ARCHAEOLOGY IN NEW ZEALAND

Multi-Scalar and Semi-Automatic Approaches to Detect Archaeological Features in NZ Using Airborne LiDAR Data

Ben Jones, *Clough & Associates Ltd.*
Simon H. Bickler, *Bickler Consultants Ltd.*

Introduction

This paper builds upon the work of Jones and Bickler (2017) which examined the potential for LiDAR to assist in the recording and heritage management of archaeological sites in New Zealand. Here we explore multi-scalar approaches targeting archaeological features of varying sizes across typical terrain and under variable vegetation types. The reasons for this work include the difficulty of access to large areas of New Zealand either because they are remote and less likely to be developed or they remain under some form of dense vegetative coverage which may be difficult to characterise without detailed vegetation clearance. Such areas often contain archaeological sites that are difficult to locate and map in detail even when the archaeological features are large. LiDAR's advantage, from an archaeological perspective, is that the terrain models generated can be examined using semi-automatic and machine-aided methods which are scalable for local and regional surveys. In the context of New Zealand archaeological survey, LiDAR data follows on from the highly successful aerial photography approaches undertaken by archaeologists such as Kevin Jones (Jones 1994, 1996, 2002; Jones and Tanner 2002; see also Gorbey 1967). LiDAR provides complementary information from aerial and satellite imagery, and modern techniques often combine the data from multiple sources for archaeological survey. We describe here work undertaken to identify new archaeological sites of Māori origin in the Waikato.

Searching for Sites

GIS processing of LiDAR data has been used for 20 years for archaeological feature identification and survey, which have been broadly orientated towards terrain visualisation techniques (VTs). A feature, here, is defined as archaeological disturbance on the surface, and is highlighted using various VTs which rely on identifying a feature based on some raster image pixel value, for example, the empirical parameters of orientation, illumination, degree of slope, local relief, ruggedness and other geographic or geological aspects.

Common VTs for archaeological feature extraction have been hill-shade analysis, sky-view factor, openness models, low relief terrain models, hydrological models, and slope relief analyses to name a few (see Guyot et al. 2018 for a current review). All these techniques accentuate features to allow the human eye to detect areas of interest at a desktop level. This is broadly based on the assumption that past behaviour at a landscape level left a footprint still visible under forest canopy, pasture, semi-urban or urban environments, characterised as anthropomorphic landforms.

Mathematical techniques in the form of principal component analysis (PCA), or classification regimes move beyond this and identify those characteristics and combinations of characteristics that are best to distinguish archaeological features from their environment (see Cochrane and Mills 2018; Deveraux et al. 2008; Freeland et al. 2016; Ladefoged et al. 2011; McCoy et al. 2011; Quintus et al. 2015). Such VTs form the baseline for manual or semi-automatic and machine learning (ML) feature identification.

Study Area

Waikato has over 10,000 archaeological sites recorded in the NZAA ArchSite database and around half may include earthwork features related primarily to pre-contact occupation of the region by Māori (Figure 1). These include pa, pits, and terraces. In addition to earth-worked features, other sites such as stone structures, sod walls, tracks, ditches and drains representing both prehistoric Māori and later colonial heritage are also present and could be identifiable and recorded using LiDAR data.

Recent LiDAR coverage of Waikato offers the potential to apply these techniques to the surrounding region. The current proposal would act as a baseline for future work as new LiDAR coverages become available. This approach can form the basis of risk assessments relating to the long-term survivability of archaeological record (see e.g., Bickler et al. 2013) by highlighting sites in vulnerable zones.

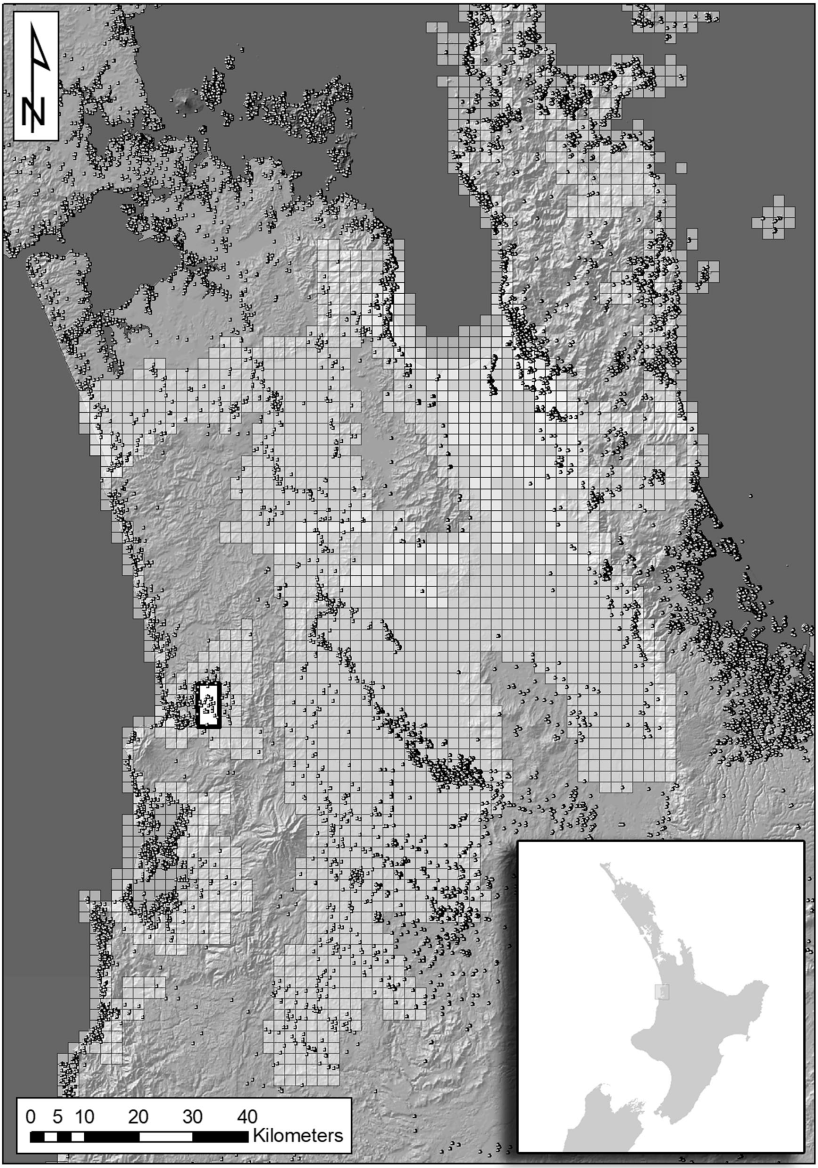

Figure 1. Recorded archaeological sites in the Waikato Region (source: ArchSite) overlaid with gridded areas of LiDAR data (Inset showing location of Paritata Peninsula)

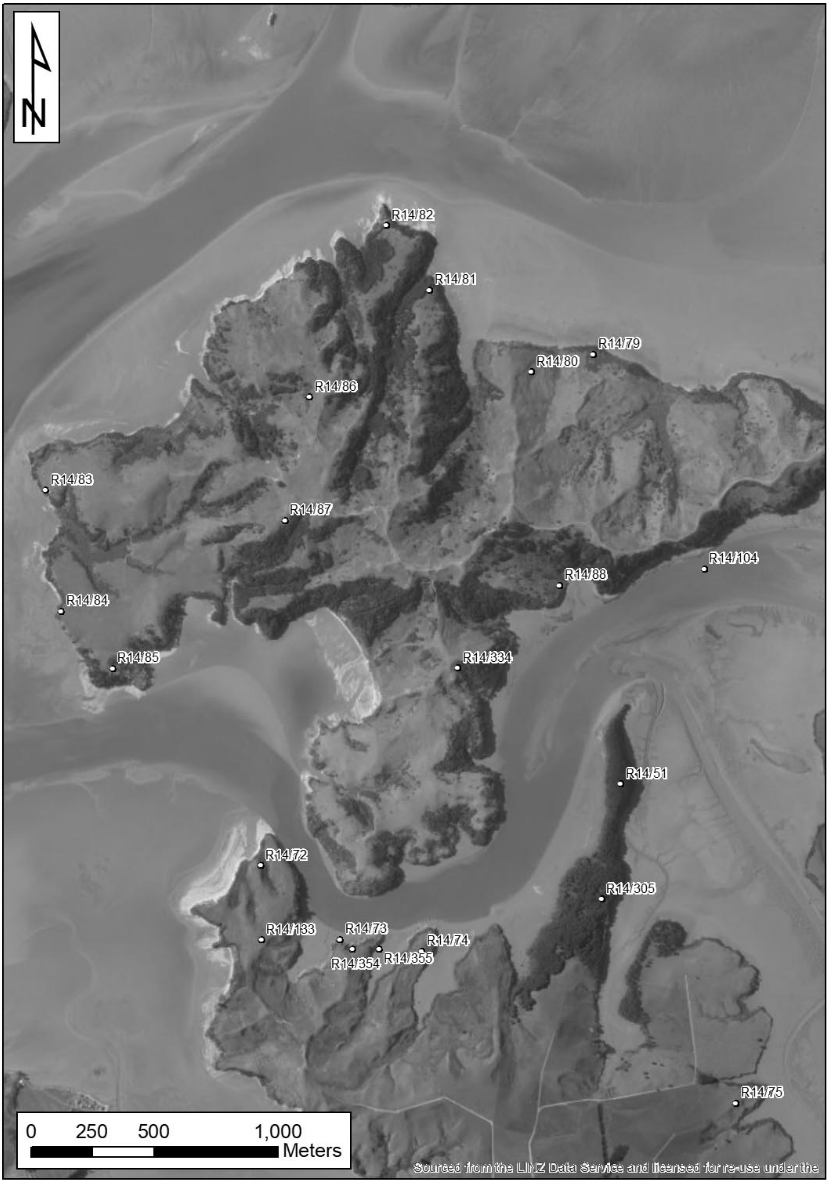

Figure 2.Map of Paritata Peninsula and previously recorded sites.

The current investigation is designed to lay the platform for a regional scale assessment process which would result in the recording and mapping of sites both in the Waikato and other areas of New Zealand as the LiDAR coverage improves. The goal in this paper is much smaller and focused on examining the usefulness of different algorithms and approaches. Here we chose a $32km^2$ block inland from Raglan, a coastal town in the Waikato Region known from its long surf break. The subject block constitutes the Paritata Peninsula, primarily farmland with bush and other secondary vegetation present (Figure 2). It has had little archaeological survey with most sites recorded based on aerial photography in the 1970 and 1980s. The area would seem to be ideal for pre-contact Māori settlement with easy canoe access, fresh water and a range of soil conditions suitable for gardens.

Classifying Features

Narrowing down the classification techniques that work best for identifying archaeological sites in New Zealand is complex. Most VTs do not consider how anthropomorphic landforms are visible at different scales. Guyot et al. (2018) discuss how archaeological surface visibility is correlated to scale brackets of micro (1:10), Meso (10:100), and macro (100:100). It is suggested that VTs only consider the spatial structure of a site on a case by case basis, and do not consider the heterogeneity of features. The challenge is therefore to scrutinise methods that work at different landscape scales and with a range of topographic conditions. A site with a prominent platform situated on a valley bottom for example, can be high in the landscape at shorter spatial scales (micro) but low-lying at a (macro) broader regional scale (Lindsay et al. 2015). Here, the feature is identified not due to the visualisation of microtopographic relief (accentuated due to slope contrast or azimuth angle), rather the way that topographic position varies over a range of scales, i.e. the scale signature (see Wood 1996 and Drăgut and Eisank 2011). Further, it can be viewed as valuable information for interpreting the structure of how anthropomorphic landforms are shaped into landscapes (Drăgut and Eisank 2011).

We therefore compare the results of two approaches. The first follows on the work described in Jones and Bickler (2017) using template matching. There we identified a "typical" storage pit based on an image of a known feature pulled out from a PCA-based hill-shaded raster image. That feature was then used as a template to identify similar features in the landscape. This method of image analysis can be effective, but it relies on the usefulness of the defined prototypical structure for template matching or some other way of characteristic spatial attributes (Guyot et al. (2018:2) but very susceptible to changes in scale and orientation of features in that landscape.

We therefore compare that with GIS-based techniques to identify features in their contexts using hydrological approaches to search landscapes. In this context, the method focuses on finding localised differences in landscape rather than a specific shape and size. This means that we move beyond identifying an archetypal template, towards accentuating anthropomorphic change at a multi-scale level (see e.g., Bedford et al. 2018). This can allow for a better base image to which machine learning techniques can be applied, broadly capturing the heterogeneity of anthropomorphic change across a landscape.

Template Matching and Crater Identification

Gumbley et al. (2018) show how hill-shading of LiDAR data can be used to show up borrow pits, related to Māori gardening activities, which are a common feature particularly concentrated along the Waikato River. They are observable on satellite imagery and show up well using hill-shading algorithms. Being relatively regular they make good templates for matching across landscapes (Figure 3) and even identifying non-circular pits such as the large site on Paritata Peninsula.

We turn to automatic classification techniques to extend the semi-automatic classification for regional analysis. Crater identification has been undertaken by many researchers over the years to explore the geological history of planetary bodies (see e.g., Benedix et al. 2018). Surface imagery from a range of sources is now routinely available and analysis and the craters range from the small, usually around the 100m diameter range detectable from modern tools, to the largest which are in the order of tens of kilometres or more (Benedix et al. 2018: 1). The obvious similarity of pits to craters is their circular shape but the methodology is adaptable to other morphology.

There are advantages to using the crater identification algorithms. Firstly, they have been designed to work with imagery covering large areas. Secondly, they can be used to identify features at different scales: the impact craters are often on the scale of kilometres while the archaeological features are only metres in diameter. Thirdly, the latest iterations of the algorithms are based on trainable models that allow for new feature types to be identified and used in the predictive model.

An example shown here uses the PyCDA library (Klear 2018) as it offers a straightforward implementation to test out the application to archaeological features. Pits are like craters but obviously a lot smaller. PyCDA has a library of crater “classifiers” built into a ML library.

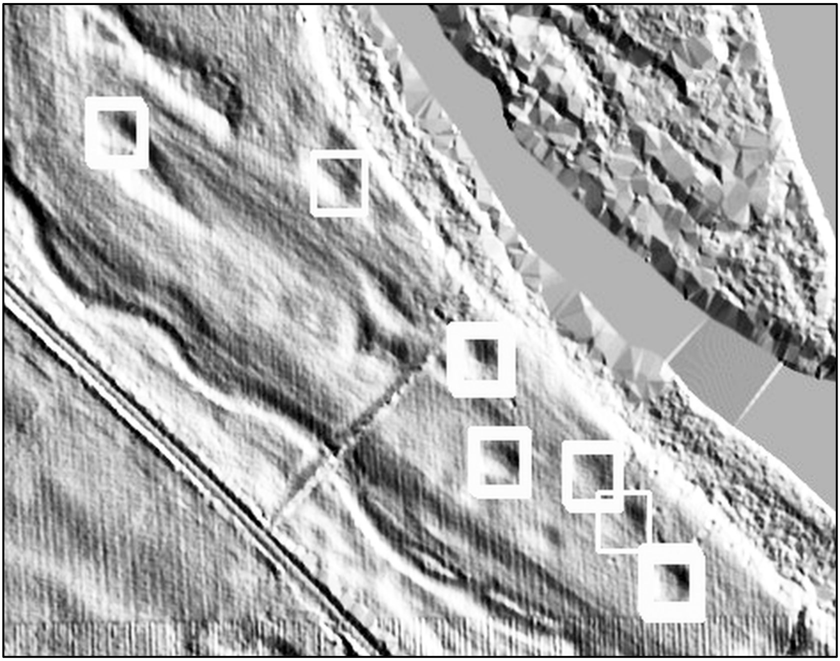

Figure 3. Results of template matching (rectangular boxes) looking for possible borrow pits near the Waikato River from LiDAR data.

The LiDAR Digital Elevation Model (DEM) for the Paritata Peninsula was processed using hill-shading from eight different angles and principal components analysis to summarise the data (see Deveraux et al. 2008, and Jones et al. 2015). This resulting raster was then analysed, and possible features identified. A close-up of the southern headland is shown (Figure 4) where a group of likely storage pits are clearly visible from the LiDAR. Isolated pits are identifiable but not where the resolution of the pits is not clear, and it falsely identifies larger areas that could not be archaeological. The latter is easy to filter out: simply discarding features that are not on the correct scale. The results are preliminary but the potential for finding other sites such as borrow pits as well as storage pits is there.

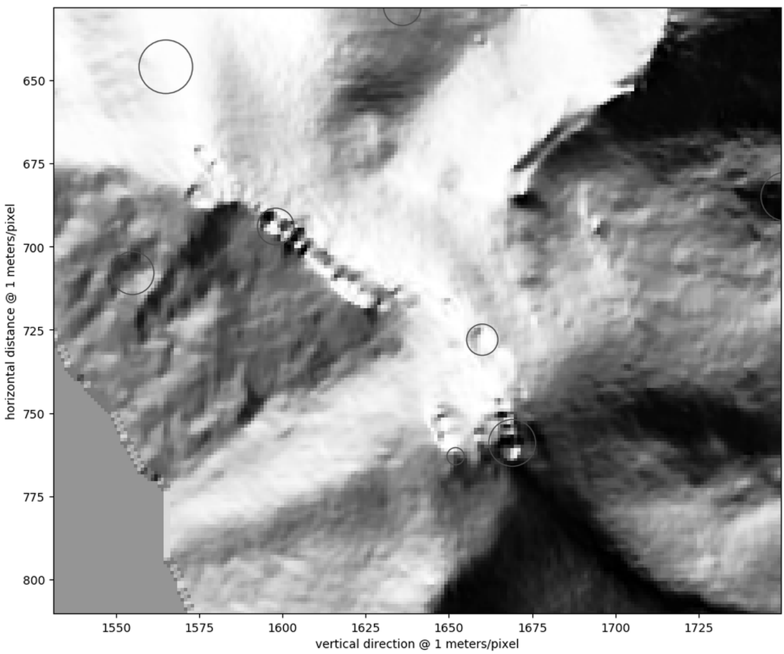

Figure 4. Identification of possible features using crater identification.

Hydrological Modelling

Variability in the shapes of features suggests that a more topographic approach should work better for finding the expected types of features. In Jones and Bickler (2017) hydrological modelling was tried on the DEM associated with the large pa site at Otāhuhu/Mt Richmond (R11/13) to see if we could detect kumara storage pits using a semi-automatic approach. The 1m resolution DEM of Mt Richmond and the surrounding area was created and then added into a hydrological sink hole model. The landscape was then "flooded", and the water then allowed to flow off the DEM. Features such as ditches, which act like drains, show up as "fast-flowing" but crucially water into "sinks", i.e. storage pits, could not flow out as the water flowed out. The results were good, and we knew which features were real, because the site had been well documented and surveyed. This time the objective was to look at a large landscape at the Paritata Peninsula which was likely to be more variable and might help us find new sites. This area is quite good from a case study perspective, as it has relatively little archaeological survey, infrequent development driven archaeology, the right location for a lot of pre-contact occupation, and looking at Archsite most of the survey was done using aerial photos.

From the point cloud the horizontal spacing was checked and multiple 1m DEMs were created from the point cloud tiles using an Inverse Distance Weighting (IDW) algorithm. A geodatabase was created with a mosaic dataset included. The DEM tiles were then merged into a single raster, from this a flow-accumulation and flow-direction raster was created, cumulating in a “sink” raster showcasing the extent of sinks in the DEM. The sink raster was then converted to a vector files with points, elevation was then extracted to the points and looking at the distribution a natural break was noted above 33m. Above 40m was crucial as it is assumed most kumara storage pits lie on ridges of higher elevation. This was the predictor value utilised to differentiate archaeological features from non-features. This elevation assumption and other shapes could be modelled to differentiate other features such as burrow pits. Solar radiation and moisture, for example, are other variables that could enhance this model.

The results of the possible features are shown in Figure 5. Close-ups of three areas show how effective the analysis was at identifying possible storage pits. Figure 6-Figure 8 show a PCA of multiple hill-shades, but the actual analysis is not dependent on the hill-shading itself and only used to visualise the features extracted by the hydrological model shown as single dots.

Area 1 (Figure 6) shows the same area as used in the template matching (Figure 4) and highlights many of the storage pits visible along the ridge line with larger pits further up the hill. Some of the likely pits were not captured, and finer resolution of the data may be needed for these to be picked up. Furthermore, it may be important to incorporate how the pits are spaced to help further differentiate anthropomorphic features.

Area 2 (Figure 7) shows a number of previously unrecorded pits. A series of large pits along the southern edge of a spur are detected with other less obvious features possibly on the flattish area of the spur. Modern farm tracks show clearly as ditches. Similarly, a very distinctive line of pits was visible in Area 3 (Figure 8) and most of the visible features were found by the hydrological modelling with the exception of one farthest north. All three sites have now been recorded in ArchSite (R11/460, 461 and 462) although many others could have been chosen as well.

Figure 6. Close-up of southern end of research area (1) showing possible archaeological features based on hydrological modelling – R14/460.

Figure 7. Archaeological sites on ridge showing farm tracks (Area 2) – R11/461.

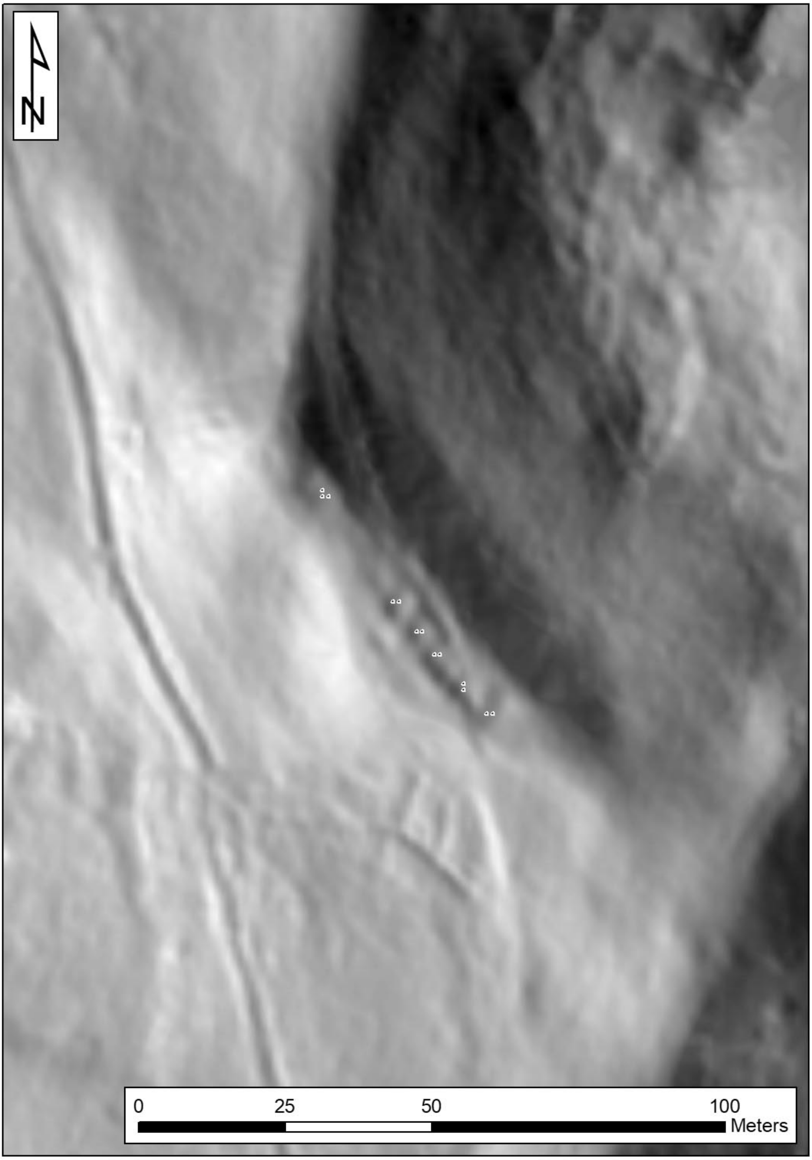

Figure 8. Archaeological sites on ridge in Area 3 – R11/462.

Discussion

Readily available, but often under-utilised, high-resolution datasets such as LiDAR imagery are an opportunity to remotely survey large areas of New Zealand to identify archaeological features. Features may then be verified via ground survey. The work illustrated here demonstrates how different types of analysis can be used to identify archaeological earthwork features and as our experience increases our ability to characterise known sites and find new sites will be useful for heritage planning work. The large scale at which such work can be undertaken is one of the main benefits of the research presented here. Applied regionally, and as with aerial photography in the past, it has the potential to not only add significantly to the catalogue of archaeological sites found in New Zealand but also provide the basis of much more comprehensive and systematic heritage management of those sites.

References

Bedford, S., P. Siméoni and V. Lebot. (2018). The anthropogenic transformation of an island landscape: Evidence for agricultural development revealed by LiDAR on the island of Efate, Central Vanuatu, South-West Pacific. *Archaeology in Oceania*, 53: 1-14.

Benedix, G. K., C.J. Norman, P.A. Bland, M.C. Towner, J. Paxman and T. Tan. (2018). Automated Detection of Martian Craters using a Convolutional Neural Network. 49th Lunar and Planetary Science Conference 2018 (LPI Contrib. No. 2083).

Bickler, S. H., Clough, R. and Macready, S. (2013). *The Impact of Climate Change on the Archaeology of New Zealand's Coastline: A Case Study from Whangarei District*. Science for Conservation No. 322. Wellington: Department of Conservation.

Cochrane, E., and J. Mills. (2018). LiDAR imagery confirms extensive interior land-use on Tutuila, American Sāmoa. *Journal of Pacific Archaeology*, 9: 70-78.

Devereux, B.J., G.S. Amable and P. Crow. (2008). Visualisation of LiDAR terrain models for archaeological feature detection. *Antiquity*, 82: 470-479.

Drăgut, L. and C. Eisank. (2011). Object representations at multiple scales from digital elevation models. *Geomorphology*, 129: 183–189.

Freeland, T., B. Heung, D.V. Burley, G. Clark and A. Knudby, (2016). Automated feature extraction for prospection and analysis of monumental earthworks from aerial LiDAR in the Kingdom of Tonga. *Journal of Archaeological Science*, 69: 64-74.

Gorbey, K. (1967). Aerial photography in New Zealand archaeology. *New Zealand Archaeology Newsletter*, 10 (4):167-175.

Gumbley, W., M. Laumea and M. Gainsford. (2018). Archaeological Investigation Report: S15/421, S15/422 & S15/427, 95 Swayne Road, Cambridge, New Zealand. Technical report.

Guyot, A., L. Hubert-Moy and T. Lorho. (2018). Detecting Neolithic Burial Mounds from LiDAR-Derived Elevation Data Using a Multi-Scale Approach and Machine Learning Techniques. *Remote Sensing* 10. 225. 10.3390/rs10020225.

Jones, B. and S.H. Bickler. (2017). High Resolution LiDAR data for landscape archaeology in New Zealand. *Archaeology in New Zealand*, 60 (3):35-44.

Jones, B.D., T.N. Ladefoged and G. Asner. (2015). Tracing the resilience and revitalisation of historic taro production in Waipi‘o Valley, Hawai’i. *Journal of the Polynesian Society*, 124 (1): 83-109.

Jones, K. (1994). *Ngā Tohuwhenua Mai Te Rangi: A New Zealand Archaeology in Aerial Photographs*. Wellington: Victoria University Press.

Jones, K. (1996). Aerial photography in New Zealand archaeology. *Australasian Historical Archaeology*, 14: 25-33.

Jones, K. (2002). Condition reporting and monitoring of archaeological sites: The use of large-scale vertical aerial photographs in New Zealand. *Conservation and Management of Archaeological Sites*, 5 (3): 131-140.

Jones, K. and V. Tanner. (2002). *Archaeological Survey of the Southern Hawke's Bay Coast from the Air*. Science for Conservation Series 202. Wellington: Department of Conservation.

Klear, M. (2018). PyCDA: Simple Crater Detection. Available at https://github.com/AlliedToasters/PyCDA,

Ladefoged, T.N., M.D. McCoy, G.P. Asner, P.V. Kirch, C.O. Puleston, O.A. Chadwick and P.M. Vitousek. (2011). Agricultural potential and actualized development in Hawai‘i: An airborne LiDAR survey of the leeward Kohala field system (Hawai‘i Island). *Journal of Archaeological Science*, 38: 3605–3619

Lindsay, J.B., J.M.H. Cockburn, and H.A.J. Russell. (2015). An integral image approach to performing Multi-Scale Topographic Position analysis. *Geomorphology*, 245: 51–61.

McCoy, Mark D., Gregory P. Asner and Michael W. Graves. (2011). Airborne lidar survey of irrigated agricultural landscapes: An application of the slope contrast method. *Journal of Archaeological Science*, 38: 2141-2154.

Quintus, S., J. T. Clark, S. S. Day, D. P. Schwert (2015). Investigating regional patterning in archaeological remains by pairing extensive survey with a lidar dataset: The case of the Manu'a Group, American Samoa. *Journal of Archaeological Science*: Reports, 2: 677-687.

Wood, J. (1996). The Geomorphological Characterisation of Digital Elevation Models. Unpublished Ph.D. dissertation, University of Leicester.

Acknowledgements

This paper was based on the presentation at the 2018 NZAA/AAA Conference held in Auckland in 2018. We would like to thank Glen Farley, Jen Low and Matthew Barrett for they assistance with the conference paper. We would also like to thank Dorothy Brown for her editing.