

Mapping changes to vegetation pattern in a restoring wetland: Finding pattern metrics that are consistent across spatial scale and time

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ABSTRACT

Tidal salt marshes in the San Francisco Estuary region display heterogeneous vegetation patterns that influence wetland function and provide adequate habitat for native or endangered wildlife. In addition to analyzing the extent of vegetation, monitoring the dynamics of vegetation pattern within restoring wetlands can offer valuable information about the restoration process. Pattern metrics, derived from classified remotely sensed imagery, have been used to measure composition and configuration of patches and landscapes, but they can be unpredictable across scales, and inconsistent across time. We sought to identify pattern metrics that are consistent across spatial scale and time – and thus robust measures of vegetation and habitat configuration – for a restored tidal marsh in the San Francisco Bay, CA, USA. We used high-resolution (20 cm) remotely sensed color infrared imagery to map vegetation pattern over 2 years, and performed a multi-scale analysis of derived vegetation pattern metrics. We looked at the influence on metrics of changes in grain size through resampling and changes in minimum mapping unit (MMU) through smoothing. We examined composition, complexity, connectivity and heterogeneity metrics, focusing on perennial pickleweed (*Sarcocornia pacifica*), a dominant marsh plant. At our site, pickleweed patches grew larger, more irregularly shaped, and closely spaced over time, while the overall landscape became more diverse. Of the two scale factors examined, grain size was more consistent than MMU in terms of identifying *relative* change in composition and configuration of wetland marsh vegetation over time. Most metrics exhibited unstable behavior with larger MMUs. With small MMUs, most metrics were consistent across grain sizes, from fine (e.g. 0.16 m²) to relatively large (e.g. 16 m²) pixel sizes. Scale relationships were more variable at the landcover class level than at the landscape level (across all classes). This information may be useful to applied restoration practitioners, and adds to our general understanding of vegetation change in a restoring marsh.

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1. Introduction

Tidal wetlands, like many other wetland types, have faced a long history of modification and loss globally. Estimates from North American suggest that 80% of tidal marshes have been lost or altered hydrologically since European settlement (Pennings and Bertness, 2001). In the San Francisco Bay area, our focus in this paper, up to 95% of tidal wetland have been lost in the last two centuries (Fretwell et al., 1996; Mitsch and Gosselink, 2000) leaving a highly fragmented, extremely modified wetland land-

scape (Euliss et al., 2008). Yet tidal marshes are some of the most productive ecosystems on the earth and provide a range of valuable ecosystem services including habitat provision for a range of fish, bird and mammals (Mitch and Gosselink, 2000). In the United States at least, recognition of these ecosystem services across public, scientific and governmental spheres has slowed the rate of wetland loss, and there is an increased commitment by government and land agencies to restore tidal wetlands where possible, promoting the many physical and biological processes that interact across multiple scales in wetlands (Baird, 2005). This change in the perception of their value also means that wetlands, and wetland restoration projects, often face expectations that a broad suite of ecosystem services be delivered (Euliss et al., 2008). These can include increased primary productivity and carbon sequestration; increased bank or levee stabilization; increased vegetation diversity; and provision of adequate habitat for native

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or endangered wildlife (Philip Williams & Associates Ltd. and Faber, 2004).

These increased expectations necessitate goal-driven monitoring of change (Zedler, 2000). The value of remote sensing for wetland monitoring has long been recognized (Hinkle and Mitsch, 2005; Phinn et al., 1996), and recent advancements have made the methods and tools more available to researcher to map and measure changes in wetland extent, or species extent, or overall wetland condition (Cowardin and Myers, 1974; Phinn et al., 1996). Early work with aerial photography and satellite imagery used visual interpretation for classification and delineation of wetlands (Ozesmi and Bauer, 2002), but increasingly, more automated computer classification methods that use multivariate clustering of spectral and spatial data are being employed (Alexandridis et al., 2009; Andresen et al., 2002; Ausseil et al., 2007; Frohn et al., 2009; Ramsey and Laine, 1997; Schmidt and Skidmore, 2003).

But importantly, wetlands are not just defined by their extent, but are complex systems, displaying a dynamic interplay between structure (the spatial relationship among distinct elements or structural components of a system) and function (the productivity, nutrient cycling, animal movement and population dynamics of a system) (Bedford, 1996; Kelly, 2001; Simenstad et al., 2006; Turner et al., 2001; Wang et al., 2008). In this landscape ecological view, at the regional scale wetlands are part of the complex matrix of other land cover types that make up the San Francisco Bay area, and at the scale of the individual wetland, the pattern of the vegetation and other physical structural elements influences biological processes like habitat provision (Roe et al., 2009; Turner et al., 2001) tidal wetlands, because they bridge estuarine systems and upland areas, contain vegetation that is influenced by and responds to multiple physical gradients across short distances. As a result, they often exhibit complex spatial patterns in vegetation cover and composition that can change through time. Thus, when monitoring a restoring marsh, we must consider not just the extent of vegetation change, but also the spatial structural attributes of a site that relate to specific functions.

One of the best ways to explore the additional component of structural change in a restoring marsh is through the use of landscape or pattern metrics, which explicitly capture spatial structure of patches, classes and landscapes (Brooks et al., 2006; Frohn, 1998; Kong et al., 2007; Langanke et al., 2007; Turner et al., 2001; Yang and Liu, 2005). Pattern metrics are calculated using equations that quantify the spatial characteristics of individual patches, or a particular class within a landscape, and the spatial pattern of the landscape as a whole, using remotely sensed imagery as the input data. The most commonly described and used set of landscape metrics are in the FRAGSTATS software package, developed by McGarigal and Marks in the 1990s and still in frequent use today. These metrics calculate information on the composition of patches, or classes or landscapes, or their configuration (McGarigal et al., 2002; McGarigal and Marks, 1994). There are hundreds of developed and published metrics; FRAGSTATS will compute more than a hundred area/density/edge metrics, shape metrics, core area metrics, isolation/proximity metrics, contrast metrics, contagion/interspersion metrics, connectivity metrics, and diversity metrics; calculated at the patch-, class-, and landscape-scale. After calculating metrics, a scientist's task is to first determine which metrics provide useful information, as many of these metrics are redundant (Cushman et al., 2008; Kearns et al., 2004), and second to link these structural characteristics to real ecological function (Calabrese and Fagan, 2004; Haines-Young and Chopping, 1996). These metrics have proved a popular method for measuring the composition and configuration of patches within a landscape and for characterizing the landscape as a whole at one time period, based on single snapshot remotely sensed imagery (Brooks et al., 2006; Diaz-Varela et al., 2009; Kearns et al., 2004; Li and Wu, 2004;

Mita et al., 2007). A common approach is to calculate metrics for an area surrounding a wetland site, defined by a simple distance buffer (Brooks et al., 2006; Walsh et al., 2003). For example, Mita et al. (2007) examined 73 wetland sites in the Prairie Pothole Region of North Dakota, USA. For the area within a 300-m buffer around each site, they calculated from Landsat imagery a suite of landscape metrics (number of patches, patch size, edge density, and other landscape diversity and configuration metrics) to aid in rapid assessment of wetland condition.

With increased availability of remotely sensed imagery, researchers are able to calculate identical metrics over time and evaluate temporal dynamics of landscapes in conservation, restoration and planning applications (Bell et al., 1997; Frohn, 1998; Lausch and Herzog, 2002; Rocchini et al., 2006; Xu et al., 2009). For example, Langanke et al. (2007) used a suite of multi-temporal landscape metrics (class area, patch size number of patches, core area, number of core areas, and proximity index) to map trends in harmful vegetation encroachment in a raised bog in Austria. Rocchini et al. (2006) used temporal metrics based on landscape composition and patch size, shape and isolation in a natural reserve in Italy to examine an ongoing process of fragmentation. These types of analyses of multi-temporal metrics are useful for detecting and quantifying dynamic ecological processes and for helping plan and prioritize management activities (Rocchini et al., 2006).

However, there are technical challenges with the use and interpretation of metrics, largely focused around the robustness of metric behavior across scale. These issues have been discussed in a number of papers (Birdsey, 2004; Saura, 2004; Saura and Martinez-Millan, 2001; Turner et al., 1989; Wickham and Riitters, 1995; Wu et al., 2000) and summarized in recent critical papers (Wu et al., 2002; Li and Wu, 2004; Wu, 2004). It is clear from this body of work that pattern metrics are influenced by data scale: both the pixel resolution and the spatial extent of the imagery can change the resulting metric calculations. How scale influences metric does vary. Wu (2004) found that scale relationships were more variable at the class level (for different mapped land cover classes) than at the landscape level (the entire mapped product and including all land cover classes) and that metrics responded more consistently to changes in grain size than to changes in spatial extent. Saura and Martinez-Millan (2001) found that simpler metrics like edge density were the most robust metrics to changing spatial extent. In an effort to develop a theory of metric response to scale, Wu et al. (2002) performed resampling to create multiple images with increasingly large pixel sizes and extents and ran pattern metrics at each step. They classified the general behavior of pattern metrics to scale changes into one of three categories: predictable and linear; stair-stepped (threshold response); or erratic and unpredictable. In a related follow-up paper, Wu (2004) ran the same multi-scaled approach across different landscapes, and further classified metrics into two broad types: those with simple scaling functions and those that exhibited unpredictable behavior. In addition to discriminating between predictable and unpredictable metric behavior, Wu was looking for metric consistency across the different landscapes and metric robustness within landscapes.

These kinds of multi-scale studies are generally agreed to be essential for informed and reliable interpretation of landscape metrics (Wu, 2004). But there are two additional components that need to be investigated in order to assist in the monitoring of a heterogeneous and dynamic system like a restoring tidal wetland. The first is an aspect of scale not considered in most of the studies mentioned above: the size of the minimum mapping unit (MMU). Most image classification processes, and especially when performed on high spatial resolution imagery, require some kind of spatial filtering to remove the spurious pixels or "speckle" that is inherent to many pixel-based classification routines (Kelly et al., 2004). This artifact is caused by the high local-scale spectral variability caused

by shadow, mixed species, and differences in reflectance values (Townsend, 1986). While this is a large problem with pixel-based classification of fine-scale images, imagery from all sources (e.g. satellite and airborne) and of all scales (sub-meters to global) have some need for post-classification smoothing techniques if spatial analyses are to be performed on per-pixel classification results. This post-classification smoothing, which is common in the mapping process, needs to be considered in addition to pixel size because it can change the size of the patches in a land cover dataset with which pattern metrics are computed (Saura, 2002, 2004). In many cases the choice of a minimum mapping unit is made *a priori* (Rocchini et al., 2006). Here we evaluate the effects of minimum mapping unit size along with grain size on metric behavior. To vary the MMU size, we used elimination filters, which remove clusters of pixels smaller than a specified minimum size. These elimination filters are a more sensitive smoothing technique than simple majority filters as they retain some of the heterogeneity in a target filter area, but they have not been evaluated for their effects on landscape metric calculation; the past studies examining the impact of MMU choice concentrate on majority filters (e.g. Saura and Martinez-Millan, 2001).

The second important aspect of this work is the examination of metric consistency across time as well as scale. The identification of appropriate spatial pattern metrics that correctly and robustly track changes in ecologically relevant patterns in a restoring marsh is important for conservation of marsh-associated wildlife species and for overall understanding of the viability of the marsh as a productive and functioning system. Many researchers have examined the change in time in metrics derived from multi-temporal imagery (Brooks et al., 2006; Xu et al., 2009), but few have looked at the effect of scale on metric predictability across time. In other words, most of these studies choose a scale or minimum mapping unit first, and compare resultant metrics across time *at this scale*. When effect across scale and time on metrics is considered, as in Lausch and Herzog (2002), the number of suitable metrics can decrease.

This paper examines how vegetation pattern metrics, derived from fine-scale remotely sensed imagery, behave across (a) pixel (or grain) size and (b) minimum mapping unit (i.e., elimination filter smoothing window), and (c) time. We examined how pattern metrics responded to combinations of these scale elements in order to

find which metrics were reliable across scale, and consistent across time. We looked at overall landscape pattern within the marsh through a suite of landscape metrics, and at the extent and pattern of an individual marsh plant through a suite metrics calculated for individual vegetation types. Our target species, perennial pickleweed (*Sarcocornia pacifica*) is the primary plant species used for cover by many endemic tidal marsh species, such as the endangered salt marsh harvest mouse (*Reithrodontomys raviventris*), whose mobility and dispersal in a wetland are highly related to a suitable arrangement of pickleweed within the site (Bias and Morrison, 2006; Boul et al., 2009; Shellhammer et al., 1982).

2. Materials and methods

2.1. Study site

The Petaluma River Marsh (PRM) is a tidal salt marsh approximately 20 ha in size and located 1.6 km upstream from the mouth of the Petaluma River on San Pablo Bay, in Sonoma County, CA (Fig. 1). The site was restored to tidal action in 1994, following the dredging of two main channels from breaches in the north and south ends of the outboard levee and the removal of soil from the site to heighten and strengthen the inboard levee, which created linear features within the site. No vegetation was planted (Siegel, 2002). The site has a clear history of vegetation change between 1994 and 2004, as measured by Tuxen et al. (2008), who used remote sensing and a general classification scheme (vegetation vs. no vegetation) to document the increase in vegetation cover from 0% to 90% over 10 years. The imagery used and the field data collected with that work were not comparable to this project in terms of floristic detail.

In 2004, dominant vegetation at PRM consisted of perennial pickleweed, an annual pickleweed (*Salicornia europaea*), alkali bulrush (*Bolboschoenus maritimus*), and the native Pacific cordgrass (*Spartina foliosa*). The marsh is surrounded by agriculture to the immediate east and north but is in relatively close proximity to many marshes, including one of the largest remaining natural marshes in the San Pablo Bay region, the ancient Petaluma Marsh. The presence of the salt marsh harvest mouse has been documented at Petaluma Marsh, as well as other sites along the Petaluma River

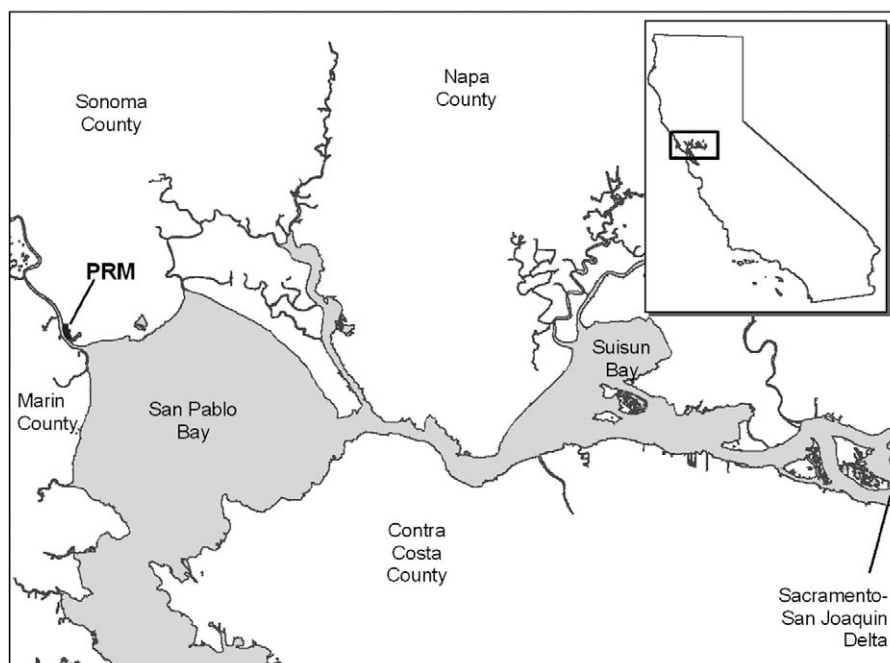


Fig. 1. Map of vicinity of study site, Petaluma River Marsh (PRM) in the San Francisco Bay Estuary.

(Shellhammer, 1989). In addition, other endangered species such as the California clapper rail have been documented at PRM and surrounding marshes (Liu et al., 2009), which further increases the need for short- and long-term monitoring and management of vegetation pattern and other habitat characteristics.

2.2. Imagery

Color infrared (CIR) aerial photography was acquired on August 14, 2003 and August 19, 2004. For the 2003 photo, imagery was acquired at low tide to optimize potential total vegetation observation; for the 2004 photo, imagery was acquired at mid- to high-tide level to capture all the channels close to bankfull. This difference in tide level did not affect the classification of vegetation types. The photos were scanned at 1200 dots per inch (dpi) at a scale of 1:9600, to render a pixel size of 20 cm on a side (0.04 m^2 pixel area).

The original image from each year (pixel size of 20 cm on a side) was resampled to larger pixel sizes in increments of 2, ranging from 40 cm ($2\times$) to 4 m ($20\times$) on a side, creating images ranging in size from 0.16 m^2 to 16 m^2 . Each resample was performed on the original image from each year using a pixel mean aggregation, where the encompassing pixels were averaged to result in the larger pixel value (Fig. 2). Resampling produced a total of ten images for each year. For this study, we did not experiment with changing the spatial extent, since the site has a distinct natural boundary.

2.3. Analysis

For both the 2003 and 2004 images, the original images (20 cm pixel) were classified into seven classes – alkali bulrush (*Bolboschoenus maritimus*), perennial pickleweed (*S. pacifica*), annual pickleweed (*Salicornia europaea*), Pacific cordgrass (*Spartina foliosa*), upland, bare, and water – using the Maximum Likelihood Classifier (MLC) supervised classification algorithm, using spectral signatures that were created for each vegetation class based on

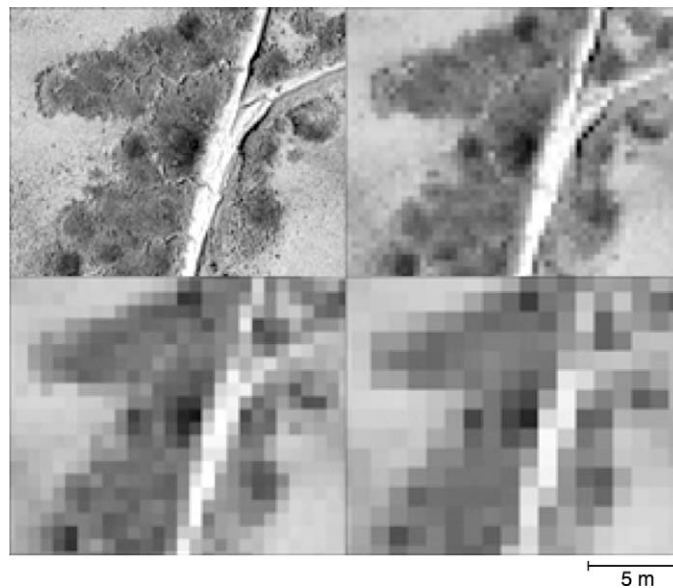


Fig. 2. A portion of imagery from the study site, showing four-grain (pixel) sizes from 20 cm pixels to 1 m pixels.

ground reference data for each year. Fig. 3 shows an example of the classified version at the 1 m pixel scale. For 2003, 253 randomly generated ground points were collected, of which 36 were used for image classification, and 217 were used for accuracy assessment. For 2004, 272 randomly generated ground points were collected, of which 25 were used for image classification and 247 were used for the accuracy assessment. The spectral signatures for each of the 2 years were then applied to all the other resampled images for that year.

For each of the ten classified images for 2003 and 2004, post-classification spatial filtering was applied in order to smooth out

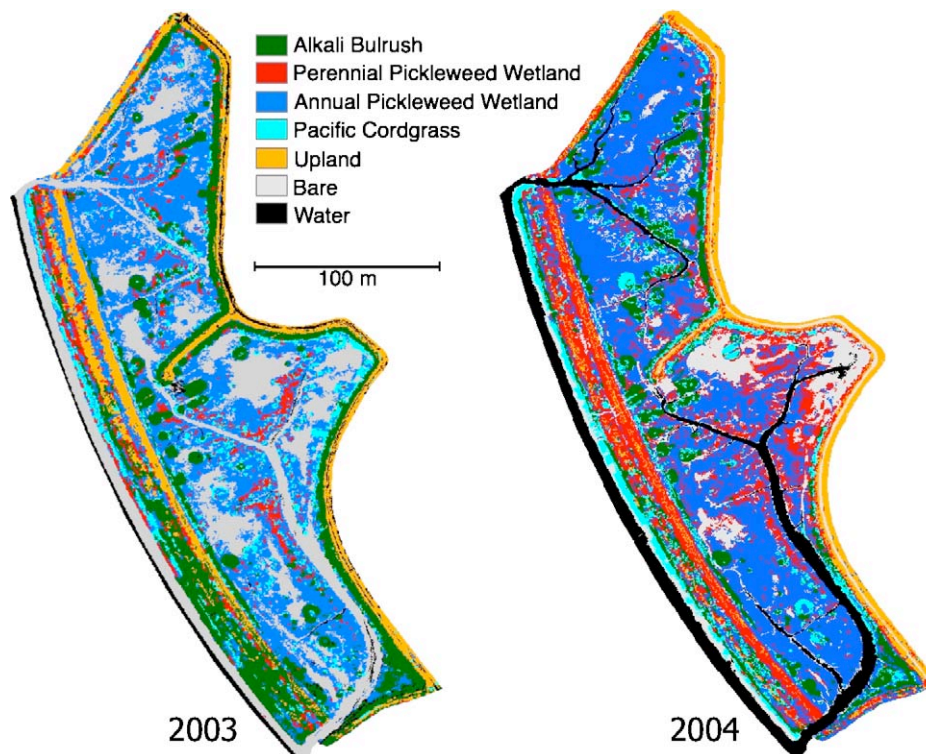


Fig. 3. Classified imagery of the site in 2003 and 2004, with 1 m pixels.

the local heterogeneity inherent in pixel-based classification outputs (Townsend, 1986). For this study, we used a pixel threshold technique that filters the classified output and eliminates clusters of pixels that fall below a minimum size, or minimum mapping unit (MMU). These smaller clusters are given the value of their neighboring pixels in an iterative fashion until there are no clusters below the minimum threshold. Elimination filters with pixel thresholds of 1, 4, 9, 16, 25, 36, 49, 64, 81, 100, 200, and 500 were performed. The eight-neighbor patch definition rule was used, determining that a cluster be defined as continuous pixels of the same class type in either the four cardinal directions or the four diagonal directions (eight neighbors total). We ran the 12 elimination filters on the classified images for each of the 2 years.

Pattern metrics were calculated using FRAGSTATS 3.3 (McGarigal et al., 2002). Rather than run the many hundreds of possible metrics and choose among them post-analysis, we chose a specific suite of ecologically relevant metrics to assess the progress of the restoring marsh. We chose metrics that measured landscape complexity and heterogeneity, and metrics that measured composition, complexity and connectivity of perennial pickleweed – the dominant salt marsh plant critical for many marsh species. We calculated 11 metrics; some were calculated for the entire landscape (shape index, contagion, Shannon's diversity and evenness), and some were calculated for the pickleweed class only (patch area, shape index, clumpiness, patch cohesion, contiguity, connectivity and nearest neighbor); and we grouped these 11 metrics into four types: composition, complexity, connectivity and heterogeneity. The metrics used, their definitions, and ecological relevance are listed in Table 1, and described here.

Composition metrics are among the simplest to measure. We calculated the area of pickleweed in each year. Complexity refers

to the shape and pattern of individual patches or of the whole landscape. These characteristics of patches or landscapes can affect population dynamics via dispersal, colonization, and genetic exchange (Forman, 1995). We calculated shape index (class and landscape), clumpiness (class only), and contagion (landscape only) (McGarigal et al., 2002).

Connectivity in this case deals with the pickleweed class only and describes how proximate or isolated similar patches are to each other and how they are connected. It can be important for processes such as materials exchange, organism dispersal, and predator/prey dynamics. We calculated the following metrics for the perennial pickleweed class: patch cohesion index, contiguity index, connectivity index (with a 5-m threshold), and Euclidean nearest neighbor distance (McGarigal et al., 2002).

Heterogeneity can be defined as the complexity or variability in space and/or time of a property or phenomenon (Li and Reynolds, 1995). In our case heterogeneity was examined with respect to all dominant vegetation types or classes in the site. It can be used as an index of habitat biodiversity and suitability. We calculated Shannon diversity index and Shannon evenness index for the landscape (McGarigal et al., 2002).

We analyzed these 11 metrics for all 120 images and plotted the output values of each metric in relation to pixel (grain) size and MMU in graphs named "scalograms" by Wu et al. (2002) and Wu (2004) with one scalogram per metric per year (Figs. 4–7). In our scalograms, each line represents a different MMU, rather than vegetation class (as in Wu, 2004). Scalograms are useful tools for monitoring pattern, since pattern and processes operate at multiple scales. In addition, scalograms can identify bias associated with using one specific pixel size or MMU of remotely sensed data.

Table 1

Summary of metrics and their link to restoration goals. Metric description from McGarigal et al. (2002).

Metric	Type	Description	Restoration question
<i>Composition</i> Patch area	Class	Amount of specific land cover class	Did pickleweed increase from 2003 to 2004?
<i>Complexity</i> Shape index	Class	Measures patch shape; equals 1 when the patch is maximally compact (i.e., square or almost square) and increases without limit as patch shape becomes more irregular	Did pickleweed patches become more irregularly shaped over time?
Clumpiness	Class	Measures the clustering of patches: equals 0 when the focal patch type is distributed randomly, and approaches 1 when the patch type is maximally aggregated	Are pickleweed patches more aggregated as they increase in size?
Shape index	Landscape	The total length of edge involving the corresponding class divided by the minimum length of class edge for a maximally aggregated class, a measure of class aggregation or clumpiness	Did all the landcover classes become more irregular in shape over time?
Contagion	Landscape	Measures landscape aggregation: approaches 0 when every cell is a different patch type and interspersed; equals 100 when the landscape consists of single patch	Are the landcover classes in the wetland landscape interspersed?
<i>Connectivity</i> Patch cohesion	Class	Measures the physical connectedness of the patch as perceived by organisms dispersing in binary landscapes	Are pickleweed patches more connected as they increase?
Contiguity	Class	Spatial connectedness of cells within a patch; it increases to a limit of 1 as connectedness increases	Are pickleweed patches more connected as they increase?
Connectivity	Class	Counts the number of functional joins between all patches of the corresponding patch type; equals 0 when none of the patches of the focal class are "connected"; equals 100 when every patch of the focal class is "connected"	Are pickleweed patches more connected as they increase?
Euclidean nearest neighbor	Class	The distance to the nearest neighboring patch of the same type, based on shortest edge-to-edge distance	Are pickleweed patches closer together they increase?
<i>Heterogeneity</i> Shannon's diversity	Landscape	Measures landscape diversity; equals 0 when the landscape contains only 1 patch and increases as the number of different patch types increases and/or the proportional distribution of area among patch types becomes more equitable	How does the wetland landscape diversity change over time?
Shannon's evenness	Landscape	Measures landscape evenness: equals 0 when the landscape contains only 1 patch and approaches 1 as the distribution of area among the different patch types becomes increasingly uneven	Are the various landcover classes at the wetland site becoming more evenly distributed?

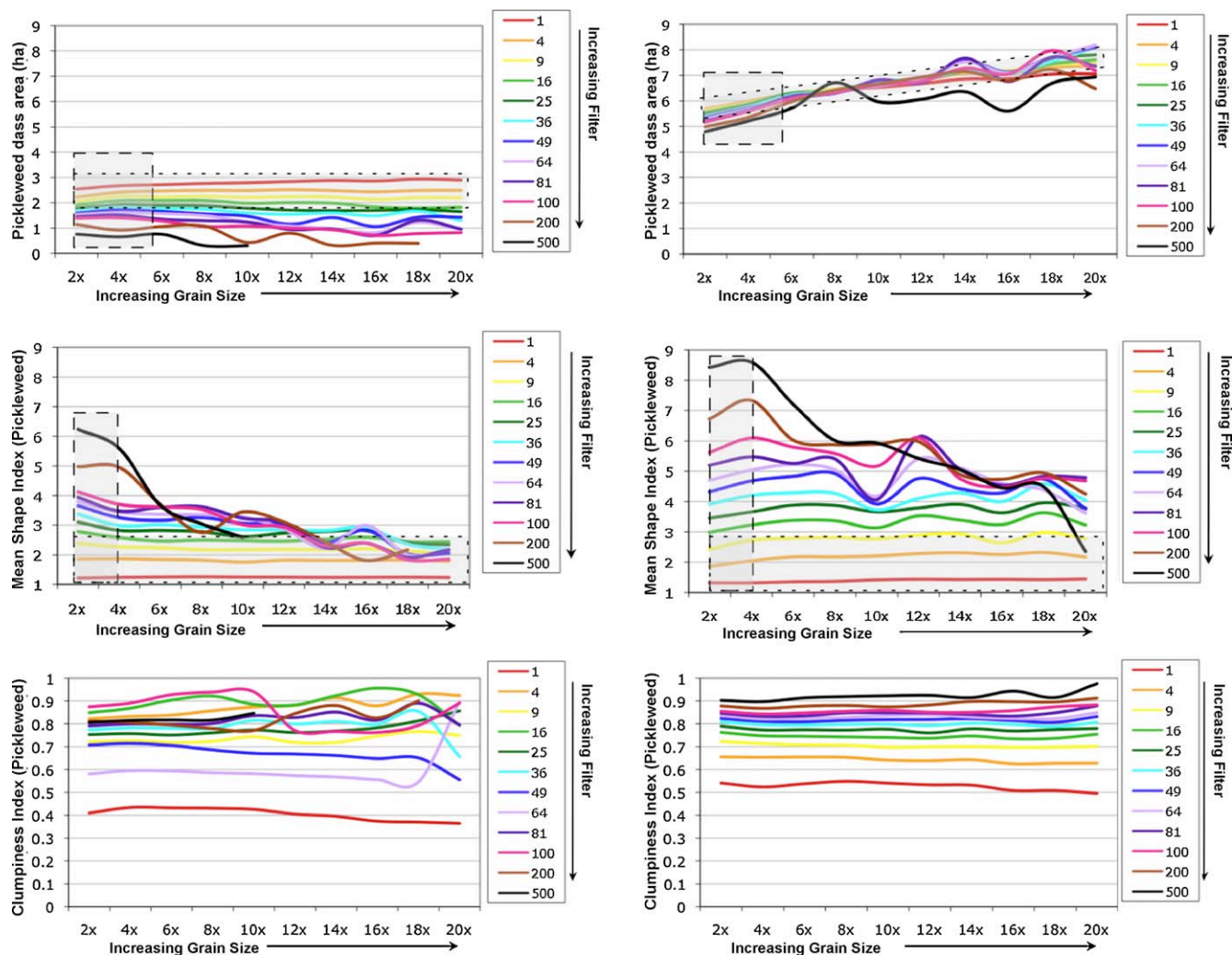


Fig. 4. Scalogram for patch area (a and b), shape index (c and d) and clumpiness (e and f) metrics for pickleweed in 2003 and 2004. Metric values (y -axis) are plotted against both pixel (grain) size (x -axis) and smoothing algorithm and level for each year. Pixel size increases from left to right, and the smoothing level increases from the top to the bottom of the legend (indicated by different colors). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3. Results

As did Wu (2004), we present our results in a series of scalograms that display metric behavior across scales. In that paper, he was interested in discriminating between *predictable* and *unpredictable* metric behavior, and finding *consistency* (across landscapes) and *robustness* (within landscapes) in metric behavior. Here we have similar goals in interpreting our scalograms, with three important differences. First, in addition to grain size, we are also interested in the behavior of metrics with changing MMU. Second, in our case *consistency* refers to similarity of metric response across time, not landscapes. Third, since many of our scalograms show some predictability at some scales, we are interested in the thresholds in scale, in both grain and MMU where metric behavior changes abruptly and thus makes interpretation of change impossible.

Similar to Wu (2004), who split metrics into two classes, based on their predictability across landscapes, we have defined two broad classes of metrics based on predictability across time. Type 1 metrics show consistency across time (rather than across landscapes, as in Wu, 2004) at some scales, and Type 2 metrics are inconsistent across time. Of the first type, Type 1a metrics are consistent only when a small grain (or a small MMU in our implementation) are used. At larger scales, in either grain or MMU, metric behavior is unpredictable and inconsistent across time. Type 1b

metrics are consistent across scales but less robust (in our case *only* if a small MMU is used). With these metrics, an increase in MMU, regardless of grain size, will result in inconsistent interpretations. Type 2 metrics are those where MMU results in inconsistent interpretations across time across all scales and are thus difficult to interpret in a monitoring context. In each of the scalograms in Figs. 4–7, we graphically show the scales within which metrics are predictable in their behavior and consistent across time with a shaded rectangle. These scale thresholds (in grain size and MMU) are also summarized in Table 2. It is these metrics at their appropriate scales that can be used in cases like this for monitoring changes to vegetation pattern in a restoring marsh.

3.1. Behavior across pixel size and minimum mapping unit

We observed the three types of behaviors across pixel sizes described by Wu et al. (2002): (1) linear, which can be predicted across scales; (2) stair-stepped, which exhibit multiple thresholds throughout the scale range; and (3) erratic, which show no consistency or predictability across scales. However, we found that these characterizations were not appropriate for all scales. Most metrics exhibited at least some linear and predictable behavior across the range of pixel sizes, at smaller MMUs; at larger MMUs, stair-stepped or erratic behavior was exhibited. This means that for

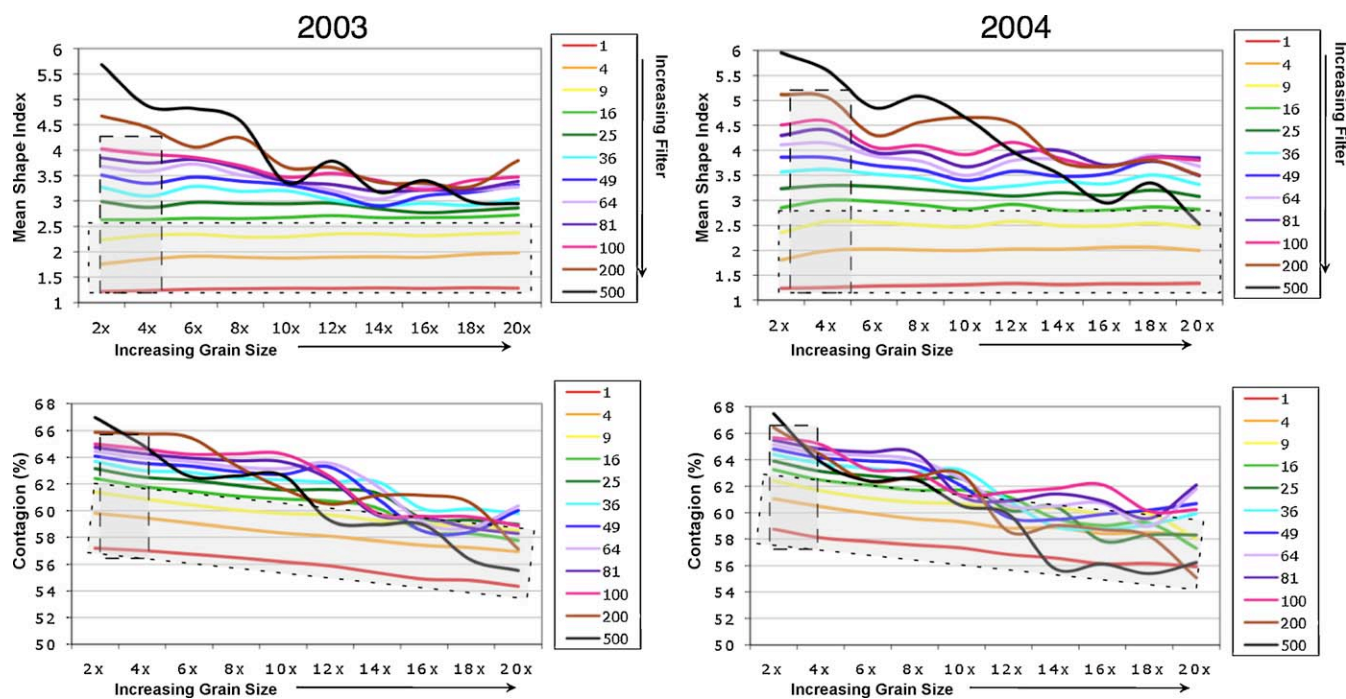


Fig. 5. Scalograms for landscape shape index (a and b) and landscape contagion (c and d) metrics for 2003 and 2004.

the majority of metrics, if a small minimum mapping unit is used (elimination threshold of 9 or smaller), relative change in metric value could be discerned for metrics computed from a range in pixel sizes.

Five metrics – the composition metric total pickleweed class area (Fig. 4a and b), three complexity metrics (pickleweed shape index (Fig. 4c and d), landscape shape index (Fig. 5a and b) and landscape contagion (Fig. 5c and d)), and pickleweed contiguity (Fig. 6c and d) exhibited consistent behavior across MMUs and are classified as Type 1a metrics (Table 2). This means that a relative change in metric value could be discerned at the range of minimum mapping units, if a suitably small pixel size was used. The thresholds for these tradeoffs are listed in Table 2, and are no larger than 6× or a pixel size of 1.2m on a side or 1.44 m².

Four metrics – two connectivity and two heterogeneity metrics, pickleweed connectivity (Fig. 6e and f), pickleweed Euclidean nearest neighbor (Fig. 6g and h), Shannon’s diversity (Fig. 7a and b) and Shannon’s Evenness Index (Fig. 7c and d) – exhibited unpredictable

behavior quickly as minimum mapping unit increased. These are Type 1b metrics. Consistency across time could only be achieved with small MMUs, usually with a pixel threshold less than 9. But given this small MMU, the metric revealed relative changes in value across time, and across pixel size up to 20× in most cases or 12× in the case of pickleweed connectivity (Table 2).

Two metrics were classified as Type 2: pickleweed clumpiness (Fig. 4e and f), and pickleweed cohesion (Fig. 6a and b) exhibited erratic behavior across time. There was no combination of grain size and minimum mapping unit that were consistent over time.

3.2. Behavior over time

Five metrics – patch area, pickleweed shape index, landscape shape index, landscape contagion, patch contiguity, and – showed consistent and reliable change, provided a small MMU (up to 9) or a small grain size (up to 6×, or 1.2 m on a side, in most cases) were used. These Type 1a metrics, in this case, can be confidently

Table 2
Summary of metrics and responses to changing scale.

Metric	Type	Fig.	Type	Threshold:		Type of change
				MMU	Grain	
<i>Composition</i>						
Patch area	Class	4a and b	1a	9	6	Increased
<i>Complexity</i>						
Shape index	Class	4c and d	1a	9	4	Increased
Clumpiness	Class	4e and f	2	NA	NA	Unclear
Shape index	Landscape	5a and b	1a	9	6	Slight increase
Contagion	Landscape	5c and d	1a	9	6	Slight increase
<i>Connectivity</i>						
Patch cohesion	Class	6a and b	2	NA	NA	Unclear
Contiguity	Class	6c and d	1a	9	6	No change
Connectivity	Class	6e and f	1b	9	12	Slight increase
Euclidean nearest neighbor	Class	6g and h	1b	9	20	Slight decrease
<i>Heterogeneity</i>						
Shannon’s diversity	Landscape	7a and b	1b	9	20	Slight increase
Shannon’s evenness	Landscape	7c and d	1b	9	20	Slight decrease

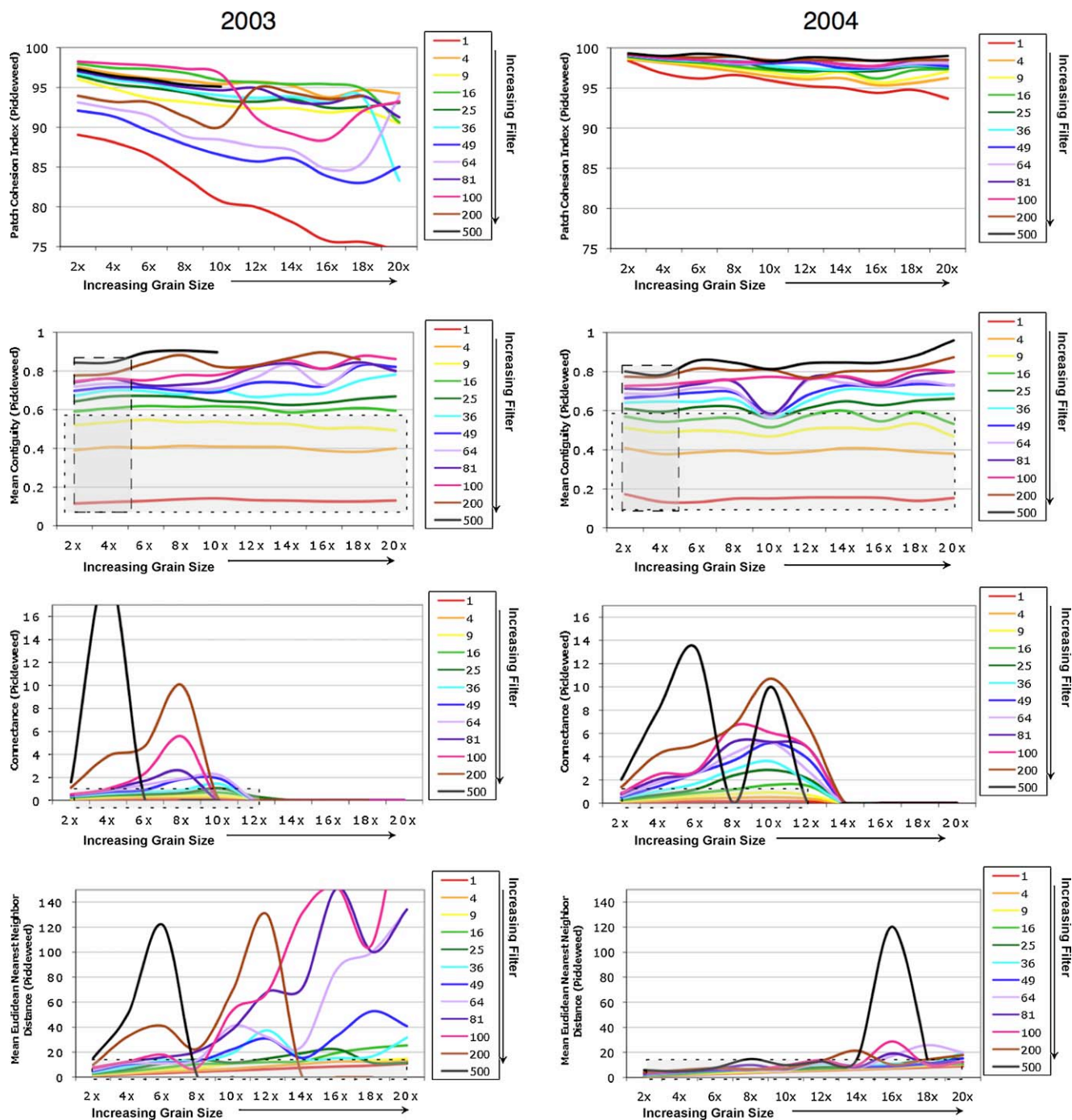


Fig. 6. Scalograms for patch cohesion (a and b), patch contiguity (c and d), patch connectivity (e and f), and Euclidean nearest neighbor distance for pickleweed patches in 2003 and 2004.

used to measure change to marsh vegetation pattern in a restoring marsh. Four other metrics: pickleweed connectivity, pickleweed nearest neighbor, and Shannon's diversity and evenness are Type 1b metrics; they were consistent across time provided a small MMU was used (up to 9). When a small MMU was used, these results were consistent across grain sizes (up to 20x for both nearest neighbor and diversity and up to 12x for connectivity). Use of a larger MMU resulted in inconsistent results across time. The remaining metrics, pickleweed clumpiness and pickleweed patch cohesion are Type 2 metrics and are not consistent and not interpretable across scales or time.

We also found that scale relationships were slightly more variable at the class level than at the landscape level: none of the

landscape metrics were unpredictable at all pixel sizes and minimum mapping units.

3.3. Ecological interpretation of metrics

We found that pickleweed increased from 2003 to 2004, and the simple class area metric was able to capture this change (Table 2) in relative terms. The amount of change however is not reliable across all grain sizes (Fig. 4a and b). With increasing pickleweed on the site, larger grain sizes tend to overestimate the extent of pickleweed. As clumps of pickleweed grew, they became more irregularly shaped, and were closer together over time. While two measures of patch connectivity and aggregation did not show an increase, one

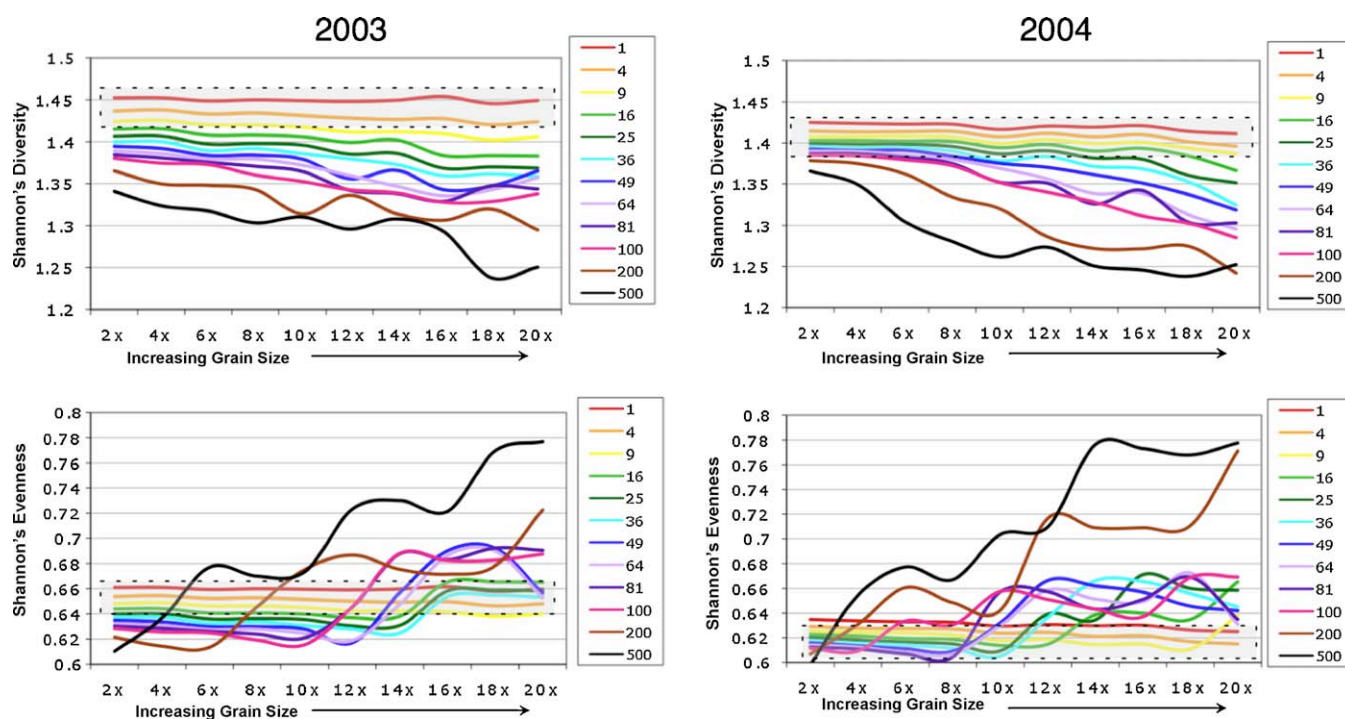


Fig. 7. Scalogram for Shannon diversity index (a and b), and Shannon evenness index (c and d) in 2003 and 2004.

did strongly. At the landscape level, all landcover classes became slightly more irregular in shape over time, and more interspersed with each other. The site decreased in evenness as pickleweed began to dominate, but increased in diversity as more vegetation types were present (based on the Shannon index).

These results show the different sensitivity of metrics. For example, as pickleweed increases across the site, we would expect that metrics of connectedness or contiguity would show this. While the patch-to-patch contiguity showed no increase (Fig. 6c and d), patch connectedness increased and Euclidean nearest neighbor decreased as expected.

4. Discussion

Tidal salt marshes in the San Francisco Estuary region display heterogeneous landscape structural pattern, a characteristic that is commonly attributed to tidal wetlands in Mediterranean climates (García et al., 1993). These patterns are functionally important – wetland vegetation pattern supports primary productivity and carbon sequestration, increased vegetation diversity, and the provision of adequate habitat for native or endangered wildlife – and thus the vegetation pattern, in addition to vegetation amount, should be monitored in a restoring marsh. For our restoration site, we found that pickleweed patches grew larger, more irregularly shaped, and closely spaced over time, while the overall landscape became more diverse (but less even). These relative changes in landscape pattern will all likely benefit a pickleweed-obligate species such as the salt marsh harvest mouse, and understanding these changes are useful in general for understanding restoration progress and vegetation change in a restoring marsh. However, we do not think specific targets of metrics would be appropriate in this context; the point of this research is to find the scale and metric to show the relative change in metrics that correspond with restoration goals.

We found that capturing pattern change in a heterogeneous landscape using high-resolution imagery and landscape metrics is not straightforward, and consideration of grain (pixel size) and

minimum mapping unit are important. With a small MMU (less than 9–16 pixels), several complexity, connectivity and heterogeneity metrics were consistent across time in interpreting relative change to vegetation structure. However, some of these metrics exhibited unstable behavior with larger MMUs, making their adoption without a multi-scale analysis potentially problematic, and two class-focused metrics – patch clumpiness and patch cohesion – were unpredictable across all scales, making their adoption for ecological monitoring impossible.

Of the two scale factors, grain size was more reliable, producing more consistent results than across MMUs. This is a positive result, as often the choice of grain size for a project is made by the choice available of image sensor. In general, increases in MMU beyond 16 pixels resulted in unstable metrics and uninterpretable results. With small MMUs, most metrics were consistent across grain sizes, from quite fine spatial resolutions (e.g. 0.16 m²) to relatively large pixel sizes (e.g. 16 m²); many metrics correctly identified *relative* change in composition and configuration of wetland marsh vegetation. This range in scales encompasses the fine resolution imagery commonly acquired through airborne digital imagery (<0.5 m on a side) and by commercially available satellites such as Quickbird and IKONOS (61 cm or 1 m pixels for their respective panchromatic bands and 240 cm or 4 m pixels for their respective multispectral bands), and suggests that this kind of monitoring can be done operationally, provided a small MMU is used. The sensitivity of the MMU relates to the fact that these changes are small on the ground; small patches can be missed with large elimination thresholds. This does not mean that one can resolve very small patches with resolutions provided by IKONOS and Quickbird, but rather that it is possible to successfully capture *relative* changes to spatial structure.

Wu (2004) found that scale relationships were more variable at the class level (for different mapped land cover classes) than at the landscape level (the entire mapped product and including all land cover classes). We found generally similar results; of our seven class metrics, two were unreliable across all scales, whereas all of our four landscape metrics had some range of grain size that produced reliable results.

While pattern metrics can highlight small but important changes in vegetation composition and configuration across years, the use of metrics to track changes over time or to validate restoration management decisions should be done with attention paid to the impact of scale on the measures. Because pattern metrics are affected by both pixel size and smoothing technique, we recommended multi-scale analyses, such as the one performed in this study, to understand *how* spatial scale (pixel size and minimum mapping unit) affects pattern metrics, and which metrics are independent of scale, or have a specific type of scaling relationship. Practically, multi-scale analyses can show which metrics show actual change as restoration progresses. An arbitrary choice of pixel size or minimum mapping unit might result in a false impression of change in a site. Of the two characteristics, choice of minimum mapping unit is the more critical: this could be interpreted as a call to do as little post-processing analysis as possible.

This paper focused on the rather mechanistic understanding of scale dependence: the effect of changing scales on image classification and pattern analysis. The other related connotation of scale dependence recognizes that natural processes operate across multiple scales, and that some functions and patterns have distinctive “operational” scales at which they can be best characterized (Bian and Walsh, 1993; Lam and Quattrochi, 1992; Wiens and Milne, 1989; Wu, 2004). Descriptions of such processes should take multiple scales into account (Hay et al., 2003; Li and Wu, 2004), and at times landscape pattern metrics have been used to characterize these operational scales, and highlight the thresholds between them. We did not do that here, although further interpretation of scale thresholds is possible.

We focused on the elimination filter and minimum mapping unit in this work, but there are other possible processing routines or analyst choices that will likely influence metric behavior. Changing spatial extent can greatly affect landscape pattern analyses (Baldwin et al., 2004; O'Neill et al., 1996; Saura and Martinez-Millan, 2001; Turner et al., 1989). The classification scheme chosen will greatly affect the thematic resolution of the classified output, which will in turn highly affect the pattern metric results and subsequent scaling relationships (Baldwin et al., 2004; Buyantuyev and Wu, 2007; Turner, 2005). The algorithm or approach chosen to classify remotely sensed imagery will affect the results. Most pixel-based classification methods (meaning the clustering algorithm focuses only on the spectral value of each pixel in the clustering) such as Maximum Likelihood Classifier (MLC) or ISODATA both result in speckle when applied to high-resolution imagery and can give different classification results depending on input values (Kelly et al., 2004). Classification approaches that use in addition to spectral information of a pixel its location and context (called object-based image analysis, OBIA) can alleviate much of this problem (Blaschke, 2010; Lang et al., 2008; Langanke et al., 2007). With this approach, images are segmented into distinct patches, or image objects, based on spatial and spectral similarity, which are then classified, reducing the need for post-classification processing and smoothing filters. Indeed, the OBIA approach in remote sensing is increasingly being used to understand landscape complexity and patterns; a good review of these developments is found in Blaschke (2010).

While sensitive to process and challenging to interpret, pattern metrics shows little sign of being abandoned in conservation, ecological and planning applications (Uuemaa et al., 2009). The abundance of remotely sensed images, at a range of resolutions, makes the process of directly calculating the spatial arrangement and configuration of landscapes computationally simple and intellectually satisfying. The process has its roots in vertical aerial photograph interpretation methods developed in the early decades of the 20th century (Langanke et al., 2007). This top-down view of the world began with aerial photography and has been

expanded and enhanced with digital remote sensing promotes discrete and detailed planimetric characterization of landscape objects. This imaging paradigm captures horizontal composition and configuration within landscapes well, while overlooking vertical heterogeneity and connectivity (Arnot et al., 2004; Hoehstetter et al., 2008; McGarigal et al., 2009). This likely will change with increased use of active remote sensors such as Lidar (light detection and ranging).

5. Conclusions

Habitat quality is not defined solely by land composition and amount, but also by configuration and heterogeneity; for this reason, pattern metrics can play a crucial role in restoration monitoring and management over the long term, as long as sufficient attention is paid to the effect that scale and pixel resolution will have on resulting metrics. Detailed mapping and characterization of restoring wetlands and the use of spatial pattern metrics can offer valuable information about changes in vegetation, which can inform the restoration process and ultimately help to improve chances of restoration success. Vegetation and habitat mapping projects are increasingly using aerial photography and satellite imagery with sub-meter pixel sizes for vegetation monitoring projects, and while understanding change to vegetation pattern is an important part of restoration evaluation, it is not completely straightforward; we recommend a multi-scale analysis such as this one to determine which metrics are consistent across scale and time.

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