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Approaches to monitor peatland subsidence in the Waikato Region

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Prepared by:
J Pronger, P Mudge and S Fraser (Manaaki Whenua – Landcare Research)
J Brasington and L Schipper (University of Waikato)

For:
Waikato Regional Council
Private Bag 3038
Waikato Mail Centre
HAMILTON 3240

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Peer reviewed by:
Thomas Paul & Loretta Garrett

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Approved for release by:
Michelle Begbie

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J Pronger, P Mudge and S Fraser

Manaaki Whenua – Landcare Research

J Brasington and L Schipper

University of Waikato

Reviewed by:	*Approved for release by:*
Andrew Neverman Scientist Manaaki Whenua – Landcare Research	Chris Phillips Portfolio Leader – Managing Land & Water Manaaki Whenua – Landcare Research

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Summary

Project and Client

- The Waikato Region has about 84,000 ha of peatlands, of which about 65,000 ha has been drained, mostly for agriculture, resulting in shrinkage, consolidation and oxidation of the organic soil. These three processes are collectively called peat subsidence, which is a gradual lowering of the land surface.
- The ongoing drainage-subsidence cycle results in an increased risk of flooding, prolonged high soil moisture, reduced wetland sustainability, reduction in drainage capacity, a requirement to prematurely upgrade, repair or install drainage and other infrastructure, and carbon emissions.
- Subsidence rates are spatially and temporarily variable, dependent on factors including: time since drainage, land use, land and drainage management, and peat type. In the Waikato region, recent work has reported an average peat subsidence rate of about 2 cm y^{-1}.
- Waikato Regional Council (WRC) require robust spatial information on regional peatland subsidence rates and spatial variation for state of the environment monitoring, to support implementation of the Waikato Regional Policy Statement (WRPS) and to inform long-term planning.
- WRC have contracted Manaaki Whenua – Landcare Research (in collaboration with the University of Waikato) to develop a new Waikato regional peat subsidence monitoring network for peatlands under agriculture.

Objectives

- The purpose of this report is to identify potential peatland subsidence monitoring methods and their accuracy and limitations, not the driving factors that are the cause for subsidence.
- Suitable methods must be able to detect significant changes in thickness in the order of 10 cm over a 5-yearly monitoring interval in addition to capturing important differences in subsidence rates between land uses or management if they are occurring.
- A second objective was to consider the accuracy and limitations of all available spatial layers for use to inform a robust spatially representative network design.

Peatland subsidence monitoring methods

- Methods to monitor subsidence can be broadly divided into those suitable for repeat measurement of peat depth and those for repeat surface height measurement.
- Approaches to measure peat depth include peat probing and ground penetrating radar (GPR). Peat probing involves pushing an extendable metal probe down through the peat substrate. Limitations include misinterpretation of the base depth and non-vertical probe orientation, but these can be mitigated with suitable control measures. GPR is based on the travel times of radar waves and is strongly influenced by water content and also affected by bulk density, root and ash layers. GPR thus requires calibration that will vary spatially and temporally.

- Many approaches are available to measure surface height change over time. Point-based approaches include laser levelling, which is limited by line of site to datum, and consequently Global Navigation Satellite System (GNSS) approaches are attractive. Of these, static GNSS is most accurate. Spatially integrative approaches include terrestrial, airborne and satellite-based LiDAR, satellite-based interferometric synthetic-aperture radar (InSAR), and structure from motion (SfM) photogrammetry. Validation of SfM at landscape scale is difficult, and at present uncertainty in accuracy and repeatability of InSAR is high. Airborne LiDAR is attractive because it is proven technology with comparatively straight forward validation procedures. Helicopter-based LiDAR will provide flexibility in flight height and speed where trade-offs between data quality and coverage can easily be adjusted to suit our purpose.

Spatial layers to inform network design

- A robust and balanced network design that captures the range of peat types and depths, land use, and drainage management approaches will depend on the quality of the spatial layers used to inform the design.
- Peat extent and type will be informed first by S-map, but where this data layer is incomplete, the fundamental soils layer (FSL) and other existing maps and reports will be used. Inaccuracies in Organic Soil boundaries can be expected and will be checked during implementation.
- Peat depth will be informed by historic survey data and will rely heavily on the digitised Daveron (1978) survey which is outdated but should capture the range of peat depths in the survey design.
- Land use will be informed by the land cover database (LCDB) and Agribase and supported by historical imagery and local knowledge.
- Drainage management will be informed by a custom WRC drainage management layer. This layer does not provide any information on drainage type or depth, and this information will be collected during the first monitoring round.
- Spatial layers limitations (e.g. boundary uncertainty, outdated) will likely result in a network that does not exactly reflect design. Through robust recording of peat type, water-table depth, and all land use and management information at the time of first sampling, and upkeep of this information in future surveys, the influence of the factors of interest should become apparent through time.

Conclusions

- A range of methods for monitoring subsidence have been considered, from simple manual-based to highly sophisticated spatially integrative surface height approaches.
- Peat depth measurement is necessary to get the peat resource during the first monitoring round and manual peat probing is a simple, robust, and low-cost option.
- Peat depth measurements must be paired with accurate surface height measurements to negate the need for repeat measures of peat depth in future surveys. Line of sight limitations of laser levelling mean a point-based GNSS approach is required, for which static GNSS provides the highest accuracy (± 1–10 mm).

- Spatial integration of surface height will also be an important component of the subsidence monitoring network. At present helicopter-based LiDAR provides the best trade-off between good spatial coverage and accuracy of measurement (± 20 mm).
- To ensure spatial variation in subsidence due to land use, drainage management, peat type and depth are captured suitable spatial layers will inform the network design.
- Depth probing of a subset of historic data points from Daveron (1978) may provide WRC early indication on spatial variation in subsidence rates attributable to land use and management

1 Introduction

The Waikato Region has about 84,000 ha of peatlands (Fig. 1) that have formed over the past ~20,000 years from the slow accumulation (mm per year) of wetland vegetation under saturated conditions forming thick organic layers, in some cases in excess of 10 m (Davoren 1978). These peat wetlands represented unique hydrological and ecological environments, and those that remain still do. However, drainage of these peat wetlands began in the early 1900s and now most of this area (about 65,000 ha) has been drained for agriculture (Wheatley Wilson & Wyatt 2024)[1]. The dominant land use is currently dairy cow grazing, and this land use is significant to the regional economy. A small area of drained peatland is used for horticulture and arable cropping, this includes the local high value blueberry industry, where the Waikato region has about 300 ha (Statistics New Zealand 2012).

Following drainage, peat soils subside due to shrinkage, consolidation, and oxidation. Subsidence rates are generally higher following initial drainage due to rapid shrinkage and consolidation and decrease through time, while the contribution of oxidation increases with time since drainage (Pronger et al. 2014). Currently under pasture in the Waikato, subsidence rates average about 2 cm y^{-1} (Pronger et al. 2014) but rates of subsidence could be considerably higher under cropping (e.g. Thompson 1980) and less under blueberries (e.g. Fitzgerald et al. 2005). Often drain deepening or other management actions in response to the effects of peat loss continuously draws down the water table, resulting in ongoing subsidence and drainage, compounding a drainage-subsidence cycle. If allowed, this process will continue until all the peat is lost (Joosten 2016).

Consequences of peat subsidence include changing drainage patterns in catchments and increased ponding due to a reduced drainage gradient, a requirement to prematurely upgrade, repair, or install drainage and other infrastructure, and reduced wetland sustainability. The oxidation component results in the eventual and complete loss of the peat mass, with carbon accumulated in the organic matter over many thousands of years lost to the atmosphere as carbon dioxide (a greenhouse gas) (Campbell et al. 2015). There is little known about the consequences of the loss of ecosystem services provided by these peatlands once the peat has completely gone and the productive performance of the remaining soils and ongoing costs required to maintain their productive potential. Whether subsidence will result in the eventual loss or reduction in agricultural production depends on local hydrological conditions, drainage options (Biancalani & Avagyan 2014), the physical and chemical properties of the remaining soil material, how the remaining peat is managed in the final stages of loss, and economic conditions.

Subsidence of drained agricultural peatlands is not a New Zealand specific problem. Drainage of peatlands has been occurring in the Netherlands for centuries (Stephens et al. 1984) and globally ongoing subsidence rates range from a few mm to multiple cm per year (e.g. Stephens et al. 1984; Rojstaczer & Deverel 1995; Gronlund et al. 2008) where the rate of subsidence is related to multiple factors including land use and land management, depth of

[1] Since writing this report in 2019 mapping of peatland area has been updated through S-Map, therefore the most recently available area is used, and is based on the area of Organic Soils as classified in the New Zealand Soil Classification.

drains and time since drainage (Stephens et al. 1984 Pronger et al. 2014). Ongoing oxidation from about 65 million ha of drained peatlands globally results in emissions of about 2 Gt of CO_2-C annually (Kaat & Joosten 2009).

Section 14.5 of the Waikato Regional Policy Statement (WRPS) tasks Waikato Regional Council (WRC) to 'manage the adverse effects of activities resulting from the use and development of peat soils, including slowing the rate of subsidence and the loss of carbon by oxidation from peat soils' (Waikato Regional Council 2016). Implementation methods in the WRPS include controlling activities on peat soils via regional plans to slow the rate of subsidence and carbon loss, mitigating adverse effects resulting from use and development of peat soils, and ensuring drainage infrastructure minimises any adverse effects on peat soils (Waikato Regional Council 2016). Limited robust and defendable local information on the drivers of peat subsidence means that WRC is unable to confidently implement section 14.5 of the WRPS.

The current WRC peatland monitoring network (Pronger et al., 2014) needs to be improved because important areas of peat are not represented, and existing monitoring transects generally run parallel to drainage ditches. These historic transects on drained agricultural peatlands are based on point measurement locations made by land drainage engineers in the 1920s and therefore were not selected with peat subsidence monitoring in mind. Their proximity to drains potentially results in higher subsidence rates and hence biased findings. Consequently, WRC have contracted Manaaki Whenua – Landcare Research (in collaboration with the University of Waikato) to develop a new regional peatland subsidence monitoring network for these agriculturally managed peatlands in the Waikato. Future work is planned to examine potential subsidence mitigation strategies for the Waikato Region.

The new monitoring network must be spatially representative and include the large, raised bogs of the Hamilton and Hauraki Basins as well as the low moor peatlands found in the lower Waikato. The network must also capture multiple strata of interest, including peat depth and type, dairy, drystock, horticulture, and maize cropping land uses and drainage types and management. The intention is that the monitoring network will, after three or more monitoring rounds, help understand the factors that drive peat subsidence. The design will also integrate historic data points where appropriate. Integration of historic data may provide early indication of land use and management effects on subsidence rates that could take a number of monitoring rounds (at 5-yearly intervals) to be detected through future monitoring, thereby giving WRC a head start in developing policy to reduce subsidence rates.

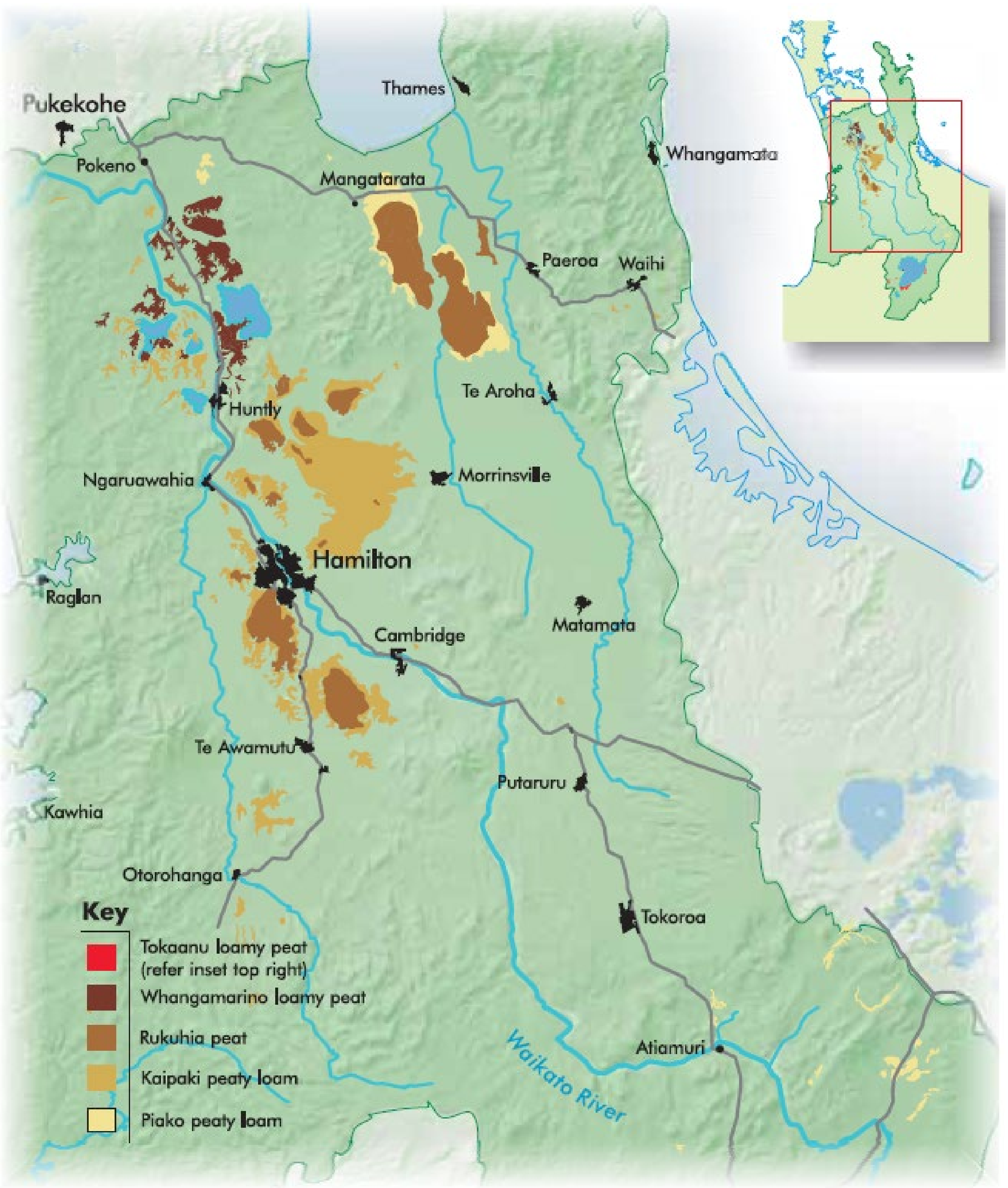

Figure 1. Peatland distribution in the Waikato Region (Environment Waikato 2006). The different colours on the map represent the broad peat soil types in the region.

2 Objectives

The purpose of this report is to identify potential peatland subsidence monitoring methods, both point-based and spatially integrative, and their accuracy and limitations. Suitable methods must be able to detect significant changes in thickness of 8–10 cm over a 5-yearly monitoring interval in addition to capturing important differences in subsidence rates between land uses or management if they are occurring. Considering the broad regional scale rate of subsidence is about 2 cm yr (Pronger et al., 2014), then any differences between land management, peatland types and depth or drainage management could be small. Therefore, a difference in the order of about 0.5 cm y^{-1} is thought to be important and may take two or more 5-yearly monitoring intervals to become apparent. A second objective was to consider the accuracy and limitations of all available spatial layers for use to inform a robust spatially representative network design. We conclude by outlining what we consider to be the best approach to balance the requirements against cost. It is not intended that the selected method will directly measure the driving factors that are the cause for subsidence.

3 Potential subsidence monitoring methods

Through expert knowledge and review of literature we identified several methods that could be used to monitor peatland subsidence in the Waikato Region that range from simple point-based approaches to technically demanding spatially integrative approaches. These approaches are discussed below and summarised in Table 1. Methods can be broadly divided into those suitable for measuring peat depth (Fig. 2; method 1 & 2) and those used for repeated surface height measurement (Fig. 2; methods 3–10).

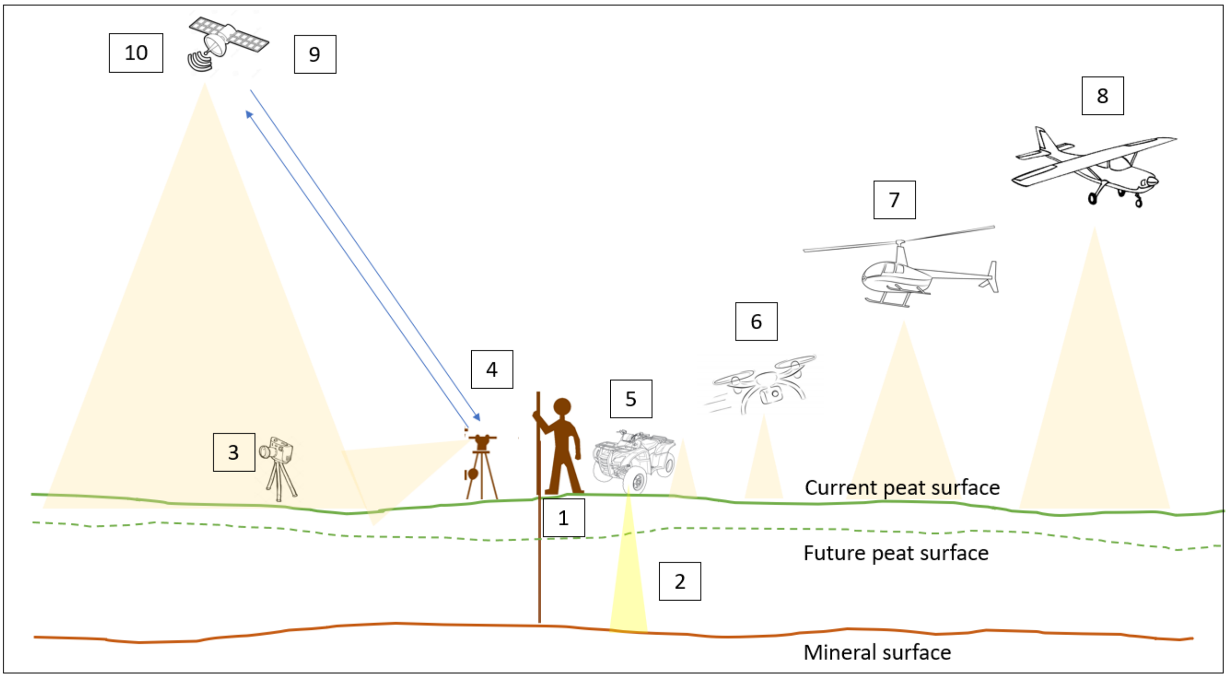

Figure 2. The range of subsidence monitoring methods considered: 1. Peat probing; 2. Ground penetrating radar; 3. Structure from motion; 4. Point-based static, RTK, and PPK GNSS and LiDAR; 5. Terrestrial mobile LiDAR; 6. Drone LiDAR; 7. Helicopter LiDAR; 8. Fixed wing LiDAR; 9. Satellite LiDAR; and 10. satellite InSAR.

3.1 Peat depth measurement

3.1.1 Manual peat probing and coring

Peat depth is most commonly measured using manual peat probing because it is a simple and low-cost approach (Parry et al. 2014). The method involves pushing an extendable metal probe down through the peat substrate until resistance is interpreted as being the peat-mineral surface interface. The length of probe extending into the peat is then measured. Several potential errors can affect the accuracy of manual peat probing. These include misinterpretation of the base depth because of interference with artefacts within the peat profile, including woody vegetation and sediment layers. Additionally, error may occur due to the nature of the transition zone from peat to mineral substrate and because of non-vertical travel of the peat probe below the surface unbeknown to the operator (Sass et al. 2010; Pronger et al. 2014). These errors can be minimised by collecting a sub-sample of material at the peat to mineral interface with a small screw auger attached to the base of the probe to ensure the operator is satisfied the base mineral substrate has been reached in addition to taking replicate probe measurements at each point, preferably a number of metres apart to avoid large artefacts within the profile (Parry et al. 2014). Following these guidelines and based on measured spatial variation in peatland subsidence rates in the Waikato region between early 2000s and 2012, and sample size, Pronger (2013) used a statistical simulation to determine that the peat probe technique was only suitable for monitoring at intervals of about 8 years or longer based on an expected subsidence rate of about 2 cm y^{-1}. This time interval does not meet WRCs goal of monitoring peat subsidence every 5-years. Peat coring may provide more certainty at each point location because a physical core could be observed at the surface. However, coring is much more time consuming relative to probing and consequently not economic when numerous observations are required at regional scales.

3.1.2 Ground penetrating radar

Ground penetrating radar (GPR) can be used to estimate peat depth based on the travel times of radar waves, and has potential to provide insight into the pattern of spatial variability of peat depth which is difficult to obtain using probing. Reflection of the electromagnetic waves (EMW) occurs when the dielectric permittivity (which is strongly controlled by water content) changes abruptly and therefore the approach will likely work best where a sharp contrast in moisture content occurs between the peat and the underlying mineral substrate. As mentioned in 3.1.1, the transition zone from peat to the underlying mineral surface is at times not abrupt due to underlying soft silts, which are in some cases mixed with peat in a transitional nature (Palmer & Hainsworth 2012). In such cases GPR may struggle to identify an abrupt change in dielectric permittivity and hence peat depth. In addition to water content, EMW velocity varies depending on peat decomposition state, bulk density, ash and root layers (Rosa et al. 2009). Therefore, calibration is required and given expected variation in the aforementioned factors both spatially, within and between peatlands, and temporally, the calibration will vary in time and space (Parry et al. 2014). Calibration can be done with manual peat probing or common midpoint surveys where the transmitter and receiver are moved apart at set intervals and EMW travel time estimated. Discrepancy between measured depth during validation of GPR estimates of peat depth typically increases with depth and GPR is usually only considered useful to depths of about

10 m (Rosa et al. 2009). Given the expected spatial variation in calibration, GPR is likely best suited to smaller scale projects where high resolution of spatial variation is required.

3.2 Surface height measurement

Given expected rates of surface subsidence of about 2 cm y^{-1} a range of methods could be used for repeat surface height measurement ranging in scale and complexity from point-based surface laser levelling to satellite-based approaches. Laser levelling approaches have been used in the past to monitor peatland subsidence often by measuring elevation differences through time off a stable infrastructural datum (e.g. Rojstaczer & Deverel, 1995). However, the method is limited because it requires line of site to datum (which can be difficult in Waikato peatlands) and does not provide location data (only elevation difference).

3.2.1 Point-based GNSS surface survey

Point surface survey methods based on the global navigation satellite system (GNSS) can overcome the dimension position limitations of laser level survey and have been used successfully to monitor peatland elevation changes through time (e.g. Reeve et al. 2013). For point-based GNSS, three approaches are possible (Leick et al. 2015) including static measurement, real time kinematic (RTK), and post-processed kinematic (PPK). Static measurement provides high 3D accuracy and precision (± 1–10 mm) but require lengthy observation times that vary with distance to a regional base station. Observation times can be in the order of 1-2 hours per point and ideally a regional baseline should be located within a 30 km radius. In comparison, RTK GNSS measurement can be done on the fly, based on either a physical base station or virtual reference derived from a regional continuously operating reference station (CORS). The method only requires very short observation times (1–5 seconds) but has lower 3D accuracy and precision (± 20–40 mm) than static measurements and requires radio or short message service (SMS) lock back to a base station (or network) with baselines ideally within a 10-km radius. PPK has a similar workflow and measurement accuracy and precision to RTK (e.g. ± 20–40 mm) but does not require radio/SMS link to base station. Observations are post-processed using corrections supplied by logged records from a local base station or regional network.

Total station survey can also be used for accurate survey observations acquired based on angular and laser distance measurements (Bannister et al. 2006). Individual observations have high accuracy and precision (1–2 mm) but require line-of-sight to a local known point. Survey traverses are used to construct a local network of measurements which introduces cumulative errors. While accurate, the method is slow because of the need to set up base stations in line of sight to known datums and this limits the number of points that can be acquired.

3.2.2 Terrestrial-acquired LiDAR

A range of spatially integrative light detection and ranging (LiDAR) based approaches have potential for monitoring peatland subsidence. LiDAR systems consist of sensors and platforms (e.g., terrestrial, aerial, mobile and static etc) and therefore some specifications can be platform specific.

Terrestrially acquired LiDAR includes both static and mobile approaches (Brasington 2017). Static terrestrial laser scanning (TLS) provides a high accuracy point cloud obtained from a static network of positions that are subsequently geo-registered using a network of 3D control points (surveyed using total station or GNSS). This approach provides a high accuracy (5–10 mm) point cloud (Lichti et al. 2002) of surface topography that can be interpolated to provide both bare earth and surface/vegetation cover models (Brasington et al. 2012). However, the typical range from sensors is limited to between 50 and 300 m (although longer range sensors are available), additionally accuracy of point and return location declines with range (this varies across systems). Consequently, survey extents are limited to 1–100 ha and dependent on line of sight. Observations are acquired as oblique, perspective views that compound line of sight problems and may enforce complex traverse geometries, slowing data acquisition.

Mobile laser scanning is similar in principle to airborne laser scanning and involves a small format scanner typically in line-scanning mode with the sensor position and orientation computed using a GNSS-support inertial measurement unit (Kukko et al. 2012). The approach generates 3D point cloud data like TLS, albeit with lower absolutely accuracy (typically 10–40 mm). Advantages lie in the speed of data acquisition – with observations achieved from a moving platform – either by backpack, quad bike or car. Platform speeds of 30 km hr^{-1} are possible, enabling large areas to be covered quickly (1–100 km^2) – although trade-off between platform speed and data quality exists. All measurements are based on oblique line of sight, but more easily managed than static TLS due to ease of navigation around objects. Mobile laser scanning is suited to relatively small-scale transects (up to several metres wide dependent on mounting height) or mapping projects along well-defined tracks. Therefore, the approach can be viable if a subsample or transect approach is suitable but considering the total area of peatland in the Waikato and the requirement to be representative these transects would need to be large (e.g. 100 – 1000 hectares).

3.2.3 Airborne LiDAR

Airborne laser scanning is possible using a variety of sensors, from miniaturized scanners to full-frame sensors. Systems vary in terms of range (from 30 to 3000 m), scan frequency (1000–1,000,000 laser pulse points s^{-1}), field of view (40–360°), vertical ranging accuracy (1–5 mm from 50 m), digitization of return waveform (enabling multiple range measurements through porous targets) and laser wavelength (532–1140 nm) with shorter wavelengths better for returns through water and wet surfaces. All systems use a GNSS-inertial measurement unit (IMU) to calculate sensor position and orientation and the quality of the integrated measurements (range + position + orientation) are strongly affected by the IMU performance. IMU performance descends in the order Fibre Optic Gyro (FOG); Ring Laser Gyro (RLG); and Micro-Electro Mechanical Systems (MEMS).

Airborne LiDAR can be deployed on fixed wing aeroplanes, helicopters and drones (Vosselman & Maas 2010). High quality survey grade systems deployed from fixed wing aircraft typically fly at 800–3000 m with a field of view of c. 70 deg. Sensors typically weigh 20–50 kg and high-quality FOG IMUs are generally used. Discrete return LiDAR sensors return one or multiple returns per laser pulse, in contrast full waveform LiDAR sensors record return signals at equal time intervals capturing an almost continuous waveform. Full waveform LiDAR (waveform digitisation) is better for detection of multiple closely spaced targets and can provide more information on ground objects (Luo et al. 2019). Point densities typically vary from 0.5 to 20 returns m^2 but can be higher for helicopter and drone based approaches. 3D accuracy and precision are strongly dependent on IMU performance and slant angle. Slant angle is the tilt of the laser beam away from the true vertical or horizontal axis and is necessary to capture 3D detail. Typical root mean square error (RMSE) is 100–200 mm, with the Land Information New Zealand (LINZ 2018) standard requiring 90% of observations with 3D accuracy of < 200 mm. Such surveys are ideally suited for medium accuracy, broad area surveys extending 100s–1000s km^2. Fixed wing airborne LiDAR is being used to develop digital elevation models (DEMs) for peatlands in the coastal lowlands of Indonesia where accuracy levels have been assessed to be ±250 mm (Hooijer et al. 2016).

Helicopter deployments typically use smaller-format sensors from lower flying heights (100-350 m) and at slower acquisition speeds (20–50 km hr^{-1}). Lower flying height and speed enable denser, more accurate observations (50-100s points m^2) with 3D accuracies between 10 and 50 mm. Lower pulse repetition rate can increase penetration through dense vegetation canopies but reduces the point density for an equivalent LiDAR system at the same height and flight speed. Sensor systems often based on mobile mapping technology, use small-format (3–8 kg) scanners and RLG or MEMS IMUs. Helicopter deployments are ideally suited to complex flight plans, enabling close-to-nadir observations and high quality, low elevation ranging. The drawback is the slower rate of data acquisition, limiting scale of surveys to 10–1000 km^2.

Drone deployments (Lin et al. 2011) typically use cheaper mobile mapping systems, although an increasing number of survey grade systems are emerging (e.g. Reigl miniVUX, VUX-1UAV and VUX-LR). Again, lower quality IMUs are typically incorporated. Gains come from low survey height (30–60 m) enabling very high return density (hyper-scale resolution). The downside is flying time, which is typically limited by battery power (15–20 mins) and by a requirement for line of sight to the pilot.

3.2.4 Structure from motion (photogrammetry)

Structure from motion (SfM) photogrammetry is often considered a cheap and fast approach capable of producing high resolution DEMs at sub-centimetre resolution and has been used to monitor topographic change in peatlands at relatively small scales (e.g. Li et al. 2019). The approach involves 3D reconstruction based on a non-linear bundle adjustment to solve simultaneously camera position, pose, distortion and 3D coordinates (Westoby et al. 2012). The approach requires imagery from highly redundant camera networks and typical applications use small-format, compact (non-metric) cameras. A strong network of ground observations is required to provide exterior constraints to optimize the models. The approach is well suited to small scale projects (1–1000 m^2) where dense placement of ground control can be used to manage compensation between interior and exterior camera geometry, resulting in significant bowl/dome distortion of resulting point clouds (Carbonneau & Dietrich 2017). With strong ground control, 3D reconstruction accuracies can be ±5–20 mm, depending on camera optics and distance.

For larger areal extents, involving faster moving aerial platforms (fixed wing, drones or helicopters), object space resolution falls and sparse ground control results in poor calibration of camera geometry. Significant systematic errors result from bias to ground control distribution and typical 3D accuracies fall to 100–500 mm.

3.2.5 Satellite based approaches

As near to ground remote sensing from aeroplanes and helicopters is expensive, satellite-based approaches are attractive because the data are often inexpensive and spatial and temporal coverage can be improved (Alshammari et al. 2018). Satellite-based LiDAR and interferometric synthetic-aperture radar (InSAR) data are available, but both approaches have significant limitations at present.

LiDAR

Satellite-based LiDAR is suitable for very large spatial coverage (region-to-national) but for currently available satellite products vertical resolution is poor (± 0.2 m). The recently launched (2018) IceSAT 2 provides open-source satellite LiDAR data which have the potential to provide wide-area mapping capabilities. However, this LiDAR sensor provides ranging data from only three pairs of beams, separated at 3.3 km with 90 m paired observations (Narine et al. 2019). Regional characterization will therefore require compilation of multiple satellite overpasses, spanning months to years to establish continuous coverage. Such a product would therefore implicitly incorporate dynamic landscape features, such as seasonal vegetation growth and short-term peat surface oscillation.

InSAR

Interferometric synthetic-aperture radar (InSAR) was principally developed to measure difference in range to targets with stable signatures (discrete reflectors) through time. Differential InSAR (DInSAR) has been used to monitor subsidence in urban environments (Teatini et al. 2007) and in bare or rocky landscapes (Zhou et al. 2009) and the approach is ideally suited to monitor change in built environments where large uniform reflective surfaces are present. The approach exploits the radar phase shift of images captured over the same area that form an interferometric pair (Crosetto et al. 2016) and requires pixels to display consistent coherent reflectance over time. Therefore, common DInSAR approaches are not suitable for monitoring subsidence over vegetated surfaces where vegetation changes often result in diffuse scattering of the radar signal (Alshammari et al. 2018). More recent developments based on diffuse reflectors, such as the ISBAS (intermittent small baseline subset) SAR has the potential to provide high accuracy measurements of elevation change across vegetated surfaces. Alshammari et al. (2018) used ISBAS to monitor subsidence over large areas of peatlands in Scotland, and while advocating for the approach they concluded there were uncertainties in the vertical magnitude and direction of motion and suggested further, well-resourced, validation work was required. While attractive, the technique is still in development and would require significant ground control to calibrate and validate the regional signals observed. Theoretically vertical resolution could be ± 10 mm.

3.3 Modelling Elevation Change

As reviewed in Section 3.2, there are a wide range of alternative sources of topographic information which can be used to measure land surface heights. These data can be used to measure subsidence directly by comparing timeseries of elevation measurements either in the form of individual or groups of points (i.e. a 3D point cloud) or, more commonly, by 'differencing' digital elevation models (DEMs) derived by interpolating the survey observations. While apparently straightforward, this approach can be confounded by the difficulty of extracting the signal of physical elevation change (i.e. due to subsidence, uplift, erosion or sedimentation, vegetation height and density) from uncertainties in the survey observations and terrain models that arise through a combination of instrument errors, sampling design and interpolation.

3.3.1 Accounting for DEM Uncertainty

Regional models of elevation change are most commonly derived by comparing DEMs derived at two or more epochs (e.g. Brasington et al. 2000). This approach reduces the change detection problem to a single axis (i.e., the vertical) and obfuscates the need to match point (xyz) observations that, as is commonly the case for remotely observed data, are rarely registered to the same horizontal sampling frame. DEMs, however, inevitably represent only approximate models of the land surface and incorporate a spectrum of potential sources of uncertainty. These include: a) intrinsic instrument measurement errors (e.g. timing errors for radio and laser ranging); b) geo-registration errors resulting in datum shifts between surveys; c) sampling bias and sub-pixel variability; d) inaccurate detection of ground versus off-ground points; e) interpolation artefacts (see Vericat et al. 2017). These uncertainties are propagated into the analysis of elevation change, determined by differencing surface models to yield so-called DEMs of Difference or DoDs (Brasington et al. 2003; Wheaton et al. 2010).

The most commonly adopted procedure to manage DEM uncertainties involves the specification of threshold minimum level of detection ($_{min}$LoD) to distinguish likely surface changes from the inherent noise (Brasington et al., 2000). This threshold thus provides a basis to segment the DoD into spurious observations and changes considered to reflect real physical processes, from which metrics of global and spatially-variable elevation change can be extracted. The process of determining a $_{min}$LoD requires both a theory of change detection and a metric of DEM quality. Conventionally, this is addressed by applying the classical statistical theory of errors (Taylor 1997) and using independent checkpoint observations to define a measure of DEM quality (e.g. the Root Mean Squared Error or RMSE). This approach can be extended to develop probabilistic change models that threshold elevation changes at a user specified confidence interval (see Brasington et al. (2003) and Lane et al. (2003) for further details).

3.3.2 Defining DEM Quality

Both $_{min}$LoD and probabilistic thresholding require a metric of vertical DEM quality which is typically estimated from a set of independent checkpoint data. The American Society for Photogrammetry and Remote Sensing (ASPRS 2015) published positional accuracy standards and testing protocols for both LiDAR and photogrammetric data that have become a benchmark for DEM quality assurance and control. This protocol defines vertical accuracy classes for elevation data with nominal recommended point densities required to represent sub grid variability and reproducibility standards within and between single LiDAR swaths. For example, Class 1 vertical data must have an accuracy of 0.01 m (with a 95th percentile of data within 0.02 m), a recommended pulse density of 20 points/m^2, within-swath hard surface variability of 0.006 m and between-swath variability of 0.016 m.

By contrast, the aerial LiDAR procurement documentation recently published by LINZ (2018) is less detailed, suggesting a Base Specification for broad area (regional scale) LiDAR that requires only 95% (2σ) of observations to lie within 0.2 m of checkpoint elevations. Guidelines for checkpoint sites are also limited, suggesting a minimum of 25 observations with a 5-m spacing on a flat and smooth surface.

It is useful to compare the LINZ (2018) specification against the ASPRS (2015) vertical accuracy class standards. For example, the criterion specified by LINZ (2018) (95% at 0.2 m) conforms approximately to the ASPRS 10 cm vertical class standard, for which the within-swatch reproducibility rises to 0.06 m and the between swath to 0.16 m and the nominal pulse density is only 2 points/m^2.

Such quality metrics are generally reported as global statistics for the entire surface model. The ASPRS (2015) do, however, provide guidance on documenting swath errors in aerial LiDAR surveys (associated with trajectory errors between flight lines) which offers the potential to account for the spatial pattern of DEM uncertainty. Wheaton et al. (2010) take this approach further and use semantic data rules to synthesize spatial error models based on a fuzzy inference system.

3.3.3 Defining Ground Observations

Intimately linked to the development of spatial error models is the requirement to separate ground observations from those associated with image matches (in photogrammetry) or backscatter returns (associated with LiDAR or radar) from vegetated or man-made surfaces. Various classification routines (see Meng et al. (2010) for a review) have been developed to segment point cloud data into ground and off-ground observations and thereby into vegetation classes and other surfaces/objects (e.g. powerlines, water, etc.). The ability to distinguish ground is however, ultimately dependent on the penetration of the observation technique which in turn reflects: (i) the density of spatial sampling; (ii) the footprint of observations (i.e. LiDAR pulse size or pixel dimensions for radar/photogrammetry) and; (iii) the surface characteristics (density, rigidity, and reflectivity).

For airborne LiDAR, there exists a trade-off between flying height, speed, and swath width that determines the local pulse density (and thereby the likelihood of achieving reliable 'ground hits') against the time taken to acquire data and thus the overall cost. Until recently, most aerial LiDAR surveys were based on fixed wing platforms that limited the capacity for slow, high density surveying. The recent advent of small form-factor LiDAR (e.g. the Reigl VUX systems discussed in 3.2 above) offers the potential for flexible low speed, low altitude surveying from helicopters and UAVs and the opportunity to acquire data at significantly higher spatial resolution and precision (Glira et al. 2016).

3.3.4 Reproducibility

The evaluation of DEM quality through comparison with checkpoint data provides a rapid procedure to generate statistical measures of model accuracy and precision. This process, however, is arguably poorly conditioned, often relying on a very limited set of sampled observations that are unlikely to represent the full range of surface cover types or address systematic elements of survey design such as independent assessment of individual flight lines and overlap areas. A more spatially robust approach to assess DEM quality involves comparison of DEM replicates, generated ideally by repeat surveys of the same target region, or through sub-setting the raw observations and regenerating multiple models. Brasington et al. (2012) used this approach to quantify the controls on the spatial distribution of DEM uncertainty in high-resolution terrestrial laser scan data, demonstrating the effect of terrain complexity (micro-topography and slope) as the principal determinant of elevation uncertainty. While clearly desirable, replication of logistically complex and costly aerial surveys presents a challenge for update of this approach.

3.4 Methods summary

A wide range of potential methods for monitoring peatland subsidence have been outlined ranging from simple manual-based approaches to measure peat depth (probing) and surface height (laser levelling) to highly sophisticated spatially integrative surface height approaches such as LiDAR and InSAR. Given the need to quantify peat depth for the initial monitoring round, peat depth measurement is necessary and for this manual peat probing is a simple, robust (assuming control measures are adhered too), and low-cost option. Peat depth measurements must be paired with accurate surface height measurements to negate the need for repeat measures of peat depth in future surveys. Line of sight limitations of laser levelling mean a point-based GNSS approach should be considered of which static GNSS provides the highest accuracy (± 1–10 mm). Spatial integration of surface height will also be an important component of the subsidence monitoring program and for this we have considered terrestrial, airborne and satellite-based LiDAR and satellite based InSAR. At present satellite-based LiDAR does not provide the necessary accuracy (± 500 mm) and InSAR approaches include significant uncertainty in their accuracy. The optimum trade-off between good spatial coverage and accuracy of measurement is currently considered to be helicopter-based LiDAR. Airborne LiDAR is a proven and well-used technology and recent advances in LiDAR technology combined with robust error modelling and uncertainty analysis should allow expected differences in peat thickness over 5-yearly monitoring intervals to be detected.

Table 1 Strengths and weaknesses of potential peatland subsidence monitoring approaches that range from point-based approaches (top of table) with spatial scale of integration increasing downward

Approach	Summary/limitations	Vertical accuracy (mm)	Included or excluded from proposed network design
	DEPTH MEASUREMENT APPROACHES		
Peat probing	Simple approach but provides no information on ground surface height, accuracy is highly dependent on underlying substrate	± 100	**Peat probing included** because provides estimate of peat depth and hence volume
Ground penetrating radar	Potential to measure peat depth but signal requires calibration and may be affected strongly by water content and peat type	±100–500	Excluded because requires calibration by peat probing and calibration will vary depending on peat type and water content
	SURFACE HEIGHT MEASUREMENT APPROACHES		
Point-based surface survey	GNSS point-based measurements.		
	Static measurement. High 3D accuracy/precision but observation times 1–2 hours per point	± 1–10	
	PPK (post-processed kinematic). Similar to RTK but does not require radio/SMS link to base station.	±20–40	**Static GNSS included** to provide high accuracy point measurements.
	RTK (real time kinematic) measurement. Very short observation times (1–5 sec) but with lower 3D accuracy and precision and requires radio or SMS lock to base station (or network). Baselines ideally < 10 km.	±20–40	RTK and PPK GNSS not selected for surface height because of low vertical accuracy but RTK GNSS will be used to rapidly measure water table depths.
	Total Station Survey and levelling: survey observations acquired by laser distance (and angular) measurements. High accuracy and precision but require line-of-sight to a datum.	±1–5	Total station survey excluded because line of sight requirement will limit spatial range
Structure from motion	3D reconstruction based on simultaneous estimation of camera position, pose, distortion and 3D coordinates. Well suited to small scale projects from 1 to 1000 m^2, where dense placement of ground control can be used to manage compensation between interior and exterior camera geometry, which can introduce significant systematic errors.	± 5–400	Excluded because ground control will be too difficult at the scale required
Terrestrially acquired LiDAR	Static TLS: High accuracy point cloud data obtained from a static network individual scan. Wide area surveys require line of sight leading to slow survey coverage.	± 5–10	Static TLS excluded because requires line of sight
	Mobile laser scanning: Similar principle to airborne laser scanning but from a moving terrestrial platform, i.e. a car. Typically uses a small format scanner in line-scanning mode with sensor position and orientation computed using a GNSS-support inertial measurement unit (IMU).	±10–40	Mobile LiDAR excluded because requires access onto land that may be difficult for future surveys

Airborne LiDAR	Airborne laser scanning possible using a variety of sensors, from miniaturized scanners to full-frame sensors. Systems vary in terms of range, wavelength, scan frequency, field of view, range accuracy and digitization of return waveform. All systems use GNSS-IMU to calculate sensor position and orientation.		**Helicopter based LiDAR included** to provide spatial integration. Optimal spatial method because allows measurement at scale suited to project with flexibility in flight speed and height to optimise spatial coverage verses data quality.
	Helicopter deployments and drone deployments: Smaller-format sensors from lower heights/speeds enabling denser, more accurate observations. Slower rate of data acquisition. Spatial coverage and range of drones often limited by battery power and need for line of sight to operator.	±10 – 20	Drone LiDAR excluded because of limited battery life and hence flight time, inability to cover large spatial areas, and potential reliability issues.
	Fixed wing deployments: Point cloud densities 0.5-20 points/m^2 with moderate 3D accuracy and precision. Ideally suited for medium accuracy, broad area surveys extending 100s–1000s km^2.	±100 – 200	Fixed wing excluded because higher required flight speeds limit data acquisition flexibility.
Satellite based LiDAR	Suitable for very large spatial coverage (national) but for currently available satellite products vertical resolution is poor.	± 200	Excluded due to low vertical accuracy.
Satellite based InSAR	InSAR principally developed to measure difference in range to targets with stable surfaces through time, ideally suited to built environments. Recent development, such as the ISBAS (intermittent small baseline subset) SAR suggest the potential to provide high accuracy measurements of elevation change across vegetated surfaces. Technique still in development and require significant ground control to calibrate and validate data models (Alshammari et al. 2018).	Theoretically < 10	Excluded because less suited to natural vegetation and requires further science led development and testing to better constrain uncertainties

4 Spatial layers to inform monitoring network design and their limitations

A robust and balanced monitoring network design will depend on the quality of the spatial layers used to inform the design. Several spatial layers will need to be combined to achieve the clients desire that the subsidence network is balanced across the range of peat types and depths, land uses (dairy, drystock, horticulture, and maize cropping), drainage types and management. Each spatial layer includes inherent uncertainty and inaccuracies and the impact of this on the desired outcome must be considered. Additional constraints on design include a budget that is limited to 100-point locations, the need to include a subset of historic sampling locations, and the need for the network to be able to be flown with helicopter-based LiDAR. Below we discuss these limitations and the potential impact on the monitoring network design.

4.1 Peat soil extent and type

Peat soils fall within the Organic Soil Order of the New Zealand Soil Classification (NZSC) system and must have at least 30 cm (cumulative) of organic material within 60 cm of the soil surface and be formed from organic materials that have accumulated under wet conditions (Hewitt 2010). Organic Soils are divided into Groups which are defined based on their state of decomposition into Fibric Organic (little decomposed material), Mesic Organic (moderately decomposed material), or Humic Organic (well decomposed organic material); a fourth Group 'Litter Organic' are formed in forest leaf litter and are not relevant to the Waikato peatland subsidence monitoring network. Organic Soils are further divided into Sub-groups based on pH ≤ 4.5 or > 4.5; however, for this project peat type will only be subdivided to soil Group level of the NZSC.

Organic Soils were mapped as part of the Ministry of Works land resource inventories (LRI) conducted in the North Island during the 1980s, and from this layer the Fundamental soils layer (FSL) was created which is a derived soil map with national coverage. Much of this derived data is from legacy soil surveys conducted between the 1940s and 1980s and some Organic Soils may have become mineral soils since they were first mapped as a result of continued decomposition of the organic material. For large areas of the Waikato region the extent of Organic Soils mapped have been uploaded to S-map Online, which provides the most up to date spatial coverage of organic soil types across large areas of the Waikato. There are, however, large areas yet to be integrated into S-map in the lower Waikato (north and west of Huntly) and a strip from Pukemokemoke extending as far south as Karapiro (Fig. 3), where a significant portion of the Komakarau peatland is located. Currently Manaaki Whenua is completing a contract for WRC to complete mapping soils in these areas but for now the most up to date spatial data for parts of the lower Waikato valley is from a report by Palmer and Hainsworth (2012). A complete spatial layer of peat soils in the Waikato is available by stitching these three data layers together, using S-map where available, Palmer and Hainsworth (2012) in the lower Waikato and FSL to fill any remaining gaps.

High uncertainty exists in the polygon boundaries between Gley and Organic Soils because both soil orders occupy a similar landscape position (flat low-lying) where it can be difficult to define soil boundaries. The FSL has the most complete coverage of the Waikato but the resolution is coarse. During production of the FSL, where there was an existing legacy soil survey, LRI mappers relied on this data, but in the absence of soil survey data LRI derived soil information is imprecise. Legacy maps were dependant on a high intensity of field observations, particularly where peat distribution was patchy (i.e. outside of the five main peat domes) while modern DEM based digital soil mapping techniques also struggle as terrain attributes are the most important co-variates used for predicting soil patterns. Therefore, differentiating boundaries between organic and adjacent mineral soils and between fibric, mesic, and humic Organic Soils is labour intensive and temporarily variable because of continued decomposition, which drives organic soils towards the humic end of the spectrum, where they may ultimately become a mineral soil. These spatial uncertainties could foreseeably result in the selection of Gley Soil sites where shallow Humic Organic Soils were expected and the selection of Organic Soil Groups that are more toward the humic end of the spectrum than was expected, based on map units. We propose that where a Gley Soil is encountered during the field campaign a new site is selected. Where the Organic Soil Group does not match the selected group, we propose this is recorded and the site group is modified. Modification of the site group will be an ongoing process during future monitoring campaigns as decomposition and subsidence continue. Considering this and any other future possible changes, it is recommended that any changes to the monitoring approach or selected sites should be recorded in the report associated with each survey in a section titled method changes.

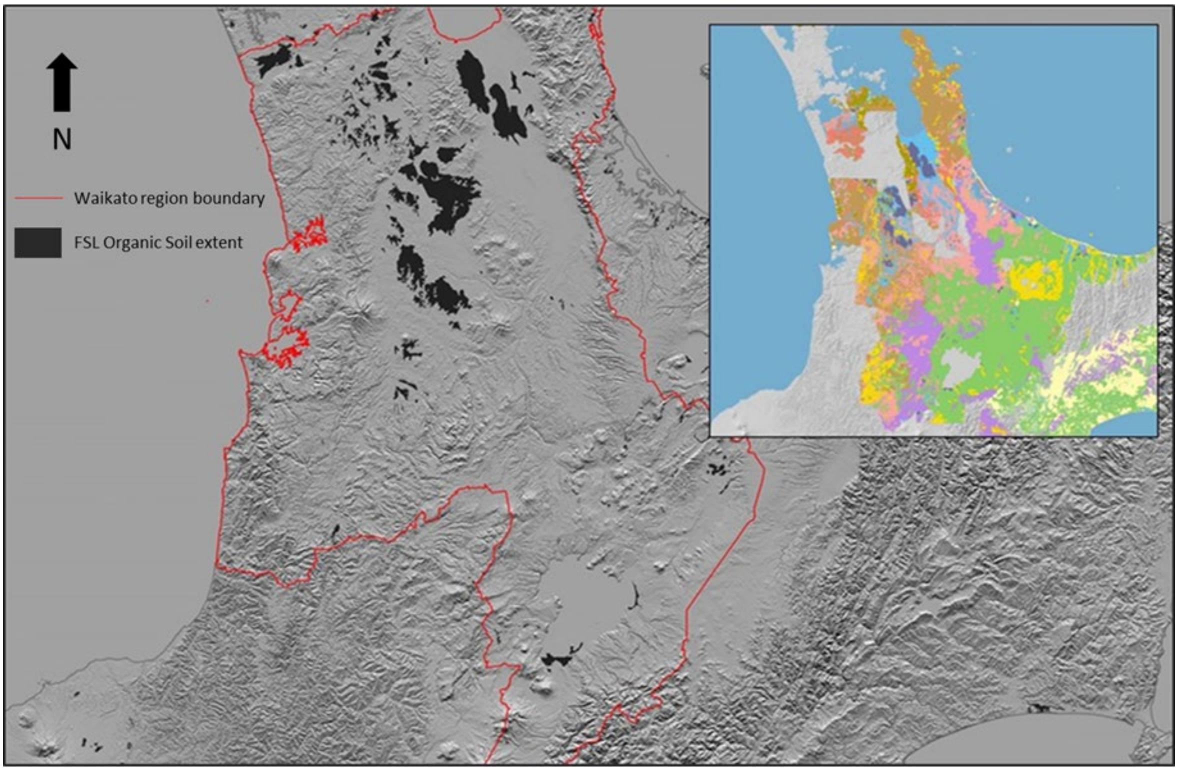

Figure 3. Organic Soil extent for the Waikato Region from FSL and inset showing current extent of S-map in the Waikato Region (NZSC Soil Orders, Organic Soils are black) with large areas of Organic Soils yet to be integrated into S-map in the lower Waikato (north and west of Huntly) and a strip from Pukemokemoke extending as far south as Karapiro.

4.2 Peat depth and integration of historic monitoring locations

Peat depth likely has an effect on subsidence rates (Stephens et al. 1984) and will govern total potential subsidence. Therefore, monitoring sites need to be spread across the range of peat depths in the region. Some information on peat depth is available at point locations from the current monitoring network last surveyed in 2012 and other localised surveys such as Palmer and Hainsworth (2012) in the lower Waikato. The most extensive source of historic peat depth is older data from Daveron (1978) based on survey work done in 1976. However, the supporting peat depth measurements and coordinate location for the Daveron (1978) data set have been lost. WRC have digitised these historic maps, which involved some stretching to align landmarks, and peat depths in 1976 can now be interpolated for any location based on the contours of these maps. Given there has been 40 odd years of subsidence since the Daveron (1978) survey, peat depths have likely reduced by about 80 cm on average, based on mean rates of subsidence for the Waikato region from Pronger et al. (2014). Expected subsidence since 1976, together with the loss of original data and correction and interpolation of contour maps, means uncertainty around peat depth at selected points during the network design phase will be high. However, given our lack of alternative data sources and the need to only represent the range of peat depths in the region, these historic data will strengthen the network design. Following field sampling, peat depth for the monitoring network will be known moving forward.

4.3 Land use

The monitoring network needs to capture the main land uses on peat soils because land use and management can affect subsidence rates; for example, it has been suggested that subsidence is faster under cropping than under pasture (Thompson 1980) and could be slower under blueberries (Fitzgerald et al. 2015). The main land use on drained peatlands in the Waikato Region is grazing of dairy cows but other land uses to be represented include: drystock, maize cropping, and blueberry production. Therefore, area weighted sampling stratification could be considered for the monitoring network design. Additional alternative land uses with potential to reduce subsidence have yet to be identified but could also be included in the network if suitable areas exist and can be identified before the regional network design phase (WRC are currently building a case to fund work to identify options for alternative land uses on peat soils). Land use will largely be informed by Agribase and the New Zealand Land Cover Database (LCDB, v4.1) but local knowledge and historical imagery will be used to support Agribase and LCDB. For example, sites where long-term maize cropping has occurred will be identified from local knowledge and historical imagery. LCDB does not separate grassland management (e.g. dairy from drystock) and will not identify rotational maize cropping because of its transient nature. Previous experience has shown that Agribase land use data are not always up to date. Given the transient nature of land use, the network will be designed with the most up-to-date information available and land use information will be collected during field sampling so that land use information will be accurate at the time of establishment. Assuming future monitoring moves to aerial or remote sensing approaches it would be pertinent for WRC to monitor changes in land use going forward and update the monitoring network as required. Information obtained through Waikato Regional Plan Change 1 (Healthy Rivers/Wai Ora) and other future regional plan changes (e.g. farm plans) will potentially provide a good source of land use and management information in the future.

4.4 Drainage type and management

Water table depth and drainage design and management can affect subsidence rates (Fitzgerald et al. 2005) and therefore the subsidence monitoring network must capture the range of drainage type and management approaches. Drainage type can broadly be divided into either hump and hollow (with spinner channels leading to larger primary drains) or paddock boundary drains with crowned paddocks. Where peatlands have more recently been developed as agricultural peatlands, the hump and hollow approach is often used (e.g. Moanatuatua) and as the raw peat consolidates over time re-contouring may occur to form crowned paddocks with paddock boundary drains. Paddock boundary drainage is now most common, with hump and hollow mostly constrained to Moanatuatua where conversion from hump and hollow to paddock boundary drainage is currently occurring.

Broadly drainage management on peat falls under at least one or a grouping of the following drainage methods: gravity, flood gated, and pumped. WRC have an internal drainage management spatial layer which delineates drainage management zones. At present information for most of the Waikato region is good except for the Hauraki area. WRC plan to improve drainage management spatial information for the Hauraki area over the coming months and make this information available prior to the regional network design phase. Currently there is no spatial information on drainage type or drainage depth and this information will be important given the likely relationships between drain outlet depth, water table depth, and subsidence. The drainage management layer will be used to select drainage management categories during the sampling campaign to ensure different methods of drainage management are represented without compromising the overall network design. During field sampling, we will record the drainage type at each monitoring location and water table depth at the point and in surrounding drains so that we will ultimately have information on depth of drainage and drainage type along with the management for each location. Where conversion of hump and hollow is planned, but yet to occur (e.g. for large areas of Moanatuatua), careful consideration must be given to selecting areas where relocation of soil material will be minimal. This disturbance affect must be recorded against the monitoring point and when recontouring occurs data from that 5-year period discarded.

4.5 Spatial information summary

Peat extent and type will be informed first by S-map and then by Palmer and Hainsworth (2012) and FSL where gaps in S-map occur. Peat depth will largely rely on historic data from Daveron (1978), but will also be informed by local surveys where they exist, for example Palmer and Hainsworth (2012) in the Lower Waikato. Land use will be informed by Agribase and LCDB combined with local knowledge and aerial photography when required. Spatial information on drainage management will be informed by the custom WRC drainage management layer. Currently no information on drainage type and water table depths exist and this information will be generated during field sampling. All spatial layers used to inform network design have limitations (Table 2) that will ultimately result in a network that does not exactly reflect design. However, given the transient nature of drainage management and land use on peatland soils and the complex spatial variation in peat soil depth and type (that is linked to natural variation in the underlying landscape, vegetation, time since drainage and development history) achieving a network that exactly reflects design is not realistic, and even if achieved will change in the future. Through robust recording of peat type, water table depth, and all land use and management information at the time of first sampling, and upkeep of this information in future, the influence of the factors of interest should in time become apparent.

Table 2. Summary of spatial layers and their limitations

Spatial layer	Limitation	Approach to overcome limitation
Peat soil extent and type	Data spread across sources (S-map, FSL, and lower Waikato survey). Delineation of boundary between Gley and Organic soils difficult. Fibric, Mesic, Humic group changes through time.	Integrate data sources taking most up to date data source for each area. Where Gley soils are found at sample location relocate point to peat. Where wrong soil Group located record new Group.
Peat depth and historic monitoring location	Peat depth information based on out of date contour depths from Daveron (1978) where supporting data (depth and coordinate location) has been lost.	Need to capture the range of peat depths and despite continued subsidence, the Daveron (1978) contours will still help ensure the range of depths are represented.
	Non Davoren (1978) peat depth information spatial coverage is limited or poorly located.	Use a mix of all available historical peat depth monitoring locations (e.g. using Davoren (1978) and Non Davoren (1978)).
Land use	LCDB does not differentiate land use only land cover. Agribase information is often outdated and Agribase is not suitable for identification of long-term cropping.	Bolster information with local knowledge, examination of historical imagery to help identify areas of interest (i.e. continuous cropping).
Drainage management	No information on drainage type or depth of drainage (only drainage management). Disturbance effect associated with conversion of hump and hollow to paddock boundary drains must be considered.	Use local knowledge of drainage type and during monitoring collect and record information on drainage type and depth.

5 Other contributors to apparent surface level change

The purpose of this project is to monitor permanent peat soil subsidence attributable to consolidation, shrinkage, and oxidation of drained peat soils. However, other factors may contribute to changes in surface level including movement of and underlying geology and peatland surface oscillation. Movement in underlying geology is especially likely in the Hauraki graben where the long-term vertical subsidence rate is between 0.08 and 0.4 mm y^{-1} (Persaud et al. 2016). The rate of vertical movement varies among segments of the fault and it is likely much of the average displacement occurs episodically during earthquakes with single event displacements of between 1 m and 1.8 m (Persaud et al. 2016). Large episodic events would be of concern but will be obvious and the mean subsidence rate is at least an order of magnitude lower than the expected rate of peat subsidence and therefore of little concern. Given LiDAR flights will cover both peat and mineral soil any subsidence which is consistent between mineral and peat surfaces over a 5-year monitoring period will be apparent and can be separated from the rate of peatland subsidence.

The surface of natural peatlands can oscillate seasonally because of changes in water-table (Fritz et al. 2008). The magnitude of this process in drained and consolidated agricultural peatlands is often assumed to be minimal but data to support this assumption is lacking. In the most recent re-measurement of peatland thickness across the Waikato (Pronger 2013) the measurements were done at a similar time of year to the previous survey to minimize differences related to seasonal surface oscillation. Depending on its magnitude, surface oscillation has potential to confound shorter term (e.g. 5-yearly) re-survey intervals and consequently seasonal timing of 5-yearly re-measurements could be critical. While this problem requires further science-led research, during the project development phase we will make repeat measurements of peat surface height at a small number of points over a period when water table depth varies (e.g. between winter and summer). Depending on findings, we will include recommendation in the monitoring protocol to ensure 5-yearly re-surveys are done when regional water table depths are similar between re-survey intervals.

6 Recommendations

We recommend a monitoring approach that combines methods of point measurements of peat depth using probing, high accuracy GNSS surface height survey at the same points, and spatially integrative low-altitude helicopter-based LiDAR. Labour-intensive peat probing is only necessary during the first round of monitoring for comparison with historic data and to help determine the current peat resource (it is envisaged that data from re-probing of a subset of historic Daveron (1978) data could be used by WRC to estimate the current peat volume). The point locations of peat depth will be combined with a concurrent ground-based height survey using static GNSS that is more accurate than probing (± 5 mm cf. to ±100 mm estimated for probing) and will maximise ability to detect significant differences in peatland thickness through time and between land uses in future. Low-altitude helicopter-based LiDAR has been chosen because flight height and speed can be reduced relative to fixed wing approaches to increase accuracy and quality of data. Helicopter-based LiDAR will also provide significantly greater surface coverage (we will endeavour to get about 10% coverage of surveyed peatlands) compared with what could be achieved using UAV LiDAR. Given increasing labour cost, anticipated impediments to accessing farmland (e.g. mycoplasma bovis), and rapid improvement in LiDAR technology, we envisage future monitoring will be done by airborne LiDAR and in time satellite-based approaches. The ground-based, point surface height network is important during the first round of monitoring to future-proof the network in the event LiDAR monitoring becomes problematic in future and for integration with historic data that may provide early indication of land use effects to WRC. We will optimise the regional network design to ensure future monitoring can be done by air and fit within the $100,000 future monitoring budget, based on costs in 2019.

The anticipated monitoring method will first be tested at Moanatuatua. During the development phase, LiDAR trials based on different flight heights and speeds will be compared to evaluate the trade-off between ranging error and spatial coverage. The influence of variation in pasture cover and our ability to see through pasture and other vegetation types (e.g. blueberries) will also be assessed. These data will be used to support the development of a spatially variable uncertainty model for the LiDAR derived DEM products that will be used to define a statistically robust level of detection to quantify subsidence in subsequent repeat surveys. During this design and development phase we will also re-probe a subset of the Daveron (1978) points within the footprint of the helicopter LiDAR that cover the range of land uses, anticipated to be dairy, drystock, blueberries, and maize cropping. At the same points, we will measure surface height using static GNSS, and water-table depth will also be measured at a subset of sites using lower accuracy, but faster, RTK GPS (± 30 mm) at the sample point in a temporary dip well (where water table is < 1 m) and in surrounding drains. During this testing phase we will also bring together the spatial data sets that will inform the regional network design to ensure we can representatively and adequately sample all factors of interest including peat types and depths, land use categories, and drainage management. We will also develop an information pack to provide to stakeholders and a farmer questionnaire to gather required land use and management history, including time since drainage, for the proposed sampling network.

Given the fast-evolving nature of remote sensing approaches driven by rapid advances in technology, it is possible that in the future, methods such as satellite-based LiDAR or InSAR will be suitably developed for ongoing subsidence monitoring. The spatially distributed LiDAR swaths we propose to collect during the testing and development phase and during the first round of monitoring will integrate well with satellite-based approaches and will likely be important for future validation of remote sensing methods. Therefore, we see the current close-to-ground LiDAR measurements as necessary, and complementary, to future development of remote sensing approaches.

On completion of this design and testing phase at Moanatuatua, we will meet with WRC representatives to discuss apparent limitations and how these may be overcome. Once satisfactory and agreed solutions are identified, we will move on to designing the regional network and implementing the first round of monitoring (Fig. 4).

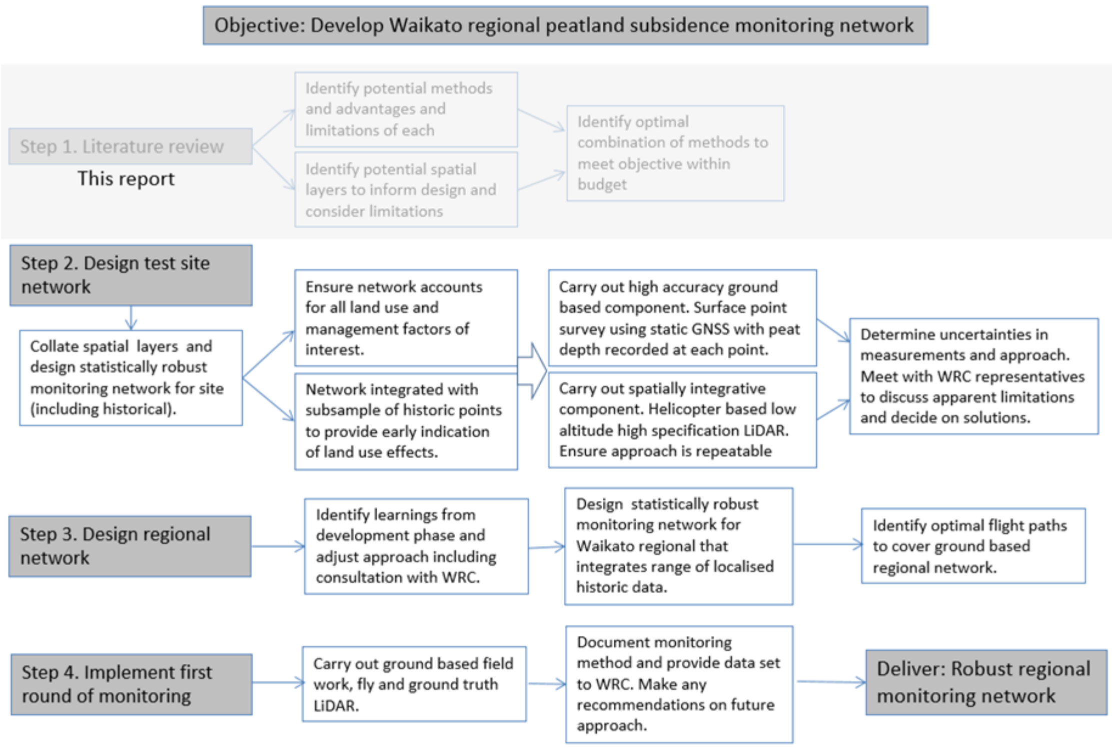

Figure 4. Overview of proposed project path.

7 Acknowledgements

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8 References

Alshammari L. et al. 2018. Long-term peatland condition assessment via surface motion monitoring using the ISBAS DInSAR Technique over the Flow Country, Scotland. Remote Sensing 10: 24.

American Society for Photogrammetry and Remote Sensing published (ASPRS) 2015. ASPRS positional accuracy standards for digital geospatial data. Photogrammetric Engineering & Remote Sensing 81: A1–A26.

Bannister A, Raymon S, Baker R eds 2006. Surveying. Englewood Cliffs NJ: Prentice Hall.

Biancalani R, Avagyan A 2014. Towards climate responsible peatlands management. Mitigation of Climate Change in Agriculture Series 9.

Brasington J 2017. Terrestrial laser scanning. In: Aberle J, Rennie C, Admiraal D, Muste M eds Experimental hydraulics: methods, instrumentation, data processing and management. London: Chapman and Hall. Pp. 212–224.

Brasington J, Vericat D, Rychkov I 2012. Modeling river bed morphology, roughness, and surface sedimentology using high resolution terrestrial laser scanning. Water Resources Research 48.

Brasington J, Langham J, Rumsby B 2003. Methodological sensitivity of morphometric estimates of coarse fluvial sediment transport. Geomorphology 53: 299–316.

Brasington J, Rumsby BT, McVey RA 2000. Monitoring and modelling morphological change in a braided gravel-bed river using high resolution GPS-based survey. Earth Surface Processes and Landforms: The Journal of the British Geomorphological Research Group 25: 973–990.

Campbell DI, Wall AM, Nieveen JP, Schipper LA 2015. Variation in CO_2 exchange for dairy farms with year-round rotational grazing on drained peatlands. Agriculture, Ecosystems and Environment 202: 68–78.

Carbonneau PE, Dietrich JT 2017. Cost-effective non-metric photogrammetry from consumer-grade sUAS: implications for direct georeferencing of structure from motion photogrammetry. Earth Surface Processes Landforms 42: 473–486.

Crosetto M, Monserrat O, Cuevas-González M, Devanthéry N, Crippa B 2016. Persistent scatterer interferometry: a review. ISPRS Journal of Photogrammetry and Remote Sensing, 115: 78–89.

Daveron A 1978. A survey of New Zealand peat resources. Hamilton, New Zealand: University of Waikato.

Environment Waikato 2006. For peat's Sake – good management practices for Waikato peat farmers. Hamilton, New Zealand: Environment Waikato.

Fitzgerald N, Basheer S, McLeod M 2005. Peat subsidence near drains in the Waikato Region. Hamilton, New Zealand: Environment Waikato.

Glira P, Pfeifer N, Mandlburger G 2016. Rigorous Strip adjustment of UAV-based laser scanning data including time-dependent correction of trajectory errors. Photogrammetric Engineering & Remote Sensing 82: 945–954.

Gronlund A, Hauge A, Hovde A, Rasse DP 2008. Carbon loss estimates from cultivated peat soils in Norway: a comparison of three methods. Nutrient Cycling In Agroecosystems 81(2): 157–167.

Hewitt AE 2010. New Zealand Soil Classification. Landcare Research Science Series 1. Lincoln, New Zealand:, Manaaki Whenua Press. 136 p.

Hooijer A. et al. 2016. The use of LiDAR data in peatland mapping and management. Visit of the delegation Indonesian Ministry of Environment and Forestry. Wageningen University.

Joosten H 2016. Peatlands across the globe. In: Bonn A, Allott T, Evans M, Joosten H, Stoneman R eds Peatland restoration and ecosystem services: science, policy and practice. Cambridge: Cambridge University Press.

Kaat A, Joosten H 2009. Factbook for UNFCCC policies on peat carbon emissions. Wageningen, Netherlands: Wetlands International.

Kukko A, Kaartinen H, Hyyppä J, Chen Y 2012. Multiplatform mobile laser scanning: usability and performance. Sensors 12: 11712–11733.

Land Information New Zealand 2018. New Zealand National Aerial LiDAR Base Specification. Wellington, New Zealand: Land Information New Zealand.

Lane SN, Westaway RM, HicksMD, 2003. Estimation of erosion and deposition volumes in a large, gravel-bed, braided river using synoptic remote sensing. Earth Surface Processes and Landforms 28: 249–271.

Leick A, Rapoport L, Tatarnikov D 2015. GPS satellite surveying. Hoboken, NJ: Wiley. 836 p.

Li C, Grayson R, Smith M, Holden J 2019. Patterns and drivers of peat topographic changes determined from Structure-from-Motion photogrammetry at field plot and laboratory scales. Earth Surface Processes and Landforms.

Lichti D, Gorden SJ, Stewart MP 2002. Ground-based laser scanners: operation, systems, and application. Geomatica 56: 21–33.

Lin Y, Hyyppa J, Jaakkola A 2011. Mini-UAV-Borne LIDAR for fine-scale mapping. IEEE Geoscience and Remote Sensing Letters 8: 426–430.

Luo S, Wang C, Xi X, Nie S, Fan X, Chen H, Ma D, Liu J, Zou J, Lin Y and others 2019. Estimating forest aboveground biomass using small-footprint full-waveform airborne LiDAR data. International Journal of Applied Earth Observation and Geoinformation 83: 101922.

Meng X, Currit N, Zhao K 2010. Ground filtering algorithms for airborne LiDAR data: A review of critical issues. Remote Sensing 2: 833–860.

Narine LL et al. 2019. Estimating aboveground biomass and forest canopy cover with simulated ICESat-2 data. Remote Sensing of Environment 224: 1–11.

Palmer D, Hainsworth S 2012. Lower Waikato Catchment peatland survey. Hamilton, New Zealand: Manaaki Whenua – Landcare Research.

Parry LE, West LJ, Holden J, Chapman PJ 2014. Evaluating approaches for estimating peat depth. Journal of Geophysical Research: Biogeosciences 119: 567–576.

Persaud M, Villamor P, Berryman KR, Ries W, Cousins J, Litchfield N, Alloway BV 2016. The Kerepehi Fault, Hauraki Rift, North Island, New Zealand: active fault characterisation and hazard. New Zealand Journal of Geology and Geophysics 59: 117–135.

Pronger J 2013. Historic and contemporary subsidence rates of drained agricultural peat, Waikato, New Zealand. Hamilton, New Zealand: Department of Earth and Ocean Sciences. University of Waikato.

Pronger J, Schipper LA, Hill RB, Campbell DI, McLeod M 2014. Subsidence rates of drained agricultural peatlands in New Zealand and the relationship with time since drainage. Journal of Environmental Quality 44: 1442–1449.

Reeve AS, Glaser PH, Rosenberry DO 2013. Seasonal changes in peatland surface elevation recorded at GPS stations in the Red Lake Peatlands, northern Minnesota, USA. Journal of Geophysical Resources-Biogeosciences 118: 1616–1626.

Rojstaczer S, Deverel SJ 1995. Land subsidence in drained histosols and highly organic mineral soils of California. Soil Science Society of America Journal 59: 1162–1167.

Rosa E, Larocque M, Pellerin S, Gagne S, Fournier R 2009. Determining the number of manual measurements required to improve peat thickness estimations by ground penetrating radar. Earth Surface Processes Landforms 34: 377–383.

Sass O, Friedmann A, Haselwanter G, Wetzel KF 2010. Investigating thickness and internal structure of alpine mires using conventional and geophysical techniques. CATENA 80: 195–203.

Statistics New Zealand 2012. Area planted outdoor fruit by region type, as at 30 June 2012. http://www.google.co.nz/url?sa=t&rct=j&q=&esrc=s&source=web&cd=1&ved=2ahUKEwjwvdKH5_vgAhWHXysKHYZsAfUQFjAAegQIChAC&url=http%3A%2F%2Farchive.stats.govt.nz%2F~%2Fmedia%2FStatistics%2Fbrowse-categories%2Findustry-sectors%2Fagriculture-horticulture-forestry%2Fag-census-2012%2Farea-planted-outdoor-fruit-region-type.xls&usg=AOvVaw1iDzL9tnsyq3kFy_7Nt4FO. (accessed 12 March 2019).

Stephens J, Allan L, Chen E 1984. Organic soil subsidence. In: Holzer TL ed. Reviews in engineering geology. Boulder, CO: The Geological Society of America. Pp. 107–122.

Taylor J 1997. Introduction to error analysis. The study of uncertainties in physical measurements. Sausalito CA: University Science Books.

Teatini P et al. 2007. Assessing short- and long-time displacements in the Venice coastland by synthetic aperture radar interferometric point target analysis. Journal of Geophysical Research: Earth Surface 112.

Thompson K 1980. Peat and peatlands: economic and scientific importance. In: van der Elst F, Kinloch DI eds Soil groups of New Zealand. Part 4: organic soils. Wellington New Zealand: New Zealand Society of Soil Science. Pp. 17–25.

Vericat D, Wheaton JM, Brasington J 2017. Revisiting the morphological approach: opportunities and challenges with repeat high-resolution topography. In: Tsutsumi D, Laronne JB, eds Gravel-bed rivers: processes and disasters. Hoboken NJ: Wiley. Pp. 121–158.

Vosselman G, Maas H 2010. Airborne and terrestrial laser scanning. Dunbeath UK: Whittles Publishing.

Waikato Regional Council 2016. Waikato Regional Policy Statement, Policy 14.5 Peat soils. Hamilton, New Zealand: WRC.

Wheaton JM, Brasington J, Darby SE, Sear DA 2010. Accounting for uncertainty in DEMs from repeat topographic surveys: improved sediment budgets. Earth Surface Processes and Landforms 35: 136–156.

Westoby MJ, Brasington J, Glasser NF, Hambrey MJ, Reynolds JM 2012. Structure-from-Motion photogrammetry: a low-cost, effective tool for geoscience applications. Geomorphology 179: 300–314.

Zhou X, Chang N-B, Li S 2009. Applications of SAR interferometry in earth and environmental science research. Sensors 9: 1876.