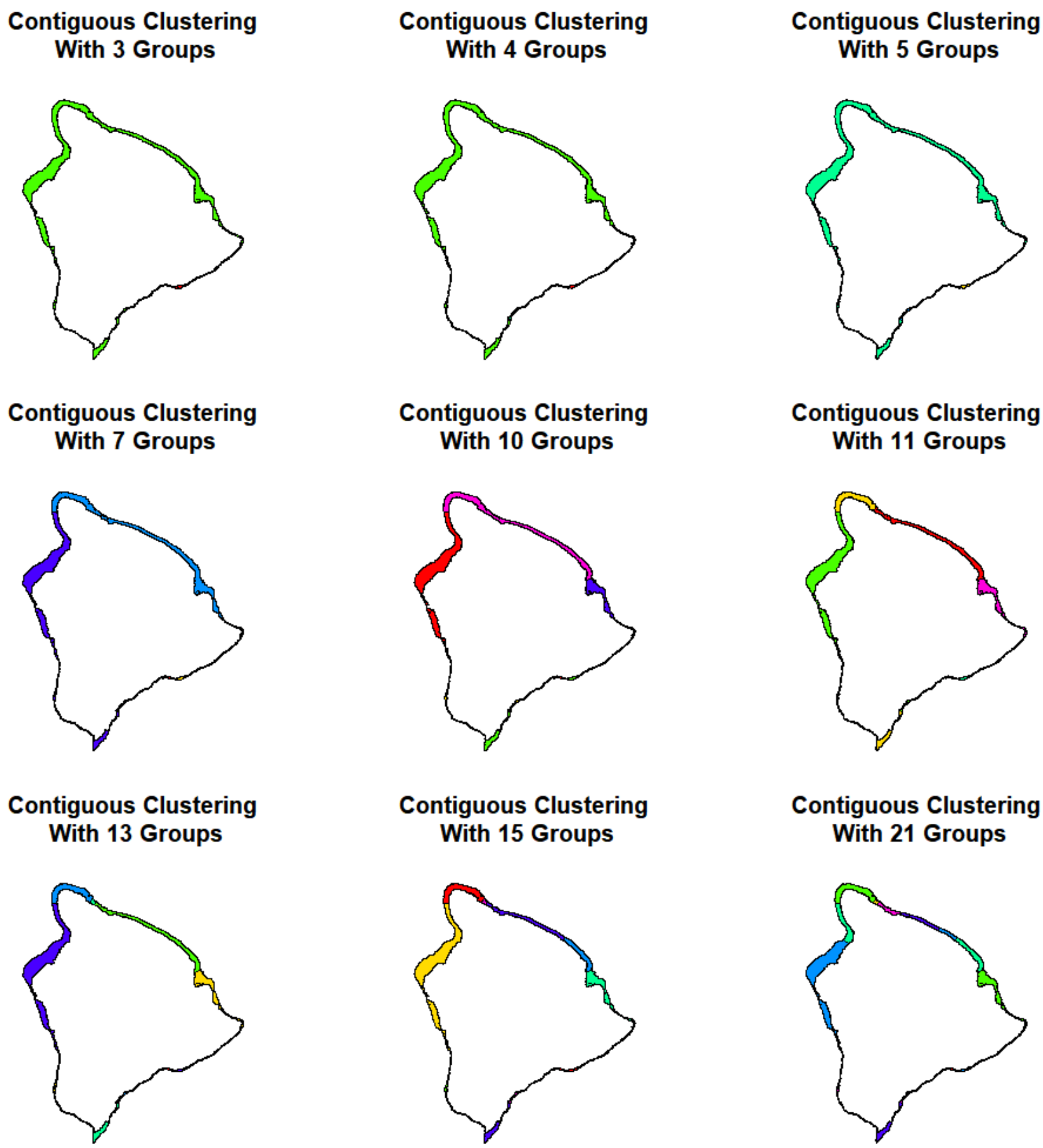


Figure A 2: Hierarchical spatial clusters.

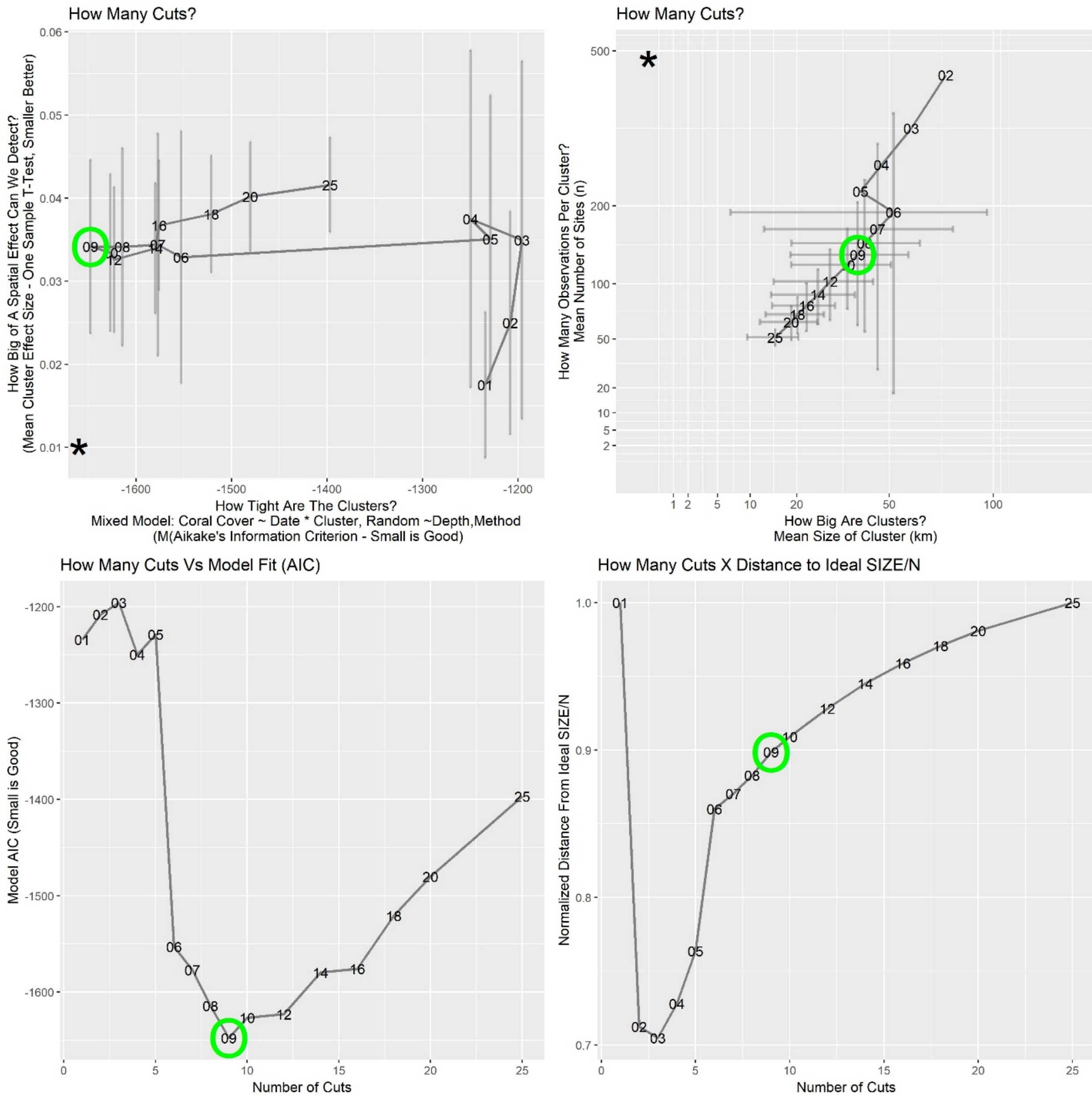


Figure A 3: How many cuts? Hawai‘i Island.

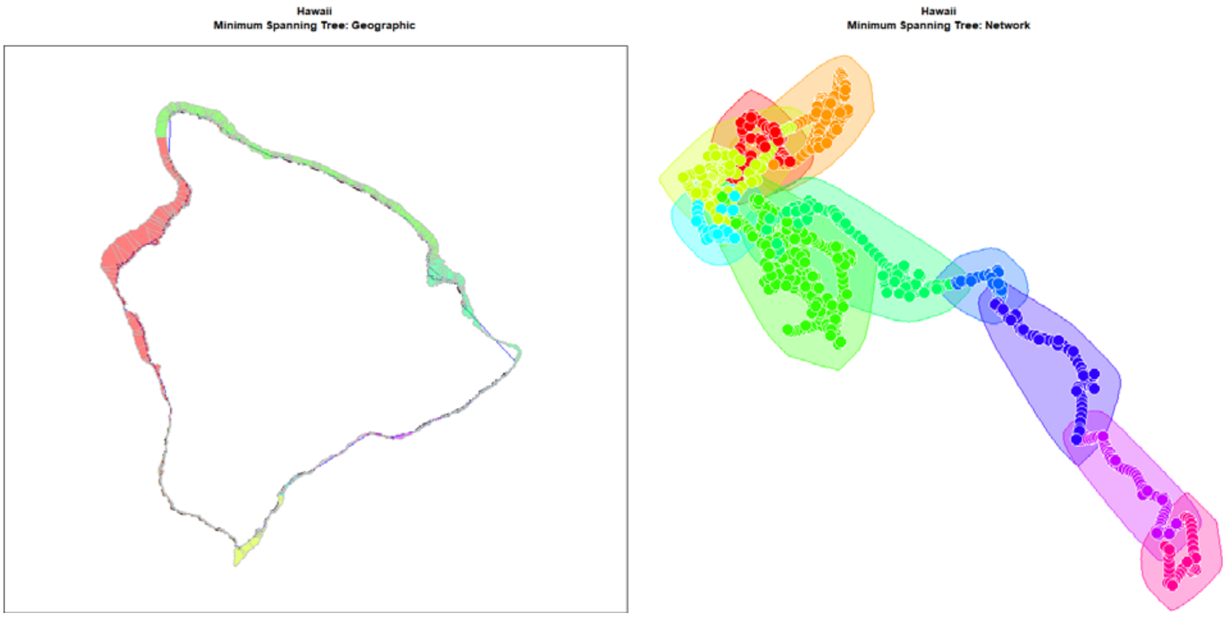


Figure A 4: Minimum spanning tree with highlighted clusters, Hawai‘i Island.

Maui: Clustering Process Plots

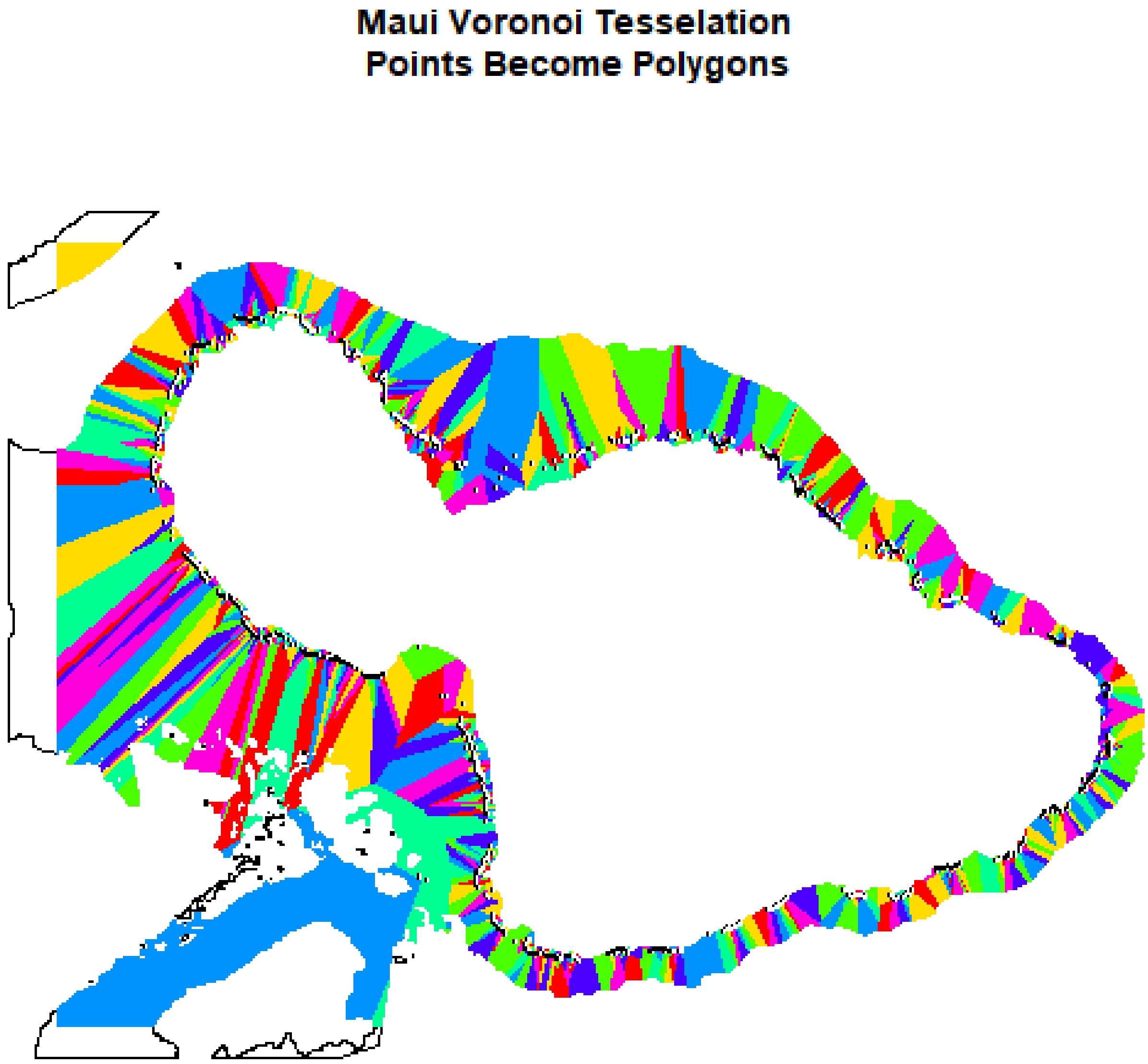


Figure A 5: Voronoi tessellation visualization, Maui.

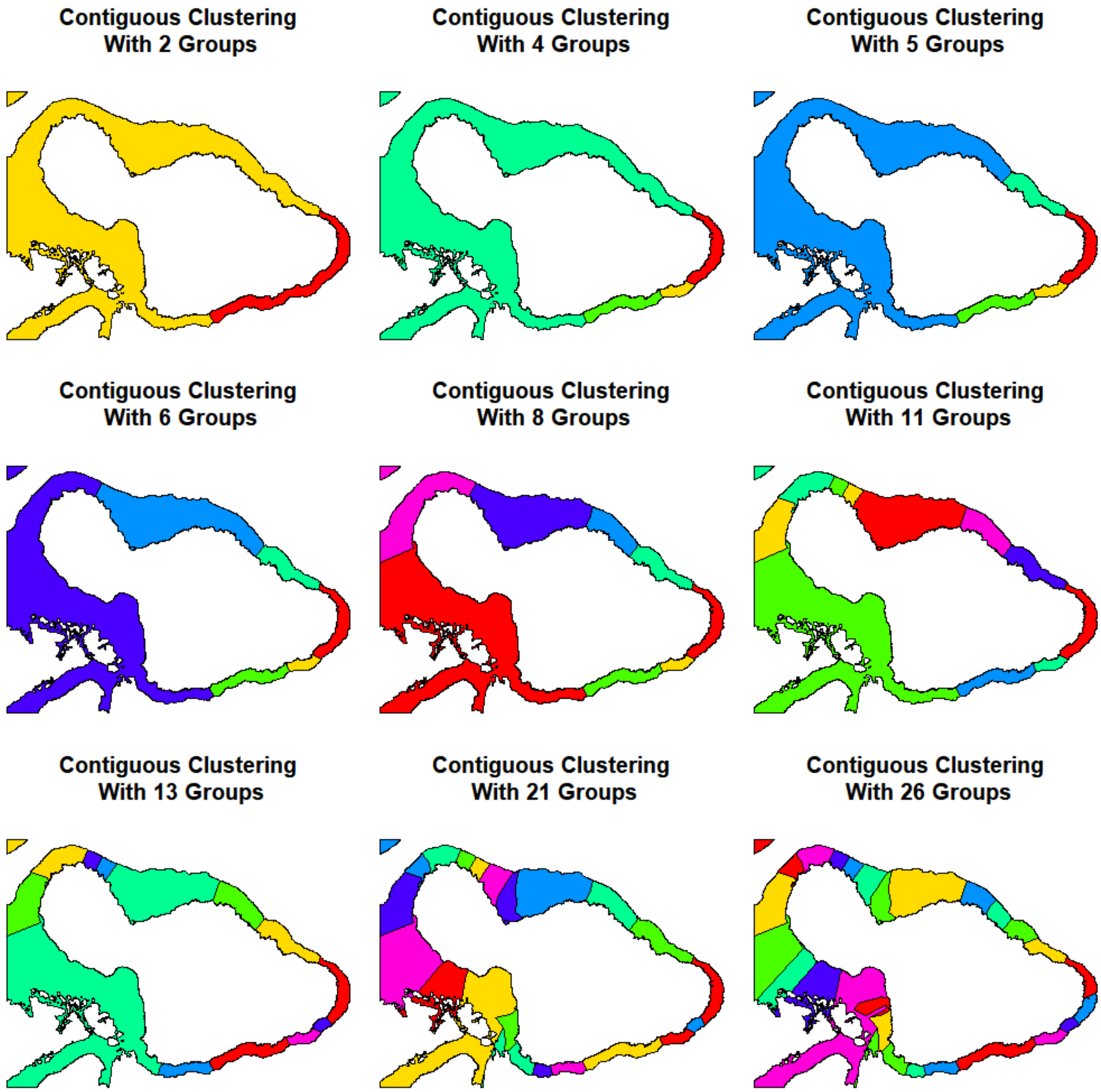


Figure A 6: Hierarchical spatial clusters, Maui.

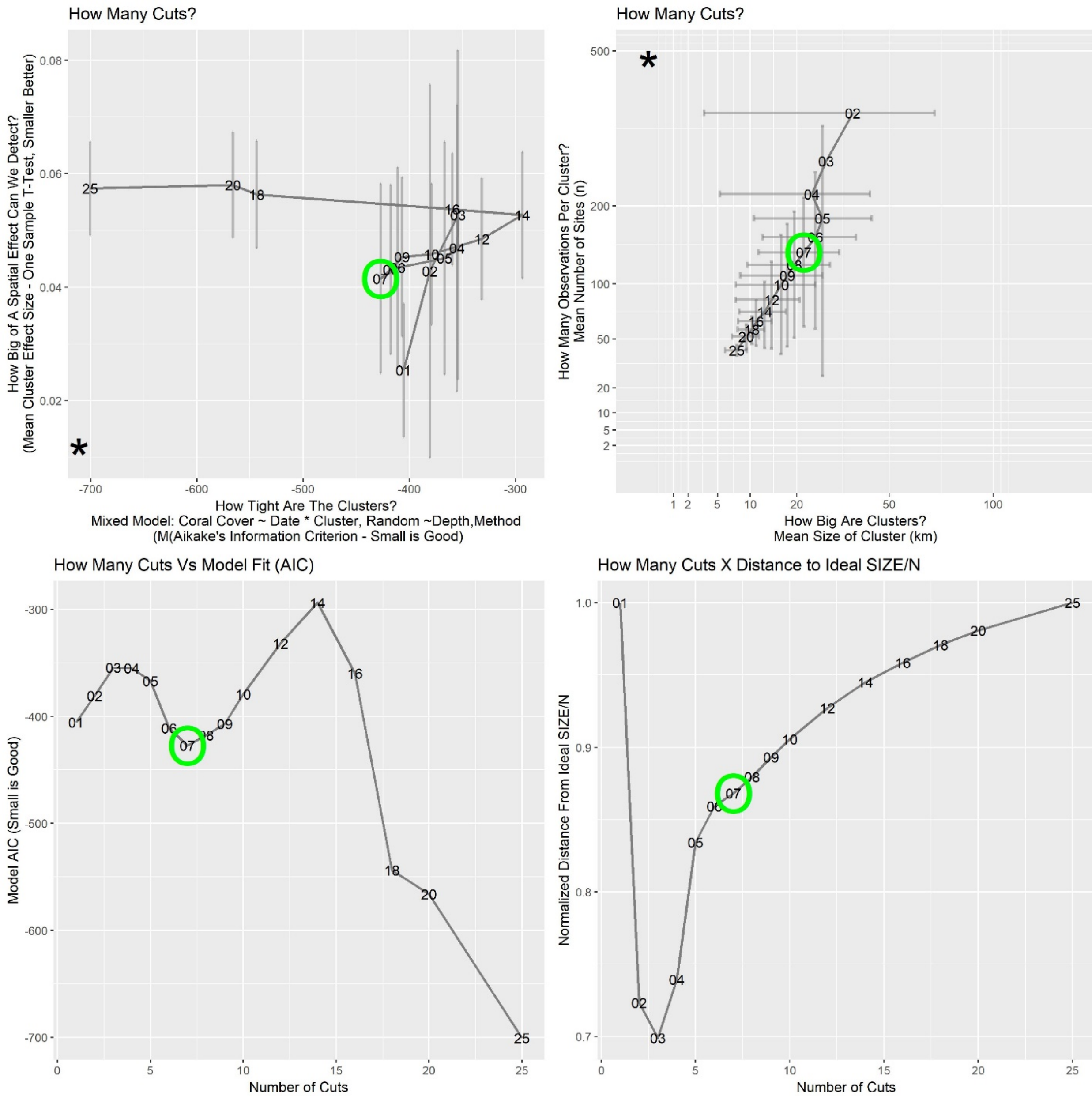


Figure A 7: How many cuts? Maui.

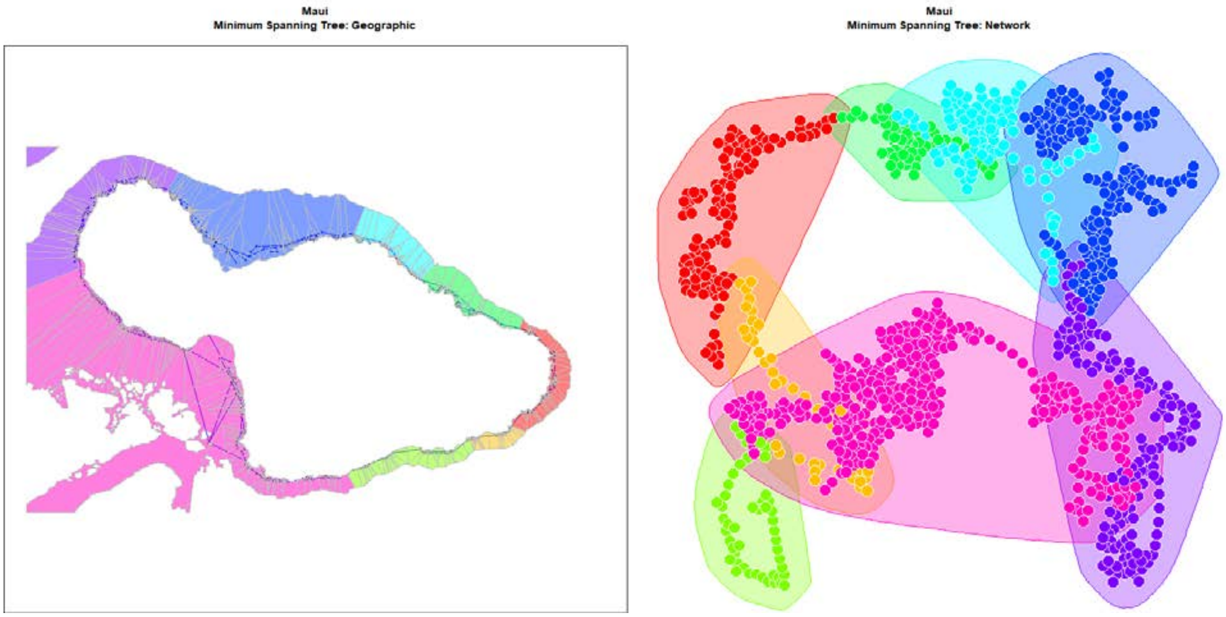


Figure A 8: Minimum spanning tree with highlighted clusters, Maui.

Lanaʻi: Clustering Process Plots

See body of document.

Moloka‘i: Clustering Process Plots

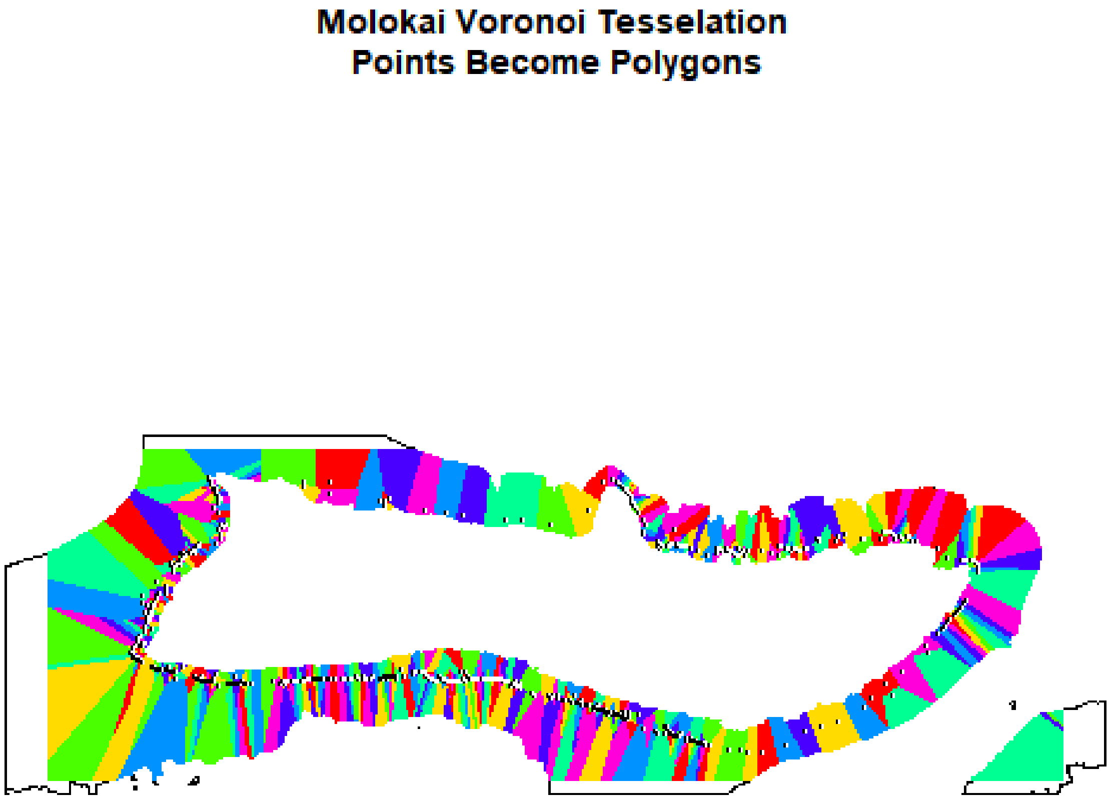


Figure A 9: Voronoi tessellation visualization, Moloka‘i.

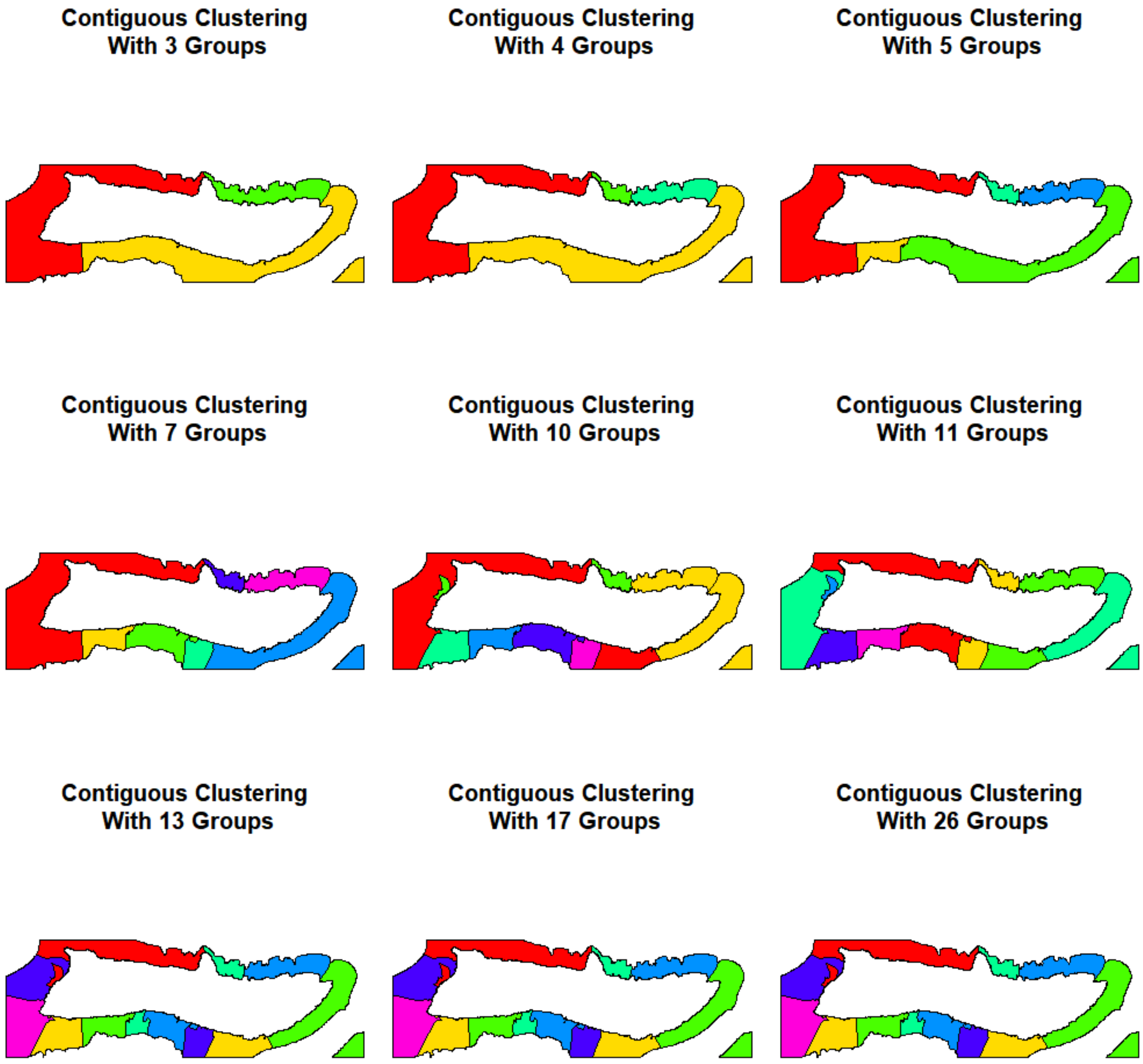


Figure A 10: Hierarchical Spatial Clusters, Moloka‘i.

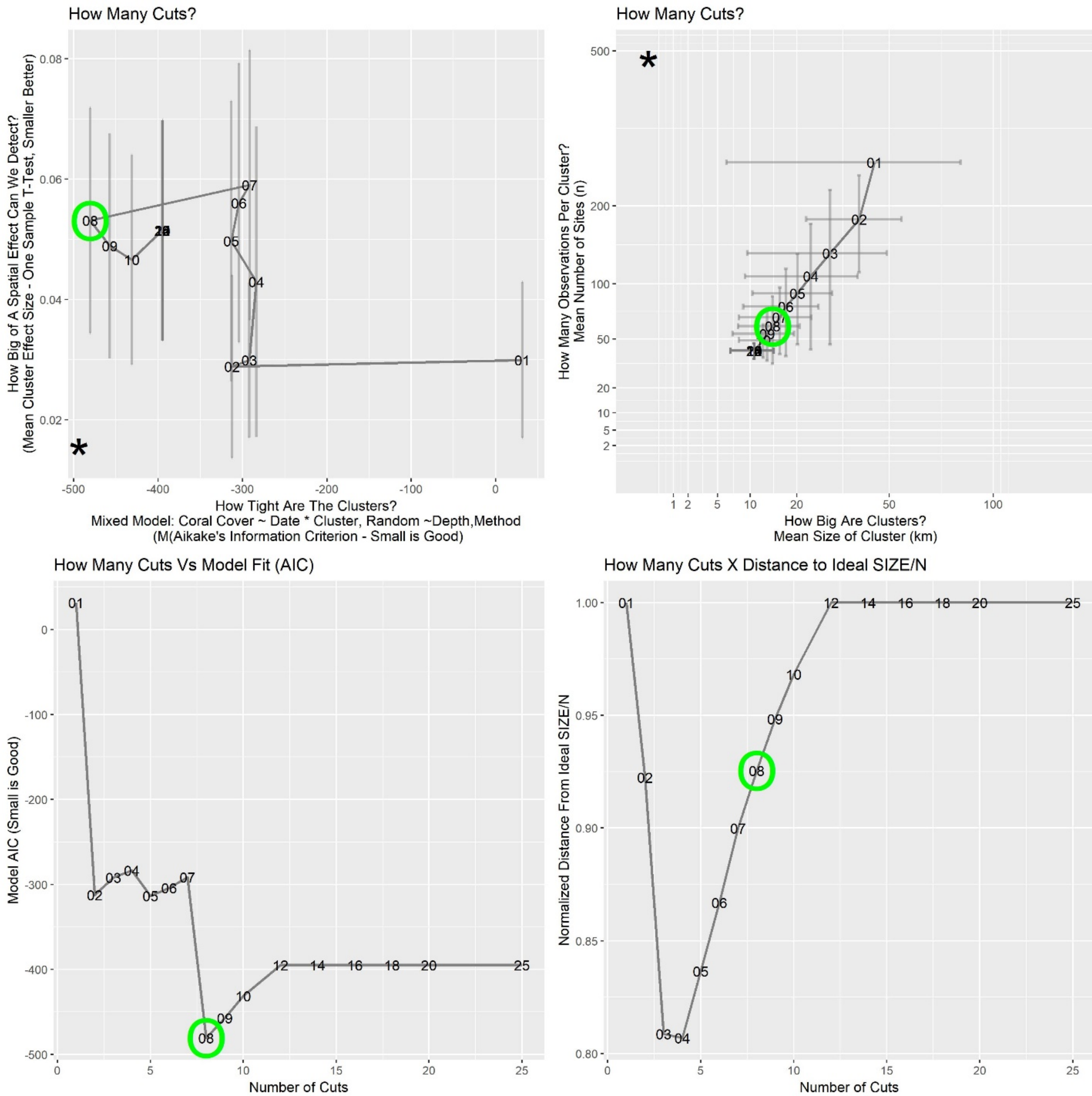


Figure A 11: How many cuts? Moloka‘i.

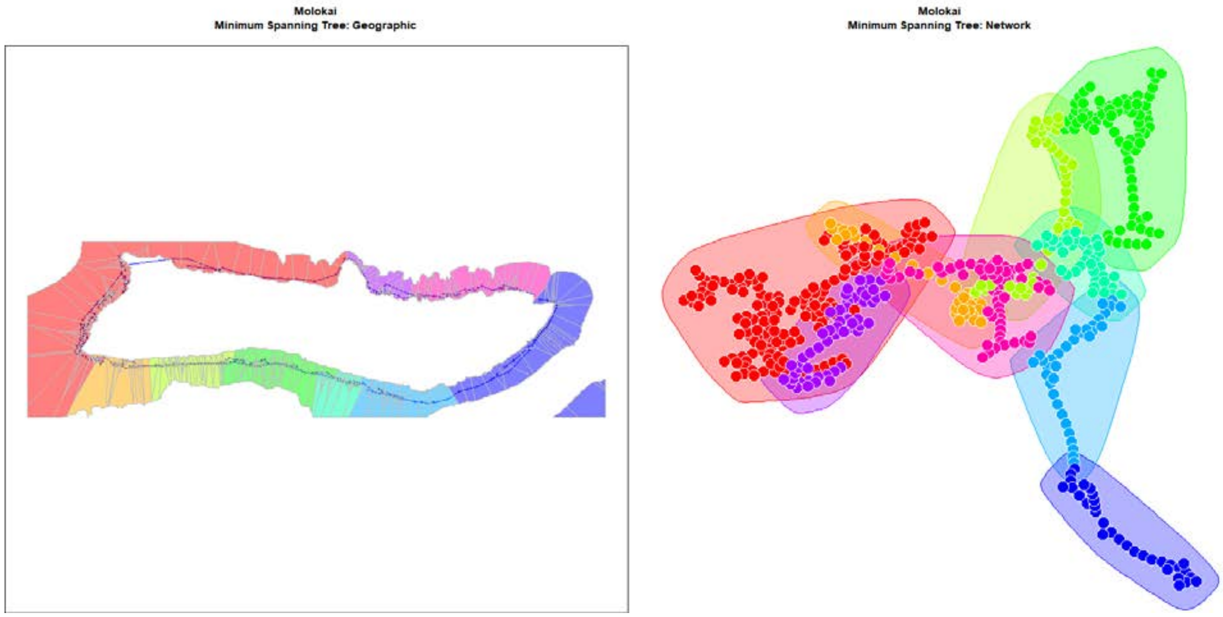


Figure A 12: Minimum spanning tree with highlighted clusters, Moloka‘i.

O‘ahu: Clustering Process Plots

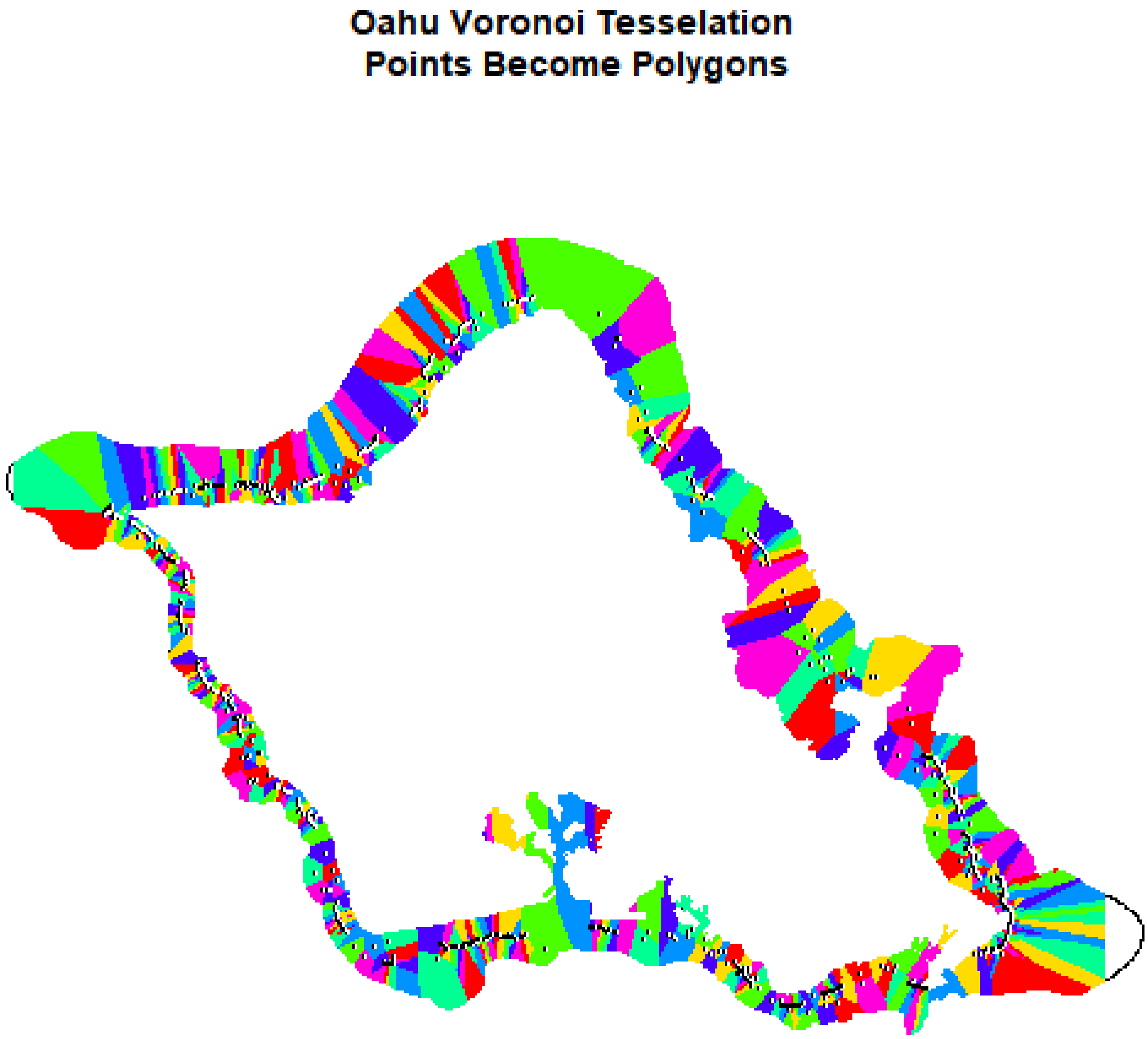


Figure A 13: Voronoi tessellation visualization, O‘ahu.

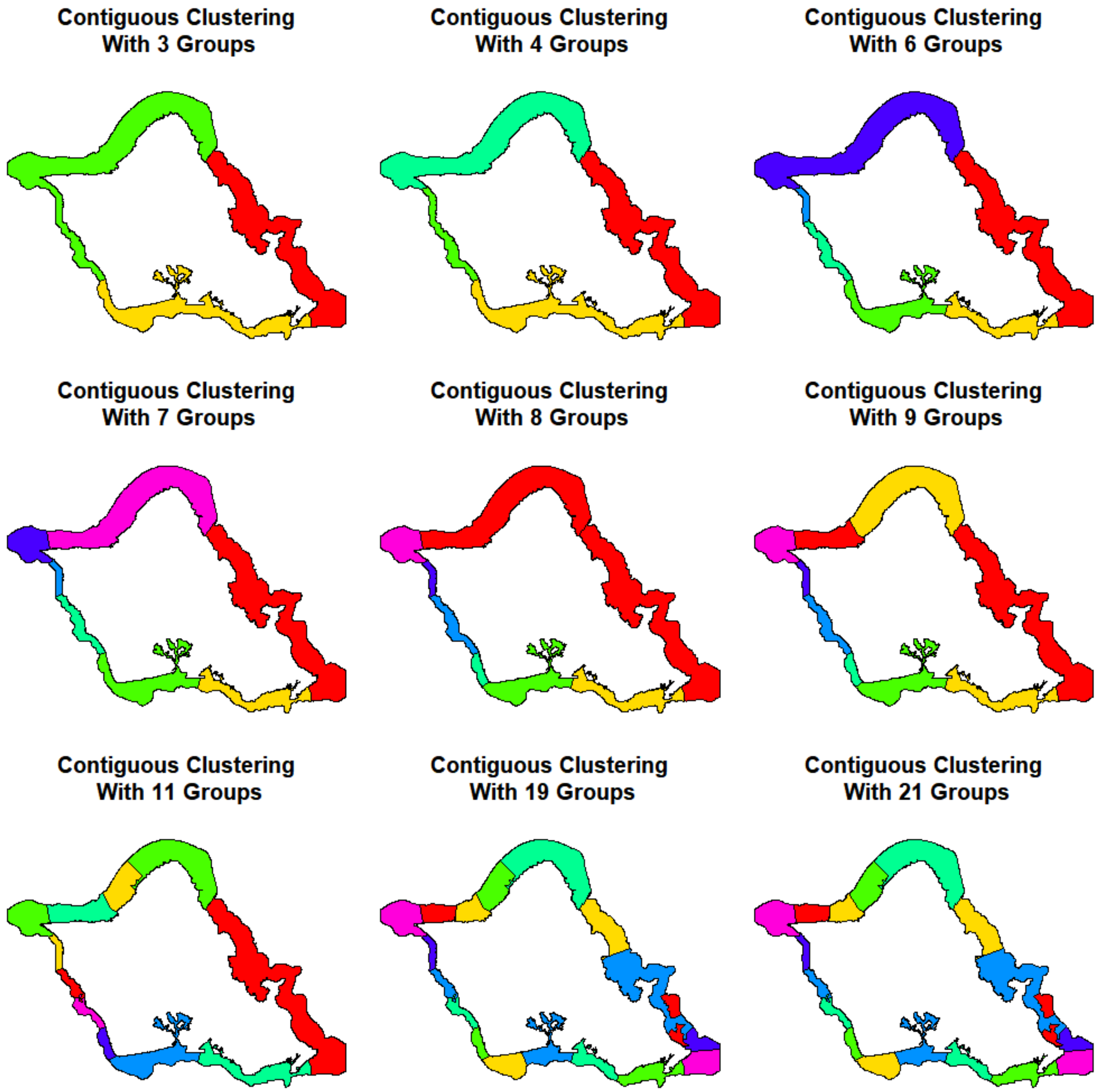


Figure A 14: Hierarchical Spatial Clusters, O‘ahu.

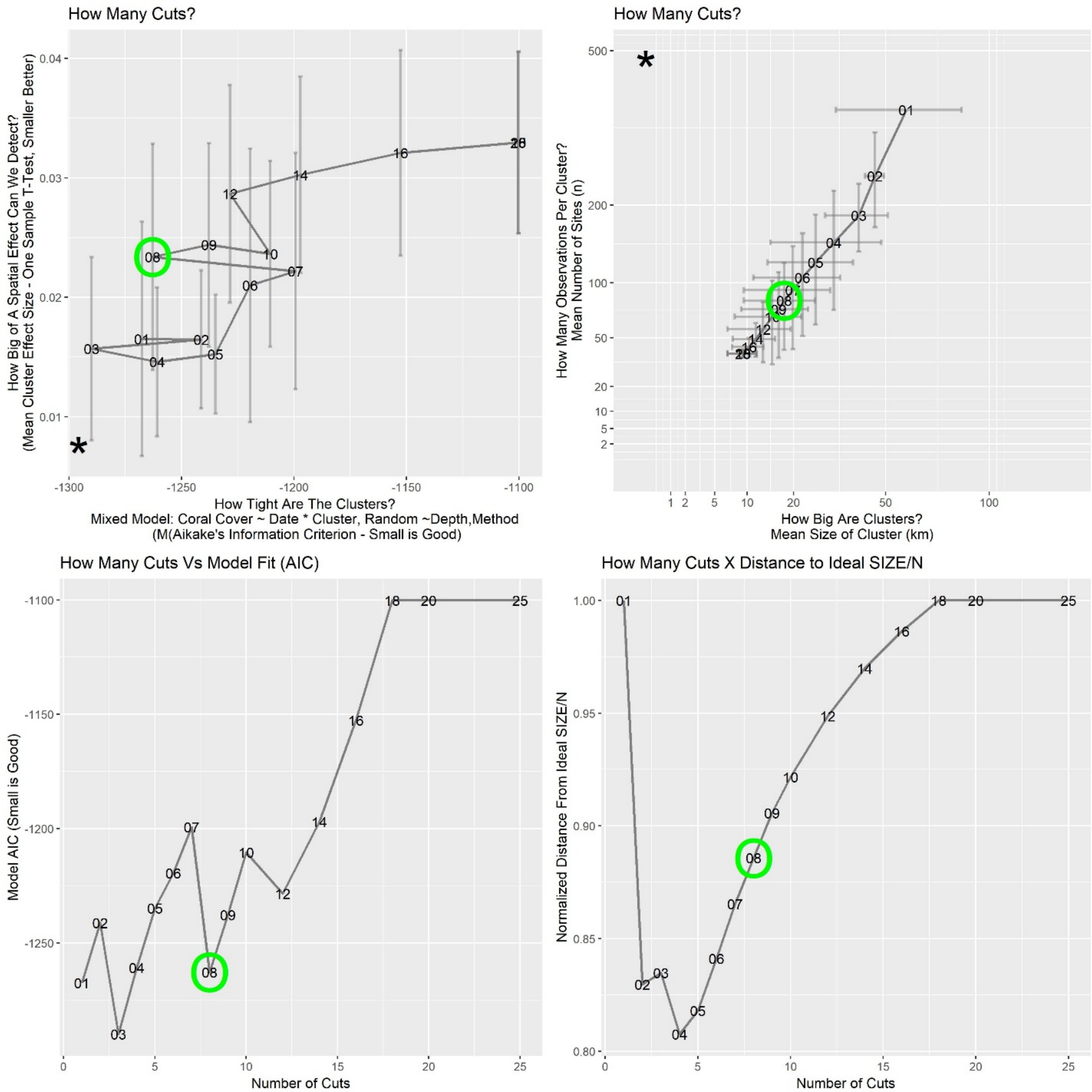


Figure A 15: How many cuts? O‘ahu.

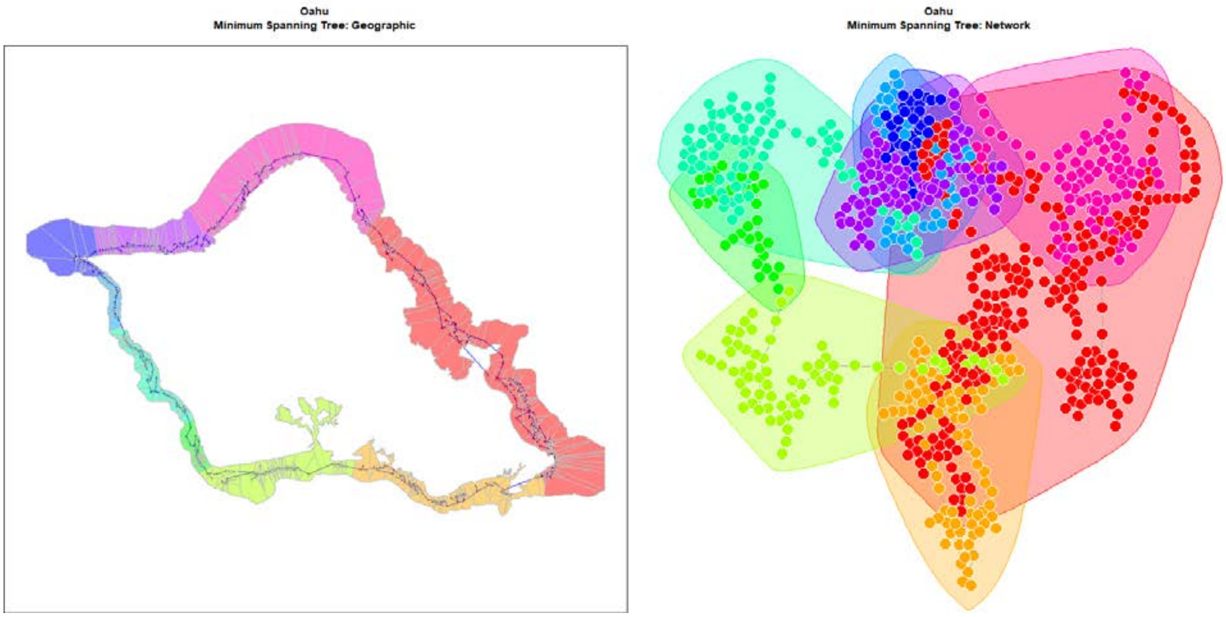


Figure A 16: Minimum spanning tree with highlighted clusters, O‘ahu.

Kaua‘i: Clustering Process Plots

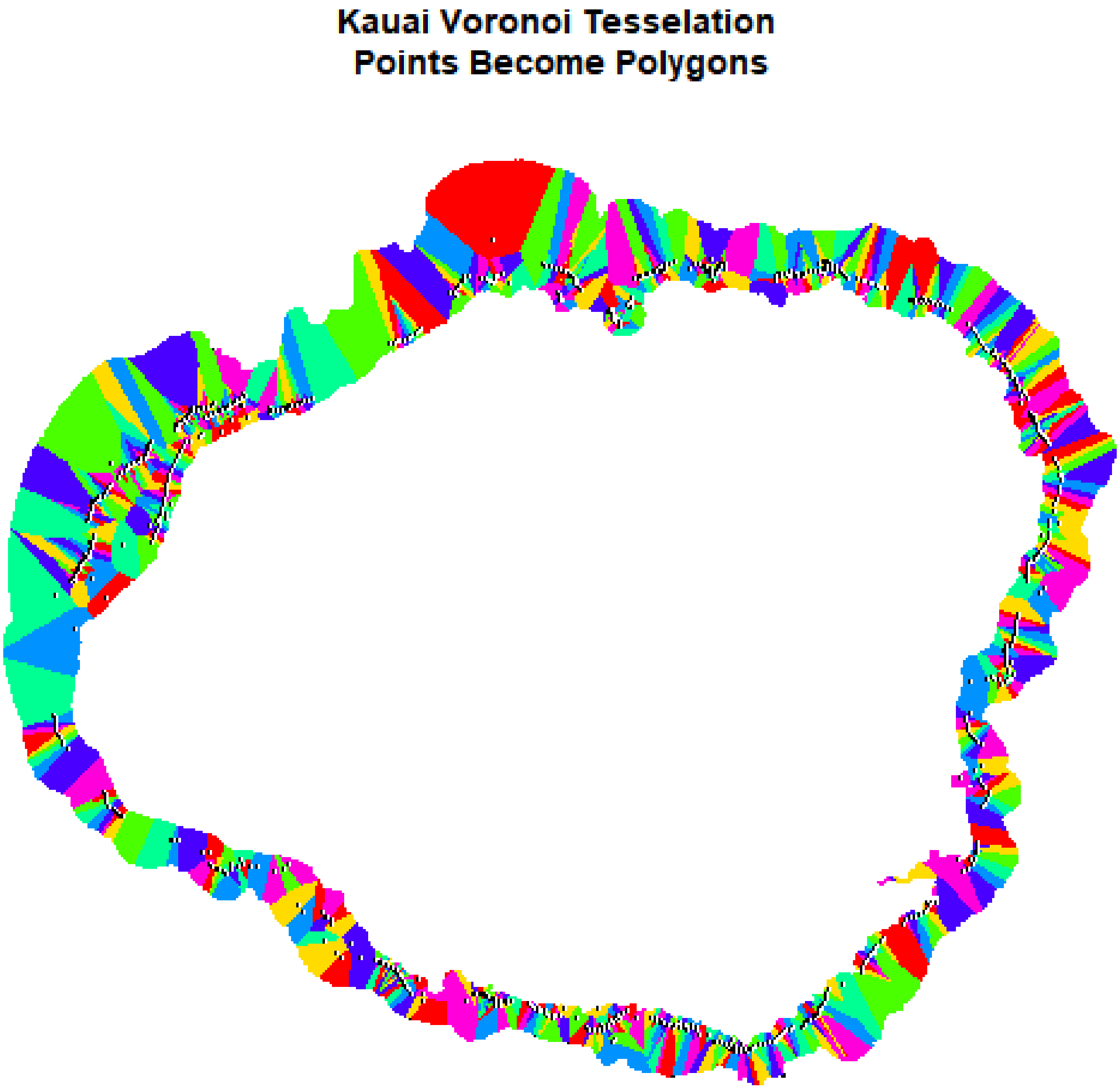


Figure A 17: Voronoi tessellation visualization, Kaua‘i.

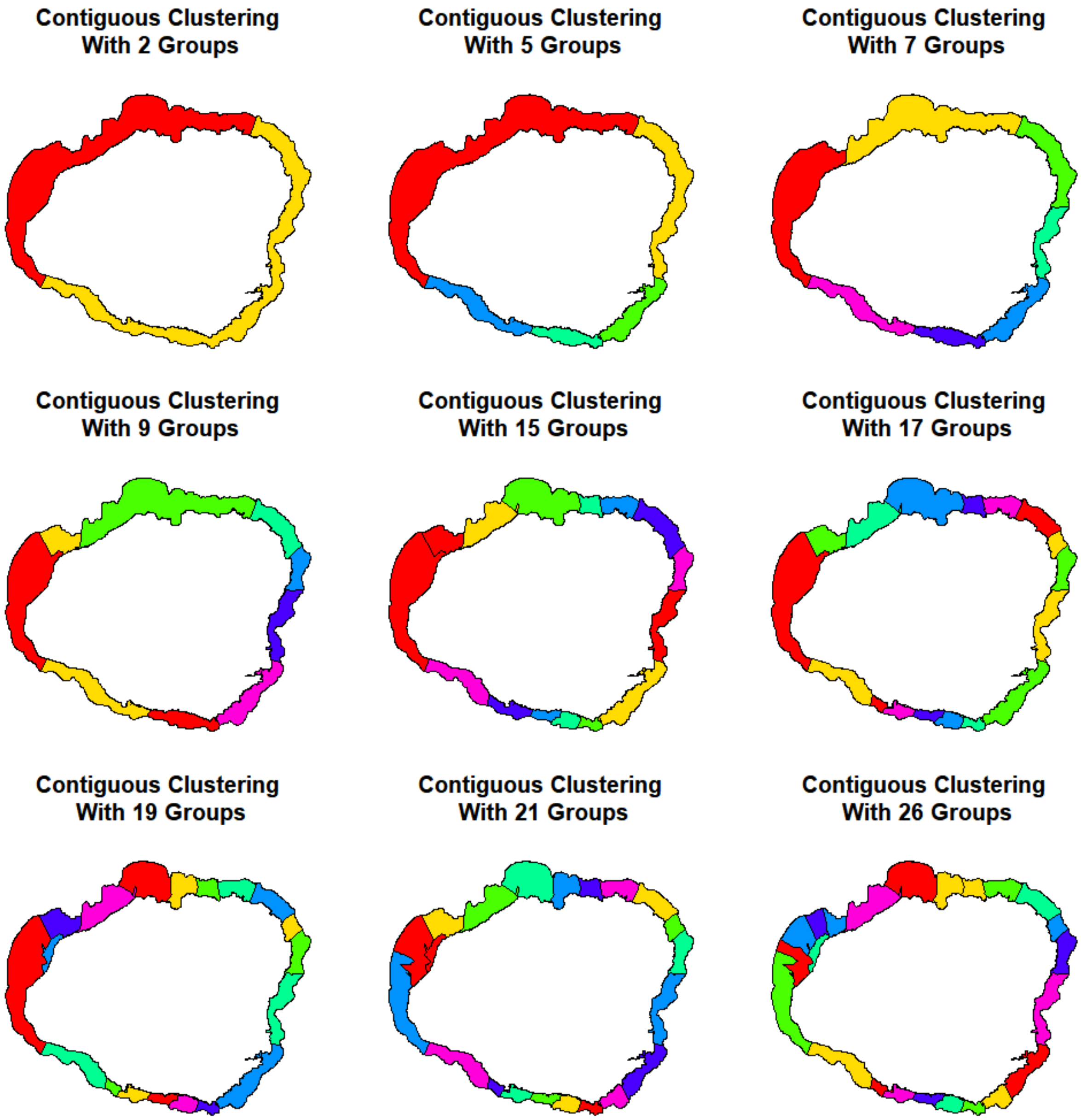


Figure A 18: Hierarchical Spatial Clusters, Kaua‘i.

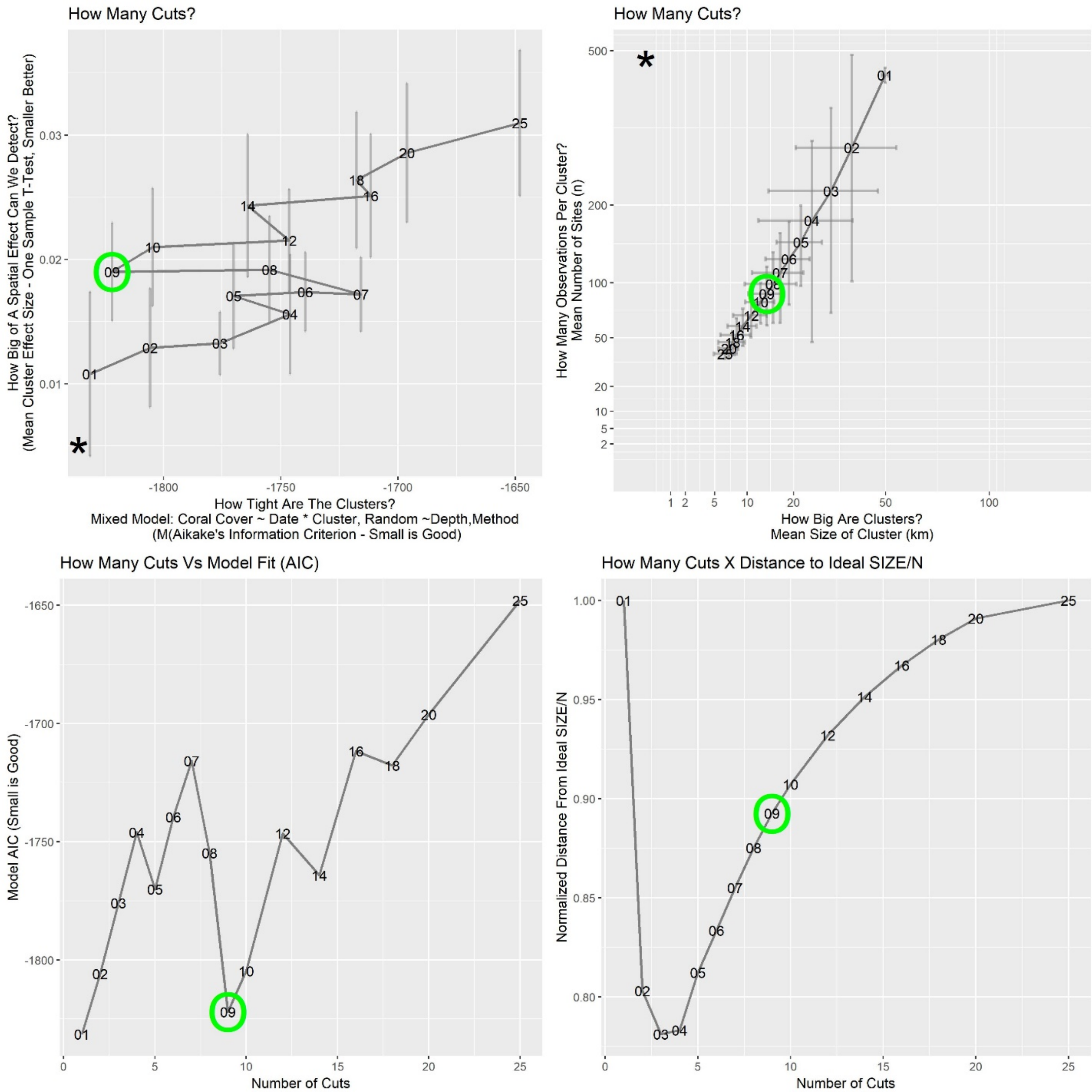
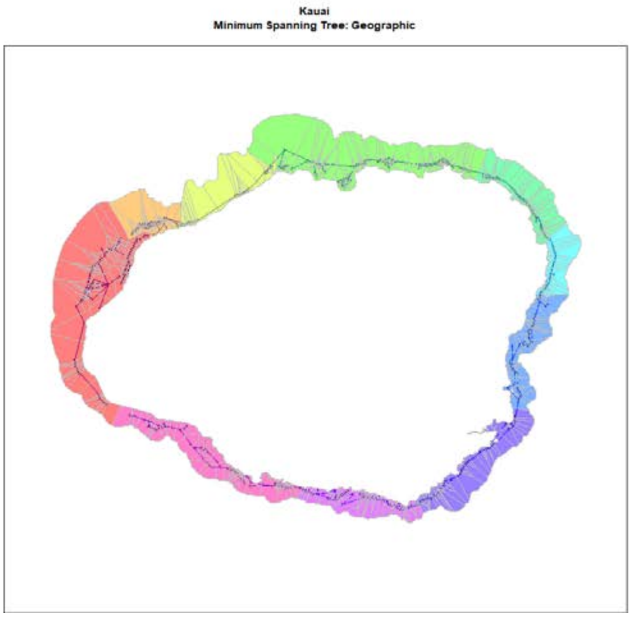


Figure A 19: How many cuts? Kaua'i.



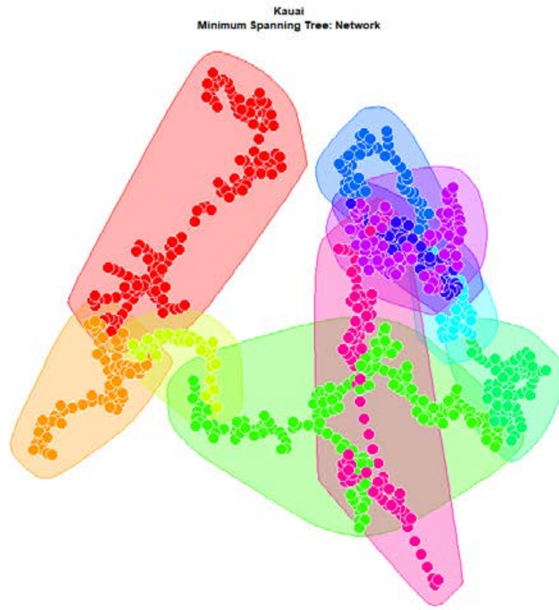


Figure A 20: Minimum spanning tree with highlighted clusters, Kaua‘i.

Niʻihau: Clustering Process Plots

Figure A 21: Voronoi tessellation visualization, Niʻihau.

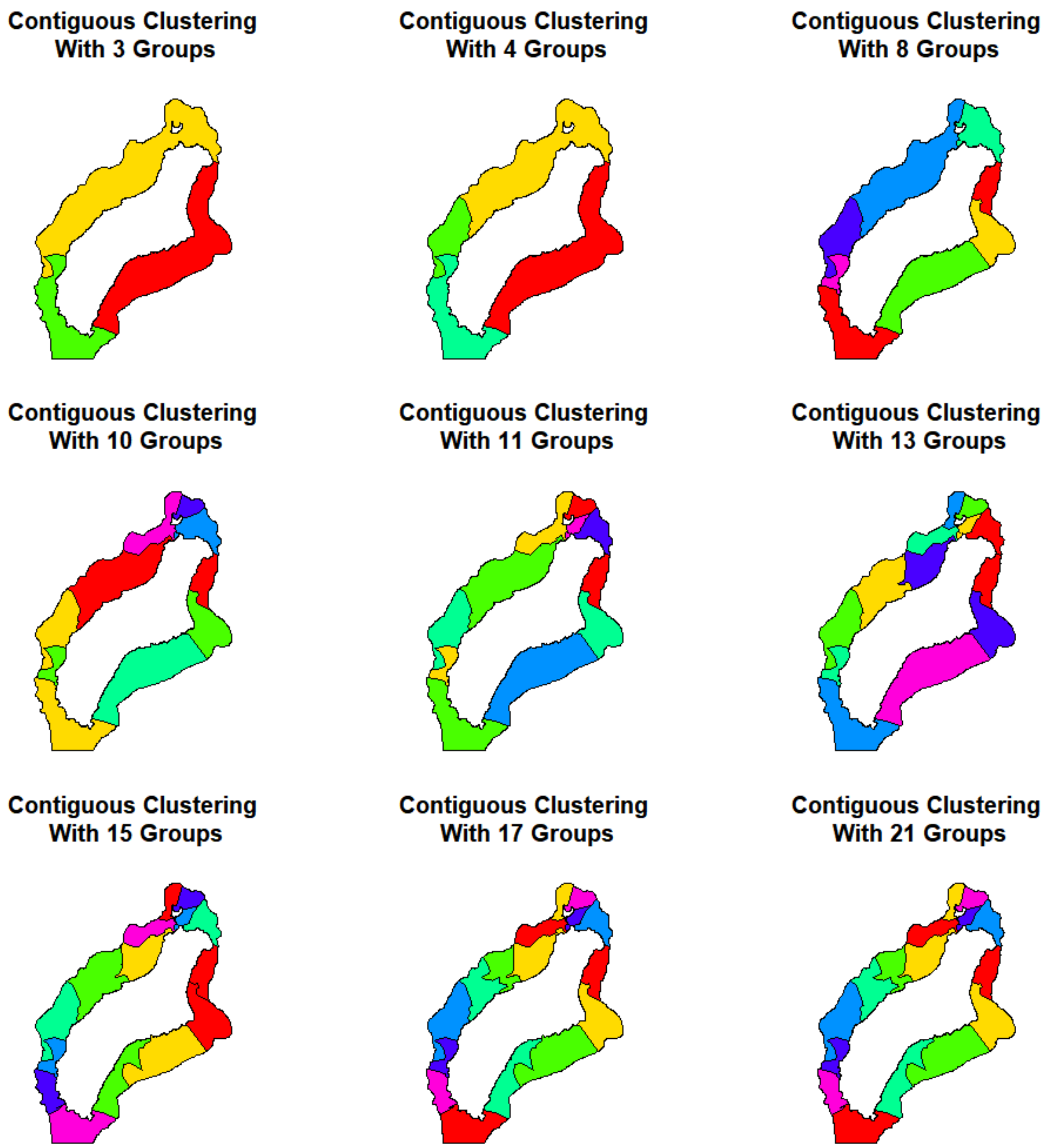


Figure A 22: Hierarchical Spatial Clusters, Ni‘ihau.

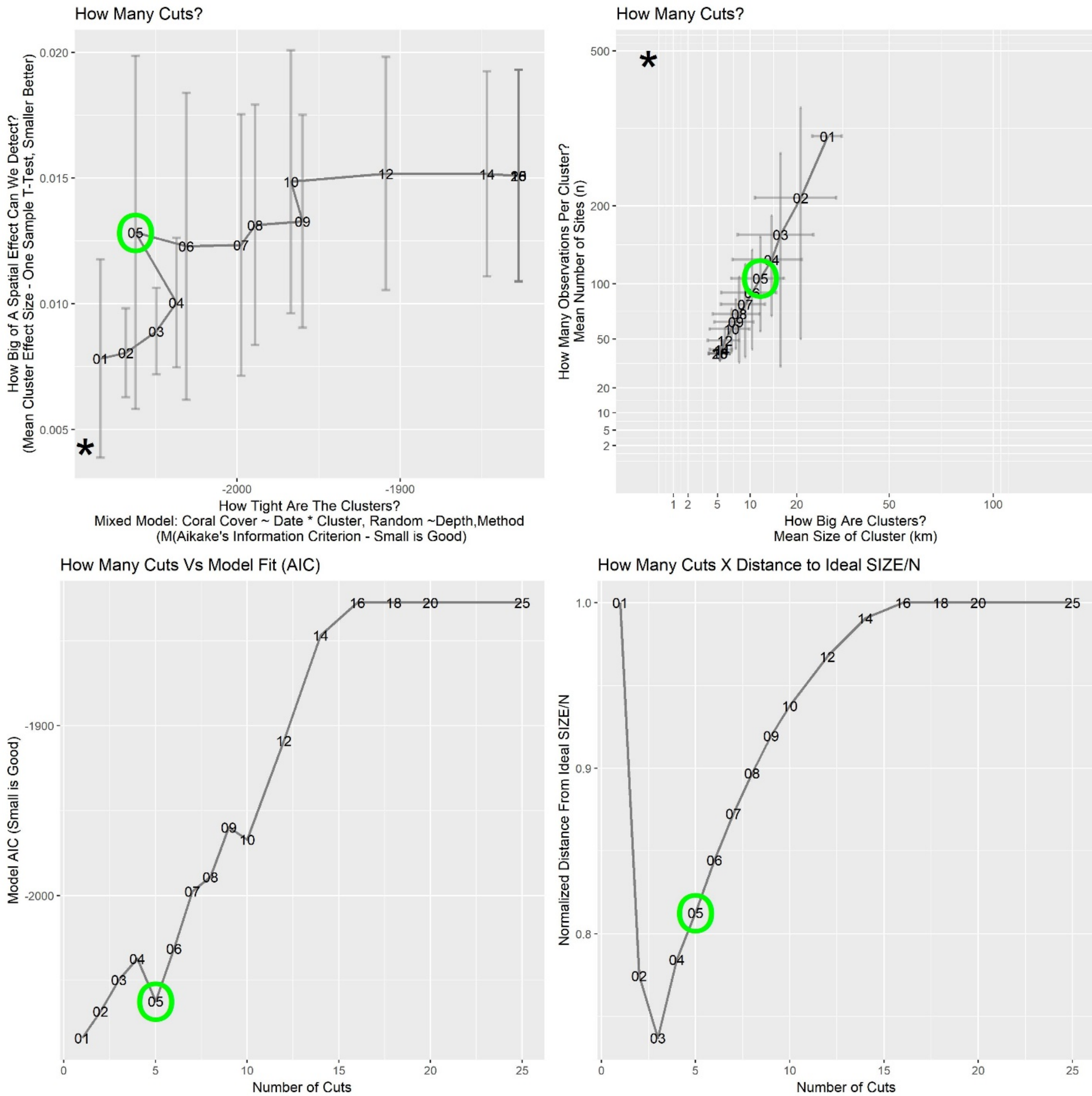


Figure A 23: How many cuts? Ni‘ihau.

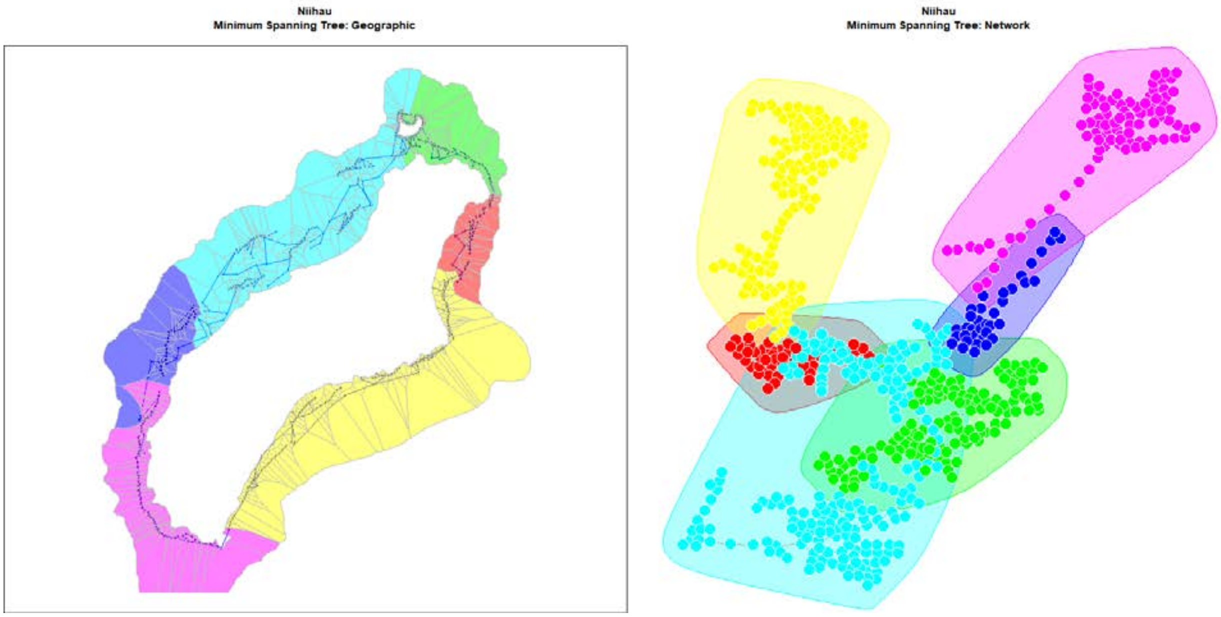


Figure A 24: Minimum spanning tree with highlighted clusters, Ni‘ihau.