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Keywords

capture, micro, topography, antarctic, moss, unmanned, beds, aerial, vehicle, uav

Disciplines

Medicine and Health Sciences | Social and Behavioral Sciences

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Using an Unmanned Aerial Vehicle (UAV) to capture micro-topography of Antarctic moss beds

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Abstract

Mosses, the dominant flora of East Antarctica, show evidence of drying in recent decades, likely due to the regional effects of climate change. Given the relatively small area that such moss beds occupy, new tools are needed to map and monitor these fragile ecosystems in sufficient detail. In this study, we collected low altitude aerial photography with a small multi-rotor Unmanned Aerial Vehicle (UAV). Structure from Motion (SfM) computer vision techniques were applied to derive ultra-high resolution 3D models from multi-view aerial photography. A 2 cm digital surface model (DSM) and 1 cm orthophoto mosaic were derived from the 3D model and aerial photographs, respectively. The geometric accuracy of the orthophoto and DSM was 4 cm. A weighted contributing upstream area was derived with the *D-infinity* algorithm, based on the DSM and a snow cover map derived from the orthophoto. The contributing upstream area was used as a proxy for water availability from snowmelt, one of the key environmental drivers of moss health. A Monte Carlo simulation with 300 realisations was implemented to model the impact of error in the DSM on runoff direction. Significant correlations were found between these simulated water availability values and field measurements of moss health and water content. In the future ultra-high spatial resolution DSMs acquired with a UAV could thus be used to determine the impact of changing snow cover on the health and spatial distribution of polar vegetation non-destructively.

Keywords: moss health, water availability, snowmelt, Digital Surface Model (DSM), Structure from Motion (SfM), multi-view stereopsis

1. Introduction

Polar regions are experiencing rapid and severe climatic shifts, with major changes in temperature, wind speed and ultraviolet-B (UV-B) radiation already observed in Antarctica (Adams et al., 2009; Convey et al., 2009). The climate of Antarctica has experienced major changes due to both ozone depletion and as a result of increases in greenhouse gases (Thompson and Solomon, 2002; Perlwitz et al., 2008; Son et al., 2010). The rate of climate change in the high latitudes renders Antarctica one of the most significant baseline environments for the study of climate change impacts on biota. Rapid changes in vegetation have been documented in maritime Antarctica and the sub-Antarctic islands, where temperature changes are particularly pronounced (Convey et al., 2009). However, changes in temperature have been less severe across East Antarctica and this, coupled with the slow growth rates of Antarctic vegetation, suggests that change in continental Antarctica would be difficult to detect (Anisimov et al., 2001; Robinson et al., 2003). Contrary to earlier Intergovernmental Panel on Climate Change (IPCC) predictions, there is some evidence that climate change is already impacting the vegetation around Australia's

East Antarctic stations (Robinson et al., 2012; Clarke et al., 2012), whilst other recent studies also show that the climate in East Antarctica may be changing more rapidly than anticipated (Chen et al., 2009; Turner et al., 2009, 2013).

Water availability, temperature, and UV-B have been identified as three key drivers for vegetation health in Antarctica (Newsham and Robinson, 2009; Wasley et al., 2006a,b; Clarke et al., 2012). Despite this, there have been few long-term studies of the response of Antarctic vegetation to climate change, especially on the continent (Robinson et al., 2003; Brabyn et al., 2006; Selkirk and Skotnicki, 2007; Convey et al., 2009). Most focus on the Antarctic Peninsula, where dramatic shifts in recorded temperature (of up to 5 °C) have resulted in the subsequent expansion of local plant communities (Turner et al., 2009), and a small number of studies have documented climate-induced change in terrestrial communities in Continental Antarctica (Brabyn et al., 2006; Selkirk and Skotnicki, 2007; Robinson et al., 2012; Clarke et al., 2012).

Some of the best-developed and most extensive vegetation communities on the continent are found in the Windmill Islands region of East Antarctica (Lewis Smith, 1988), with distribution of vegetation strongly influenced by microclimatic conditions, particularly water availability. Relatively small variations in water availability over small areas (e.g. <1 ha) can result in a change in community composition from moss- to lichen-dominated (Selkirk and Seppelt, 1987; Lewis Smith,

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1990; Wasley et al., 2006a,b, 2012). The moss- and lichen-dominated communities are best developed where melt streams or lakes provide summer melt water and there is a rich supply of nutrients from guano in ancient penguin rookeries (Melick et al., 1994; Emslie and Woehler, 2005; Wasley et al., 2012). Evidence of long-term drying, exhibited by the prevalence of lichen-encrusted moribund moss beds, suggest a contraction of moss communities to the wettest areas with reliable water supply due to continuing isostatic uplift (Wasley et al., 2012).

Recent studies have shown that growth rates of mosses in the Windmill Islands region have slowed since the 1980s, which is consistent with accelerated drying associated with increased wind speeds around the continent as a result of ozone depletion (Clarke et al., 2012). Accelerator Mass Spectrometry (AMS) carbon dating of these mosses confirms that growth rates are very slow (mm per year) but strongly linked to water availability (Clarke et al., 2012). Mosses, which are the dominant plants around the coast of Antarctica, grow terminally with the youngest growing cells at the tip and the initial cells preserved at the base of shoots. In a manner similar to tree rings, this growth form sequesters carbon in a chronological sequence, meaning these old growth mosses also preserve a biochemical record ($\delta^{13}\text{C}$) along their shoots that could provide quantitative information of water availability at the time that part of the shoot was growing (Clarke et al., 2012; Royles et al., 2012). Studies in the region have also shown a decrease in live moss and a concomitant increase in moribund moss with associated changes in turf colouration from green through red to black (Robinson et al., 2012), likely a stress response reflecting the transition between live and moribund moss as a result of drying. In addition, it is expected that further regional drying will cause a contraction in the extent of healthy moss beds (Wasley et al., 2012).

Since vegetation is largely isolated to the coastal fringe, and instrument records only extend back 50 years with limited spatial resolution, new methods of determining the location, spatial extent, and dynamics of moss beds are urgently required to resolve the extent to which Antarctic coastal climate is changing. The scale, and scattered spatial distribution, of the moss beds (tens of m^2) makes even very high spatial resolution satellite imagery (pixel size of 0.5 m) unsuitable for mapping their extent in sufficient detail. Due to logistical and weather constraints full-scale aerial photography is impractical in Antarctica and is also not detailed enough. One of the key requirements for mapping the distribution of Antarctic moss beds is the acquisition of ultra-high spatial resolution imagery, e.g. 10 cm pixel size or better, in order to capture the fine-scale spatial variability of moss health. In addition, a digital elevation model (DEM) at high resolution is required, to capture the micro-topography of small channels, rocks and boulders that affect water flow from snowmelt.

Recent developments in the use of Unmanned Aerial Vehicles (UAVs), also known as Unmanned Aircraft Systems (UAS), for remote sensing applications provide exciting new opportunities for ultra-high resolution environmental mapping and monitoring (Rango et al., 2006; Zarco-Tejada, 2008; Zhou et al., 2009; Hardin and Jensen, 2011; Watts et al., 2012). The

recent special issues on UAVs for remote sensing applications (*IEEE TGRS*: March 2009; *GIScience and Remote sensing*: March 2011; *Geocarto International*: March 2011; *Remote Sensing*: June 2012) in addition to dedicated conferences, such as *UAV-g*, indicate an increasing popularity of UAVs for remote sensing and photogrammetry applications. The primary advantage of UAV-based remote sensing is the ability to bridge the scale gap between field-based observations and full-scale airborne or satellite observations. In addition, UAVs enable users to collect imagery with multiple sensors on-demand, at an unprecedented level of detail and in a cost-effective way. From a scientific perspective, UAVs allow optimisation of the sampling technique, in terms of spatial resolution and sensor type, to the objects of interest for a specific application (D'Oleire-Oltmanns et al., 2012).

In recent years, Structure from Motion (SfM) computer vision techniques have been successfully employed on multi-view UAV imagery for the generation of high resolution digital surface models (DSM) and orthophotos. The SfM technique can be applied to large collections of overlapping photographs to obtain sparse point clouds for a wide range of objects, such as buildings and sculptures. The power of this technique was demonstrated by Snavely et al. (2007) who developed the Bundler software and used it to construct 3D models of well-known world sites, such as Notre Dame, based on hundreds of overlapping photographs available from community websites. The SfM technique is based on identifying matching features in images taken from different viewpoints. Image features are identified by the scale invariant feature transform (SIFT) algorithm (Lowe, 2004), which is robust in terms of its feature descriptors for image features at different viewing angles.

More recently, several studies have successfully demonstrated the use of SfM for generation of very high resolution 3D point clouds and surface models from UAV imagery. For example, a photogrammetric technique was used to derive a DSM and orthophoto for a landslide in southern France at a spatial resolution of 4 cm (Niethammer et al., 2012), and photogrammetric and SfM approaches have been used to generate sub-decimetres resolution DSMs from overlapping aerial photography acquired by a fixed-wing UAV for the purpose of soil erosion monitoring (D'Oleire-Oltmanns et al., 2012). SfM techniques have been used to generate accurate orthophoto mosaics from a multi-rotor UAV at 1 cm resolution with 10 cm absolute geometric accuracy (Turner et al., 2012), and the accuracy of the SfM derived point clouds was quantified for a coastal erosion study, which concluded that absolute accuracies between 25–40 mm can be reached with a multi-rotor UAV flying at 40 m above ground level (AGL) (Harwin and Lucieer, 2012). Eisenbeiss and Sauerbier (2011) reviewed a range of UAVs and 3D processing workflows for photogrammetric applications and Verhoeven (2011) described a software workflow based on Agisoft Photoscan for 3D reconstruction from aerial photographs in the context of an archaeological application. Finally, Rosnell and Honkavaara (2012) compared an online processing approach, Microsoft PhotoSynth, to a more rigorous photogrammetric approach using SOCET SET. These recent studies all

indicate that accurate 3D point clouds and surface models can be derived from multi-view UAV imagery at ultra-high spatial resolutions of several centimetres (depending on flying height). With the recent introduction of commercial software packages, such as Agisoft Photoscan¹ and Pix4UAV² (Vallet et al., 2012), and the increase in computing power (on both CPU and GPU) the SfM approach will become more readily available for UAV users.

The objective of this study is to use aerial photography acquired by a multi-rotor UAV to generate ultra-high resolution DSMs of Antarctic moss beds. The study builds onto work carried out by Turner et al. (2012) by applying an improved SfM technique for DSM generation and developing a Monte Carlo simulation framework for snowmelt modelling. The workflow of DSM creation is described, and the accuracy of the DSM and orthophoto mosaic are assessed. Finally, a terrain modelling technique based on the DSM is used to derive a proxy for water availability. The overall aim is to model the spatial distribution of water availability from snowmelt and relate it to physiological field measurements of moss health and water content.

2. Methods

2.1. Study area

The Windmill Islands region in East Antarctica has the most extensive and well-developed vegetation in Eastern Antarctica. The study was conducted at Robinson Ridge (66.368°S, 110.587°E) in the Windmill Islands, East Antarctica (Fig. 1), one of two sites used for a long term monitoring system established in 2003 (Robinson et al., 2012; Wasley et al., 2012). This site has a northerly aspect, with a gentle slope and northward-flowing meltwater streams, into which water is released as snow melt from a snow bank to the south-east of the site. The heights in the study site vary from 36 m at the top of the ridge to 2 m close to the shoreline. Robinson Ridge is the only area in the southern Windmill Islands region to have well-developed vegetation communities, associated with nutrient supply from a nearby ancient penguin rookery, abandoned more than 5,000 years ago (Melick et al., 1994; Emslie and Woehler, 2005; Wasley et al., 2012).

The site is approximately 200 m by 100 m with several tens of m² occupied by Antarctic vegetation communities, comprised of bryophytes and lichens. The location of vegetation communities is largely driven by water availability and is restricted to wet locations that receive water during the summer snowmelt. Topographic factors, such as micro-topography (e.g. boulders and rocks), water drainage, upstream catchment, slope, and intensity of solar irradiance, all play a key role in vegetation community health and distribution. Within the moss turves, cryo-perturbation produces ridges and valleys on a centimetre scale, causing plants growing on the tops of ridges to be subject to more drying and wind abrasion than those protected in the valleys (Fig. 2(b), Lovelock and Robinson (2002)). This

contributes to the turf colour variation, with valleys typically varying shades of green, and ridges ranging from red through brown to black as moss becomes increasingly moribund.

2.2. UAV image collection

For this study a MikroKopter OktoKopter³, a multi-rotor helicopter with eight rotors and a payload capacity of 1–1.5 kg, was utilised. It was equipped with an autopilot and navigation-grade GPS receiver. A Canon 550D digital SLR camera was used on a motion compensated gimbal mount. The camera took a photograph every 1–2 seconds, triggered by the on-board flight controller. The flight path of the micro-UAV was recorded by the on-board GPS logging at 1 Hz. Before each flight, the camera time was synchronised with GPS time. Due to the extreme magnetic declination of 98° West, the autopilot failed to function in navigation mode, which forced the operator to fly the OktoKopter manually. The altitude hold mode was used to fly at approximately 50 m above ground level (AGL). A live radio link allowed visualisation of real-time position information on a map, which helped the UAV pilot to follow overlapping flight paths that covered the study area. Each 18 megapixel photograph covered approximately 64 by 43 m on the ground at 1 cm resolution. Around 200 photographs were captured for the site covering the core area of the moss beds, however, the ridge was too large to cover the whole watershed. The photographs were visually assessed on the basis of quality, viewing angle, and overlap, in order to remove blurred and under- or over-exposed images from further processing and analyses. For more detail on the UAV setup also see Turner et al. (2012).

All photos were collected during a single flight on 24 February 2011 (Austral Summer). During UAV data acquisition 12 circular, aluminium reference disks with a 22 cm diameter, bright orange rim, and a clearly defined centroid (visible as a single black pixel in the images) were laid across the study area for georeferencing purposes. Another 30 aluminium orange disks with a 10 cm diameter were spread out for independent accuracy assessment (Fig. 1). Both types of ground control points (GCPs) could be easily identified on the collected imagery. Their exact locations were measured directly after UAV image acquisition using a Leica 1200 DGPS system in dual frequency real-time kinematic mode, providing centimetre positional and height accuracies (2–4 cm).

2.3. 3D point cloud generation

After visual pre-selection, approximate coordinates were assigned to the photographs based on the synchronised GPS flight path. Geotagging⁴ software was used to write the coordinates to image JPEG EXIF headers. Agisoft Photoscan Professional (0.85) software was used for the 3D reconstruction of the camera positions and terrain features. The specific algorithms implemented in Photoscan are not detailed in the manual, however, a description of the SfM procedure in Photoscan and commonly used parameters are described in Verhoeven (2011).

¹<http://www.agisoft.ru>

²<http://pix4d.com>

³<http://www.mikrokopter.de>

⁴<http://www.GeoSetter.de>

Figure 1: Orthomosaic of the Robinson Ridge study area at 2 cm resolution generated from overlapping UAV aerial photography and SfM algorithms. The GCPs for georectification and geometric accuracy assessment, and the quadrat locations are shown.

(a)

(b)

Figure 2: Moss bed at Robinson Ridge fed by snowmelt: (a) overview of a moss plot showing the high spatial variability of healthy (green), stressed (brown/red), and moribund moss within a small area; (b) detailed subset of the above photograph showing the influence of small topographic variation (micro-topography) on moss health (the disks are 10 cm in diameter).

Photoscan follows a common SfM and multiview stereopsis (MVS) workflow starting with image feature identification and feature matching. The approximate GPS coordinates of the camera stations were used at this stage to guide the matching process. Image matching was carried out with the PhotoScan accuracy set to high. The initial bundle adjustment resulted in a position and orientation for each camera exposure station and the 3D coordinates of all image features. These coordinates formed a sparse 3D point cloud of the terrain (1.85 million points). A dense geometry reconstruction based on multi-view stereopsis resulted in a more detailed 3D model with 10 million facets. This model was used to identify the 12 large GCPs to improve the absolute accuracy of the bundle adjustment and the 3D model. After the recomputed bundle adjustment a new 3D model with 50 million facets was generated with the PhotoScan accuracy for the geometry build set to high. Finally, a DSM was generated by gridding the 3D model based on a given cartographic projection (WGS84 UTM 49S) and cell size (2 cm). Projecting the original photographs onto the 3D surface and blending their overlap zones produced an orthophoto mosaic (orthomosaic) of the whole area. Due to the relatively low flying height we were able to generate a DSM at 2 cm resolution and an orthomosaic at 1 cm.

An assessment of the geometric accuracy in easting (X), northing (Y), and height (Z) was carried out for the orthomosaic and DSM. Thirty of the small orange GCPs (excluded from georeferencing in the SfM process) were identified in the orthomosaic. The coordinates of the disk centroids were retrieved from the image mosaic and compared to the corresponding surveyed GPS coordinates, resulting in mean and root mean squared error (RMSE) accuracy measures in the X and Y direction. The height value was derived from the DSM for the GCP centroids and also compared to the GPS observations, producing mean and RMSE accuracy measures for the Z direction (Höhle and Höhle, 2009; Harwin and Lucieer, 2012).

2.4. Monte Carlo Simulation of contributing catchment area

The key aim of this study was to capture the micro-topography of the terrain to determine the effect of snowmelt water availability on moss health. Several spatially distributed snowmelt models have been reported in the literature, see for example Marks et al. (1999), Giesbrecht and Woo (2000), Wang and Li (2001), Zhang et al. (2008), and Abudu et al. (2012). However, these models have been designed to model melt at catchment levels of hundreds, if not thousands, of km² in size. The spatial snowmelt dynamic for our small study area is highly dependent on the micro-topography and the local climate. It would be difficult, impractical, and unrealistic to apply catchment-scale models, such as the Snowmelt Runoff Model (Abudu et al., 2012), the Soil and Water Assessment Tool (SWAT) (Zhang et al., 2008), or Image Snowcover Energy and Mass Balance model (ISNOBAL) (Marks et al., 1999), to our small study area given the uncertainty in the parameterisation of the models. The nearest weather station is 10 km north of the study site and it is notoriously difficult to measure snow precipitation in Antarctic areas. The majority of snow accumulation constitutes snow drift that is carried in by blizzards rather

than direct precipitation. Snow drift is very difficult to model, hence the focus for this study was on modelling the *relative* spatial distribution of water availability based on the ultra-high resolution DSM and weighted contributing upstream area as a proxy for snowmelt (Revill et al., 2007; Kopecký and Čížková, 2010).

The snow cover boundary was derived from the orthomosaic using several small training areas and a maximum likelihood classification. Water availability was modelled using the TauDEM command-line tools (Tarboton, 1997; Tesfa et al., 2011). The *D-Infinity* Contributing Area algorithm was used to calculate the contributing upstream area for each grid cell in the 2 cm resolution DSM. The advantage of the *D-Infinity* algorithm (Tarboton, 1997) is that it calculates flow direction as a continuous angle. It also allows the distribution of water over multiple downstream cells. This results in a more realistic flow field compared to the widely used D-8 algorithm (Tarboton, 1997) that only allows water to flow in one of eight azimuth directions.

In addition, a Monte Carlo simulation of the flow accumulation was employed to account for errors in the DSM (Höhle and Höhle, 2009) and allow for uncertainty in flow direction due to the thickness of the moss and subtle variations in sub-surface topography not captured by the DSM. Monte Carlo simulation is based on creating several realisations of the DSM by adding a random error in the height value. Several hundred realisations of the DSM were used in subsequent calculations of DSM derivatives, such as slope, flow direction and flow accumulation to model the effect of error in the DSM input on the derivatives. Flow direction is especially sensitive to errors in the DSM. The outputs can be summarised with basic descriptive statistic indicators for each grid cell, such as mean and standard deviation. The mean provides the most likely output of the Monte Carlo simulation, whereas the standard deviation can illustrate the impact of error in the input (DSM) on the output derivatives by highlighting the variability in the output (Oksanen and Sarjakoski, 2005; Hengl et al., 2010). In this study, we generated 300 DSM layers imputed with a random error for each grid cell drawn from a Gaussian error model defined with a mean of 0.0 m (no bias) and a standard deviation equal to the RMSE (0.044 m), which was derived from the DSM accuracy assessment (section 2.3). The ArcGIS ModelBuilder (ESRI Inc., USA) was used to impute the 300 DSMs (Zandbergen, 2011) and to write the output to GeoTIFF files compatible with the TauDEM tools. A Python script was implemented to run the following TauDEM command-line tools: *pitremove* (removal of pits), *dinfldir* (calculation of flow direction), *areadinf* (calculation of contributing area). To simulate the contribution of snowmelt, a weight layer was used in the calculation of the contributing area. A value of 1 was applied to all grid cells that were snow free and a value of 1 million was applied to all grid cells containing snow (derived from the orthomosaic). This approach essentially simulated a much greater upstream area (hence water availability) for the snow covered part of the study site. After simulating 300 scenarios, the mean contributing area was calculated for each grid cell. The DSM derivatives were then compared to field measurements.

2.5. Moss health estimates and water content measurements

Data for moss health was collected in 2008 as part of a long term monitoring study for the Australian Antarctic State of the Environment Indicator 72 (SOE72) (Robinson et al., 2012), which commenced in 2003 and collects samples at five year intervals. Field measurements from 2008 were used in this study as these samples had been collected in the key snowmelt period at the closest time point to the UAV flight year. The snow line reached a similar position at maximum summer melt in Feb 2003, 2008, 2010, 2011 and 2012. Due to logistical constraints we were not able to collect UAV-based imagery until late February 2011, which was too late in the season for collection of field samples in that year (moss turf was already frozen). In 2008, vegetation community composition was sampled at 30 quadrat locations, across 10 transects, 60–70 m in length, which spanned a water gradient across the site and encompassed the vegetation composition and health gradient; from pure bryophyte stands, to the point at which the bryophyte turf was predominantly moribund and encrusted with lichens (as detailed in Robinson et al. (2012) and Wasley et al. (2012)). An inner 20 by 20 cm quadrat, divided into a 10 cm grid, was placed in each quadrat (25 by 25 cm) and a tweezer-pinch sample (approximately 20–50 gametophytes) was collected at each of the nine grid line intersections (8 external and one central point). Samples were air dried and stored until analysis. Bryophytes within the samples were scored microscopically as live (green/red) or moribund (brown/black). For each quadrat sampled in January 2008, live moss and moribund moss abundance were determined (a sum of the scores from the 9 tweezer pinch samples for each quadrat), and moss health was calculated as

$$\frac{(\text{live moss})}{(\text{live moss} + \text{moribund moss})} \quad (1)$$

Community water content (CWC) was measured across the site in January 2008. Sponge cores, 2–3 cm diameter and 3 cm depth, were inserted into the moss beds adjacent to each quadrat, and were retrieved after 24 hours. The sponges were placed in airtight tubes, returned to the laboratory within one hour and weighed to determine fresh weight. The sponges were then left to dessicate in the laboratory, at a relative humidity of 22 %, until a constant dry weight was reached. This method has been shown to give a good correlation with true turf water content while avoiding destructive analysis of the vegetation (Robinson & King unpublished data). The CWC was calculated as

$$\frac{(\text{field wet weight} - \text{final dry weight})}{(\text{final dry weight})} \quad (2)$$

The quadrat locations were measured with a geodetic differential GPS receiver at 2–4 cm accuracy. For each quadrat centre a circular 1 m buffer was generated to summarise the terrain characteristics, based on the DSM and its derivatives, in the direct neighbourhood of the quadrat. These buffers were used to account for the topographic variation and sub-surface water availability in the direct vicinity of the 25 by 25 cm quadrats.

Zonal statistics were then used to calculate the average contributing area for each quadrat, so that the relative water availability based on the DSM could be related to the moss health and water content measurements in the field.

3. Results and Discussion

Fig. 3 shows an overview and detailed section of the 3D model. The surface faces are coloured based on the average neighbourhood colour in the UAV aerial photographs. The model in Fig. 3 is deliberately not texture-mapped in order to show the true detail in the model. The 1 cm resolution orthomosaic is shown in (Fig. 1). The results of the geometric accuracy assessment based on the 30 GCPs (Fig. 1) are reported in Table 1. The overall RMSE was 0.042 m, which is comparable to other SfM studies (D'Oleire-Oltmanns et al., 2012; Harwin and Lucieer, 2012; Niethammer et al., 2012) and better than our previous study (0.10–0.15 m reported in Turner et al. (2012)). The 0.044 m error in the height value was subsequently used to define the standard deviation of the Gaussian error model in the Monte Carlo simulation. The magnitude of the errors in the orthomosaic and DSM is within the error margin and measurement precision of the GPS measurements that are used as the reference coordinates.

The Monte Carlo simulation was conducted for 300 iterations with a randomly imputed DSM created for each realisation. The simulation took 16 hours on a desktop with an Intel i7-3930 CPU for the 3657 by 7138 cell DSM. The mean grid layer for the contributing upstream area of each grid cell was calculated and the natural logarithm applied to effectively visualise the differences between high and low values. Fig. 4 shows a map of the contributing upstream area weighted by the snow area to simulate the effect of snowmelt. The map also shows the moss quadrats coloured by moss health values. The spatial distribution of the contributing upstream area seems to be a good proxy for water availability from snowmelt. There appears to be a strong relationship between moss health as measured at the quadrat locations and the contributing upstream area as evidenced by the quadrats dominated by healthy moss growing in or near melt streams. The western side of the study area is much drier than the eastern side due to the lack of snow cover in the higher parts of the catchment. It is therefore important to use the snow layer to increase the weight of the upstream area on the eastern side to simulate the increased water availability from snowmelt.

Fig. 5 summarises the results of the Monte Carlo simulation. The mean of the 300 realisations has been calculated for the DSM, the slope derivative, and the weighted flow accumulation. The standard deviation for each derivative is also shown in Fig. 5. The standard deviation in the height values is in the order of 3.4–5.4 cm, which is indicative of the input error of 4.4 cm. The spatial distribution of the error is random. In reality the error in the DSM is likely to be spatially autocorrelated and is strongly related to the geometry of the camera network. An interesting avenue for future research is to derive the spatial distribution of the error from the bundle adjustment and run the Monte Carlo simulation with a spatially dependent error model.

(a)

(b)

Figure 3: 3D surface derived from UAV survey: (a) overview of the 3D model of the study site showing the camera exposure stations (the extent of Fig. 3(b) is shown in red); (b) detailed subset of the 3D surface model showing the detail in the topography. Note that this is not an orthophoto, but a 3D model with its facets coloured based on the average colour from the photographs.

Table 1: Spatial accuracy [m] of the orthophoto and DEM.

	X	Y	Z	Absolute average
Mean	0.017	-0.028	0.005	0.016
RMSE	0.037	0.045	0.044	0.042

Figure 4: Map of relative water availability as modelled by contributing upstream area weighted by snow.

The impact of the simulated error in the DSM on the slope derivative is shown in the standard deviation for slope. The maximum standard deviation is 3.2° . The greatest variability in slope values is found on the steepest slopes, whereas the flat areas show very limited variability. Finally, the standard deviation for the flow accumulation shows that the greatest impact of the simulated DSM error occurs in areas where the flow accumulation is high. The standard deviation in flow accumulation shows a significant spatial variability within the existing stream channels. The Monte Carlo simulation has the greatest effect on flow accumulation as it forces the stream channels to ‘jump around’ between iterations by introducing subtle, but significant, variations in height values. The DSM did not cover the full spatial extent of the ridge line, which means that the watershed is larger than the DSM. This has implications for flow accumulation modelling in that the upstream area is larger in reality than what can be derived from the DSM. Given the morphology of the study area, we do not expect this to have a substantial effect on the analysis, however, for future field visits we plan to capture the complete watershed to account for the edge effects.

The relationship between the natural logarithm of the contributing area for each quadrat, and the community water content and the moss health measurements are shown in Fig. 6 and Fig. 7 respectively. There was a significant correlation between the 2008 field measured variables and modelled water availability with R^2 values for the natural log of water content: .44 ($n = 30, p < .0001$) and moss health: .57 ($n = 30, p < .0001$).

Moss health is probably a better long term integrator of water available at the site for the whole of the growing season. The CWC is only measured over one 24 hour period in each season and represents a point measure of likely maximal water availability. We are exploring other, better long term integrators of community water content, including the $\delta^{13}\text{C}$ signature of the moss turf that has been shown to correlate with growth rates and overall site wetness (Clarke et al., 2012; Wasley et al., 2006b, 2012). However, these all rely on destructive sampling and ultimately a non-intrusive and non-destructive method of estimating water availability is required to avoid ongoing sampling and damage to these fragile and finite Antarctic communities. The outliers in Fig. 7 showing 0% moss health can be explained by the fact that these quadrats have a small upstream area (hence their low value on the x-axis), however, they are not directly fed by the snow pack.

Other DSM derivatives, such as slope, total solar radiation for the month of January, and a topographic wetness index did not result in significant correlations with moss health or water content. The results in Fig. 4 are encouraging, given the similarities in spatial distribution of moss health and simulated water availability. Improvements to the approach presented in this study would include the implementation of a physically-based snowmelt model rather than the model based on contributing upstream area described here. We will explore the possibilities of installing a weather station to measure the local weather conditions. In addition, a timelapse camera could be used to acquire daily images of the study site to determine the retreat of the snowline during the summer season. This equipment,

however, is potentially expensive and logistically challenging to install and operate in Antarctica. The meteorological and snowline data in combination with the ultra-high spatial resolution DSM generated in this study could be used to adapt one of the existing catchment-scale snowmelt models, such as the SRM model (Abudu et al., 2012). The key advantage of the detailed and accurate DSM is the ability to simulate changes in the snow cover and snowmelt given past and future climate scenarios. For example, the western side of the study area contains extensive moribund moss in dry drainage channels. It is likely that at some point in the past these channels were fed by a more extensive snow field. Future work will also include the acquisition and analysis of multispectral and thermal imagery collected from our UAV. A multi-sensor approach could provide direct information about the spatial distribution of turf water availability, moss health, and if spectral libraries are developed the possibility of distinguishing key components of the vegetation. In the future, such technology could be used to map and monitor communities without the need for destructive sampling of these unique and fragile ecosystems.

4. Conclusion

This is the first study to acquire low altitude aerial photography over Antarctic moss beds with a multi-rotor UAV. SfM algorithms were used to derive a 2 cm resolution DSM for a 1 ha study area in the Windmill Islands region, East Antarctica. Surface water flow direction and contributing upstream area were derived to simulate water availability from snowmelt. The contributing upstream area derived from a Monte Carlo simulation provided a proxy for water availability from snowmelt. R^2 values of 0.44 and 0.57 were found between simulated water availability, and water content and moss health, respectively. These results suggest that moss health is strongly influenced by water availability from upstream snow banks. With this detailed spatial information we can model the impacts of dynamically changing snow cover conditions in the past and future, and their influence on moss health. Future research will focus on multi-sensor UAV data collection and processing of multi-spectral and thermal imagery, in addition to a physically-based snowmelt modelling approach. Multispectral and thermal imagery have the potential to map the health distribution of moss over the whole study area. This study has demonstrated that low altitude aerial surveys with UAVs are very promising given their ability to collect ultra-high spatial resolution imagery on-demand, even in remote and harsh environments.

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Figure 5: The mean and standard deviation layers for the DSM, slope, and flow accumulation derived from the Monte Carlo simulation.

Figure 6: Scatter plot of the relationship between the natural log of the contributing area of each quadrat and the combined community water content (CWC) measurements.

Figure 7: Scatter plot of the relationship between the natural log of the contributing area of each quadrat and the moss health measurements.

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