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USING UNSUPERVISED CLASSIFICATION TECHNIQUES AND THE HYPSOMETRIC INDEX TO IDENTIFY ANTHROPOGENIC LANDSCAPES THROUGHOUT AMERICAN SAMOA

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Locating ancient and historic settlements and other anthropogenically modified areas that have been abandoned is a challenging task. These areas are likely small, and they are typically obscured by vegetation and the redistribution of sediment. In many locations, the terrain may be difficult for investigators to traverse, and anthropogenic features may be subtle. A variety of remote sensing technologies are now improving our ability to locate prehistoric anthropogenic landscapes around the world. While much of the current remote sensing in the archaeological literature focuses on satellite imagery (i.e., Garrison *et al.* 2008; Gupta *et al.* 2017; Lasaponara *et al.* 2016; Law *et al.* 2017), the use of aerial LiDAR is also widespread. Aerial LiDAR is particularly ideal in places where dense vegetation obscures the ground surface from satellite imagery and where anthropogenic modifications have left a topographic signature, both of which are true in many locations throughout the Pacific (Chase *et al.* 2010; Freeland *et al.* 2016; McCoy *et al.* 2011; Parcak 2009).This includes the islands of American Samoa.

The ability of aerial LiDAR to capture high-resolution data on the earth's surface, even through dense vegetation, has shifted how we understand the natural variability of a landscape and the modifications that people make to it. In American Samoa, most prehistoric landscape modifications focused on creating flat terraces in the steep interior for residential and non-residential (e.g., agricultural) activities (Quintus 2015; Quintus *et al.* 2015). Additional modifications were made by creating large steep-sided mounds with flat tops, referred to as star mounds, which were used for chiefly sports and ceremonial purposes (Herdrich 1991), as well as ditches used for routing water and sediment or as land boundaries (Quintus 2015; Quintus and Clark 2012), and walls for dividing fields (Quintus *et al.* 2017). Of all of the prehistoric anthropogenic modifications in American Samoa, terraces are the most widespread and are present in nearly all known settlements; star mounds, ditches and walls are not. Flat surfaces are therefore the focus of this paper and will be referred to as terraces throughout. It is important to note that other flat surfaces, including those that were not artificially created, will be identified with this methodology, yet on this steep terrain these are still potential areas of anthropogenic activity.

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Flat terraces disrupt the natural slope by representing a notch cut into it. While this modification certainly impacts local slope, it also impacts other topographic measures, including the one addressed here: hypsometry. Hypsometry is defined as a measure of elevation relative to sea level. Geomorphologists have used this measure to examine hillslope processes by creating a non-dimensional curve and hypsometric index (HI). On a hillslope scale, high HI values are associated with unstable basins or diffusive processes while lower HI values (<0.5) are stable or dominated by fluvial processes (Schumm 1956; Strahler 1964; Willgoose and Hancock 1998). HI is defined as

$$HI = \frac{E_{mean} - E_{min}}{E_{max} - E_{min}} \qquad \text{(Eq. 1)}$$

where E_{mean} is the mean elevation, E_{max} is the maximum elevation value and E_{min} is the minimum elevation value. On a completely flat surface, HI is undefined because $E_{mean} = E_{max} = E_{min}$. For any even slope where there is no variation HI will be 0.5 because E_{mean} will be exactly equidistant between E_{max} and E_{min}. Departure between these two values occurs when any variation exists in the slope. In the case of terraces, the HI value will vary based on the computational area and location being considered. If evenly distributed terraces are being considered over a large sloped area, the HI value will be 0.5. This is because although the elevations are distributed differently, E_{mean}, E_{max} and E_{min} do not change. If a smaller computational area is used and only a portion of the terrace is considered, the HI values will vary from nearly 1 at the downslope edge to nearly 0 at the upslope edge depending on if E_{mean} approaches E_{max} or E_{min} (Fig.1). The idea of creating a small moving window and measuring the HI value within that window was first introduced as a measure of topographic roughness and is also referred to as the relative topographic position or topographic position index (Jenness 2004). In this paper, it is used to identify patterns of anthropogenic landscapes specifically focused on the signature of terraces and other flattened surfaces. This index may provide an advantage over a simpler slope classification as it can account for areas that were artificially flattened but do not adhere to the typical very low slope definitions used for terraces.

In addition to taking advantage of HI to identify anthropogenic landscapes, I also attempt to automate the process by creating a combined dataset that is then used for an unsupervised classification. Other researchers have applied supervised classifications to highlight different anthropogenic landscapes in American Samoa (e.g., Quintus *et al.* 2015; Rieth *et al.* 2008). Unsupervised classification provides a unique advantage over supervised classification

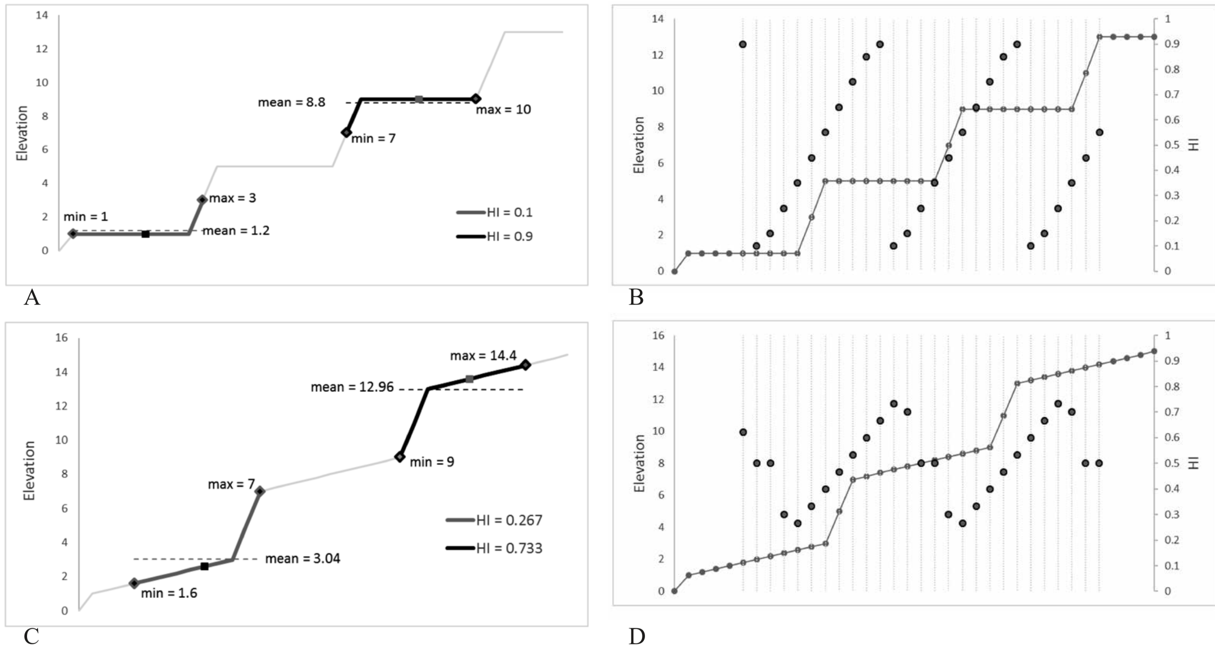

Figure 1. If the hypsometric index (HI) is calculated using a moving window over a small area of a terrace, the HI values will vary across the surface of the terrace. In the charts above, HI was calculated over a ten-unit window across an idealised terrace surface. For a given terrace surface HI calculated near the upslope edge will approach 1 while HI calculated near the downslope edge will approach 0. For A and C the heavy lines indicate the area over which the HI value was calculated for the point marked with a box. The mean, maximum and minimum values are provided. B and D show how the HI value changes moving across the terrace surface. Comparing the flat and sloped terrace surface shows that HI varies across the terrace more strongly if the tread is very flat, yet even for steeply sloped terraces HI values vary from front to back.

because it can be used in areas where specific class locations or breakpoints are unknown. In the case of American Samoa, large-scale anthropogenic areas are well documented on some islands (Ofu and Olosega: see Quintus 2011, 2015, 2018; Quintus and Clark 2012, 2016; Quintus *et al.* 2015) and poorly defined on other islands (Tutuila: Clark and Herdrich 1988, 1989, 1993; Frost 1976, 1978; Kikuchi 1963; Pearl 2004). I can identify the classification parameters first by using known anthropogenic areas and then extend the method to other areas.

Site Description

American Samoa is made up of five main islands and two coral atolls. The islands are part of the Sāmoan Archipelago, which also includes the islands of the Independent State of Samoa. The islands are all volcanic in origin, with a clear west-to-east trend of younger islands. Tutuila, the oldest and largest island in American Samoa, is also the most dissected. Well-developed channels have carved the uplands creating a rugged inland topography. Aunuʻu, which lies to the southeast of Tutuila, was likely formed at the same time as Tutuila (Natland 1980) and is included in the Tutuila dataset for this paper. Ofu and Olosega lie 96 km east of Tutuila and formed at approximately the same time geologically. These islands are separated by a narrow channel, which today is spanned by a bridge. Unlike Tutuila, many areas of the uplands of Ofu and Olosega have not been dissected by channels, leaving large areas of sloped interior. Furthest east is Taʻū, which lies 10 km southeast of Olosega. Taʻū is the youngest island in American Samoa and as such is the least dissected. Only a few young channels exist on this island, leaving much of the interior undissected. It is in these evenly sloped, undissected areas of the interior that anthropogenic landscapes are most likely to be found. Channel valleys were difficult places to settle as these areas generally are steep and subject to more erosion.

This study focuses on the islands of Tutuila, Ofu and Olosega. Taʻū is excluded because aerial LiDAR data are not available for the entire island, and the most well-documented anthropogenic area has walled terraces rather than the classic cut-fill terraces present on the other islands in American Samoa (Quintus *et al*. 2017).

METHODS

LiDAR data collection was funded by NOAA and the American Samoa Government, and collected in 2012 by Photo Science Inc. LiDAR point clouds were then processed to create one-metre bare-earth digital elevation models (DEMs). All the following products used in this project were derived from these DEMs using ArcGIS v10.3.

Hypsometry

As described above, hypsometry is a way of simplifying landscape variability in such a way that it can be described by a curve or by a single number. While hypsometry is typically calculated on the scale of an entire landscape, hillslope or watershed, here I am using it on a smaller scale to examine topographic roughness. This approach allows us to examine change across the landscape and to locate areas potentially modified by humans.

Each input for the hypsometric index equation (Eq. 1) was found using the focal statistics tool. This tool uses a moving window to calculate the mean, minimum and maximum values of the DEM for a defined window. For this project, 10 × 10, 20 × 20 and 30 × 30 m windows were used, as these window sizes scale approximately with the features of interest. After the raster products were derived, the raster calculator was used to calculate HI values for each cell.

Variability of HI values was also computed. HI values are likely to have high variability in anthropogenic landscapes with closely spaced terraces and lower variability on ridge tops or unmodified slopes. Variability was measured using the focal statistics tool to measure range and standard deviation within a 100 × 100 m window. The 20 × 20 m HI values were used to measure this variability because this window size preserves the large details of these anthropogenic features while smoothing the subtle variation expected in the natural landscape. Additionally, each factor in the HI equation was squared, and an HI-squared value was calculated. This value emphasises subtle differences in HI. The HI-squared parameter can be particularly beneficial in areas where the differences in HI are subtle, such as on sloped terraces.

Classification

To perform the classification, five composite band raster datasets were created. These composite raster datasets are made up of four to six bands of raster data selected from derived data sets including the 10 × 10 m moving window HI, the 20 × 20 m moving window HI, the 30 × 30 m moving window HI, the 20 × 20 m moving window HI squared, the slope, the 100 × 100 m moving window of the standard deviation of the 20 × 20 m moving window HI, and the 100 × 100 m moving window of the range of the 20 × 20 m moving window HI (Table 1).

Unsupervised classification was performed using all five composite datasets for Ofu and Olosega as well as Tutuila. The iso cluster unsupervised classification tool in ArcGIS was used to classify the data. This type of classification groups pixels that have similar values in each band of the composite dataset. The number of classes needed to best capture anthropogenic landscapes was tested on Ofu and Olosega, where anthropogenic areas have been well documented (Quintus 2011, 2015,

Table 1. Composite raster datasets tested.

Band [1]	Composite 1	Composite 2	Composite 3	Composite 4	Composite 5
10 × 10 HI	x	x			
20 × 20 HI	x	x	x	x	x
30 × 30 HI	x	x			
20 × 20 HI2				x	x
Slope	x		x	x	
20 × 20 HI 100 St Dev	x	x	x	x	x
20 × 20 HI 100 Range	x	x	x	x	x

[1] Bands are arranged on the table in the order they were added to the composite raster.

2018; Quintus and Clark 2012, 2016; Quintus *et al.* 2015). It was found that using three to five classes was most appropriate, because when more classes were used two or more classes in combination captured the known anthropogenic areas, and fewer classes combined non-modified areas with areas of anthropogenic modification. Visual inspection was used to identify what class or classes corresponded to known anthropogenic areas, or in the case of Tutuila, areas that appeared to be anthropogenically modified based on the DEM and associated derived products.

After classification was complete, confusion matrixes were created for each classification completed for Ofu and Olosega (Story and Congalton 1986). Accuracy, precision, true positive and true negative were all calculated from the confusion matrixes on the full island scale. In addition, the true positive rate was calculated for each individual anthropogenically modified area as described by Quintus (this issue).This step highlighted how different classifications were better for different anthropogenic areas.

RESULTS

Based on visual observation, moving-window hypsometry highlighted terraced areas. This made them easier to identify when compared with the DEM and hillshade alone. Areas of known or probable prehistoric anthropogenic landscapes could be identified even when examining the data over large areas because of the stark contrast between the flat terrace and the sloped areas between (Fig. 2). The classification results below quantify how successful moving-window hypsometry is at identifying anthropogenic landscapes. Results from Ofu and Olosega are discussed separately from Tutuila, as the locations of prehistoric modifications are better documented on these two islands.

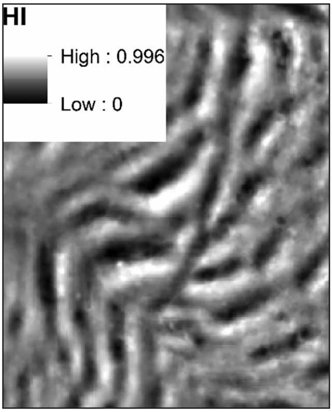

Figure 2. This area showing terraces on Olosega demonstrates the contrast between high-HI areas near the upslope areas of the terrace and low-HI areas at the downslope edge of the terrace.

Ofu and Olosega

The total area delineated as interior anthropogenic landscapes for Ofu and Olosega makes up 23% of the island area where there is no modern anthropogenic modification (interior anthropogenic area = 2.7 km^2, modern anthropogenic area = 0.73 km^2, total island area = 12.5 km^2). A total of 14 classifications were completed, for five composite datasets and the slope classification, to automatically identify the areas of anthropogenic landscapes. All but four classifications overestimated the total anthropogenic area finding that 20 to 36% of the island where there is no modern anthropogenic modification has evidence of prehistoric modification. Accuracy and precision ranged from 58 to 78% and 16 to 53% respectively for all classifications (Table 2). While slope had the highest accuracy along with all other composite datasets that included slope (1, 3 and 4), the precision for slope alone was slightly lower than those composite datasets where slope and hypsometry was combined. In addition, the composite data sets that included slope also had higher true positive and true negative rates than slope alone.

The composite datasets that did not include slope (2 and 5) had the lowest rates of accuracy, precision, true positives and true negatives when considering all anthropogenic areas on the islands combined. When the true positive rate for each anthropogenic area is considered individually those composite datasets without slope have the greatest true positive rates at both Sili-i-uta and Sili-i-uta South; in the case of Sili-i-uta, composite datasets 2 and 5 had a true positive rate 20% higher than found for all other composite datasets (Fig. 3).

Table 2. Classification results for Ofu and Olosega.

Composite Dataset	Number of Classes	Accuracy	Precision	True Positive Rate	True Negative Rate
1	4	78%	53%	50%	87%
1	3	77%	50%	74%	78%
2	5	66%	33%	49%	71%
2	4	60%	21%	26%	70%
2	3	59%	17%	21%	70%
3	4	78%	53%	52%	86%
3	3	76%	49%	76%	76%
4	4	78%	52%	50%	86%
4	3	76%	49%	75%	77%
5	6	68%	32%	35%	78%
5	5	66%	34%	50%	71%
5	4	60%	16%	18%	73%
5	3	58%	17%	22%	69%
Slope[1]	2	78%	51%	69%	80%

[1] Slope was classified as above or below 20º.

The combined effectiveness of the four composite datasets that were the best for each anthropogenic area, classifications 2/5, 3/3, 3/4 and 5/5 (where the convention is: composite #/# of classes), was examined (Fig. 4). Using this combined dataset, 4 to 31% of each anthropogenic area was classified appropriately by all four datasets, and 65 to 93% of the anthropogenic area was identified correctly by at least one dataset.

Tutuila

On Tutuila, only a limited number of known interior prehistoric anthropogenic areas exist (Clark and Herdrich 1993; Pearl 2004), with the assumption that many more likely exist than have been formally identified. As a result, the calculation of formal confusion-matrix statistics is impossible; rather, these data can be used to reveal general anthropogenic trends and identify areas of likely anthropogenic landscapes.

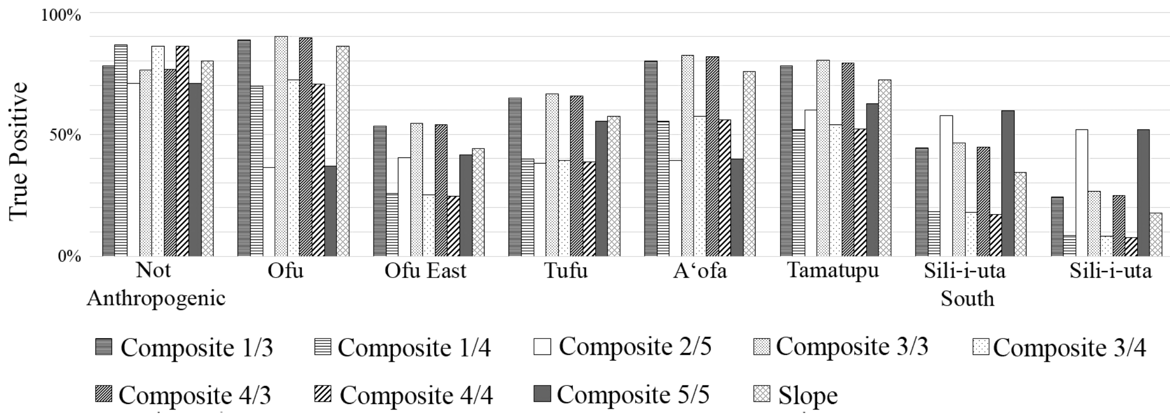

Figure 3. Calculating true positive rates by anthropogenic area shows that while composite datasets that include slope do a better job overall of predicting anthropogenic areas, certain anthropogenic landscapes which do not adhere well to the slope model are better predicted by a composite dataset that excludes slope, and rather relies on hypsometry alone.

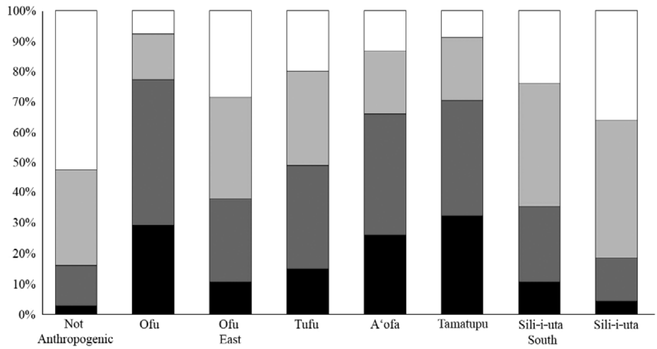

Figure 4. Classifications 2/5, 3/3, 3/4 and 5/5 were combined to find the total area in each anthropogenic area captured by one, two, three or all four of these datasets. Moving down through each column, the darker shades of grey indicate the number of datasets identifying that fraction of the total anthropogenic area where black is all four datasets and white is none of the datasets. Note that for "Not Anthropogenic" ideally none of the datasets would identify that area as anthropogenic.

The same set of composite datasets was used for classification on Tutuila as those used on Ofu and Olosega. The only modification made was that composites 2 and 5 were only classified using five classes as this was revealed to be the most effective. Unlike on Ofu and Olosega, it was not clear which class corresponded to the likely anthropogenic areas for composites 2 and 5 with two potential candidates for both classifications; therefore two classes are reported for both of these classifications. For all classifications, 7 to 23% (averaging 12.7%) of the island is classified as likely anthropogenic landscapes (Table 3).

A combined dataset was created for Tutuila using all available composite dataset classifications. In total, ten datasets were combined, but because two were based on the same classification (yet represent two separate classes) the maximum number of datasets that could classify a given area as anthropogenic is eight. Figures 5 and 6 show the cumulative percent of island area represented as anthropogenic by a decreasing number of classifications. Four or more classifications identify 12% of the island as anthropogenically modified, and they appear to capture all known anthropogenic areas as well as most areas observed as likely anthropogenic based on the hypsometry moving-window dataset and the hillshade.

Table 3. Results from Tutuila classification.

Composite Dataset	Number of Classes	Class Selected as Settled	Percent Settled
1	3	1	14%
1	4	1	10%
2	5	3	8%
2	5	4	7%
3	3	1	14%
3	4	1	10%
4	3	1	14%
4	4	1	10%
5	5	2	23%
5	5	3	18%

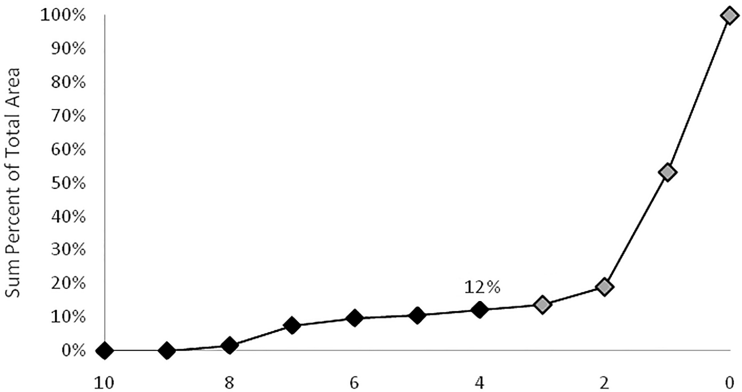

Figure 5. All classifications were combined on Tutuila to highlight areas that were most likely anthropogenic. The graph above shows the total area of the island classified as anthropogenic by a decreasing number of classifications. For this analysis it was determined that the areas that were most likely to be true positives were those identified as anthropogenic in at least four classifications. Those areas with three or fewer classifications were determined to be likely unmodified areas.

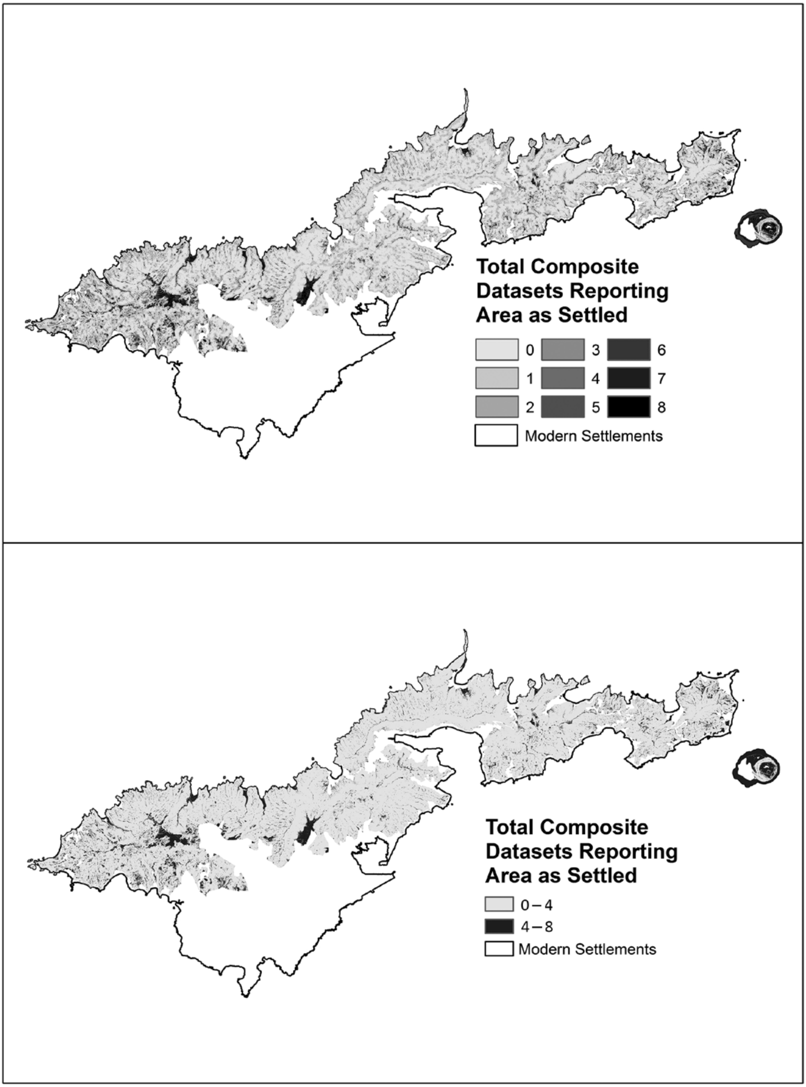

Figure 6. These maps show the results of combining classifications on Tutuila. Those areas classified as settled by four or more classifications are the areas most anticipated to be anthropogenic landscapes.

DISCUSSION

The use of a moving-window hypsometric index to model topographic roughness is an effective tool for identifying anthropogenic modification on complex landscapes. Simply as a visualisation tool, this technique highlights the changes in slope in anthropogenic areas. In addition, unsupervised classification is effective at delineating anthropogenic areas. While there was no classification that captured the complete known anthropogenically modified area, each known anthropogenic area was identified partially, and the high accuracy achieved is a strong indicator of success. Currently there is no method that consistently and completely identifies anthropogenic modification and therefore this method has advanced our ability to quickly identify anthropogenic landscapes with accuracy. In areas where the distribution of anthropogenic modification is unknown this technique can provide a first pass at identifying areas of interest that require further investigation, yet it is critical to note that those areas not identified may also have features of interest and should be surveyed where possible or before any modern modification to a potential site occurs.

Classification on Ofu and Olosega

For most anthropogenic landscapes, the inclusion of slope in the composite dataset appeared to improve identification, but for those anthropogenic areas like Sili-i-uta (where slopes are higher) excluding slope from the composite dataset greatly improved classification. Because most interior anthropogenic landscapes can be defined as areas of low slope, it is unsurprising that when slope is included in the composite dataset it becomes the strongest classification indicator. While the exclusion of slope in the composite dataset does reduce the true positive rate for anthropogenic landscapes that adhere to the defined slope relationship, it markedly increases the true positive rate for those areas that do not have large areas of low slope.

Combining classification results may be useful in identifying diverse anthropogenic landscapes and improving confidence in some areas. Where classification results are combined those locations present in all classifications are very likely to be true positives. On Ofu and Olosega, where four datasets were combined, only 2% of the area that is currently identified as unmodified interior was identified as anthropogenically modified by all classifications. Because field surveys do not exist for all areas of Ofu and Olosega, it is possible that these areas that were consistently identified as likely anthropogenic by all classifications are unidentified anthropogenic areas such as settlements, star mounds or fortifications that have a similar topographic signature. For all known anthropogenic areas at least 50% of the area was identified by two or more classifications.

Based on visual inspection of these data, the areas that were most likely to be identified by all classifications were near the centre of the anthropogenically modified area in the most seaward position. The areas of the anthropogenically modified area least likely to be identified are those areas furthest upslope or along the edges of the modified area (Fig. 7). This trend follows well-documented Polynesian settlement dynamics where the most prestigious areas of a settlement are either in the centre of the settlement or in the centrally located most seaward position (Mead 1969; Quintus and Clark 2016; Shore 1982). These areas also typically have the largest features. It appears that on Ofu and Olosega all datasets are capable of identifying these documented settlement cores, which have been noted as likely residential areas, yet have less success near the periphery, which is likely dominated by agricultural

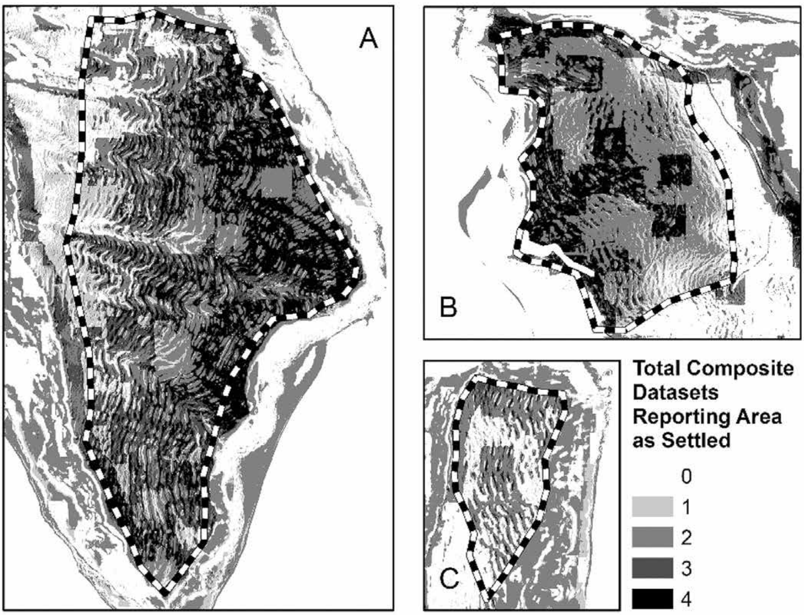

Figure 7. The greatest number of classifications identify the most seaward and central areas of the anthropogenic area, while the periphery is less well identified. This holds true for all known anthropogenic landscapes. The examples provided are: (A) Tamatupu: ocean east of anthropogenic landscape, (B) Ofu: ocean west of anthropogenic landscape and (C) Sili-i-uta: ocean north and east of anthropogenic landscape.

activity (Quintus and Clark 2016). The extent to which classification can identify these types of dynamics is unclear, yet because the data appear to follow well documented trends this may suggest that classification could provide insight into how anthropogenic areas developed.

Classification on Tutuila

As noted earlier, there are few well-documented prehistoric interior anthropogenic areas on Tutuila. Three settlements (Lefutu, Old Vatia and Levaga Village) have been described, and others have been speculated but remain undocumented (Clark and Herdrich 1988, 1989, 1993; Frost 1976, 1978; Kikuchi 1963; Pearl 2004). Part of the difficulty with identifying anthropogenic landscapes in the interior of Tutuila is the size of the island. Tutuila is 11 times the size of Ofu and Olosega combined. In addition, deeply dissected river valleys make the terrain more rugged than on Ofu and Olosega. As a result, having a methodology to identify areas where anthropogenic landscapes are likely is critical for guiding field research and identifying the likely location and extent of anthropogenic modification.

On Ofu and Olosega, classification of the composite datasets appeared to be effective in identifying areas of likely anthropogenic modification. Because there are a limited number of known anthropogenic landscapes on Tutuila, it is impossible to complete a confusion matrix or generate the precision and sensitivity of the model; rather, the model provides data on the likely distribution of anthropogenic alteration on the island. On Tutuila, the model suggested about 12% of the island has evidence of interior anthropogenic modification. This is 45% less than the known anthropogenic area on Ofu and Olosega, where (as noted earlier) the classifications typically overpredicted anthropogenic area. If total anthropogenic area corresponds with population (Quintus this issue) it might suggest that population density in the uplands of Tutuila was lower than on Ofu and Olosega, yet because of island size total populations in the interior may have been about five times greater than on Ofu and Olosega, assuming comparable agricultural practices. In addition to having a smaller area anthropogenically modified on Tutuila, potential anthropogenic areas also appear to be more dispersed. This is particularly true on the eastern portion of the island, where most research has been done. The western portion of the island is less incised and has larger areas of low slope, which are ideal for anthropogenic modification. While these western anthropogenic areas are the most extensive on Tutuila, the largest anthropogenic area is still approximately the same size as the largest anthropogenic area on Olosega, because the rugged topography on Tutuila limits further growth.

* * *

While the methods reported here will not replace careful pedestrian survey, they may help focus initial survey to areas that are most likely to be anthropogenic. In addition, these methods can provide initial estimates of the size and distribution of anthropogenic areas. When compared to a simple slope-based classification, classifying using composite datasets that include the hypsometric index improves predictions of anthropogenic landscapes. The inclusion of the hypsometric index is particularly useful in areas where slopes are greater than expected for an anthropogenic area. While this methodology was tested exclusively in American Samoa, it is likely that it will work in any area where anthropogenic modification has resulted in topographic change.

While most anthropogenic areas on Ofu and Olosega are already well documented through careful digital and/or pedestrian survey, the results of this classification suggest there may be at least one more anthropogenic area. All known anthropogenic areas were identified to some degree, with the cores being the best identified and periphery areas being only sporadically identified. On Tutuila, the absence of detailed data did not allow for a full confusion matrix of results, yet the classification did highlight several areas of known or suspected anthropogenic modification. Among the results, it is clear that anthropogenically modified areas on Tutuila are generally smaller than those on Ofu and Olosega and more dispersed over the large island. This is likely a result of the rugged, deeply dissected topography.

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ABSTRACT

Aerial LiDAR data offers a valuable tool in locating ancient anthropogenic landscapes around the world. This technology is particularly ideal in places where thick vegetation obscures the ground surface, reducing the utility of satellite imagery. On the islands of American Samoa, many interior anthropogenic landscapes remain unsurveyed, largely because the terrain makes it difficult and there is only general knowledge of where the anthropogenic modification may have existed. Aerial LiDAR flown in 2012 is proving to be a valuable tool in locating these prehistoric anthropogenic areas, yet improvements can be made on the methodology. This paper provides an unsupervised classification method to identify anthropogenic landscapes based on slope and hypsometric index: a topographic measure of roughness. Areas of American Samoa with known anthropogenic modifications were used to develop the classification techniques, which were then extended to areas where anthropogenic landscapes are undocumented and unexplored. The findings presented here suggest that interior anthropogenic patterns may be strongly dependent on island topography.

Keywords: LiDAR, unsupervised classification, hypsometry, American Samoa

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