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Landscape heterogeneity and scale considerations for super-resolution mapping

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Super-resolution mapping (SRM) is a rapidly emerging field of remote sensing that seeks to map the spatial distribution of land cover proportions resulting from soft classification techniques. Many methods have been proposed, but there has been little impetus to converge these efforts or compare the results. One reason for this lack of comparison is the issue of landscape heterogeneity and the range of scaling issues it embodies. Landscape heterogeneity refers to the complex distribution of land cover types across the landscape and the spatial patterns or spatial frequency of those land cover types. Landscape heterogeneity and the spatial patterns it produces are inherently scale-dependent while SRM is fundamentally an inverse scaling challenge being applied to real landscapes. The result is that SRM techniques developed for a particular landscape or scaling factor may not translate well when applied to other landscapes with different heterogeneity or computed for a different scaling factor. This lack of transferability due to landscape heterogeneity has largely been ignored in the literature. Heterogeneity is rarely reported in SRM studies and its behaviour across resolutions rarely integrated into SRM techniques. This article discusses the importance of heterogeneity in SRM, demonstrates how heterogeneity impacts SRM results, proposes several solutions for reporting landscape heterogeneity, and discusses the difficulties associated with incorporating heterogeneity into SRM. By highlighting the interrelatedness between landscape heterogeneity and SRM, the aim is for studies to begin reporting heterogeneity to facilitate inter-comparisons and ultimately incorporate the scale-dependency of landscape heterogeneity into SRM techniques to improve accuracy and applicability.

1. Introduction

Super-resolution mapping (SRM), also known as sub-pixel mapping (Atkinson 2005), is a rapidly emerging field within remote sensing concerned with predicting the spatial locations of fractional land cover components that result from soft classification techniques such as spectral unmixing. In contrast to hard classifications, which assign a single land cover to each pixel, soft classifications (i.e. sub-pixel classifications) stem from the recognition that pixels often contain a mixture of land covers and instead predict the proportion of different land covers within a single pixel. However, soft classifications are unable to locate the spatial distribution of land cover class components within a pixel. Therefore, the spatial resolution of the map does not actually improve despite the increased information. The specific aim of SRM is to delineate the most accurate spatial locations for these fractional land cover components within a pixel, where the resulting
output is a hard-classified map at a finer spatial resolution than the input imagery (Atkinson 2009).

Over the past decade, there have been a plethora of efforts to develop SRM techniques (Atkinson 1997; Foody 1998; Verhoeve and De Wulf 2002; Aplin and Atkinson 2001; Tatem et al. 2002; Atkinson 2005; Kasetkasem, Arora, and Varshney 2005; Boucher and Kyriakidis 2006; Thornton, Atkinson, and Holland 2006; Atkinson, Pardo-Iguzquiza, and Chica-Olmo 2008; Boucher, Kyriakidis, and Cronkite-Ratcliff 2008; Boucher 2009; Dai et al. 2009; Ling et al. 2010, 2011; Huang, Chen, and Wu 2014; Xu, Zhong, and Zhang 2014; Wang, Shi, and Atkinson 2014; Li et al. 2014; and many others), but despite sufficient accuracies for individual studies, a universally operational method or paradigm has yet to emerge. Atkinson (2009) recognized this drawback and set forth a set of considerations to foster comparisons between studies as a first step towards interoperability and ubiquity. Primary considerations were the need for studies to report the method of image creation/simulation, method of target selection, and accuracy assessment techniques. Many SRM studies now report these factors, but unfortunately most still do not compare their results to existing techniques when presenting results.

The lack of inter-comparisons may signal a larger issue, which is the inability to compare techniques created and tested for one landscape to landscapes with different heterogeneity. Heterogeneity is the complexity or variability of a certain property across space and/or time (Li and Reynolds 1995). In particular, landscape heterogeneity refers to the complexity and variability of land covers and is characterized by the unique spatial patterning of land covers within a particular landscape. These patterns are unique to each landscape, and their distribution across a landscape is scale-dependent, meaning the patterns will change as scale (i.e. grain size or pixel resolution) changes (Turner et al. 1989, 2001; Kolasa and Rollo 1991; Allen and Hoekstra 1992; Dutilleul and Legendre 1993; O’Neill et al. 1996; Wu and Hobbs 2002; Wu 2004, 2007). Rescaling grain size, which is the exact process being attempted in SRM, impacts the quantification of heterogeneity (Li and Reynolds 1995), and thus heterogeneity will impact SRM accuracy. Several studies have recognized this connection (Atkinson, Pardo-Iguzquiza, and Chica-Olmo 2008; Boucher, Kyriakidis, and Cronkite-Ratcliff 2008; Dai et al. 2009; Li et al. 2014), but most have not tested the impact on the SRM technique. Aside from these few studies, there has been little discussion in SRM research on the impacts of landscape heterogeneity on specific techniques.

Several issues in SRM can be attributed to the scale-dependency of heterogeneity. First, many SRM techniques rely on landscape pattern information to guide the placement of sub-pixels, but since heterogeneity is not consistent across resolutions, quantifying heterogeneity at a coarse resolution and using that value to guide SRM for a finer resolution is inappropriate. Even in situations where robust scaling relationships can be built across multiple resolutions, those relationships do not consistently translate to finer resolutions (Argañaraz and Entraigas 2014; Frazier 2014). Second, techniques built and tested for specific landscape types (e.g. urban) may perform well for scaling the heterogeneity characteristic of urban areas but perform poorly for landscapes with different heterogeneity characteristics (e.g. forests), thereby preventing their widespread adoption. Third, because heterogeneity is linked to scale, scaling factor (sf) is extremely influential to the success of SRM techniques. A technique that is successful when tested for a scaling factor (i.e. zoom factor) of 2 may not perform as well using a scaling factor of 10, yet multiple scaling factors are rarely tested in SRM studies. Indeed, the linkages between scale and landscape heterogeneity need to be understood with respect to their effect on
SRM if mapping techniques are ultimately to become universally applicable across landscapes.

Considerable efforts have been devoted to understanding the linkages between scale and heterogeneity in other disciplines, and several key findings may have implications for SRM. For example, in their study of the effects of the modifiable areal unit problem (MAUP) on image classification, Arbia, Benedetti, and Espa (1996) observed that while ‘everything is related to everything else,’ per Tobler’s first law of geography (Tobler 1970), ‘things observed at a coarse spatial resolution are more related than things observed at a finer resolution’ (p. 124). Similar studies have found that broad-scale variability for semi-variograms, which are widely used in many SRM studies (Verhoeye and De Wulf 2002; Boucher and Kyriakidis 2006, 2007; Boucher, Kyriakidis, and Cronkite-Ratcliff 2008; Boucher 2009), may overpower the fine-scale variability, which can in turn obscure any multi-scale structure (Meisel and Turner 1998; Wu et al. 2000). Dungan et al. (2002) also found that semivariance analyses can be affected by changing grain, size, lag, and extent of data sets. Yet despite extant knowledge that spatial heterogeneity does not translate across scales, many SRM studies rely on assumptions that it does. For example, Verhoeye and De Wulf (2002) used spatial dependency computed at 1 km to map fractions at 500, 200, and 100 m, and more recently Wang, Shi, and Atkinson (2014) used the same spatial relations calculated at the coarse resolution to map multiple finer resolutions. Based on the inherent interrelatedness of scale and heterogeneity (Wu 2007) as well as the recognition that SRM is an inverse scaling problem that is performed on land cover classes across real landscapes, developing sub-pixel mapping solutions without considering the role of landscape heterogeneity is impractical. Moreover, if landscape heterogeneity and its scale-dependency can be integrated into SRM techniques, it may allow more widespread application of techniques.

The purpose of this research article is to (1) examine the role of landscape heterogeneity in SRM through the extant literature and highlight several options for reporting landscape heterogeneity in SRM studies as a first step towards fostering inter-comparisons, and (2) demonstrate how the changing behaviour of heterogeneity across scales can potentially be incorporated into the scaling process for SRM studies and discuss the opportunities and difficulties associated with this task.

2. Examining and reporting landscape heterogeneity in SRM studies

Different landscapes (i.e. images) typically have varying degrees of spatial heterogeneity, but even a single image can exhibit differing amounts of spatial variability in different parts of the landscape (Boucher and Kyriakidis 2006). For example, an image that comprises the wildland–urban interface would likely have low heterogeneity in the wildland portions where a single type of forest may dominate and high heterogeneity in the urban portions where there are many mixed land cover types. If homogenous areas dominate the image extent, they can overinflate accuracy measures (Mertens et al. 2003; Atkinson 2009; Wang, Shi, and Atkinson 2014), making it difficult to know the true power of the SRM technique. Therefore, the first step in considering landscape heterogeneity in SRM studies is to measure and report that heterogeneity.

2.1. Measuring and reporting heterogeneity for thematic maps

There are several commonly used methods for measuring and reporting spatial heterogeneity for thematic maps. Fourier analysis is a widely used technique to mathematically
separate an image into its spatial frequency components (Jensen 2005), and the technique has been applied to thematic maps (Merriam and Jewett 1988). However, Fourier analysis relies on description over a particular region or in a certain direction, so it may be of little value for assessing an entire image, especially large extents. Lacunarity analysis or fractal analysis (Mandelbrot 1983) can also be used to measure heterogeneity of classified objects and is applicable across an entire map. Lacunarity measures how similar parts from different regions of a geometric object are to one another (Gefen et al. 1983), and it is a scale-dependent measure of spatial complexity (Plotnick, Gardner, and O’Neill 1993). It can be measured easily through methods such as box counting, which examines how features change according to the size of the window being used to inspect them, and has been applied in landscape studies (Plotnick, Gardner, and O’Neill 1993). However, it has been suggested that remotely sensed images of land cover units are not true fractals (Myint and Lam 2005; Myint 2003), so these analyses may not be an optimal choice for quantifying heterogeneity for SRM.

Thematic map heterogeneity is commonly measured in landscape ecology by quantifying the complexity in the composition and configuration of land cover patches (Li and Reynolds 1995), which form the basis of heterogeneity. Individual patches can be measured and categorized according to their size, perimeter, or shape, but the collection of patches in the landscape can provide much more information about the composition and distribution of the land cover across the landscape. Patch configuration can be quantified using landscape metrics (i.e. spatial pattern metrics), which are statistical tools that measure the composition and spatial arrangement of an entire landscape at the land cover class or landscape level. Landscape ecologists have spent considerable effort developing a comprehensive suite of metrics for thematic maps (O’Neill et al. 1988; Turner 1990; Turner and Gardner 1991; Gustafson 1998; McGarigal and Marks 1995), and several software packages have been developed specifically for spatial pattern computation (Fragstats (McGarigal, Cushman, and Ene 2012), V-Late for ArcGIS™, r.le/r.li for GRASS GIS, etc.). Landscape metrics rely on the identification of land cover patches from thematic maps, and since many SRM studies begin with a hard-classified high resolution image that is ultimately degraded to coarse resolution fractions, metrics can easily be computed for the base map to provide an initial measure of landscape heterogeneity.

For example, statistics such as mean patch size (MPS), patch size range, variance, and many others can be assessed for patches of a certain land cover class. Landscapes with many uniformly sized, small patches of a particular land cover (e.g. houses in a suburban neighbourhood) will have a smaller MPS, range, and variance than a landscape with a mixture of large, medium, and small patches (e.g. mixed residential and commercial buildings). Simply reporting these class-level metrics can provide an initial indication of land cover heterogeneity. Furthermore, these metrics can be computed for different local neighbourhoods through focal analysis, thereby allowing heterogeneity to be computed and reported separately for different areas within the image. Metrics can also be computed at the landscape-level across all classes to measure heterogeneity through the configuration of patch types. For example, the metric ‘percentage of like adjacencies’ (PLADJ) quantifies the frequency with which similar land cover types occur side-by-side in the landscape (McGarigal, Cushman, and Ene 2012). Logically, landscapes with high PLADJ are advantageous for SRM because spatial autocorrelation and the subsequent opportunity for pure pixels is greater. Contagion indices, which measure the spatial aggregation of the landscape, can be interpreted in a similar fashion. Contagion is high when a single class occupies a high percentage of the landscape, so it follows that contagious land covers
would be easier to map at the sub-pixel scale than dispersed land covers due to a greater number of pure or near-pure coarse pixels. Many previous SRM techniques have relied on assumptions of maximum spatial dependence (Mertens et al. 2003; Verhoeye and De Wulf 2002; Thornton, Atkinson, and Holland 2006; Ling et al. 2010, 2011; and others), but metrics such as PLADJ and Contagion, among others, can provide information on the true spatial dependence of the landscape, which may help limit assumptions and foster improvement of techniques.

Landscape metrics are a simple and effective method to measure and report heterogeneity in thematic maps, but there are several scale issues to note. First, since landscape heterogeneity changes with map grain (i.e. pixel size), the metric values that quantify heterogeneity change as well (Turner, Gardner, and O’Neill 2001; Wu 2004). Metrics computed at the fine resolution have much different values than metrics computed at coarser resolution (and vice versa), even though the landscape does not change. Therefore, the fine-scale metrics cannot be used to describe the heterogeneity at coarse scales (and vice versa). Additionally, the relationships are rarely linear, which makes it difficult to translate values across scales. A simple, hypothetical study area of an urban residential site has been mapped at different resolutions to illustrate this concept (Figure 1). Some metrics do exhibit fairly robust scaling relationships (Wu 2004), such as the linear or power law (Figures 1(e)–(g)), but these relationships (1) have been established primarily for majority aggregated hard classifications (Figures 1(a)–(d)), and (2) are not universal across all metrics or landscapes. Therefore, each metric/landscape must be tested explicitly. There can also be discontinuities in the scaling relationships (Figure 1(h)), making it difficult to mathematically model them. Furthermore, recent research has found that even when these scaling relationships are consistent and robust across a landscape, their predictive power for forecasting spatial patterns at resolutions finer than the original data were collected is not reliable (Saura and Castro 2007; Argañaraz and Entraigas 2014; Frazier 2014). In terms of SRM, this means that scaling relationships cannot be built from aggregations of hard-classified coarse imagery and extrapolated backwards to derive heterogeneity. The relationship will not predict the true metric value of the landscape at a finer resolution.

Lastly, landscape heterogeneity changes with analysis extent and thematic resolution (Wu et al. 2002; Li and Wu 2004; Shen et al. 2004; Wu 2004; Buyantuyev and Wu 2007) as well. These scale issues have been examined to a lesser degree than pixel size, but the interplay between various combinations of all three issues can exacerbate effects (Wu 2004). Therefore, it is helpful to also report study area extent and the number of classes being mapped, which is already routinely being done in SRM studies. Lastly, it should be noted that many metrics are correlated (McGarigal and Marks 1995) and thus reporting multiple metrics may be redundant.

2.2. Defining and measuring heterogeneity for sub-pixel classifications

The ultimate goal of SRM is to start from a soft classification, not a synthesized fraction map derived from a high resolution hard classification, so computing landscape metrics for the fine resolution thematic map provides limited opportunity for progress beyond initial reporting. There are several options for measuring heterogeneity for numerical maps (i.e. sub-pixel classifications) though. For example, the degree of departure from randomness of the distribution of the property of interest can be used as a measure of heterogeneity (Li and Reynolds 1995), specifically variations in trend, autocorrelation, and anisotropy. These types of measurement are fairly straightforward and can be
computed directly on the classification. Lacunarity and fractal analysis (Mandelbrot 1983) discussed above are another means to measure heterogeneity in numerical images (Myint and Lam 2005) as are wavelet analysis and spectral analysis (Ripley 1978), but these techniques have yet to see extensive applications on sub-pixel classifications. Additionally, these techniques often produce only a single value to describe the entire landscape (e.g. fractal dimension), which can be limiting for images with varying levels of heterogeneity.

Sub-pixel classifications present a problem for computing configuration and composition metrics because traditional landscape pattern tools require discrete class boundaries (Frazier and Wang 2011). Several approaches have been developed to overcome this issue. One method reclassifies data into non-overlapping, discrete sets based on pixel proportional membership (Rashed 2008; Walsh et al. 2008; Van de Voorde, Jacquet, and Canters 2011). Conceptualized as a ‘range approach’, the method groups all pixels that contain fractional values falling within certain ranges (e.g. 0.0–0.1, 0.1–0.2, etc.) and computes metrics on the different ranges. An alternative method sets multiple thresholds

Figure 1. Change in heterogeneity metric values as map resolution changes. Images (a)–(d) show a classified map at different resolutions. Graphs (e)–(h) show the values of the metrics MPS, Range, PLADJ, and Contagion at these four pixel resolutions. Metrics are computed for dark grey class, and data were aggregated using majority rules.
along the continuum of fractional values and groups all pixels with values greater/less than the threshold (Arnot et al. 2004; Frazier and Wang 2011). In both the range and threshold methods, multiple maps are produced from a single classification, and metrics are computed for each map in the set. The multiple metric values can be plotted to view the change in heterogeneity across different characterizations of the landscape. A hypothetical diagram has been constructed to illustrate these techniques (Figure 2). Ultimately, researchers have found that the shape of the graphs resulting from either the range or threshold methods can be examined to provide information about critical land cover ranges or thresholds in the landscape (Frazier and Wang 2013). When using the threshold approach, the loss of spatial heterogeneity can be minimized by setting very small threshold intervals. However, the range approach is more suitable when the landscape is dominated by a consistent mix of land covers with uniform proportions throughout (Frazier and Wang 2011). Both approaches provide more information about the landscape than single-value metrics computed for hard-classified maps.

Another potential option for deriving landscape-level metrics from sub-pixel classifications is surface metrics (McGarigal, Tagil, and Cushman 2009), which compute measures of heterogeneity directly on numerical surfaces without the need for discretization. However, application of these techniques to landscapes is relatively new, and they have seen limited application (but see Moniem and Holland 2013). Surface metrics will need to be tested rigorously before their effectiveness for quantifying heterogeneity for sub-pixel classifications can be determined. In sum, each of the above methods provides a way to

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**Figure 2.** Comparison of the (b) range reclassification and (c) threshold reclassification approaches for computing metrics from (a) a soft (i.e. sub-pixel) classification. Graphs (d) and (e) are constructed from metrics computed for individual rasters produced by each approach (b and c), respectively.
define and measure heterogeneity for the coarse resolution, soft-classified base maps that are used in SRM studies and, if reported, can ultimately allow cross-comparisons on the heterogeneity of the landscapes.

3. Incorporating heterogeneity into SRM techniques

Beyond defining and measuring heterogeneity, actually incorporating its behaviour across scales into SRM techniques is the next step towards constructing methods that are applicable across landscapes. Theoretically, if a scaling function can be derived directly from the sub-pixel classification that defines the amount and change in heterogeneity as pixel resolution changes, then this scaling function can be incorporated into the SRM technique to predict the changes in heterogeneity at finer resolutions. This scaling relationship would be unique for each class within an image, and would ideally explain the change in heterogeneity across a myriad of scaling factors, not just a single scale transition (e.g. 30 m to 15 m, 10 m, 6 m, 5 m, and 3 m: sf = 2, 3, 5, 6, 10, respectively; not just 30 m to 15 m: sf = 2). To date though, there has been very little research examining the scaling relationships of heterogeneity built from sub-pixel classifications, and this is an area to target future work to improve SRM techniques. Some possible directions are highlighted in the following text.

Techniques such as fractal dimensions, wavelet transforms, variograms, and spectral analysis show promise for building scaling relationships, such as those shown in Figure 2. Variograms are already used in SRM studies (Verhoeye and De Wulf 2002; Boucher and Kyriakidis 2006, 2007; Atkinson, Pardo-Iguzquiza, and Chica-Olmo 2008; Boucher, Kyriakidis, and Cronkite-Ratcliff 2008; Boucher 2009), but as Meisel and Turner (1998) and Wu et al. (2000) point out, their broad-scale values may obscure the true patterns at finer scales. Therefore, defining variograms for landscapes along with a complementary scaling function for that variability is the next step towards improving their ability to incorporate heterogeneity into SRM techniques. Discrete wavelet transforms have displayed scaling relationships in certain directions (Mallat and Hwang 1992), and they are already used in SRM studies (Mertens et al. 2004; Li et al. 2014), but since they cannot directly interpolate from coarse to fine resolutions (Mallat 1999), work is needed to solidify how scaling relationships can be built to predict heterogeneity. Fractals also have potential in this realm. Since fractal dimensions are not unique to landscapes, if their patterns can be reconstructed, they may have an advantage over other techniques.

Spatial allometry (Schneider 1998, 2001) has yet to be explored for SRM but may provide a key for integrating heterogeneity. Spatial allometry is adapted from biological allometry, which uses power law functions for body size scaling. In spatial allometry, non-linear power law functions are used to describe ecological systems where the independent variable is spatial scale (Wu and Li 2006). By constructing spatial allometric scaling relationships where the dependent variable is a measure of heterogeneity, it may be possible to capture the inherent scaling characteristics of individual landscapes and ultimately incorporate that scale-dependency into SRM techniques. Additionally, discontinuities in these non-linear relationships can also signal the presence of critical thresholds where there is an abrupt change in an environmental characteristic (Muradian 2001; Turner, Gardner, and O’Neill 2001), such as heterogeneity. Identifying these thresholds may help improve SRM techniques that break down beyond a certain scale factor. A recent study examined metric scaling functions using spatial allometric power law scaling functions built from sub-pixel classifications (Frazier 2014) and found that downscaling
accuracy (i.e. prediction of landscape metrics at a higher resolution than the original map) is highly related to landscape heterogeneity.

The following example demonstrates a potential approach for incorporating heterogeneity and its changing behaviour into the SRM method. Many SRM studies use 30 m coarse data to mimic Landsat imagery and then attempt to predict fine resolution values at 15 m (sf = 2) or 10 m (sf = 3), or similar. By examining how heterogeneity behaves for that particular image at the same scaling factor but using coarser resolutions, it may be possible to capture the scaling behaviour of the heterogeneity and incorporate it into the method. For example, per Figure 1, many landscape metrics follow scaling relationships across image resolutions, and these scaling relationships can be used to capture the changing behaviour across different resolutions. Following this logic, Figure 3 shows a 30 m soft classification for impervious surface for an area in Austin, Texas. The SRM goal is to predict land cover locations at two finer resolutions (i.e. 15 m and 10 m), corresponding to scaling factors of 2 (Figure 3(a)) and 3 (Figure 3(b)), respectively. To first examine how heterogeneity behaves differently for each of these scaling factors, the 30 m image is aggregated to several coarser resolutions according to the desired scaling factor. For sf = 2, the 30 m resolution image is aggregated to 60 m, 120 m, and 240 m. For sf = 3, the 30 m image is aggregated to 90 m, 270 m, and 810 m. In this example, the surface metric ‘Surfaces Area Ratio’ (Sdr) was computed for each coarse surface. Sdr expresses the increment of the interfacial surface area relative to the area of the projected, flat plane (McGarigal, Tagil, and Cushman 2009). Larger values of Sdr represent increasing spatial heterogeneity. Scalogram graphs were created to plot the change in Sdr (heterogeneity) at different resolutions. The scaling behaviour of the heterogeneity across resolutions is clearly allometric and is best fit with a power law function ($y = ax^b$). The actual function fit to each set of surfaces changes based on the different scaling factors, even though the landscape is the same. Consequently, the scalogram and associated equation for sf = 2 (Figure 3(a)) is able to better predict the value of Sdr at a resolution of 15 m than the equation fit with the sf = 3 data (Figure 3(b)), despite the greater range encompassed by the sf = 3 data. This may be due to the fact that the sf between each surface matches the downscaling sf, which follows findings by Šímová and Gdulová (2012), who found that scaling functions are dependent on the range of resolutions represented as well as the increments between each resolution. However, comprehensive rigorous testing is required across many scale domains and factors before scaling laws can be applied in SRM.

4. Conclusions

Heterogeneity describes the complexity of landscape patterns and is inherently linked to scale. However, most SRM studies, which are inverse scaling problems, take place absent landscape heterogeneity considerations. This article draws attention to the need for considering heterogeneity in SRM studies by examining the impact of heterogeneity on scaling through analysis of the extant literature across multiple disciplines that deal with scaling issues and offers several options for defining and measuring landscape heterogeneity for thematic maps and sub-pixel classifications to foster inter-comparisons. The letter also highlights the need to also integrate heterogeneity behaviour across scales into SRM techniques moving forward in order to increase the applicability of methods across landscapes. There are many difficulties associated with incorporating heterogeneity into SRM that will be challenging to overcome, such as the present inability to predict
heterogeneity at fine scales from coarse resolution data sets. However, recognizing the relationship between landscape heterogeneity and SRM will ultimately lead to improvements in the accuracy and transferability of these methods to diverse landscapes.

Figure 3. Example showing how power law scaling functions fit to surface metric values of Surfaces Area Ratio (Sdr) at different resolutions change according to scaling factor (sf) used for aggregation. (a) A scaling factor of 2 was used to construct the scaling relationship from surface metrics computed for the images, and (b) a scaling factor of 3 was used to construct the scaling relationship from surface metrics computed for the images.
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References


