Eco-index

Remote Sensing for Environmental Decision-Making in Aotearoa New Zealand

Prepared by Eco-index for the Parliamentary Commissioner for the Environment

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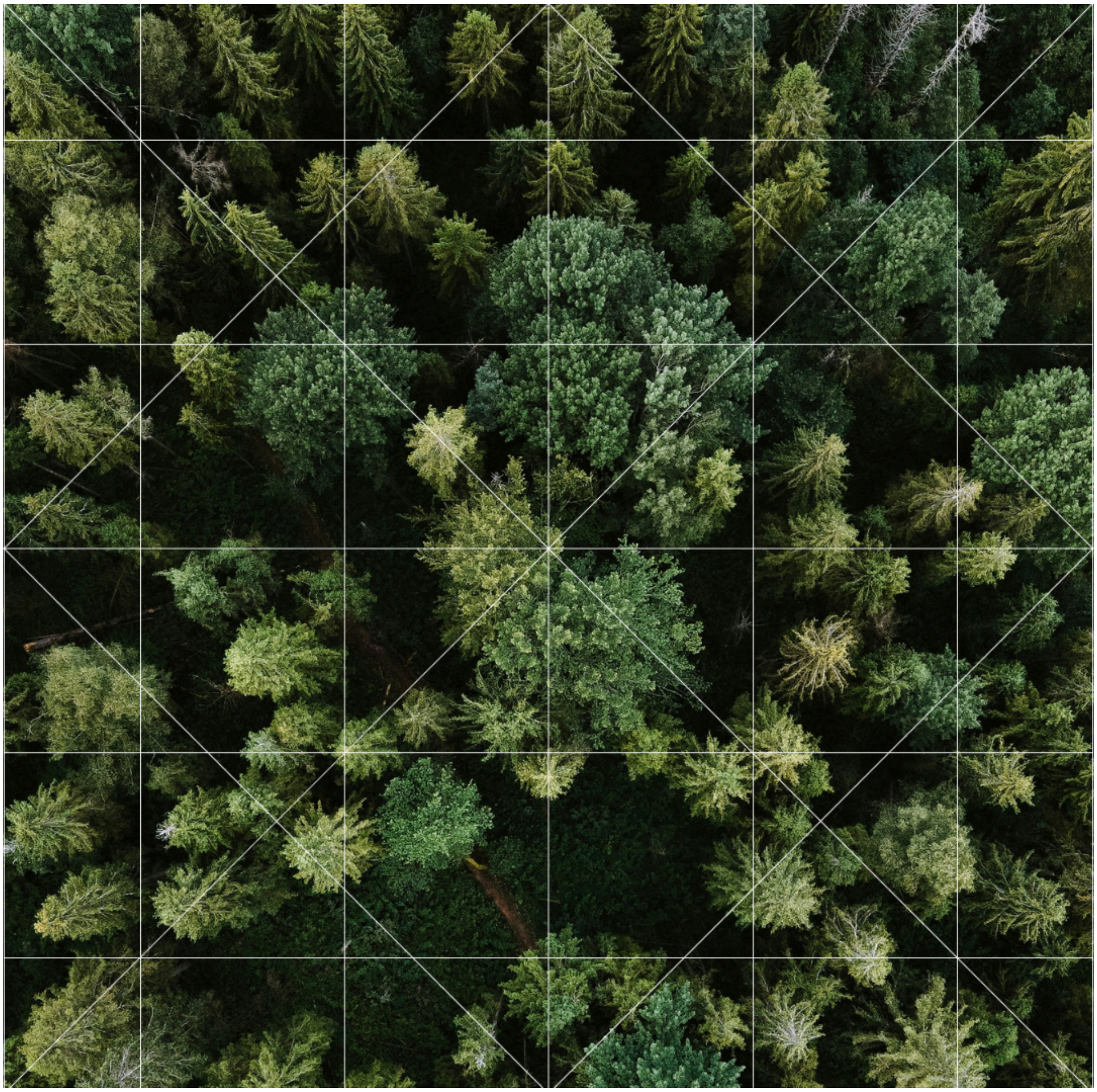

Table of Contents

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Executive Summary

Advances in remote sensing technology are transforming how Aotearoa New Zealand's (A-NZ) environment data is collected, understood and managed. This report reviews how remote sensing, i.e. capturing data from afar via satellites, aircraft, drones, and ground-based sensors, can improve environmental information available to decision-makers. This report has been commissioned as part of the Parliamentary Commissioner for the Environment's (PCE's) broader investigation into technologies that "unlock environmental information". The report examines current capabilities, gaps, and opportunities for applying remote sensing to improve environmental monitoring and enhance policy. The result is a technical review (Sections 1-4) integrated with strategic recommendations (Section 5) to strengthen A-NZ's environmental data systems in an accessible, cost-effective manner.

Key findings: Remote sensing as a data collection approach supports A-NZ's environmental monitoring focus areas: biodiversity, greenhouse gases and climate change, land cover and land use, carbon sequestration, soils, water quality and hydrology, and marine condition. Advances in remote sensing technology type and scale can be used in concert to show a clearer, more updated environmental status than ever before. From sky to soil, this includes satellite imagery for tracking land cover change and greenhouse gas emissions, to drone-based surveys of threatened wildlife, and ground-based sensor networks measuring water quality. Notably, many of these technologies are reaching operational maturity, e.g. satellite imagery of A-NZ's coastal waters is now available regularly, within hours of capture, and Artificial Intelligence (AI) powered drones can autonomously locate and identify critically endangered Māui dolphins in real time. These innovations enable timely, detailed environmental insights. With widespread, coordinated adoption they will empower decision-making at a new level.

Despite advances in remote sensing technology, there are many gaps and barriers to its application and subsequent effective use of data. Social and political barriers currently limit adoption, coordination and scaling. Many organisations are unaware of the novel technologies, or hesitant to adopt due to capital expenditure or perceived teething issues which may cause further expense or delays. Remaining reliant on more conventional, established, labour-intensive methods such as sampling by hand or conducting laboratory analyses appears less risky in the short term. When remote sensing technology is successfully adopted, environmental data it generates often remains siloed in disparate agencies or private companies, with inconsistent standardisation. There are also technical barriers including processing the huge volume and velocity of new data streams and integrating them across scales (from high-resolution drone data to global satellite data). Once data is captured, ground-truth validation often needs to occur to ensure accurate measurement of A-NZ's unique environment. Further, even when all barriers are overcome, that is, data is captured, shared, processed and validated adequately, the result rarely represents a national-scale picture. For example, only around 51% of A-NZ's farmable land has detailed soil mapping coverage (as of 2022), illustrating data gaps.

Clear, provisioning governance is critical to overcome these many gaps and barriers at a national scale, but presently there is no single system for linking environmental data, including increased remote sensing data, for easy interpretation by decision-makers. Further, national-scale funding for environmental monitoring via remote sensing and other means is limited and generally fragmented. Clear protocols for data sharing need development, including respect for Māori data sovereignty.

Recommendations: This report identifies five strategic areas for action. Implementing these strategic actions will move A-NZ toward a collaborative, optimised, and accessible remote sensing environmental data system, maximising best decision-making for environmental stewardship and policy.

(1) Improve computational capability, capacity and infrastructure to handle large remote sensing datasets.
(2) Encourage cross-organisational collaboration and data sharing across government, research institutions, iwi, and the private sector.
(3) Improve availability and discoverability of environmental data by leveraging international open-data platforms for non-sensitive data and developing secure domestic platforms for sensitive data.
(4) Promote publicly available data for decision support by continuing and increasing use of open environmental data in public early-warning systems and decision-making tools to demonstrate value and reliability.
(5) Establish robust governance, validation, and innovation frameworks to ensure recommendations 1-4 have a long-lasting foundation. A coordinated governance framework, and a supported environmental data platform or consortium, is recommended.

Introduction

Aotearoa New Zealand faces immediate and complex environmental challenges such as biodiversity loss, climate change impacts, and water quality degradation that demand timely, high-quality information for management decision-making. Traditional environmental monitoring methods (e.g. field surveys, manual sampling) are often labour-intensive, spatially limited, and slow. Remote sensing technologies collect data without a human on site and largely overcome conventional limitations. By observing the Earth's environment using satellites, aircraft, drones (also known as unmanned aerial vehicles or UAVs), and automated ground-based instruments, remote sensing provides continuous data quickly across large and sometimes inaccessible areas.

This report addresses the question: *How can remote sensing be used to improve environmental information available to decision-makers in New Zealand?* It builds on extensive prior work. In particular, it leverages findings from the Kaitiaki Intelligence Platforms (KIPs) research programme, which reviewed over 225 scientific papers published 2013–2023 and analysed dozens of commercial and governmental initiatives in environmental monitoring. The KIPs programme explored the design of a comprehensive environmental sensor network in A-NZ, with an emphasis on Māori environmental data needs. Insights from KIPs and related efforts, such as A-NZ's Biological Heritage National Science Challenge and government environmental reporting reviews, largely inform this report's analysis and recommendations.

This document's structure first provides an overview of remote sensing technologies and their current use in environmental monitoring (Section 1). It outlines what environmental qualities (i.e. variables) are being measured, data collection and processing (Section 1). It then broadly describes key players in A-NZ's remote sensing landscape - at a high level these include government agencies, research institutions (like the Crown Research Institutes[1]), private companies, international providers, and community initiatives (Section 2).

It then presents seven 'focus areas' which are environmental challenges for the country that remote sensing applications would greatly support (Section 3). These include biodiversity, greenhouse gases and climate change, land cover and land use, carbon sequestration, soil condition, water quality and hydrology, and marine condition. This 'focus areas' section describes current remote sensing applications in these focus areas with illustrative case studies in green 'Spotlight Boxes' (both domestic and international).

[1] During this report the seven Crown Research Institutes (CRIs) were reorganised into four Public Research Organisations (PROs), however legislation had not passed for the PROs creation. Therefore, CRIs are referred to throughout the report by their group name at the time of report publication for clarity. The most relevant groups for the purposes of this report are: National Institute of Water and Atmospheric Research (NIWA) and GNS Science (GNS) as part of the New Zealand Institute of Earth Sciences (operating as Earth Sciences New Zealand); Manaaki Whenua Landcare Research (MWLR), New Zealand Forest Research Institute (Scion), Plant & Food Research, and AgResearch, as part of the New Zealand Institute for Bioeconomy Science (operating as Bioeconomy Science Institute).

Next is an assessment of A-NZ's current environmental data systems supporting decision-making (Section 4). It identifies systemic challenges such as data fragmentation, accessibility issues, and capacity gaps. There is a brief comparison with international environmental monitoring systems. Finally, the report presents recommendations for improving governance, infrastructure, and collaboration frameworks so that remote sensing data can be more effectively integrated into A-NZ's environmental decision-making (Section 5). These recommendations emphasise building an integrated data system that is collaborative (across public & private sectors), optimised (technically robust and fit-for-purpose), and accessible (data and insights are available to those who need them, including the public).

Intended audience: While technical in parts, this report is written for a broad audience involved in decision-making from environmental data collection to management and policy. This includes central and local government agencies (policy makers, environmental regulators, and regional councils), research institutions, Māori environmental organisations, private sector companies, and community groups or citizen science networks. By presenting technical details and strategic context, the report is relevant to data providers and decision-makers alike. Ultimately, the goal is to improve informed decision-making to enhance A-NZ's environmental outcomes through better use of remote sensing information.

Section 1: Overview of Remote Sensing

Remote sensing refers to collecting information from a distance, without direct contact (Campbell & Wynne, 2012). In environmental monitoring, this means using sensor technologies to measure aspects of ecosystems, land, water, and atmosphere from afar, whether from satellites orbiting Earth, aircraft and drones flying overhead, or automated ground-based instruments transmitting data wirelessly. By eliminating the need for a person to physically visit each site, remote sensing enables more frequent, widespread, and sometimes otherwise impossible measurements. Remote sensing platforms often carry multiple sensor types (e.g. a satellite might have an optical camera and a radar unit) to collect complementary data simultaneously (Melesse et al., 2007).

At its core, remote sensing expands ability to observe critical environmental variables across various spatial and temporal scales. These variables include physical features like topography (e.g. terrain, shape, elevation), biological variables like vegetation cover and species occurrence, chemical variables such as water nutrients or atmospheric gas concentrations, and meteorological variables like temperature and rainfall. The following sections provide an overview of what variables can be measured, how data are collected (the platforms and sensors used), the types of data generated, scales of data collection, and how data are processed into useful information.

Crucially, remote sensing can operate across a range of spatial scales (Yin et al., 2019). At the broadest scale, satellite sensors provide from national to global coverage. For example, the Cyclone Global Navigation Satellite System (CyGNSS) satellite constellation (a group of satellites) is focussed on the tropics and gathers data at latitudes as far south as Tamāki Makarau Auckland (but for all longitudes). This large coverage capability enables climate monitoring, landscape-wide data collection, and international comparisons (Posselt et al., 2012). At intermediate scales, aircraft and high-altitude drones can survey regions or catchments in more detail (Chabot & Bird, 2013). At smaller scales, low-flying drones or ground-based platforms can collect data from individual properties or streams using high resolution sensors[2] (Zhang et al., 2022). Together, this multi-scale capability allows connection of big-picture trends with local specifics (Feng et al., 2021), for instance, linking global climate patterns with site-specific land management decisions. In today's context, remote sensing across scales is increasingly seen as essential for addressing environmental challenges, from tracking climate change and biodiversity loss (Han et al., 2024) to guiding sustainable land use and resource management.

[2] Scale and resolution are not the same thing. Scale refers to the size of the area being measured (i.e. global, regional, individual property), while resolution is the fixed level of detail captured (i.e. data might have a resolution of 3 metres per pixel at ground level).

What are the data types?

The term 'remote sensing' is used in its broadest sense throughout this report, meaning both satellite/airborne and ground-based platforms and the environmental sensing networks they can collectively comprise. In these initial sections there is a particular focus on the satellite/airborne applications because of the huge advances in these areas, but ground-based platforms are discussed at the end.

The raw forms of data are collected with sensors attached to a platform such as a satellite, airplane, UAV etc. The sensors read the data that is returned from the ground either due to an active signal being sent and returned to the sensor (e.g. LiDAR or radar) or by reading passive signals that are reflected from another source (e.g. visible imagery using the reflection of light from the sun). These different types of signals are summarised into categories of data types described below.

The Electromagnetic Spectrum

The raw data from remote sensors come in different spectral and signal types, each suited to certain applications. The common remote sensing data types span the electromagnetic spectrum and include optical imagery (human-visible light like Red Green Blue 'RGB', and invisible infra-red) and human-invisible light wavelengths like hyperspectral and multispectral data and thermal infrared (thermal IR; Figure 1). Understanding the electromagnetic spectrum of data types is important, as it provides insight into what environmental features can be measured.

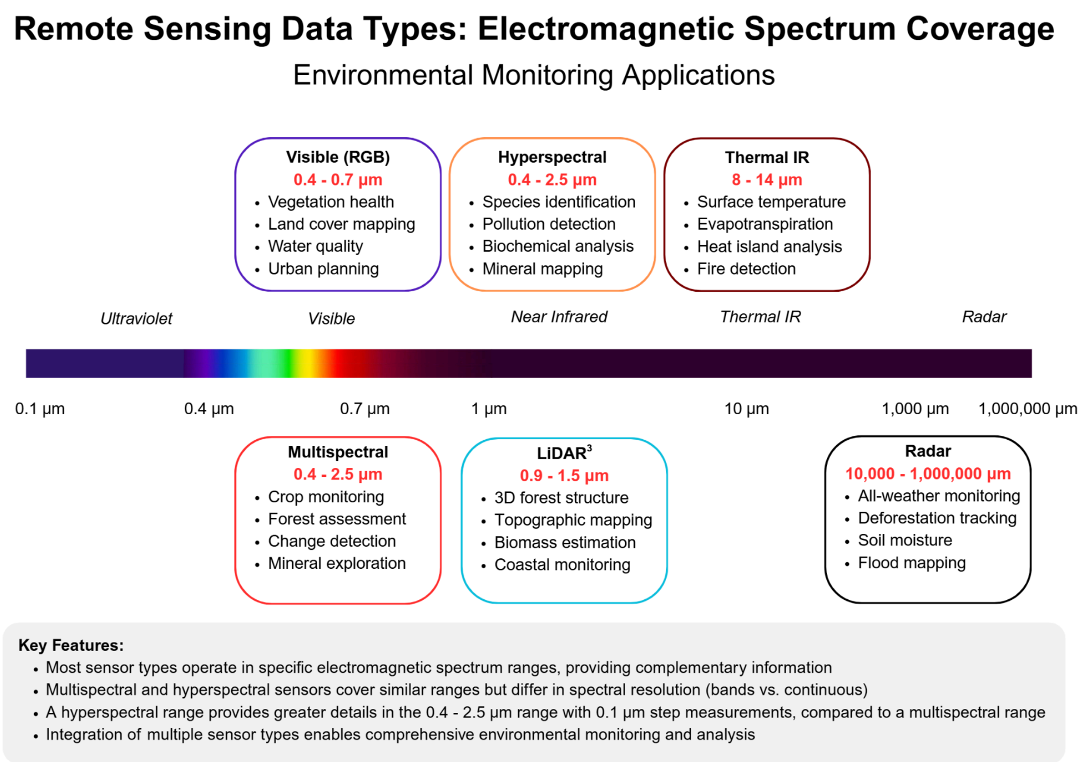

Figure 1. Remote sensing data types span a wide array of wavelengths on the electromagnetic spectrum. Note: green LiDAR has a wavelength of 0.532 µm and is commonly used to map underwater features.

Visible (RGB)

The data from the visible part of the light spectrum form images composed of red, green, and blue light wavelengths (similar to a standard photograph). Multispectral sensors can capture this visible light. Generally, RGB imagery is produced by nearly all optical remote sensing platforms: satellites (Lillesand et al., 2015) (Sentinel-2, Planet Labs, etc.), aerial cameras, drones, and even some ground sensors (e.g. time-lapse cameras). Because it matches human vision, RGB imagery is intuitive to interpret (e.g. the human eye can see deforested areas, sediment plumes). Historically, by itself, RGB has had limited analytical use because it doesn't capture wavelengths outside the visible range. However, with the advent of computer vision and other machine learning techniques it has greater utility now. Typically, RGB data is combined with other light wavelength bands (groups of similar-sized wavelengths) for more insightful analyses. Resolution of RGB imagery can range from 10 m (Sentinel-2) or 15 m (Landsat), to sub-metre for commercial satellites and just a few centimetres for low-altitude drones. Use cases for RGB data include creating base maps which other data types can be layered over, identifying land cover types, and change in extent by colour via satellite imagery time series (Coppin et al., 2004). RGB is often the base layer upon which additional spectral indices are computed, although infrared data is also used.

Multispectral

Multispectral data expands on the RGB wavelengths by including additional spectral bands, typically in the near-infrared (NIR) and sometimes shortwave infrared part of the spectrum. Common bands include NIR (which highlights vegetation health via reflectance[3] differences with the red band; Musfir Ahamed et al., 2025) and red edge (which can infer vegetation chlorophyll content; Ju et al., 2010). Sentinel-2 satellite data, for example, has 11 bands spanning visible RGB, 3 red-edge bands, NIR, and shortwave IR, all at 10–20 m resolution[4]. Many drones can be equipped with multispectral cameras (e.g. the 5-band camera capturing RGB, red-edge, and NIR from MicaSense). These extra bands enable calculation of vegetation indices like NDVI (Normalized Difference Vegetation Index) which is widely used for mapping vegetation vigour and is essential in biodiversity and agriculture applications (Donovan et al., 2018). In the UK, multispectral data has been used for nutrient leaching studies, for instance, identifying areas of high nitrogen runoff risk by looking at vegetation stress in NIR and red-edge bands (Llewellyn, 2009). Methane detection can also leverage multispectral data as certain bands (around shortwave IR of 2100 nm to 2400 nm) can pick up spectral absorption features of methane when high concentrations occur (Kumar et al., 2020). Overall, multispectral data strikes a balance of providing more widely usable information than RGB while keeping data volume manageable. Multispectral data is valuable for broader environmental monitoring requirements (Figure 2), indeed many of the 'focus area' illustrative case studies later in this report benefit from multispectral data capture.

[3] Reflectance is the measured magnitude of a certain wavelength by the sensor.
[4] Sentinel-2 has two additional bands "Coastal Aerosol" and "Water Vapour" which are provided at 60 m resolution.

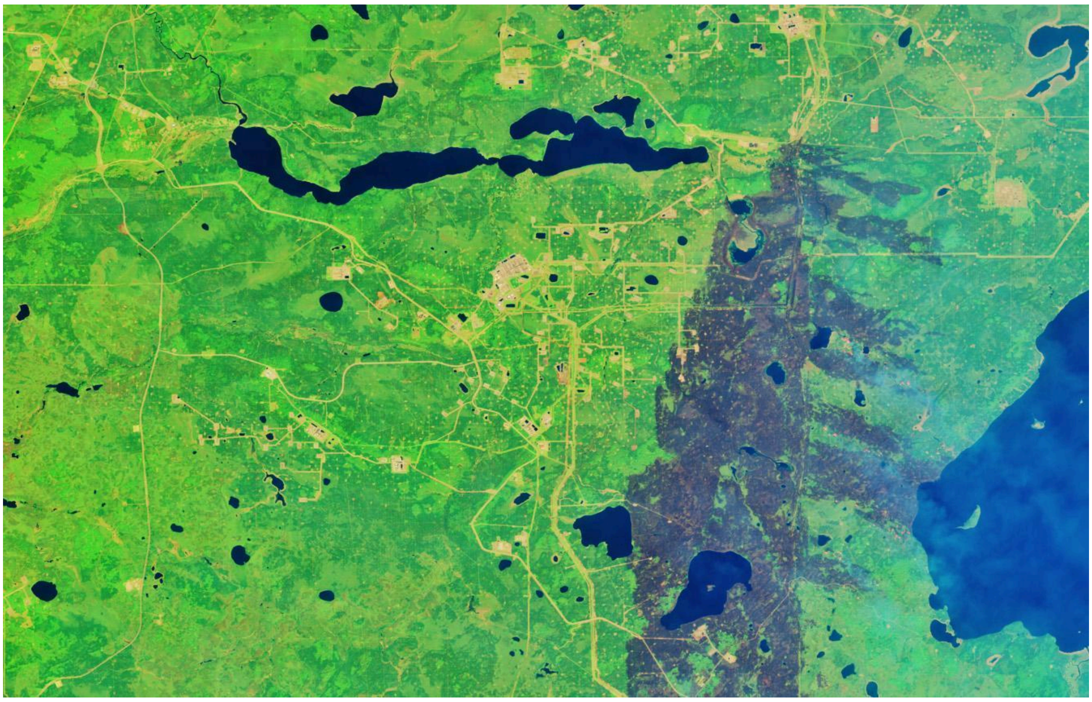

Figure 2. A Multispectral image from NASA's Operational Land Imager on Landsat 8 showing visible and non-visible bands of light combined to identify areas charred by wildfire (dark grey areas to the east of the city) in Alberta, Canada. Image: NASA.

Hyperspectral

Hyperspectral data collection is a more advanced form of multispectral sensing. Instead of a handful of bands, hyperspectral sensors capture hundreds of narrow spectral bands, often capturing visible through to shortwave infrared wavelengths. Some sensors collect 300 to 400+ bands, effectively recording a near-continuous spectrum for each pixel measured. This level of spectral detail can provide great detail, e.g. identification of specific grassland species based on their spectra (Psomas et al., 2011). Hyperspectral data can also be used to monitor plant health status (Qin et al., 2023), detect subtle chemical signals (like certain pigments; Blackburn, 2006), moisture content (Clevers et al., 2010), or mineral composition (Galvão et al., 2008), and improve detection of gases like methane (Kumar et al., 2020).

Until recently hyperspectral sensors have only been available on airborne platforms, however, new hyperspectral satellite missions have recently been put into orbit. Planet Labs has launched a hyperspectral satellite constellation named Tanager-1, providing ~5 nm spectral resolution across 400–2500 nm of the electromagnetic spectrum. Each Tanager sensor captures over 400 bands at 30 m resolution, a significant advancement for global biodiversity monitoring. However there is a trade-off of a lower resulting resolution compared to Planet Lab's multispectral satellites which capture 40 cm resolution. Using hyperspectral data in A-NZ could mean much more precise detection of non-native invasive plant species over large areas or monitoring of water quality (like chlorophyll-a).

Hyperspectral data is complex and often requires a form of AI called machine learning to interpret (given the high dimensionality[5]), but it holds great promise for detailed environmental assessments that were previously only possible via laborious ground sampling. The cost of hyperspectral data is coming down as more satellites are launched, and computing power allows rapid processing of the complex datasets. According to market analyses, the global hyperspectral imaging market is expected to roughly triple from $16 billion in 2023 to $60 billion by 2032 (Zion Market Research).

Thermal Infrared

Thermal infrared data measures heat emitted by surfaces. It's collected by thermal infrared sensors (typically wavelengths ~8–14 µm). Landsat 8 has a thermal band capability (~100 m resolution), and some drones carry thermal cameras for local surveys. Thermal imagery is used to monitor many temperature-related phenomena: identifying warm ocean currents (upwellings; Klemas, 2012), mapping urban hotspots (Coutts et al., 2016), detecting forest fires (Payra et al., 2023) and underground coal seam fires, geothermal activity (Wang et al., 2024), and monitoring plant water stress (stressed plants have higher canopy temperature due to reduced transpiration; N. Liu et al., 2020). In agriculture, thermal images can guide irrigation by highlighting which crop areas are water-stressed (hotter) versus well-watered (Ahmad et al., 2021).

In biodiversity-related work, thermal cameras on drones have been game-changers for finding wildlife at night, for example, detecting heat signatures of kiwi or bats (McCarthy et al., 2021) in dense forest where optical methods fail. Thermal data also contribute to atmospheric studies. Satellites like National Aeronautics and Space Administration's (NASA) Moderate Resolution Imaging Spectroradiometer (MODIS) and National Oceanic and Atmospheric Administration's (NOAA) Advanced Very High Resolution Radiometer (AVHRR) have thermal channels for sea surface temperature (Figure 3) which the National Institute of Water and Atmospheric Research (NIWA) uses in ocean models. With climate change occurring, long-term thermal records track changes such as increasing land surface temperatures or the frequency of marine heatwaves (Benthuysen et al., 2020). Like hyperspectral data, thermal infrared measurement can capture methane leaks. This specific emerging use of thermal infrared is possible because large methane releases can cause small temperature contrasts (Scafutto et al., 2018) as well as be associated with combustion (in gas flaring). Thermal sensors like the planned Albedo satellite constellation will augment direct gas sensing with thermal context (also note missions such as HotSat-1 and SatVu). Typically, the limitations of thermal infrared data are a lower resolution compared to the equivalent visible or multispectral sensor (e.g. Landsat 8 has a 100 m resolution while the visible and multispectral sensor on the same satellite has a 30 m resolution). Additionally, thermal sensors can be affected by changing atmospheric conditions more so than visible sensors.

[5] Dimensionality is the "depth" of an image. For a standard visible RGB image there is a depth of 3 for each colour. Since hyperspectral data can contain over 400 bands there is a much higher image depth, known as high dimensionality.

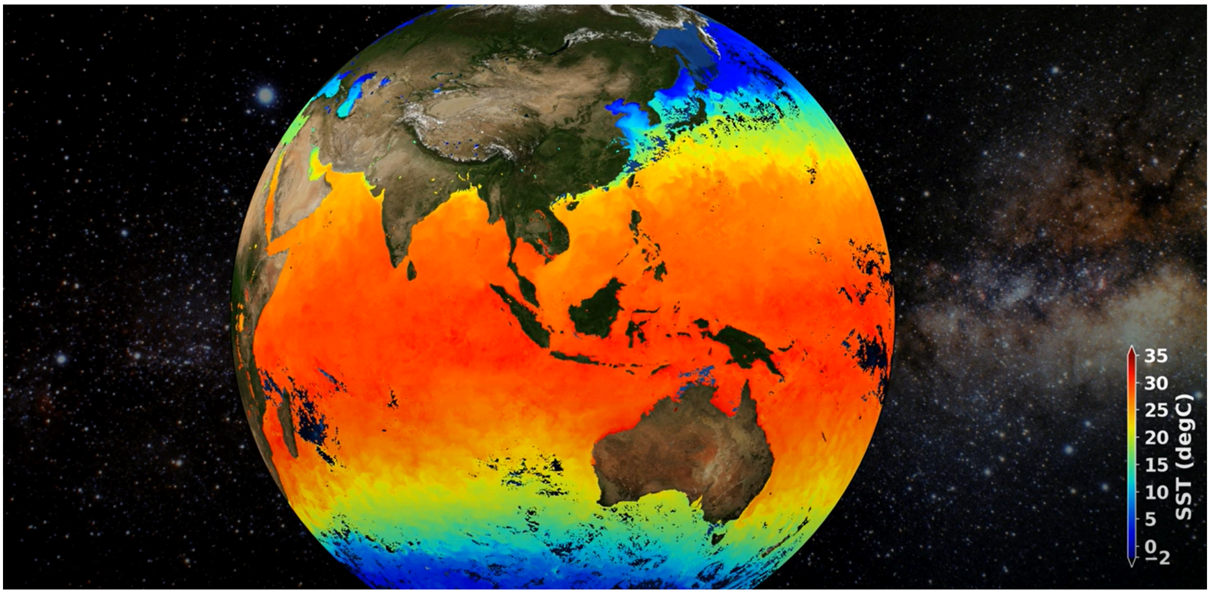

Figure 3. National Aeronautics and Space Administration's (NASA) MODIS-Terra was used to produce this thermal infrared image showing daytime ocean temperatures at 4.63 km spatial resolution. Black areas are data gaps over the ocean are due to cloud cover. Image: NASA.

Radar (Microwave)

Radar (microwave) remote sensing involves sending microwaves to the Earth's surface in a targeted manner to measure the returned (reflected) data. The data comes in the form of backscatter (as opposed to a focused reflection as from a mirror[6]), intensity and phase, which can relate to surface roughness and moisture (Rahman et al., 2008). This type of data is often captured by sensor types like Synthetic Aperture Radar (SAR). Unlike optical sensors, SAR can penetrate cloud cover and is effective day or night, making it reliable for frequent monitoring in cloudy regions (e.g. West Coast A-NZ). SAR is widely used in A-NZ for soil moisture mapping (Hajdu et al., 2018) and can even measure water inundation extent under vegetation (but only longer L-band imagery can do this). This type of data is captured by the Sentinel-1 satellite mission (C-band radar, wavelength of ~5 cm), Japanese Earth Resources Satellite (JERS), Advanced Land Observing Satellite (ALOS) and the recently launched NASA-ISRO Synthetic Aperture Radar (NISAR) satellite (L-band 24 cm wavelength, and S-band radar ~12 cm). SAR data is appropriate for soil moisture measurements because wetter soils reflect microwaves differently than dry soils. As radar wavelengths increase in length ability to penetrate the surface increases. C-band (5 cm wavelength) is often used in soil moisture measurement in the top 5 cm (Schmugge, 1983), whereas L-band (24 cm wavelength) penetrates deeper and is better for understanding forest biomass or root-zone moisture. S-band (~12 cm wavelength) is similarly used to penetrate tree canopy structures (Chang et al., 1980).

Indeed, radar is used in forest carbon studies by complementing optical data because it helps estimate woody biomass (Sinha et al., 2015) and detect changes even under cloud or canopy covered conditions. In A-NZ, researchers combine Sentinel-1 satellite

[6] In physics, backscatter is reflection of waves, particles, or signals back to their originating direction. It is usually a diffuse reflection due to scattering, as opposed to reflection as from a mirror.

radar data with Sentinel-2 satellite optical imagery to improve mapping of flood extent (radar sees flooded soils under clouds) and landslide scars (Joyce et al., 2008) across regions. SAR data, in particular radar altimetry[7], supports global initiatives such as monitoring sea level rise and observation of other coastal changes. A limitation is that radar data can be harder for non-specialists to interpret (as it's not a typical optical image), but advanced processing of radar data yields useful products like moisture indices, vegetation classification, and deformation maps (i.e., detecting ground movement, Figure 4). Notably, with SAR's all-weather capability, it ensures continuous data collection for critical monitoring, for example, tracking a river's spread during a storm even when satellites can't "see" it using optical data capture.

Because it provides data in such a reliable way, radar is an especially active research area. There are numerous recent studies and new missions planned to capture radar data. These include advanced sensors to conduct polarimetry[8] or interferometry[9] to measure variables such as topography. Recent missions include the European Space Agency's P-band BIOMASS and passive missions using GNSS-reflectometry (GNSS-R) like The CyGNSS, HydroGNSS, Spire and other bistatic/multistatic satellite constellation missions in development.

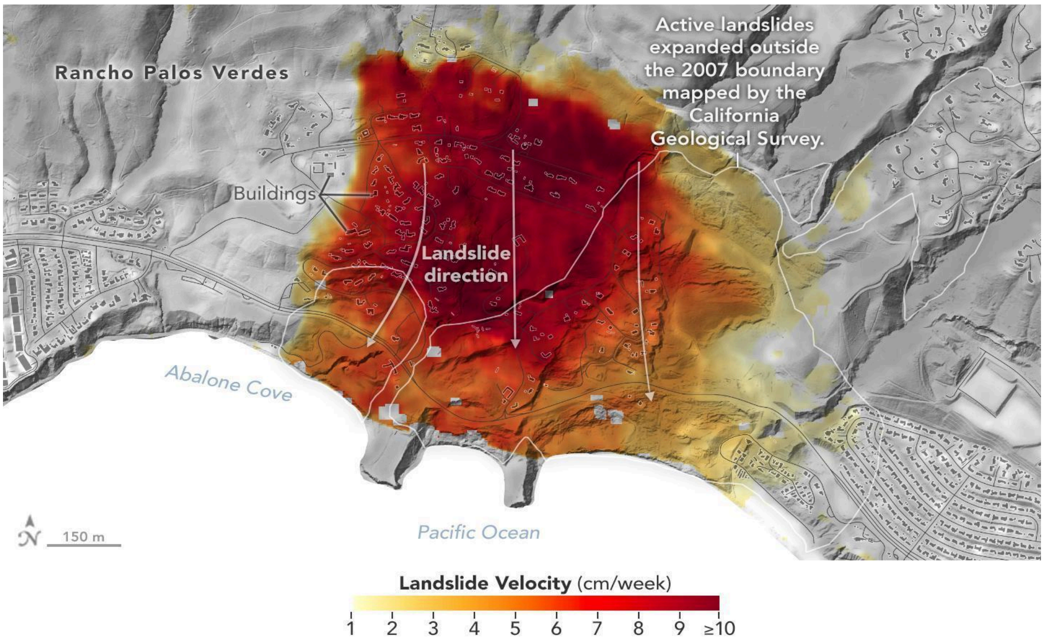

Figure 4. A Synthetic Aperture Radar (SAR) image showing radar (microwave) a decades-long active landslide. Darker colours indicate higher velocity. Image compiled from four flights of NASA's Uninhabited Aerial Vehicle SAR mounted on an aircraft flown Sept and Oct 2024. Los Angeles, USA. Image: NASA.

[7] Altimetry, also called a radio altimeter, electronic altimeter, reflection altimeter, or low-range radio altimeter, measures altitude above the terrain presently beneath an aircraft or spacecraft by timing reflection of radio waves.
[8] Polarimetry is the measurement and interpretation of the polarisation of transverse waves, most notably electromagnetic waves, such as radio or light waves. Typically polarimetry is done on electromagnetic waves that have travelled that have been reflected by some material in order to characterise that object.
[9] Interferometry is a technique which uses the interference of superimposed waves to extract information.

LiDAR

LiDAR (Light Detection and Ranging) is an 'active' scanning technique. It provides extremely detailed 3D information by emitting laser pulses (often using near-infrared light) and measuring their return time after reflecting off surfaces (Dong & Chen, 2017). The resulting data from a LiDAR instrument is referred to as a point cloud (Figure 5). When all points in a point cloud are brought together, they can be used to create a digital elevation map (DEM) or a digital surface map (DSM)[10]. These DEMs can also be produced from data collected through other means (e.g. SAR interferometry, stereo photogrammetry). LiDAR data can be used to map variables like ground elevation and vegetation structure at high resolution (often 0.5 to 1 m horizontal resolution and<20 cm vertical accuracy from aircraft surveys). In both tree plantations and natural forests, LiDAR is unparalleled for capturing structure, as it can measure canopy height, detect understory shrub and sapling layers, and even estimate tree biomass (van Leeuwen & Nieuwenhuis, 2010; Figure 5). The drawback is the expense of monitoring this way. An alternative is satellite SAR, which can also capture this data, but at larger scales and more frequently. Scion has utilised drone-mounted LiDAR to create a prototype "digital twin" of pine tree plantations (Stewart & Hartley, 2022), capturing tree growth in 3D detail.

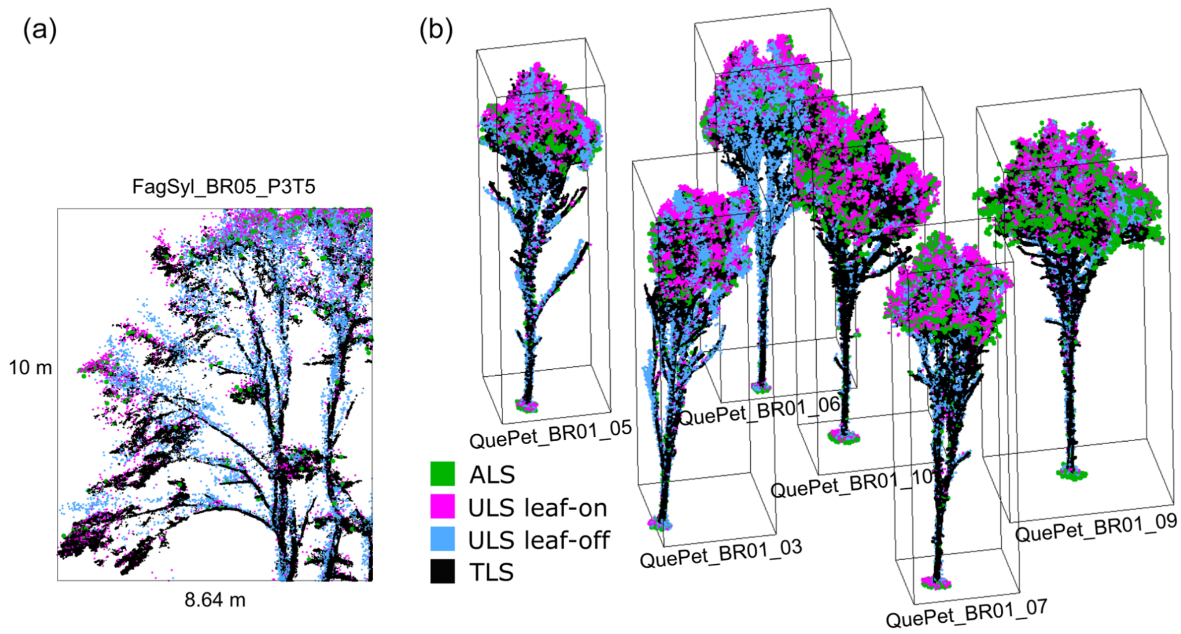

Figure 5. LiDAR point cloud visualisations showing the structure of (a) a beech tree (genus Fagus*) and (b) oak trees (genus* Quercus*). Image: Weiser et al., 2022.*

[10] The LiDAR point cloud output is a dataset of individual points each representing the measured height at that particular spot. Calculations can be done to convert these measurements into a surface representation called a DEM or DSM. DEM is the reflected ground surface representation while a DSM is the topmost surface representation. For example in a forest the DEM would reflect the base of the trees while the DSM would reflect the tops of the trees.

LiDAR data also underpins flood risk models (Sole et al., 2008) (mapping precisely where water will flow or pool) and urban planning (through detailed surface models and building heights; Dawood et al., 2017). The A-NZ government, via Land Information New Zealand (LINZ), has coordinated regional LiDAR acquisitions that now cover the majority of the country at a 1 m horizontal resolution[11] and these datasets are being made openly available[12]. There is also satellite-based LiDAR data capture like NASA's Global Ecosystem Dynamics Investigation (GEDI) and Ice, Cloud, and Land Elevation Satellite (ICESat-2). However, satellite LiDAR resolution is coarser, with a 25 m resolution, compared to what can be captured via drone (UAV).

Summary

Each data type offers unique "eyes" on the environment: optical and multispectral imagery reveal colour and composition differences, hyperspectral provides diagnostic spectral detail, thermal infrared shows heat-related processes, radar senses structure and moisture under all conditions, and LiDAR maps 3D form. Environmental monitoring efforts typically combine multiple data types to get a complete assessment. For instance, to understand wetland status, multispectral indices are used for vegetation health, LiDAR for micro-topography and canopy structure, and radar to detect water inundation under vegetation cover. This multi-sensor approach is becoming standard as integrated analysis techniques improve. New technological missions (NASA's NISAR satellite and technology from NASA's Surface Biology and Geology mission) will further enrich the data availability but also require robust data management due to the data volume and complexity.

[11] A-NZ LiDAR coverage is minimum 1 m resolution; however, many regional councils have finer resolutions available.
[12] LiDAR datasets are available via the Toitū Te Whenua Land Information New Zealand Data Service.

How is the data being collected?

Remote sensing data collection of all types relies on a hierarchy of platforms to carry sensors: satellites, aircraft, drones (UAVs), and ground-based automated systems (Figure 6). Each offers different advantages in scale and resolution.

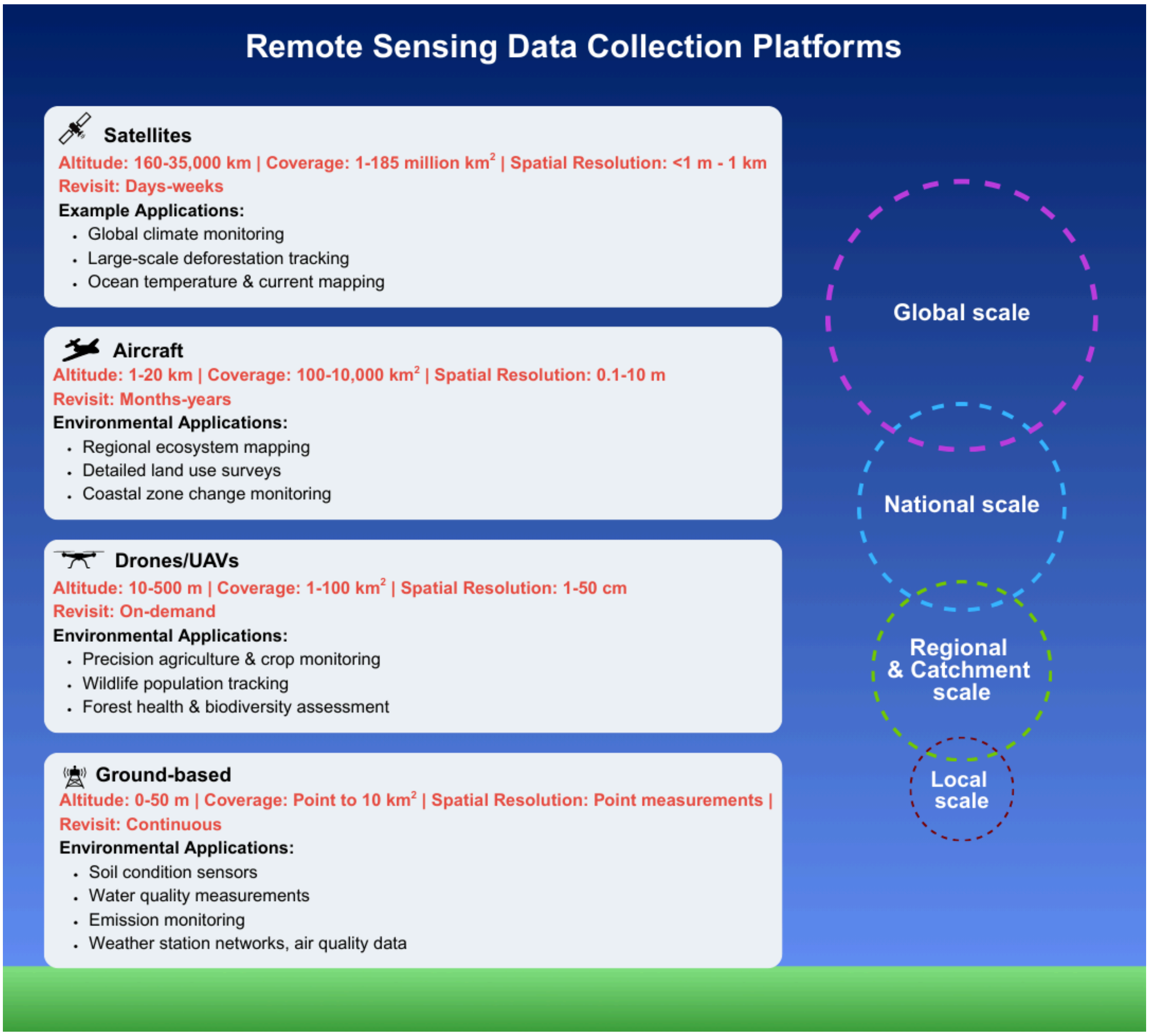

Figure 6. The hierarchy of platforms used to carry remote sensing data collection sensors, from largest scale capture furthest from the Earth's surface to smallest scale capture at the bottom, closest to the Earth.

Satellites

Satellites play a critical role in environmental monitoring due to their ability to measure at the global to continental scale and measurement frequency from repeated orbit passes. Aotearoa New Zealand benefits from some particular general-purpose satellites which provide open access (publicly-available) data, including the European Space Agency (ESA) Sentinel-2 (10 m resolution multispectral imagery) and USGS/NASA Landsat-8/9 (15–30 m resolution; Figure 7), which together provide frequent nationwide coverage. These are invaluable for national-scale monitoring of land cover, vegetation change, and large events, e.g. wildfire scars (Thangavel et al., 2023) or algal blooms (S. Liu et al., 2022). Given A-NZ's remote, isolated location, there are some satellites which do not cover the entirety of the country such as CyGNSS, which measures equatorial areas and lower latitudes, and as such only covers Northland, A-NZ. Specialised environmental satellites collecting publicly-available data over A-NZ include the ESA Sentinel-1 radar satellites (for soil moisture and structure), ESA Sentinel-3 (ocean and land temperature, ocean colour), ESA Sentinel-5P (atmospheric gases), and others like NASA SMAP (soil moisture active/passive) and NASA GEDI LiDAR (forest structure).

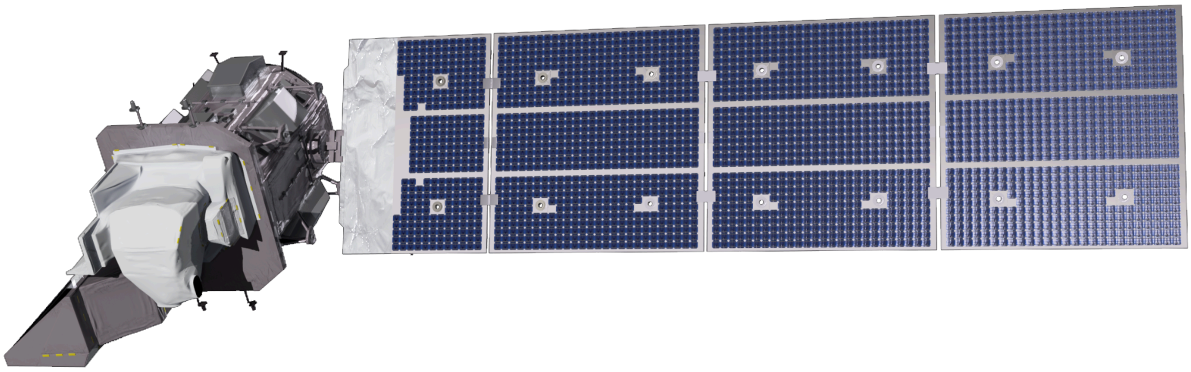

Figure 7. USGS/NASA Landsat 9 satellite. Image: NASA.

On the commercial satellite scene, data is available for purchase from Planet Labs' Dove satellites, which image A-NZ daily at 3 m resolution, and Maxar's WorldView satellite constellation, which offers very high resolution (30 cm) imagery on demand. Commercial, sub-metre imagery costs NZD $30-45 per km² depending on licensing.

The drawbacks of satellite imagery include resolution limitations and temporal coverage at fine scales. Satellites can't achieve a sub 10 cm resolution due to the physical distance requirement for sensor placement. When such fine resolutions are required, aircraft or UAV must collect the data. Similarly, the repeat time of satellites is based on the time it takes to orbit the earth as well as how many satellites are in operation by a provider. The Sentinel-2 satellites (two in orbit) have a longer repeat measurement time than Planet Scope satellites (over 200 in orbit). If there is a need to measure an area multiple times a day, then data from a UAV would likely be needed, not satellite data.

In summary, satellites provide broad coverage and consistency, forming the backbone of remote sensing data inputs for climate and land change analyses. For a comprehensive list of satellite data providers, their satellites and missions, and A-NZ organisations who utilise them see Table 1. General points to note include: NIWA appears to be the most active government-related user of multiple satellite systems, research institutions (Dragonfly, MWLR, Cawthron) are major users of satellite data, MBIE has facilitated several commercial satellite partnerships and free/open data (Sentinel, Landsat) has much broader adoption than commercial systems.

Table 1. Satellite Data Providers

Provider/Agency	Satellites/Missions	Primary Application	Aotearoa New Zealand Users
Albedo (USA)	Planned constellation	Ultra-high resolution thermal	Not specified
Canadian Space Agency	RADARSAT	SAR	Research applications (mentioned in general context)
Capella Space (USA)	Capella Space	Ultra-high resolution Synthetic Aperture Radar	Not specified
China National Space Administration (CNSA)	Gaofen, Fengyun	Meteorological, environmental	Not specified
European Organisation for the exploitation Meteorological Satellites (EUMETSAT)	Various meteorological satellites	European weather data	Research applications (mentioned in general context)
European Space Agency (ESA)	Sentinel-1 (radar), Sentinel-2 (optical), Sentinel-3 (ocean/land), Sentinel-5P (atmospheric), PRISMA (hyperspectral), GRACE (Gravity fields), PROBA-V (land use)	Open-access environmental monitoring	Xerra Earth Observation Institute (Sentinel-2 for lake monitoring across NZ's 3,800 lakes); General research community (widely used since open access)
Germany (DLR)	TerraSAR-X, EnMAP	SAR and hyperspectral	Research applications (mentioned in general context)
Greenhouse Gas Satellite (GHGSat) (Canada)	GHGSat constellation	Commercial methane detection	Research applications (mentioned as complementary to MethaneSAT)
ICEYE	ICEYE	Ultra-high resolution Synthetic Aperture Radar	Not specified
Indian Space Research Organisation (ISRO)	NISAR, PSLV-C61/EOS-09	Earth Observation and navigation	Not specified
Italian Space Agency (ASI)	ERS-1, ERS-2, ENVISAT, the Meteosat	Research	Not specified
Japan Meteorological Agency	Himawari-8/9	Geostationary weather monitoring	Fire and Emergency NZ (piloting wildfire detection system using Himawari-8 data)
JAXA (Japan)	ALOS PALSAR, GOSAT-1	Radar and GHG monitoring	Research applications (mentioned in general context)

Table 1. Satellite Data Providers

Provider/Agency	Satellites/Missions	Primary Application	Aotearoa New Zealand Users
Maxar Technologies	WorldView constellation, WorldView Legion	High-resolution commercial	MBIE (Night Light data partnership for research)
MethaneSAT	MethaneSAT (failed 2025)	Agricultural methane detection	NIWA (lead agency); University of Auckland Space Institute (co-lead for agricultural emissions science)
Muon (USA)	Hydrosat	Multispectral imaging, thermal IR	Not Specified
NASA/Indian Space Research Organisation(ISRO)	NISAR (upcoming)	Dual-frequency radar	Research community (anticipated use)
National Aeronautics and Space Administration (NASA)	Landsat-8/9, MODIS, GEDI LiDAR, ICESat-2, SMAP, GOES, Terra/Aqua, SWOT, PACE, SBG	Earth observation and climate monitoring	NIWA (MODIS for sea surface temperature, various missions); Dragonfly Data Science (NASA partnership for GEDI forest mapping); CarbonCrop (GEDI LiDAR data); Cawthron Institute (processes MODIS-Aqua data via CawthronEye)
National Centre for Space Studies (CNES) (France)	International Space Station, PARASOL, CLIPSO	Environmental Research	Not specified
National Institute for Space Research (INPE) (Brazil)	Not Applicable	Environmental (Rainforest) Research, Weather	Not specified
National Oceanic and Atmospheric Administration (NOAA)	AVHRR, GOES, JPSS	Weather and climate monitoring	NIWA (AVHRR for thermal data in ocean models)
Pixxel (India)	Firefly constellation	Hyperspectral imaging	Not specified
Planet Labs	Dove satellites, PlanetScope, Tanager constellation	High-frequency commercial imagery	MBIE (various research partnerships); CarbonCrop (Planet's constellation for daily global coverage); Various A-NZ projects
U.S. Geological Survey (USGS)	Landsat-8/9 (with NASA)	Land cover and change detection	MWLR (LUCAS system uses Landsat); General NZ research community (dramatically increased usage since free access in 2008)

Aircraft

Aircraft, including both planes and helicopters, are platforms used for a variety of targeted aerial data capture. These manned aircraft can carry high-end sensors such as large LiDAR rigs, thermal imagers, or hyperspectral scanners to map areas in finer detail than satellite-carried sensors can (Watts et al., 2012). In A-NZ, aerial LiDAR campaigns are often conducted by companies such as Aerial Surveys Ltd., which operates advanced LiDAR systems (e.g. Teledyne Optech sensors) under contract. These campaigns have mapped significant parts of A-NZ's terrain (e.g. river floodplains, forests, urban areas) at resolutions of 1 m or better, and are useful for engineering, forestry and hazard management. Even aquifers can now be measured using sensors on aircraft, as has been happening in Hawke's Bay. GNSS-R data is available through the Rongowai project.

Aircraft can also capture high-resolution aerial photos (visible and infrared wavelengths), historically used for regional scale 'orthophoto mosaics' (i.e. joining many individual photographs into one large image greater than a single photograph could capture). An advantage of aircraft for carrying sensors is the flexibility in sensor payload and timing (Whitehead & Hugenholtz, 2014). Flights can be booked when needed (weather permitting) and sensors can be swapped or tuned to specific project requirements. For example, after major events like the Kaikōura earthquake or cyclone-induced floods, aerial surveys were commissioned to rapidly assess landslides and flooding damage (Jones et al., 2025). Aircraft remain important for filling the gap between satellites and ground-level sensor placement, as they can cover an entire region in a day with much higher detail capture than satellites, albeit at higher cost and planning effort.

Drones or Unmanned Aerial Vehicles (UAVs)

Drones are a valuable platform for localised scale remote sensing data collection. Both fixed-wing and rotary UAVs are employed in environmental data capture for planning and monitoring (Figure 8). They excel at flexibility and detail capture and can be deployed at short notice to survey a specific wetland, river stretch, or forest stand. They can fly at low altitudes (10-500 m) to capture ultra-high-resolution data (cm-level imagery or point clouds; Son et al., 2021).

In A-NZ, many organisations use drones, for instance, Dronescape (NZ) specialises in aerial mapping for agriculture and plantation forestry, capturing multispectral imagery to assess crop health and tree condition. Drones are used in biodiversity management to monitor wildlife and non-native invasive species (Singh et al., 2024). For example, the Cornerstone Conservation group pairs drone thermal cameras with on-ground methods like detection dogs to locate non-native animals and assess biodiversity in remote areas. Drones typically carry cameras (visual, multispectral, or thermal) (Tripolitsiotis et al., 2017) and sometimes miniaturised LiDAR units.

The trade-off is drone flights have limited scale coverage compared to manned aircraft or satellites, as a drone might only cover a few km^2 per flight or perhaps a small catchment for a fixed wing UAV. However, for many management applications (like farm-scale mapping or small reserves), this smaller scale coverage is sufficient. Importantly, drones have enabled community groups and smaller agencies to gather their own data, thereby democratising data collection. As regulations allow beyond-visual-line-of-sight (BVLOS) flights, as in the MAUI63 project, the capture reach of drones can extend out from the coastline and over wide areas.

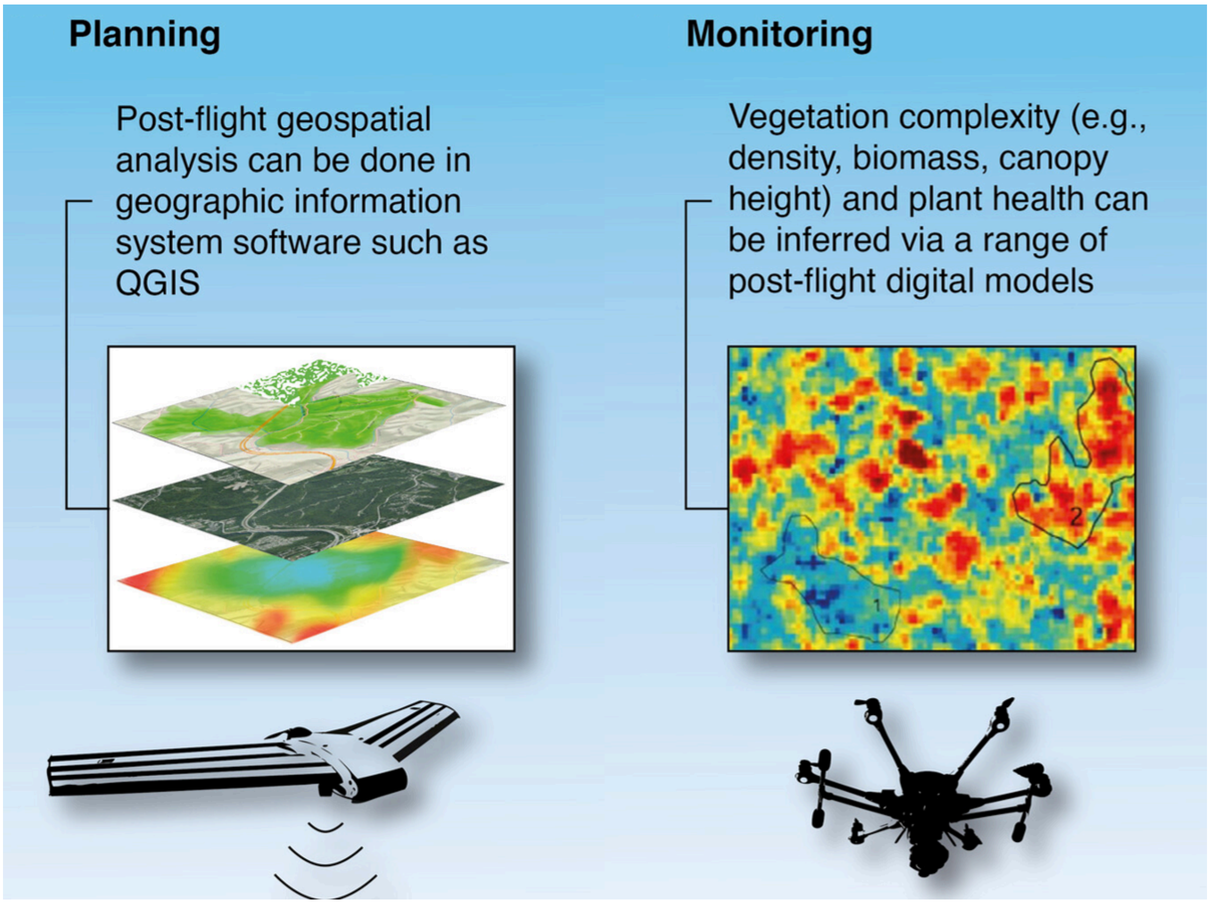

Figure 8. Examples of drones and their applications in environmental data collection. Left: representation of a fixed-wing drone system able to collect baseline ecological and geophysical conditions over large spatial scales, very useful for planning. Right: representation of a rotary drone able to conduct fine-scale assessments of vegetation complexity (e.g. canopy height models, tree species counts), useful for targeted species control. Image: Adapted from (Robinson et al., 2022).

Ground-Based Platforms

These are automated ground-based or water-based sensor stations or sensor networks that operate *in situ* (in place, on site) but remotely transmit data (often in real time) to central databases. Examples include climate stations, river flow gauges, air quality sensors, and Internet-of-Things (IoT) environmental sensor networks. Companies like Adroit in A-NZ provide integrated IoT sensor solutions, for instance, deploying networks of water quality sensors in streams and transmitting the data via cellular or satellite uplink to an online dashboard.

Ground-based remote sensing platforms often host sensors that cannot cover large areas individually, but a dense network like an IoT enables a wider coverage (Lombardo et al., 2018). These types of systems can complement data collected by satellite and aerial platforms by providing ground-truthing and continuous monitoring at key points. They effectively form the "eyes on the ground" that space or air-based remote sensing can be calibrated against (Hanzl et al., 2025). As sensor costs drop and wireless connectivity improves, such ground-based systems are expanding in use (including community-driven uses). Sensor stations are a specific form of ground-based monitoring where sensors are attached to very large platforms (e.g. bridges, towers in conservation areas). These stations can greatly hone analyses by providing continual, long-term calibration of air and space-derived data (Adnan et al., 2025).

Environmental Sensing Networks - A Unique Form of Infrastructure

When multiple sensors are linked, each measuring different variables, they collectively generate a more comprehensive picture of the current environmental state. This linkage also enables the modelling of relationships between variables. Sensors linked together in this manner connected to a data warehouse and user interface form a type of infrastructure known as an Environmental Sensing Network (ESN; Reid et al., 2025). In its most basic form, an ESN is composed of three parts (Figure 9).

For instance, to monitor lake water quality, satellite imagery might detect algal blooms, a drone could map the bloom's finer structure or extent, and instrumented buoys (water-based sensors) would record exact chlorophyll and nutrient levels for validation purposes. Combining these data types from multiple remote sensor platforms, processing them, and enabling queries would enable a comprehensive picture of lake quality. An A-NZ use case example of an ESN is the Farmax farm management model, which can incorporate NIWA weather data with various ground-based monitoring systems to forecast pasture growth and predict methane emissions (Harris-Wright et al., 2022). NIWA also operates CarbonWatch-NZ, a system that combines air monitoring stations with weather data to create a comprehensive view of A-NZ's carbon balance.

Environmental Sensing Networks are necessary to gain an overall understanding of environmental conditions and undertake effective environmental monitoring in A-NZ. By understanding the strengths of each platform type (satellites for synoptic view, drones for detail, etc.), decision-makers can design a cost-effective observation strategy.

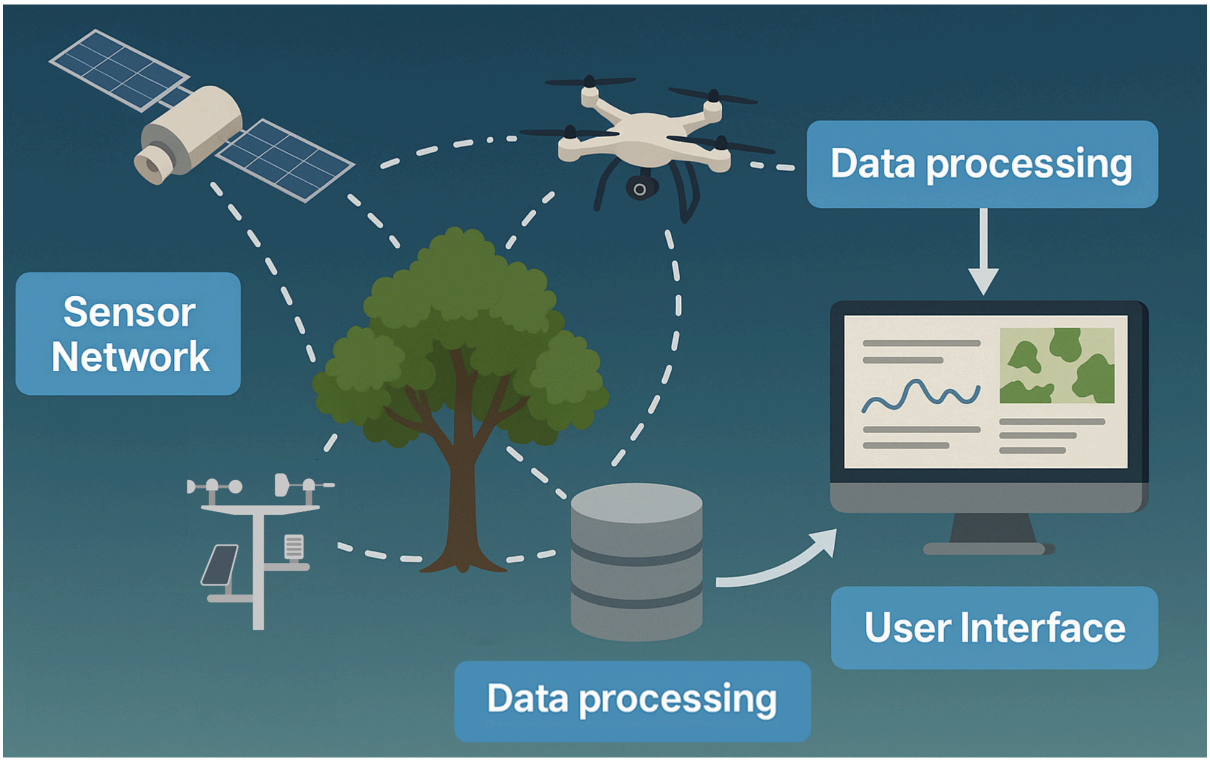

Figure 9. A visualisation of an Environmental Sensing Network, with an array of ground-based in situ *(in place) and aerial or space-based remote sensors that gather and transmit data, a data warehouse that receives the data and processes it from an unstructured state into standardised formats using models or machine learning techniques, and a user interface that enables complex queries, generates meaningful environmental insights from the data, and facilitates effective and bespoke information dissemination.*

At what scales are data collected?

Data is collected at several geospatial scales, each serving different data collection and therefore decision-making needs. Four scales are considered here, from largest to smallest these are: global, national, regional & catchment, and local. Understanding the role of scale is important because remote sensing technologies and their generated datasets are tailored to different scales. While sensor data collection is often ongoing temporally, scale (or coverage) is limited to specific areas, and the data used for only specific applications.

There is an important delineation to make between raw data collection (e.g. remote sensing imagery captured by satellites) and products derived from it for a specific purpose (e.g. the global land cover dataset produced by Google AlphaEarth Foundations). The derived products are often available only at a coarser spatial resolution because of the processing required, e.g. a satellite's raw data is modelled and the output is a derived prediction (e.g. the mapBiomass dataset produced from modelling using the Google AlphaEarth Foundations dataset).

Global scale

Remote sensing at the global scale allows A-NZ's environment to be placed into an internationally comparable context. Examples include climate change-related satellite data (monitoring global temperature, ocean currents and velocity, atmospheric composition) and global datasets like the Food and Agricultural Organization of the United Nation's forest cover maps or global biodiversity indicators. While global datasets often have coarse resolution (e.g. 0.25° climate grids or 1 km global land cover maps), they are vital for monitoring dynamics at the large scale like climate change (Yang et al., 2013) and species migrations (Riede, 2004). A-NZ taps into global data collection systems such as the Copernicus programme (which provides global Sentinel satellite data and services) and NASA's Earth observation datasets (a derived product). These allow comparisons of forest carbon stocks or pollution levels in A-NZ with those of other countries (Hu et al., 2016). Global scale remote sensing data and derived datasets also support international environmental reporting and treaty obligations, e.g. United Nations Framework Convention on Climate Change (UNFCCC) GHG inventories use remote sensing-derived land use data (DeFries et al., 2007). In short, global scale remote sensing ensures A-NZ's environmental monitoring is not done in isolation, by being benchmarked and informed by planet-wide information.

National scale

At the country level, remote sensing data is used to create nationwide environmental datasets (derived products) that inform national policy and resource management. For instance, Land cover type databases produced by categorised satellite imagery (e.g. Land Cover Database (LCDB); historically at 30 m resolution) provide national land cover maps across 33 land cover categories (e.g. forest types, farmland, urban). National-scale monitoring of emissions relies on remote sensing too; the Land Use and Carbon Analysis System (LUCAS) uses satellite imagery and LiDAR data to track land-use change for A-NZ's carbon accounting. The Our Environment web portal (hosted by Manaaki Whenua Landcare Research (MWLR)) offers an array of regularly-updated national datasets (e.g. vegetation indices, thermal anomalies). National scale often implies only moderate resolution (10–100 m) is available, but with the trade-off of full geographical coverage. National scale datasets are crucial for central government agencies (Ministry for the Environment, Department of Conservation, Ministry for Primary Industries, etc.) to identify where major changes are occurring, e.g. deforestation hotspots (Brockerhoff et al., 2008), drought events, flooding. Only then can they make well-informed decisions about nationwide initiatives (e.g. biodiversity management targets or water flow management).

Regional & Catchment scale

Regional councils and catchment groups require data at moderate scales, of tens to hundreds of km^2, because of the size of their regions or watersheds. At this scale, both aerial surveys and high-resolution satellites are very useful. For example, the

Hawke's Bay region commissioned aerial imagery capture over flooded areas post Cyclone Gabriel in 2023. This data could now be used to improve flood prediction models and emergency plans. Catchment scale land use can be monitored in higher detail than national scale. Some councils now use imagery with very high resolutions, for example Hawke's Bay has 0.125 m, Canterbury 0.2 m, Northland 0.3 m and Auckland City Council has aerial photos at 0.075 m resolution. With such high resolution imagery, Waikato Regional Council have shown it's possible to map small wetlands or riparian vegetation that national scale maps miss (such as the LCDB).

State of environment reporting often requires data be collected against specific indicators, which remote sensing can typically capture. For example, a council can report changes in regional forest cover derived from Sentinel-2 satellite data (Reinosch et al., 2025), or use satellite-derived soil moisture data to assess drought severity (Mol et al., 2017). Importantly, many environmental processes (water flow, sediment transport, pollution, ecological connectivity) are most meaningful at catchment scale, so remote sensing data is often aggregated or analysed at that scale. Programmes such as NIWA's Seas, Coasts and Estuaries NZ provide regionally-focused satellite data products for coastal water quality, delivering 500 m resolution MODIS-Aqua data tailored to A-NZ's coastal zones. The regional scale is where local detail often meets policy. Remote sensing here needs to be detailed enough for on-ground action, but broad enough to cover the whole region evenly.

Local scale

As the smallest scale considered in this report, remote sensing can occur at the local, or property, level. This may be as small as a paddock, farm, forest patch or small estuary. Here, high-resolution drones or satellites (sub-metre to a few metres resolution) and *in situ* sensors are typically used. For instance, an individual farm might use drone multispectral imagery to assess pasture health in each paddock to identify where fertiliser application is needed (Advexure). Plantation forestry companies might use drone-based LiDAR measurements to inventory a forest stand's tree heights and densities (Daryaei et al., 2025; Chen et al., 2024). Biodiversity management projects might deploy camera traps and acoustic sensors across a sanctuary to monitor wildlife presence (Crunchant et al., 2020; Australian Wildlife Conservancy). Local scale data often provides immediate, actionable insight, e.g. a farmer gets soil moisture mapped across fields to guide weekly irrigation (MWLR), or a river restoration group identifies the exact locations of erosion (Gisborne District Council) or illegal dumping along a river's banks from a detailed drone survey. Many commercial providers in A-NZ target this local scale with value-added services. For example, precision agriculture firms use satellite and drone data to create farm maps for variable-rate application of fertiliser inputs (e.g. AgriDrone Specialists).

The challenge at the local scale is handling data volume and detail. A single drone flight can produce tens of gigabytes of data from a survey of just a few km^2. Processing, analysing and making decisions informed by such substantial datasets requires specific software and significant computing power. But as software and computing design and access improves, small organisations can more frequently harness local remote sensing data to inform their decision-making. In sum, at the local scale, remote sensing becomes very tangible, it directly informs operational decisions and site-specific management.

Summary of Scales

By collecting and linking data across all scales, A-NZ can produce a powerful, informative nested environmental data system. Large scale patterns (like global climate drivers or national land use trends) provide context for regional and catchment observations, while local scale data validate and enrich the broader picture. It is worth noting that scale integration is an active area of research. Methods like downscaling (to infer local detail from coarse data (Xu et al., 2025) and upscaling to generalise site measurements to larger areas via models (Psomiadis et al., 2025) can connect scales. A key recommendation later in this report is to invest in multi-scale integration capabilities, so that, for example, high-resolution drone data (i.e. sub 1 cm resolution) can enhance satellite data (i.e. 10 m resolution) to both feed into a national scale data system seamlessly.

How is the data being processed and analysed?

Collecting remote sensing data is only half the story. Turning it into useful information to make decisions requires extensive data processing and analysis. Data generated by sensors affixed to space, air or ground-based platforms is processed to identify patterns revealing the state of environmental variables, e.g. particular aspects of water or soil condition. Steps in processing include basic preprocessing (e.g. correcting images for sensor errors or alignment to standard geospatial grid systems), processing, analysis, and validation. For the analysis step, approaches have developed from traditional statistical approaches into advanced computational methods like AI-driven classification and modelling. Appendix A provides a list of some common analytical techniques and their use cases.

Preprocessing and Processing

In preprocessing, raw remote sensing data must be converted and calibrated[13]. For satellite imagery, this means converting sensor readings to physical units (e.g. reflectance, temperature), correcting for atmospheric effects (e.g. haze, moisture), and geometric corrections so that image pixels line up with real-world coordinates. After that, processing includes computation of indices (like NDVI from red and NIR bands; Figure 10), generating composites (e.g. median image over a season), or simple change detection (subtracting one date's image from another to see differences).

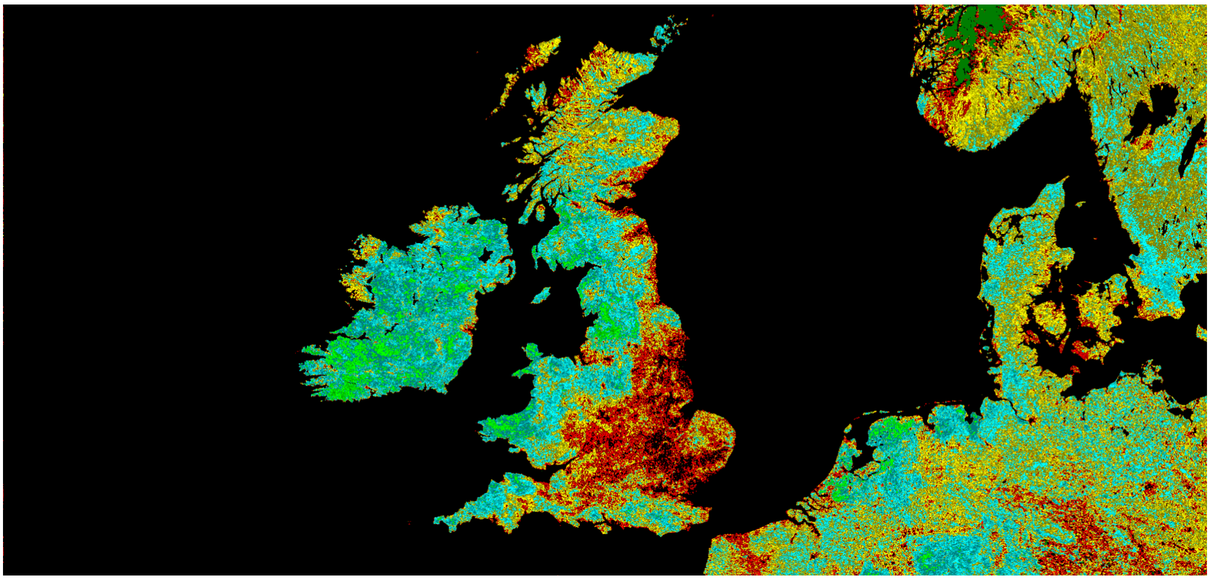

Figure 10. Average NDVI over the British Isles for one year from NOAA Advanced Very High Resolution Radiometer (October 2003). Green colours represent healthier vegetation while black and red represent very little vegetation. Image: G. Cappelluti.

[13] Calibration is the comparison of measurements delivered by a device with those of a calibration standard of known accuracy, in remote sensing, often a very accurate GPS ground point.

Next, in analyses to detect deforestation, for example, analysts might compare NDVI-informed images across years and flag areas that decreased from high NDVI (forest) to low NDVI (bare ground). These tasks often use Geographic Information System (GIS) software in conjunction with remote sensing software (like QGIS, ArcGIS, ENVI) that are programmed with algorithms, essentially applying formulas or thresholds to interpret datasets.

Cloud computing and big data frameworks are necessary for processing large scale or decades-long remote sensing data archives and can pose a technical barrier to a nationwide approach. However, today A-NZ researchers and agencies increasingly utilise cloud platforms such as Google Earth Engine, Amazon Web Services, or ESA's Copernicus Data Space for big data processing. This avoids downloading terabytes of data locally and lowers this technical barrier substantially. This approach is used successfully by MapBiomas in Brazil, by starting with open access Google Earth Engine data and the Google Cloud Platform, and then refining land classification to fit their country. A theoretical use case would be if all Sentinel-2 satellite images for A-NZ were analysed in Google Earth Engine to compute a national wetlands map by applying a classifier across the entire archive. This report recommends boosting capacity in this technical area, ensuring enough people in A-NZ are trained to use these platforms and that partnerships with big computational providers are available.

Analysis: Traditional statistics and the growing role of Artificial Intelligence (Machine Learning)

Traditional statistical analyses using simple software have included techniques such as regression analysis, correlation, time-series trend analysis, and geostatistics. These have been used when there is historically an established relationship between the remote sensing measurements and a response variable of interest. For instance, it's common to develop a linear regression model relating satellite-measured brightness in certain light bands to field-measured chlorophyll or suspended particles in a lake to analyse water quality (Figure 11; Allan et al., 2015). Or use multiple regression to predict soil organic carbon from a combination of spectral indices and terrain attributes (Mundada & Jain, 2025). Statistical approaches also include principal component analysis (PCA) to reduce data dimensionality or isolate patterns, and time-series analysis to identify seasonal cycles or long-term trends in pixel values. Further, researchers have also used ordinary least squares trends on 30-year satellite time series data to quantify where vegetation health and density is increasing or decreasing (Yan et al., 2021). Statistical analyses of small datasets using basic software is relatively transparent, relies on assumptions (normality, linearity, etc.), but may not capture complex non-linear relationships.

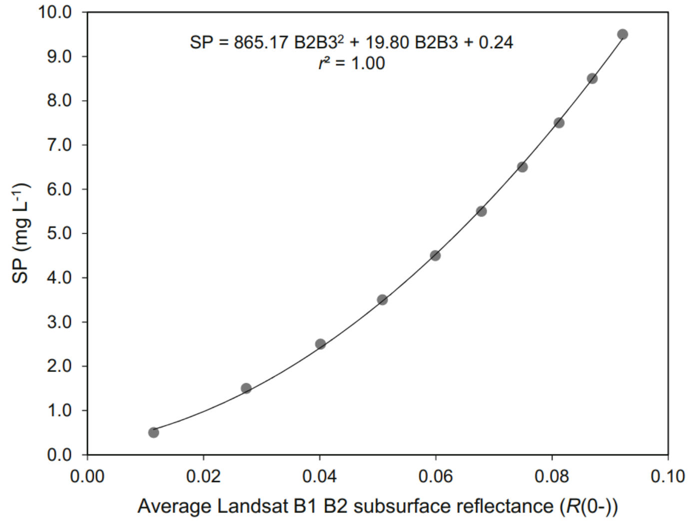

Figure 11. A linear regression model showing the statistical relationship between lake water suspended particle (SP) concentrations and subsurface reflectance in imagery captured by Landsat B1 and B2 (averaged). This relationship is useful for establishing expected suspended particle concentrations in lake water from satellite imagery. Image: (Allan et al., 2015)

With the rapid growth of remote sensing data volume and complexity (especially with hyperspectral and multi-sensor set ups), an AI technique called machine learning has become crucial for employing statistical analyses. Classification tasks (like mapping land cover from imagery) often use machine learning algorithms for making sense of data, such as random forest models, support vector machines, or neural networks (see Appendix A for full description of statistical approaches). In fact, random forest classifiers are popular in A-NZ's remote sensing community for land cover mapping because they handle many input features well and are less prone to model overfitting[14] (Khan et al., 2025). For example, a modern day biodiversity mapping project using random forest modelling could utilise dozens of satellite data bands plus LiDAR metrics to classify habitat types. Random forest analysis dominates machine learning approaches in A-NZ remote sensing data interpretation (Gavaghan et al., 2019), while more complex deep learning approaches (i.e. neural networks first developed in the 1980s) have had slower uptake (except in specialised areas like hydrology).

Deep learning is an emerging field, where convolutional neural networks (CNNs) and new architectures (like transformer models) can automatically learn features from imagery to execute tasks such as object detection (e.g. locating individual trees or animals in images) or semantic segmentation (pixel-wise classification). For example, a mask R-CNN (a type of deep learning CNN) has been applied in research to detect methane plume shapes in hyperspectral images (Kumar et al., 2020).

[14] Overfitting is the production of a model that corresponds too closely to a particular dataset and may therefore fail to fit to additional data or predict future observations.

Accuracy and Validation

Regardless of the analytical approach, results need to be validated against trusted data and then assessed for prediction accuracy. Accuracy and validation are distinct but related concepts where accuracy is a metric and validation is a process. Accuracy refers to how close a measured or predicted value is to the true or actual value. In machine learning, it quantifies the proportion of correct predictions made by a model on a given dataset. For example, if a model correctly classifies 90 out of 100 images, its accuracy is 90%. An accuracy assessment involves comparing remote-sensing-derived information to a trusted dataset of the same kind of data. For land classification maps (where an area is classified as a certain category i.e. land cover types), accuracy is often assessed with confusion matrices or use of intersection over union (IOU) calculations by comparing the predictions to field verified samples; see Appendix A for descriptions. For quantitative products (e.g. a map of carbon stock), statistical error metrics are often calculated against validation plots (Root Mean Square Error, bias; see Appendix A).

Validation, in a broad sense, refers to the process of ensuring that something is correct, consistent, or meets specific requirements. In machine learning, validation specifically refers to the process of evaluating a model's performance on a separate trusted dataset, known as the 'validation dataset', that was not used during the model's training. This assesses how well the model generalises to unseen data and prevents overfitting. Validation is a persistent challenge in A-NZ because of limited availability of already trusted, ground-truthed data sources. An ideal validation approach is to compare against existing datasets in a similar format (e.g. using the LCDB as a baseline for new land cover predictions). However, this only allows for comparison between these two datasets and prevents reporting on changes with absolute certainty. Without readily available validation datasets, analysts require generation of new validation data, often an expensive proposition entailing substantial people time on the ground. While feasible for smaller areas, and somewhat dependent on data type, this can become financially prohibitive if the scale is large, say region size. In these situations, a sub-sample of the area is often used for validation data collection, followed by extrapolation to estimate a value for the entire area (with some uncertainty associated). This report later emphasises the importance of establishing constant ground-truthing sites across environmental domains to improve the availability of remote sensing validation datasets.

Which analysis when?

Analysis approaches tend to differ by application area depending on output needs. For GHG monitoring, atmospheric inverse modelling is undertaken using remote sensing data as inputs to atmospheric models to estimate emissions sources and sinks (Bukosa et al., 2025). For hydrology, remote sensing data feeds into hydrological models (like using radar rainfall estimates to drive river flow models). For biodiversity, species distribution models might combine occurrence records (sometimes derived from remote cameras or acoustic sensors) with environmental data layers from remote sensing to predict habitat suitability. These models often integrate statistical methods (like logistic regression or Bayesian models) with remote sensing-derived predictors.

In summary, data processing and analysis using remote sensing data requires a blend of highly technical skills. It requires technical knowledge to process the data, apply algorithms and interpret results, as well as understanding of environmental context to choose the right approach from those available. A current trend of note is the movement toward automation and use of AI, seen in platforms that automatically detect data changes (like deforestation alerts from Planet Labs) or near-real-time processing pipelines (e.g. The CawthronEye system delivers processed coastal satellite images within 3 hours for public use). Aotearoa New Zealand's capability in remote sensing processing is growing, but continued investment in software, training, and collaboration (including open-source code sharing) will be important to fully capitalise on the data deluge from new sensor types.

Section 2: Who is Doing Remote Sensing?

Remote sensing of the environment in A-NZ currently involves a mix of players including public sector (government agencies), research institutions and academia, private companies, international providers, and community initiatives. Each brings different expertise and has differing motivations for involvement. There are some partnerships, and some of the data collected is shared open access, but efforts are largely siloed with collected data remaining proprietary. Understanding who the players are helps in identifying opportunities for better coordination and collaboration (Table 2 provides a list of key players).

Hubs that foster remote sensing collaboration and uptake are critical. A large one being the A-NZ chapter of the Institute of Electrical and Electronics Engineers Geoscience and Remote Sensing Society (IEEE GRSS). Such organisations directly affect the future of remote sensing use in A-NZ, as GRSS membership includes representation from all the sectors mentioned below and increases partnerships and data sharing.

To illustrate the variety of contributors, Table 2 lists the organisations and initiatives mentioned throughout this report, from A-NZ government agencies to private companies (both domestic and international) to community groups, along with their remote sensing-related activities. The appendix serves as a quick reference to who does what. The key takeaway is that A-NZ has a varied but fragmented ecosystem of organisations with remote sensing capability. One of this report's central recommendations is to improve cross-organisation collaboration and data sharing (see Recommendations section), so that these groups can more easily build on each other's data and expertise, rather than duplicating efforts or guarding data. Encouragingly, initiatives like Eco-index's free and open digital public goods deliver "science-based spatial intelligence" by bringing multiple datasets together for users, pointing toward the kind of integrated, open approach that benefits the whole country.

Government Agencies

Government departments are both users and producers of remote sensing data. Central government agencies like the Ministry for the Environment (MfE) and Stats NZ incorporate satellite-derived data into national environmental reporting (e.g. using satellite-captured land cover data in *Our Environment* reports). The Department of Conservation (DOC) uses remote sensing for monitoring large tracts of public conservation land and water (tracking habitat change, detecting wildfires, measuring suspended solids or tracking vegetation health issues (Pinkerton et al., 2022). Regional councils are particularly active, as they routinely commission aerial surveys (e.g. LiDAR for flood modelling) and are increasingly deploying their own drones for resource consent monitoring (like checking compliance on forestry cut-blocks or dairy effluent ponds).

One noteworthy collaborative initiative is the Provincial Growth Fund LiDAR project, where central and local government have co-funded LiDAR mapping for many regions to improve hazard mapping and planning. Another example is LINZ, which runs the NZ Imagery Strategy that coordinates periodic national aerial photography so that baseline imagery is constantly updated. NIWA and GNS are under contract to the central government to operate many environmental sensor networks. For example, NIWA has run satellite data receiving stations and the *NIWA-SCENZ* portal for coastal satellite data (Gall et al., 2022), while GNS has used satellite InSAR (radar interferometry) to monitor land deformation for earthquake and volcanic risk. These government agencies typically focus on one or two aspects of remote sensing aligned with their mandates (e.g. NIWA on water and climate, GNS on geological hazards).

Research Institutions and Academia

Aotearoa New Zealand's universities, independent research institutions and Crown Research Institutes (CRIs) contribute a great deal to remote sensing research and application. The CRIs each have relevant programmes. Scion uses a vast array of remote sensing data, for example LiDAR and satellite data are used for forest inventory and carbon monitoring. Manaaki Whenua Landcare Research uses remote sensing data for land cover mapping, soil surveys (to guide where to sample soils), and to evaluate ecosystem extent changes. Remote sensing data is used for horticultural applications by AgResearch (e.g. using hyperspectral data to detect crop diseases) (Ram et al., 2024) as well as for pasture and emissions studies (Farmax, Overseer). NIWA has scientists dedicated to satellite oceanography, climate, and methane monitoring. GNS has a Spectral, Thermal and Active Remote Sensing (STARS) data resource which contains spectral images and SAR remotely sensed images that can be used to detect changes in different surface features, particularly in A-NZ and the Pacific Islands. Importantly, researchers often engage in international projects which bring global expertise to A-NZ, e.g. NIWA's participation in NASA's Total Carbon Column Observing Network (TCCON) for atmospheric gases.

The University of Canterbury hosts a Geospatial Research Institute which works to develop algorithms using remote sensing data from their partnering initiatives like the Rongowai programme. The UC School of Forestry contributes to the Forest Insights platform. The University of Auckland hosts the Auckland Space Institute and Earth Observation Lab. University of Otago uses remote sensing data in its School of Surveying and the Mountain Research Centre. The University of Waikato hosts research programmes focused on water quality remote sensing and is active in AI development for environmental data through the collaborative multi-institute TAIAO programme. Massey University and others conduct precision agriculture research using drones and satellite data for applications on farms (Hedley, 2015). The academic sector tends to publish results and open data, contributing to public knowledge and empowering other researchers to expand the field faster and further, but their efforts may be fragmented by discipline or region.

Private Companies

Remote sensing data is collected, analysed and made commercially available by a range of private companies both internationally and domestically. Such companies are highly diverse in the technology they use, data they provide, applications, and how they incorporate remote sensing into their business models. Companies include those which provide the hardware or software for remote sensing data collection. Hardware includes manufacturing of satellites, drones and specialised imaging equipment. Software is for conducting analytics or providing platforms for data access, visualisation and combining multiple sources of remote sensing data.

Other companies are engaged in raw data collection, such as operating satellites and satellite sensing equipment or operating aircraft or drones for aerial imaging. Such companies may collect the data, then make it available commercially to a range of users while other companies collect data commissioned directly at the request of clients (selling the data collection services rather than the data specifically). Still others focus on providing value-add elements like consulting, planning or other environmental management services, without engaging in data collection directly (and may engage with third-party providers to access data on a client’s behalf).

International Providers

Aotearoa New Zealand relies on international providers for a lot of environmental remote sensing data. Notable satellite data providers are Planet Labs and Maxar, which have contracts or programmes in A-NZ (e.g. the Ministry of Business, Innovation & Employment had a data partnership with Maxar for research, and Planet Lab’s high-resolution imagery is used by various A-NZ organisations, such as Eco-index’s Observer product).

Specialised companies overseas fill certain niches. For carbon-related monitoring, firms like Carbon Space (digital carbon monitoring, reporting and verification platform) and Global Forest Watch (a World Resources Institute platform for forest change) provide tools A-NZ groups utilise. Another example, UK-based APEM Group (which has an A-NZ presence through acquisitions) offers high-resolution aerial and satellite remote sensing for aquatic ecology and environmental impact assessments. They offer expertise in areas such as hyperspectral coastal mapping and have been contracted on projects like monitoring coastal algal blooms. Descartes Labs (USA) provides a cloud platform for analysis of satellite data and has been engaged in A-NZ for tasks like land use change detection with AI. International space agencies (NASA, ESA) also actively include A-NZ. For instance, a partnership in the MethaneSAT mission for detecting agricultural methane emissions from space (launched March

2024). Unfortunately, the MethaneSat mission lost connection in June 2025, but not before valuable data had been obtained. These links to international providers mean A-NZ can access cutting-edge data and algorithms and also ensures alignment with global standards (e.g. adopting emerging data formats, ensuring A-NZ data feeds can integrate with networks like Global Earth Observation System of Systems (GEOSS)).

Community Initiatives

Citizen science and community groups are also players on the environmental remote sensing scene. While not a large contributor in absolute terms, they can have a large effect since they typically release their data open access. For example, local environmental groups might use camera traps or drones to document changes (e.g. non-native animal numbers during trapping initiatives or river care groups mapping non-native invasive willow tree removals). The data from apps like iNaturalist (citizen-logged species observations) or eBird (citizen-logged bird sightings) are not typically remote sensing data, but they complement remote sensing data by being a ground truthed dataset source. Increasingly, these apps do incorporate remote sensing context (e.g. iNaturalist suggestions aided by satellite habitat layers from their Geomodel). Like other players on the remote sensing scene, community initiative efforts can be quite siloed.

Open-source developers also playing a role here by creating remote sensing-related tools. For example, the Google Earth Engine community of developers has shared code for processing A-NZ Sentinel satellite data, and projects like OpenDataCube are being evaluated for A-NZ use. Examples like Wilderlab's open environmental DNA (eDNA) monitoring and some government agency and university collaborations show there is a breadth of contributors to the open access space.

Table 2. Aotearoa New Zealand key players collecting, sharing, or guiding the management of remote sensing data (non-exhaustive list).

Organisation	Type	Primary Role	Example(s) of remote sensing work
AgResearch	Research Organisation (Public)	Agri-based science research	Mapping pastoral plant functional groups using aerial hyperspectral imagery
Cawthron Institute	Research Institute (Independent)	Coastal and aquatic research	CawthronEye provides regular satellite imagery for coastal monitoring, water quality observations and fishing activities
Community Groups	Community Organisations	Grassroots environmental monitoring	Thermal drones for possum detection in predator free efforts
Department of Conservation (DOC)	Central Government	Conservation land management and monitoring	Remote sensing for ecosystem health, species monitoring, coastal sediment monitoring and carbon storage assessments
EO Lab	Professional Society (informal)	Community of Practice	Data sharing, events and networking
Forest & Bird	Environmental NGO	Environmental advocacy and monitoring	Satellite imagery for deforestation mapping (e.g. Hawke's Bay) as well as open data advocacy
Geospatial Research Institute, University of Canterbury	Academic Institution	Multi-domain geospatial research including applications in remote sensing	Integration of Global Navigational Satellite System (GNSS) remote sensing measurements of soil moisture from several platforms of satellites, aircraft and ground receivers
GNS Science (GNS)	Research Organisation (Public)	Geological hazard monitoring and research	GeoNet provides InSAR remote sensing for land deformation, geothermal and coastal studies
IEEE Geoscience and Remote Sensing Society (Joint NZ Chapter)	Professional Society (formal)	Building and promoting the NZ geoscience and remote sensing community	Remote Sensing Summer School (2023) to develop and foster domestic expertise and capacity
Land Information NZ (LINZ)	Central Government	Foundational geospatial data provision	Data provision, including topography, aerial imagery, LiDAR and soils as well as national elevation mapping coordination
Manaaki Whenua – Landcare Research (MWLR)	Research Organisation (Public)	Land cover mapping, soil and biodiversity data	LCDB mapping, S-map soils database, biodiversity datasets
Massey University	Academic Institution	Precision agriculture research	Precision agriculture trials with UAVs

Organisation	Type	Primary Role	Example(s) of remote sensing work
Ministry for the Environment (MfE)	Central Government	Environmental reporting and policy oversight	Uses LCDB maps in national reports, uses satellite and aerial imagery to classify land into United Nations Framework Convention on Climate Change land-use categories
National Institute of Water and Atmospheric Research (NIWA)	Research Organisation (Public)	Climate and ocean observing systems	NIWA-SCENZ provides A-NZ wide maps of satellite water quality data, CarbonWatch-NZ provides greenhouse gas information
NZ Space Agency	Central Government	Lead government agency for space policy, regulation and sector development	Published the New Zealand Space and Advanced Aviation Strategy 2024-2030
Regional Councils	Local Government	Regional environmental monitoring and compliance	LiDAR for flood modelling, drone inspections, LAWA freshwater quality data sharing
Scion	Research Organisation (Public)	Forest research and monitoring technology	Forest Insights platform (UAV LiDAR + AI) provides overview of availability and growth of planted radiata pine over time
Stats NZ & Environmental Reporting Team	Central Government	Environmental indicator reporting and data standards	Co-produces reports with MfE, manages data.govt.nz open data portal
Te Kāhui Raraunga	Charitable Trust	Leading the action required to realise the advocacy of the Data Iwi Leaders Group	Provides guidance for system-wide governance of Māori data through the Māori Data Governance Model
Te Mana Raraunga	Māori Data Sovereignty Network	Indigenous data governance guidance	Provides principles for Māori data sovereignty and contributed to the Kaitiaki Intelligence Platform design
Te Pūnaha Ātea University of Auckland Space Institute	Academic Institution	Applied research in space science, engineering, and applications of space data	Synthetic aperture radar hardware and software development
Te Uru Rākau – NZ Forest Service	Central Government	Forest management and ETS compliance	Satellite data for deforestation alerts and GIS assessments
University of Waikato	Academic Institution	Freshwater research	Lake water quality remote sensing and TAIAO project dataset sharing
Victoria University of Wellington	Academic Institution	Climate and polar research	Antarctic and climate remote sensing research, environmental digital twin research

Section 3: Environmental Focus Areas and Remote Sensing Applications

Remote sensing enables more consistent, repeatable observation of Aotearoa New Zealand's (A-NZ's) many environments. It can be used to monitor across space and time, and to understand condition, change, and stress. As used here, a 'focus area' can be thought of as a challenge or problem area for A-NZ, to which remote sensing applications could be particularly helpful. This section provides a description of how various remote sensing data types and collection platforms are combined with advanced analytical methods to monitor and manage seven major focus areas of environmental concern: biodiversity, greenhouse gases and climate change, land cover and land use, carbon sequestration, soil condition, water quality and hydrology, and marine condition. The focus areas sometimes overlap, and integrated approaches are increasingly used to capture their interdependencies. Each subsection below describes the state of remote sensing applications in the focus area, including methods, examples, and emerging developments, while suggesting policy-relevant insights for environmental decision-making.

An introduction to Spotlight Boxes in this Report

To collect information for this report, an internet-based desktop survey of remote sensing-related organisations was conducted. This survey identified examples of how remote sensing technology is being developed and put into action by private companies and other organisations to deliver environmental monitoring solutions.

Green Spotlight Boxes are used in this section to profile examples where remote sensing technologies are applied to A-NZ's environmental challenges. All information in Spotlight Boxes was sourced from organisational webpages, survey methodology for which is described in Appendix B.

Biodiversity

Biodiversity monitoring involves the systematic observation and assessment of living organisms to track changes (Beever, 2006). Remote sensing data may inform variables such as wildlife distribution (Radović et al., 2025), non-native invasive plant and animal incursions (Peterson et al., 2024), and the extent and integrity of native ecosystems on land and in water (Kamaruzzaman et al., 2025). It reveals changes in ecological quality and connectivity, such as forest canopy complexity and fragmentation (Mahapatra et al., 2025), and supports assessments of overall ecosystem condition (such as disturbance or regeneration status), especially when integrated with data collected by other means.

Monitoring typically includes identifying and mapping different species, vegetation types, and functional indicators using various remote sensing technologies such as satellite imagery, aerial surveys, and ground-based sensors to inform conservation efforts. Remote sensing for biodiversity monitoring applications often draws on multiple data types and advanced analysis techniques to disentangle the complexity inherent in nature (Liu et al., 2023)[15].

In terms of large-scale approaches, multispectral imaging is used to map ecosystem extent and condition by assessing vegetation types and plant species. Combined with LIDAR it can be used to construct 3D maps of vegetation structure as well (Figure 5). Dense, complex canopy and understorey structure might indicate an old-growth ecosystem in good condition supporting high species richness, whereas canopy gaps or structural uniformity might reveal degradation or non-native species' impacts such as ungulate browse in the understorey (Chevaux et al., 2022).

The full suite of remote sensing technologies applied together paint a detailed picture of biodiversity status above and below ground. Space and aerial methods can be combined with ground-based sensing technologies, especially for cryptic or nocturnal species (Zukswert et al., 2024). Thermal imaging cameras detect heat signatures of some animals, making them invaluable for nighttime monitoring of wildlife. Similarly, bioacoustic sensors processed with specialised software can identify species and their abundance by their unique calls (Navine et al., 2024). A network of ground-based motion-activated camera traps in the understorey can verify presence of cryptic species like native lizards (Welbourne et al., 2020), or radio telemetry allows tracking of native bird species over large distances as they look for suitable foraging habitat (Lamb et al., 2023). Machine learning platforms can analyse thousands of camera trap images or radio telemetry signals in conjunction with acoustic data to identify species without manual review. Environmental ground-based sensors can continuously monitor temperature, humidity, water quality, and other conditions affecting biodiversity as well.

[15] eDNA is also a helpful technology for monitoring biodiversity and can perhaps be included in a broader definition of remote sensing. However, this technology is not a focus of this report.

These sorts of methods can be supported by mobile phone apps and citizen science platforms which enable broader community participation in data collection. Recent growth in this area has expanded monitoring coverage beyond what professional companies alone can achieve. Many of these technologies work with GPS systems to create geo-tagged data.

Emerging research and applications of remote sensing in biodiversity monitoring illustrate promise and some limitations in this focus area. A review of recent studies shows a heavy reliance on satellite imagery (especially free, open-access data from platforms like Sentinel-2 and Landsat), while the use of high-resolution imagery remains relatively limited due to availability (Attard et al., 2024). This suggests an opportunity to exploit drones more for fine-scale habitat and species monitoring, since drones can provide imagery at centimetre-level resolution that satellites cannot match.

For analysing biodiversity monitoring data, machine learning has become fairly common (Cipriano et al., 2025). For example, approaches like random forest modelling are dominant for classifying ecosystem types or predicting species distributions, but more advanced deep learning (neural network) approaches are only beginning to be adopted. As data volumes grow, use of deep learning to handle complex, non-linear patterns in biodiversity data is expected to increase (Pettorelli et al., 2025). Deep learning can be used to recognise subtle indicators of ecosystem change that simpler models might miss. This approach, which integrates diverse data sources, exemplifies how innovation in remote sensing can directly support biosecurity by enabling early detection of non-native invasive species for eradication (Zaka & Samat, 2024; Lake et al., 2022). Training of these models requires ground truthed data which is often difficult to obtain at the scales that the analyses are conducted (catchment or larger). Open-source datasets such as iNaturalist can provide validation data for model assessment in localised areas but fall short of nationwide coverage.

Who is conducting remote sensing of biodiversity in Aotearoa New Zealand?

The Department of Conservation (DOC) has invested in remote sensing for many years with a particular focus on LiDAR technology, drone applications and remote sensing monitoring systems for ecosystem health (Trotter & Brown, 1998; Case et al., 2019; Ryan et al., 2025), species monitoring (Greene et al., 2020; DOC & Toitū Te Whenua Land Information New Zealand, 2023), coastal sediments (Pinkerton et al., 2022) and carbon storage assessment (joint initiative with Te Uru Rākau – New Zealand Forest Service et al., 2024). In 2023 DOC and LINZ published a shared Long-Term Insights Briefing on the use of emerging technologies to help biodiversity (DOC & Toitū Te Whenua Land Information New Zealand, 2023), including remote sensing. This briefing reviewed current and potential applications and was informed by public consultation.

Many public organisations or publicly funded initiatives have been developing remote sensing-related biodiversity tools and datasets made openly available. These include the TAIAO programme, which is hosted by the University of Waikato with collaboration from Universities of Auckland, Canterbury, Victoria University of Wellington, Beca and

MetService. This large programme with diverse collaborators has curated many remote sensing datasets such as the pre-labelled Waikato aerial imagery, Sentinel datasets, and various camera trap datasets. The programme is funded publicly by the Ministry of Business, Innovation, and Employment (MBIE) and is a great example of making data collected through publicly funded research accessible.

The private sector is also involved. Several of A-NZ's biggest environmental remote sensing companies offer biodiversity-related applications. Interpine Innovation primarily focuses on tree plantation monitoring but also offers native forest biodiversity monitoring. Similarly, Dragonfly Datascience works with LiDAR data for native forest health monitoring and ecosystem responses to non-native invasive species control. The company Groundtruth emphasises ground-based integration by building interoperable sensor networks that multiple organisations (or their products) can contribute to, and therefore improve coverage. Their work includes the TrapNZ system that unifies data from multiple sensor providers through the long-range wide area (LoRaWAN) network. As a tool for management of non-native invasive species, TrapNZ uses mapping technology and heatmaps to track population management intervention efficacy.

Other companies offer services which use space-based or aerial-based data. Envico Technologies focuses on drone technologies with autonomous sensor systems (Spotlight Box 1). Envico has applied this technology to deliver immediate, autonomous responses like targeted bait distribution for challenging locations, and where large-scale coverage is a key requirement[16]. Cornerstone Conservation provides habitat and species monitoring, combining drone imaging and thermal camera detection with field-based approaches including detection dogs and surveys by humans. Their approach provides precise, GPS-tagged data across diverse, remote environments. Eco-index combines machine learning with remote sensing data to map ecosystem extent and identify areas suitable for ecosystem reconstruction at the catchment scale. The MAUI63 programme uses machine learning algorithms that automatically identify individual dolphins and create spatial distribution models. Further, decision support tools like Plant your Patch integrate location, landscape characteristics, soil type, and water levels with remote sensing imagery for optimal tree planting. It also incorporates cultural knowledge about the history and benefits of tree species.

Biodiversity applications of remote sensing technologies show a convergence of technologies: *in situ* sensors, space and aerial data, and AI analytics are used in concert to detect life. Remote sensing provides early warnings of biodiversity loss and measures intervention success (e.g. restoration planting growth or bird song increase). By integrating indigenous knowledge and community observations alongside western science, (i.e. like in KIPs), remote sensing biodiversity monitoring delivers technical insights to support on-the-ground actions. Such a holistic approach is crucial for safeguarding A-NZ's unique flora and fauna.

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[16] Traps, technology and lizard tales on the Kapiti Coast; High-flying conservation tech; Taking flight: saving nature from the sky; Bay of Plenty made technology

Spotlight Box 1: Remote Sensing in Action - Biodiversity in Aotearoa New Zealand

The Organisation
Envico is an A-NZ company that develops and deploys drones specialised for non-native invasive animal management. Their technological innovation supports large scale eradication and can support ecosystem regeneration as a result.

The Technology
Envico has a range of proprietary heavy-lift drone hardware and software that builds self-contained, intelligent aerial platforms which have integrated sensors. Their specialised baiting drones are pre-programmable, utilise 3D terrain mapping, and carry specialised bait dispersal systems more accurate and cheaper than helicopter-based methodologies. Their thermal imaging drones (developed with MWLR) capture imagery which machine learning then classifies to generate species population density maps. This occurs using automatic classification of species, making it faster and more efficient than traditional methods. Envico have also developed ground-based sensor systems like the Spitfire Smart Trap for continuous non-native invasive species control and drone seeding technology to support vegetation restoration.

The Application
Envico has delivered ground-breaking conservation projects in terms of scale and remoteness, with focus on rat eradication in island ecosystems. They have received an award for their work in the Asia-Pacific region. The company also focuses on the social, cultural and community context of conservation. A Māori company, underpinned by Māori values including kaitiakitangi, they work closely with other indigenous communities as a core part of project success. Envico partnered with local communities to deliver drone operation training and subsequent delivery of a restoration project on the islands of Wallis and Futuna. This project increased coverage and scale compared to prior projects, winning the Secretariat of the Pacific Regional Environment Programme's Pacific Invasive Species Battler of the Year Award.

Who is conducting remote sensing of biodiversity internationally?

International companies providing remote sensing for biodiversity monitoring offer a range of services based on satellite imagery, drones, and other advanced technologies used across large areas. Core services focus on:

- using LiDAR to create 3D maps of vegetation structure, like forest canopy.
- measuring forest extent to track deforestation and ecosystem condition.
- monitoring of protected areas to ensure they remain intact.
- creating detailed habitat maps for tracking changes in animal home ranges.

International companies do also provide ground-based sensor data that can provide species identification and cataloguing via trail cameras and traps, acoustic devices, telemetry and GPS animal collar tracking. International players are rapidly improving coverage, resolution, and accessibility of remote sensing data. This is done through technology advances in sensing and data collection, software platforms to process data, and improved implementation of the data outputs to manage projects.

To understand how different international companies are working in this space consider examples like software provider Esri, drone manufacturing by DJI and AgEagle's senseFly, and platform provider Global Forest Watch. Esri is a GIS software provider and has developed species distribution modelling capabilities that integrate high-resolution satellite imagery with environmental variables and species occurrence data. This software-based approach allows researchers to model habitat suitability and species migration patterns under changing climate conditions, addressing temporal gaps in biodiversity monitoring by enabling analysis across different time periods and environmental scenarios.

DJI is a drone manufacturing company that offers wildlife monitoring applications, notably thermal imaging systems for population tracking and experimental eDNA sampling developed through research collaborations with institutions such as ETH Zurich. Their Matrice drone platforms, when equipped with specialised robotic arms, can collect eDNA samples from places where species are under-sampled due to accessibility constraints (e.g. forest canopies). This approach increases spatial coverage while reducing environmental impact and research costs. Global Forest Watch, a web-based data platform operated by the World Resources Institute, has expanded beyond deforestation monitoring to provide comprehensive biodiversity mapping datasets developed in collaboration with The UN Environment Programme World Conservation Monitoring Centre (UNEP-WCMC), The International Union for Conservation of Nature (IUCN), and other large organisations. These publicly available data layers[17] visualise biodiversity intactness across forest ecosystems, allowing decision-makers to identify and prioritise areas for conservation action by indicating which forest areas support high biodiversity and also face threat.

AgEagle offers the senseFly eBee series aircraft equipped with multispectral sensors that capture detailed vegetation data across multiple spectral bands including near-infrared, red-edge, and visible light. These commercial drone systems enable computation of vegetation indices such as NDVI, Normalized Difference Red Edge (NDRE), and Optimized Soil-Adjusted Vegetation Index (OSAVI) for applications such as species identification, non-native invasive species mapping, and forest condition assessment.

Together these organisations' remote sensing technologies represent complementary aspects of biodiversity monitoring. Esri's software tools extend analytical capabilities into temporal and predictive dimensions, DJI's hardware platforms access previously

[17] For more information about the data layers, see Global Forest Watch Loss Year - Overview and About the Global Forest Review: The Data Behind the Global Forest Review

unreachable locations, Global Forest Watch provides openly accessible global-scale datasets for prioritisation, and senseFly's drone systems deliver high-resolution local data collection capabilities.

A more end-to-end approach is from MGGP Aero, who provide data collection and supply, data analysis and application, through to specialised mapping software platforms. This integrated approach develops technologies and techniques that enhance and expand data types and analysis techniques able to leverage the more complex datasets produced. This richer integrated data can then be applied in innovative ways, including biodiversity monitoring. For example, MGGP Aero delivers monitoring of non-forest Natura 2000 habitats using remote sensing methods under the HabitARS project, and has developed automated workflows for detecting dead trees, differentiating grassland habitats, and monitoring vegetation health.

Spotlight Box 2: Remote Sensing in Action - Biodiversity Internationally

The Organisation
APEM Group is an established consulting company operating across the United Kingdom, Ireland, Australia and North America. They provide biodiversity monitoring services such as wildlife surveys of amphibians, reptiles, mammals and marine species, as well as monitoring of protected species and invasive species.

The Technology
APEM Group includes in-house data collection and analysis in their services, integrating remote sensing data from aerial wildlife surveys, drone surveys, thermal imaging, LiDAR, and ground-surveys to support a range of biodiversity applications for clients. Their integrated data collection, mapping and analysis are focused on providing detailed views of terrain and topography, in-depth visual representations of locations including 3D outputs that support analysis of ecological trends, relationships and localised impacts. APEG Group has developed a range of technologies across software, hardware and analytics. For example, their WILDetect uses machine learning for detailed marine bird counts, and their Invertebase biological database of marine and freshwater phyto-invertebrates.

The Application
A key application of the APEM Group approach is in supporting clients in Biodiversity Net Gain (BNG) compliance. This includes developing baselines via vegetation assessments and botanical surveys including inventory and taxonomy aspects like the identification of non-native species. Sites are mapped using the UK Habitat Classification methodology, using APEM Group's aerial imagery technology to cover larger scale and remote locations. Their visualisation technology, including 3D representations and their H2OVER imagery product are used in habitat identification, modelling effects of intervention options, and for stakeholder engagement. Their ecological consulting is also able to provide biodiversity metrics and calculations of biodiversity units.

Greenhouse Gases and Climate Change

Monitoring Greenhouse Gases (GHGs) and related climate change via remote sensing involves measuring atmospheric concentrations of key gases such as carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), and sulphur hexafluoride (SF_6). This allows identification of both emission sources and sinks (where there is sequestration into a non-gaseous form) and observation of other climate-change related variables over time. Remote sensing allows GHG monitoring across scales from global (e.g. for climate models and international treaty verification) down to individual property level (e.g. detecting methane "hotspots" from dairy herds). Because of this a link can be formed between A-NZ's domestic emissions management and global climate change mitigation efforts.

In practice, no single sensor or platform can comprehensively monitor GHG emissions, so an integrated, multi-scale approach is required. Ground-based and aerial measurement systems complement satellite observations to capture the full picture. A range of satellite and aerial platforms are deployed to detect GHGs by inferring gas fluxes from land and ocean surfaces. Satellites (such as the GOSAT-1 equipped with infrared sensors) can quantify concentrations of CO_2 or CH_4 by analysing specific light absorption features in the air column beneath them (Butz et al., 2011). Closer to the ground, instruments like Tunable Diode Laser Absorption Spectroscopy (TDLAS) can be deployed on drones or fixed towers to directly measure methane or nitrous oxide fluxes from paddocks, effluent ponds, or landfills. Researchers also use flux chambers (small enclosures placed over soil or water surfaces) to trap gases for laboratory analysis (Collier et al., 2014), and Fourier-Transform Infrared (FTIR) spectrometers to detect multiple GHGs simultaneously by their infrared signatures (Lin et al., 2019).

Networks of atmospheric monitoring stations can be very helpful by continuously sampling GHG concentrations at key points and combining the data with high-resolution weather models (e.g. see NIWA's CarbonWatch-NZ). These yield a top-down estimate of A-NZ's carbon budget by analysing how winds transport CO_2 plumes from cities, farms, and forests. By integrating multiple data sources (e.g. satellite, aerial, and ground-based) using mathematical models, scientists can cross-verify GHG estimates and achieve a more continuous and granular monitoring system.

Who is conducting remote sensing of GHG and Climate Change in Aotearoa New Zealand?

Overall, A-NZ's GHG and climate change monitoring draws on a range of remote sensing tools in a layered approach. Satellites provide broad coverage and global context, aircraft and drones fill in medium-scale detail, and ground sensors and flux stations offer local precision. Advanced hyperspectral sensors are rapidly increasing capability to remotely detect even subtle emission changes. However, limits remain where cloud cover (for satellites), complex terrain, and the diffuse nature of agricultural emissions all pose challenges. Continuous improvement of analysis techniques (e.g. multi-sensor data fusion and AI) is underway to overcome these.

Aotearoa New Zealand's Land Use and Carbon Analysis System (LUCAS) uses satellite remote sensing to map afforestation, deforestation, and other land-use transitions since 1990 (run by MWLR). LUCAS combines data from sources like Landsat and Sentinel satellites to report on how much forest has been planted or lost, which feeds directly into the national GHG inventory and international climate change reports (under the UNFCCC). The resulting data underpin the accounting of carbon emissions and removals from land use, land-use change, and forestry (LULUCF), ensuring A-NZ meets its reporting obligations and can track progress against targets.

Aotearoa New Zealand's commitment to GHG monitoring was demonstrated in its support of the MethaneSAT mission, A-NZ's first government-funded science satellite dedicated to addressing climate change. MethaneSAT was designed to detect methane emissions worldwide, capable of measuring emission sources across a catchment or region with a resolution of 1 km^2. Unfortunately, the MethaneSAT satellite lost power and ground communications in June 2025, and is now considered irrevocably lost in space, however, during its operational time A-NZ led the agricultural emissions science for this mission (through NIWA and the University of Auckland's Space Institute). MethaneSAT was intended to complement existing related commercial efforts abroad. For example, Canadian company GHGSat operates satellites that can pinpoint methane leaks at 25 m resolution and aircraft that identify sources with less than 1 m resolution. Although the MethaneSAT is no longer operational, the data that was captured remains a good source for researchers to use to further complement other GHG analysis techniques.

As with all remote sensing, GHG data is complemented by and sometimes dependent on ground truth validation and modelling. Eddy covariance towers are an example of high precision *in situ* systems that measure gas flux exchanges between the land and the atmosphere. These consist of fast-response wind anemometers and gas analysers mounted on masts that sample the air multiple times per second. By analysing the fluctuations of gas concentrations in upward vs. downward air eddies, scientists can calculate whether a land area has a net release or absorption of a particular gas on a given day.

Ground truth data not only serve as validation for satellite estimates but also improve understanding of processes like how drought or time of day affects GHG release. Likewise, process-based ecosystem models (driven by weather data, land cover, soil info, etc.) are used to simulate GHG variations throughout a day. Remote sensing data provides key inputs and calibration points for these models (e.g. soil moisture from satellites to inform when N_2O emissions are likely occurring due to anaerobic soil conditions; Nevison et al., 2023). The interplay between remote sensing and validation data collected by other means is an active area of research (Langsdale et al., 2025) and the goal is to develop reliable "bottom-up" validation emission estimates that, when aggregated, match the "top-down" remote sensing observations through atmospheric monitoring. Any discrepancies might indicate missing emission sources or model errors, prompting further investigation.

By integrating remote sensing with traditional inventories and emerging technologies (such as potential satellite-based gravimetric tracking of water and carbon cycle changes), more data is available to inform climate policies and actions. Robust monitoring of GHGs is essential not only for tracking progress toward emission reduction targets but also for identifying new opportunities, for example, detecting previously unknown high-emission areas (like an undetected geothermal vent or wetland emissions) or verifying carbon sequestration by mass tree planting schemes. As remote sensing technology advances, it will remain a cornerstone of transparent, accountable climate change mitigation and adaptation strategies.

Who is conducting remote sensing of GHG and Climate Change internationally?

Beyond measuring current emissions and sinks, remote sensing is increasingly used to predict and manage climate-change related hazards, and climate change risks. Satellite data and analytics companies are merging climate science with Earth observation across various satellite and data technologies, including advanced satellite sensors and hyperspectral imaging, machine learning analytics, and integrated observation systems.

One area of focus for companies is delivering accurate emissions detection (particularly methane) in current-state real-time while others focus on predictive analytics across both near term and long-term time frames. Pixxel, Maxar Technologies, Descartes Lab (now EarthDaily Analytics), and Albedo are key players in this area. These companies exemplify complementary remote sensing approaches combining detection of atmospheric gases, future projections, climate-change related hazards prediction, and point source emissions pinpointing.

Pixxel leads in direct GHG detection with hyperspectral sensors capable of high-sensitivity methane emissions detection for identifying smaller emission sources and monitoring atmospheric composition changes (see Spotlight Box 3). Maxar Technologies combines operational methane detection (pinpointing sources within 5 m) with ClimateDesk's long-term climate projections to 2100, offering both immediate GHG monitoring and future risk assessment. Descartes Labs (now EarthDaily Analytics) focuses on AI-driven predictive analytics for climate-change related risks like wildfires and floods rather than direct GHG detection, using machine learning on satellite data to forecast near-term hazards. Albedo provides ultra-high spatial resolution via satellites in Very Low Earth Orbit (VLEO) at approximately 250-320 km altitude, capturing optical (10 cm), multispectral near infrared (40 cm), and thermal infrared data (2 m). This resolution is ideal for identifying emission infrastructure and facilities, but lacks the spectral capabilities needed for actual GHG measurement, so ultimately helpful for source attribution rather than detection.

Regarding climate-change related risk prediction and analytics services, there are a range of companies active globally. CARTO and ClimSystems[18] offer this as part of their broader remote sensing platforms, which service multiple industries and environmental and non-environmental monitoring applications. CARTO provides analytical infrastructure for organisations with existing climate data via their location intelligence platform that specialises in spatial analytics and visualisation. Their Climate Insights product identifies infrastructure most at risk from climate-related impacts, integrating with Google BigQuery and Earth Engine and providing access to over 12,000 spatial datasets. Companies like NetCarbon use CARTO to create "*KPI dashboards and compute indexes based on the health of vegetation, soil moisture, temperature*" for carbon dioxide monitoring, though CARTO uses existing data rather than collection of new data.

ClimSystems specialises in climate risk prediction through two flagship products. First, SimClim is a desktop modelling system that integrates CMIP6 and CMIP5 global climate models with observed weather records to provide spatially gridded climate data for education and research. Second, their Climate Insights is a commercial platform delivering site-specific climate risk assessments using over 60 metrics across atmosphere, land, and ocean domains, incorporating CMIP6 Shared Socioeconomic Pathways (SSPs) with 5th, 50th, and 95th percentile climate model outputs. Both services utilise data from complex global and regional climate models combined with observed climate and weather records, providing global spatial datasets at 0.5°x0.5° resolution (Lauer et al., 2023) and downscaled country data at 1 km resolution.

Aotearoa New Zealand benefits from these data and frameworks developed internationally. For example, from the Integrated Carbon Observation System (ICOS) in Europe, which is a comprehensive network that combines atmospheric measurements, ecosystem flux observations, and ocean monitoring to systematically track GHGs across the European continent. While ICOS is European, A-NZ's scientists engage with such efforts through the Global Research Alliance on Agricultural Greenhouse Gases (GRA) and similar knowledge networks. These collaborations ensure A-NZ stays at the forefront of methodological advances, whether it's new satellite sensors or improved atmospheric models, and can incorporate them domestically.

[18] ClimSystems is registered in A-NZ, however, operates internationally and so is classified as an international company here.

Spotlight Box 3: Remote Sensing in Action - Greenhouse Gases and Climate Change Internationally

The Organisation

Pixxel is a company that develops hyperspectral imaging satellites for various Earth observation applications, including GHG monitoring.

The Technology

Their flagship Firefly constellation began deployment in January 2025 and consists of satellites capable of capturing imagery at 5 m spatial resolution across more than 150 spectral bands in the visible to shortwave infrared range. This enables Firefly to detect subtle changes in chemical compositions, vegetation, water quality, and atmospheric conditions. This enhanced sensitivity, combined with daily revisit capabilities and a 40 km swath width, enables detection of small emission sources and precise monitoring of methane leaks (e.g. from pipelines, oil and gas facilities).

The Application

Pixxel's hyperspectral Aurora platform uses specialised indices (e.g., NDDI for drought, NDWI for flooding) to detect early vegetation stress, carbon estimation from sequestration, emission monitoring and ecosystem health assessments, and climate-related agricultural threats. This enables prediction of gradual climate impacts, rapid response to extreme weather, and provides insights into GHG emissions and storage. Pixxel has partnered with Kita, to better map, track and manage risk to large-scale carbon sequestration and mitigation projects and initiatives, particularly blue carbon, afforestation, and vegetation stress assessment.

Land Cover and Land Use

Remote sensing of land cover and land use focuses on mapping, classifying, and monitoring the Earth's surface to see how different land areas are being used and change over time. Using satellite and aerial imagery, data scientists distinguish features such as forests, croplands, wetlands, pastures, urban areas, and water bodies, often categorising land cover into standard classes for consistent change tracking (Sabaghy et al., 2025). By comparing images over time (multi-temporal analysis), changes like deforestation, urban expansion, crop rotation, or conversion of farmland to housing subdivisions are detected.

These remote observations support land management decisions and environmental monitoring by highlighting trends such as where ecosystem cover is being lost, where agricultural intensity is increasing, or how seasonal patterns (like drought or flooding) are affecting land cover (Bielecka et al., 2025; Phiri et al., 2020). In A-NZ, land cover data underpins a wide range of policy areas, from regional land-use planning and biodiversity management and conservation to water quality modelling (since land use affects runoff into water bodies) and climate change related reporting (land cover change affects carbon stocks; Motu; Dudley et al., 2020). For the large scale, satellite time-series data (such as the decades-long Landsat archive or the more recent Sentinel-2 imagery) are often processed in cloud platforms like Google Earth Engine to automate land change detection. For example, fire-burned areas are produced by analysing time-series satellite data to locate abrupt spectral changes caused by fires (Yailymov et al., 2023). Small scale observations from drones (UAVs) or aircraft are used for capturing finer details and have specialised applications.

Innovative uses of land cover remote sensing are emerging. One notable example is how Hummingbird Technologies uses satellite imagery to identify regenerative farming practices. Their algorithms can detect signatures of no-till agriculture or cover cropping practices by analysing crop residue patterns and vegetation indices. These advances illustrate that remote sensing is not limited to static mapping; it is increasingly about monitoring dynamic land use practices (like farming techniques or forestry operations) and linking them to environmental outcomes.

Recent research trends in land cover and land use remote sensing mirror those in the other focus areas, with a clear movement toward machine learning for processing data and multi-sensor integration on single platforms. Traditional linear regression statistical approaches are giving way to more flexible, advanced modelling approaches (Li et al., 2022). Studies indicate a shift, with machine learning-driven random forest classifiers now being common for land cover mapping due to their ability to handle heterogeneous inputs, although advanced convolutional neural networks (CNNs) are still underutilised in this focus area (Kasahun & Legesse, 2024). If deep learning models are appropriately applied this could lead to increased accuracy of complex land cover analyses, such as recognising subtle land use features (e.g. differentiating orchards from vineyards).

Research on remote sensing of Land Cover and Land Use at different scales has been somewhat siloed, and sometimes only conducted at property scale. There is a need for employment of methods that can bridge the gap between scales, for example, using machine learning models trained on high-resolution local data to inform broader regional analysis, thereby bridging property-to-catchment monitoring. Additionally, although drones can offer orders of magnitude finer resolution (cm scale) than satellites (m scale), academic studies in land cover have not fully capitalised on drone potential. This is likely due to the challenges of data volume, low-cost efficiency over large areas and limited flight coverage (Fassnacht et al., 2024). Increased uptake of drone data for larger scale analysis is growing and can be expected to increase. Further work in this area is covered in the journal Drone Systems and Applications.

Another trending aspect is near real-time monitoring. With increasing integration of diverse data streams (optical, radar, LiDAR) and automated classification, the goal of continuous land cover surveillance is becoming feasible (Fu et al., 2024). This could allow, for instance, detection of illegal land clearing or river sediment plumes from land erosion almost as they occur, enabling quicker management responses.

Many environmental monitoring challenges, such as classification and land use change, are being addressed by land cover and land use remote sensing. Key applications include:

- Standardisation of land use and land cover mapping classification: Using standards such as Multi-Resolution Land Characteristics (MRLC) classes to divide the land into categories such as forests, wetlands, grasslands, agricultural fields, urban areas, and water bodies. This provides a consistent nomenclature for analysis to be compared across research efforts.
- Land use and land cover change detection: Using remote sensing data to regularly update maps to detect changes such as deforestation or afforestation, urban sprawl, changes in crop patterns, or natural disturbances (fires, floods, landslides). For example, monitoring the annual conversion of pasture to pine plantations or tracking regeneration of native forest in retired farmland helps inform both economic models and conservation targets (Jayasinghe & Thomas, 2025).
- Agricultural assessment and crop analysis: Using high-resolution visible and multispectral imagery from satellites to identify crop types, assess crop health, and estimate yields. This can help with biosecurity (spotting disease outbreaks via changes in crop vigour) and optimise farm management through precision agriculture (Sebastiani et al., 2024).
- Urban expansion and infrastructure monitoring: Using a combination of UAV and satellite data to map new construction developments, impervious surface surfaces, and land use intensification in urban and peri-urban areas. This is critical for infrastructure planning, understanding habitat fragmentation, and modelling runoff (as urban surfaces replace permeable soils; Gilbert & Shi, 2023).

- Vegetation health and phenology: Monitoring seasonal changes in vegetated cover, detecting drought stress in plants, non-native invasive species infestations, or nutrient deficiencies via spectral indices NDVI or EVI across large areas to guide interventions in forestry and agriculture (Fadl et al., 2024).
- Wetland and coastal monitoring: Using specific satellite multispectral sensors (such as NIR and SWIR) to delineate wetlands, mangroves, and estuarine land cover, track sedimentation or erosion in these areas, and assess impacts of sea-level rise or land use upstream on coastal land cover (Khan et al., 2025; Esmaeel et al., 2025).

All these applications benefit from the increasing speed and automation of data processing. Machine learning-based classification has enhanced the accuracy and speed of land cover analysis, enabling some monitoring systems to approach near real-time updates (Fu et al., 2024). Algorithms can process terabytes of satellite data in days to produce new maps, and even flag anomalies or areas of rapid change for human analysts to review (Qu et al., 2023).

Who is conducting remote sensing of land cover and land use in Aotearoa New Zealand?

In A-NZ, land cover monitoring is provided by both public initiatives and private companies. Manaaki Whenua Landcare Research are stewards of the LCDB that has long provided a nationally consistent land cover map updated at regular intervals (~5 yearly), starting in 1996[19]. This database provides invaluable data for research, being one of very few datasets to cover the entire country and provide land cover change over 20 years.

There are now complementary private services emerging that update land cover and use changes more frequently with the use of machine learning techniques. The increased number of satellites generating imagery on a sub monthly basis provides the data necessary for the decrease in repeat coverage times. Private companies like Incredible Skies (Incredible Group), Landpro Limited, and Lynker Analytics are examples of specialised private providers offering these mapping services. Incredible Group flies drones equipped with high-resolution RGB cameras and LiDAR sensors to create detailed 3D maps. Their work ranges from ecosystem monitoring to disaster management. The fine detail of drone data (sub-10 cm resolution) allows for site-specific insights like identifying individual tree health or precisely measuring riverbank erosion. Through the generation of digital elevation models and orthophotos[20], this company creates data for further analysis by researchers.

[19] Global datasets using the same imagery have also been developed for public use: Global Dynamic Land Cover and WorldCover

[20] An orthophoto is a combination of multiple individual photos joined together into one large mosaic. Often used when a single image cannot capture an entire area or a higher level of detail is required than what would be possible with a single photo.

Landpro, combines aerial survey and GIS expertise with remote sensing. They operate advanced manned aircraft systems (e.g. a Topodrone 100 with post-processed kinematic GPS[21]) to capture large-area high-accuracy imagery for rural and urban planning purposes. Landpro's data support everything from designing irrigation schemes (by mapping terrain and land cover) to ensuring compliance with resource consents through accurate land use maps. Lynker Analytics is a data science and geospatial analytics consultancy focused on extracting insights from satellite imagery, aerial photography, drone data, and LiDAR using AI techniques. They provide automated land cover and land use mapping services using convolutional neural networks (CNNs) and other machine learning algorithms to classify multi-spectral imagery into detailed land cover categories. Their remote sensing expertise covers city-wide projects like Auckland Council's 5,000 square km region, as well as national-scale forest monitoring for MfE.

Who is conducting remote sensing of land cover and land use internationally?

Internationally, there are many companies focusing on remote sensing of land cover and land use, ranging from specialised startups to established large satellite imagery providers. Key players include SkyWatch, which operates a satellite data distribution platform connecting users with multiple Earth observation satellites, Trimble, offering integrated positioning and geospatial solutions for land use cover applications in the agricultural sector, Umbra, specialising in high-resolution SAR satellite technology and Vasundharaa, providing geo-ICT solutions for environmental monitoring. Major satellite imagery providers include Maxar Technologies, known for its high-resolution optical satellites, GeoEye (now part of Maxar), and BlackSky, which combines satellite imagery with AI-powered analytics.

[21] "Post-processed kinematic (PPK) is a method of using Global Navigation Satellite System (GNSS) data to accurately determine the position and trajectory of a rover/drone." Complete PPK Workflow for DJI Enterprise Drones.

Spotlight Box 4: Remote Sensing in Action - Land Cover and Land Use Internationally

The Organisation

Copernicus Global Land Service (CGLS) is part of the European Union's flagship Earth observation programme. It produces the Copernicus Global Dynamic Land Cover (GDLC) data, which is based on PROBA-Vegetation satellite observations provided by the Belgian Science Policy Office (BELSPO). As an official product of the global component of the Copernicus Land Service, access to this land cover dataset is fully free and open to all users worldwide.

The Technology

The GDLC product is generated using PROBA-V 100 m time-series satellite data combined with a database of approximately 168,000 high-quality land cover training sites and several ancillary datasets. It has dedicated pre-processing on the Sentinel-2 tiling grid (Buchhorn et al., 2020). The product provides land cover information at 100 m spatial resolution using a primary land cover scheme at three classification levels with 23 discrete classes defined according to the FAO Land Cover Classification System (LCCS) scheme. The processing workflow is sensor-agnostic and designed to transition from PROBA-V to Sentinel-2 time-series for future annual updates, with plans for yearly production continuing through the use of Sentinel satellite data.

The Application

The Copernicus GDLC data serves resource managers, policy makers, and scientists studying the global carbon cycle, biodiversity loss, and land degradation by providing synoptic overviews and broad stratification of land cover over large areas. Key applications include assessing land cover characteristics and changes related to Intergovernmental Panel on Climate Change (IPCC) land categories and supporting greenhouse gas inventories. The dataset achieves 80% overall accuracy at Level 1 classification globally and provides change detection capabilities with 99.6% accuracy for change/no-change mapping, making it valuable for monitoring over time.

Carbon Sequestration

Monitoring of carbon sequestration via remote sensing typically measures carbon stored in natural spaces like ecosystems. Focus is on vegetation (biomass of forests, shrublands, grasslands) and in soils, as well as tracking changes in these carbon stocks over time (W. Xu et al., 2025). This monitoring is a key component of climate change mitigation, as increasing carbon sequestration or avoiding carbon release from already-sequestered sites can help with GHG atmospheric concentrations (Elbakidze & McCarl, 2007). Remote sensing provides the means to estimate sequestered carbon stocks over large areas repeatedly, something that would be infeasible by ground measurements alone.

A range of remote sensing methods are deployed for carbon sequestration monitoring, each targeting different carbon pools. Above-ground biomass, like trees and shrubs, is often mapped with a combination of LiDAR and optical imagery. LiDAR gives tree height and canopy structure, while optical indices (like NDVI or others) give information on vegetation density and health. Together, these can be input to allometric models or machine learning algorithms that estimate how many tonnes of carbon per hectare are present in woody biomass (Fadil et al., 2024).

Satellite sensors are also used to infer biomass volume (a proxy of carbon content) by observing vegetation cover and structure. For example, NASA's GEDI LiDAR instrument on the International Space Station measures the vertical structure of forests and can estimate above-ground forest biomass density globally (Zurqani, 2025). By combining LiDAR data with optical satellite imagery (such as Sentinel-2 or PlanetScope) that distinguishes different vegetation types, researchers can improve these estimates, for instance using spectral data to tell a pine tree plantation from native forest to apply the correct carbon density values for tree group type (Zhou et al., 2025). Satellite radar missions (like ALOS PALSAR) have been used to estimate biomass of dense forests, and upcoming missions like NASA's NISAR will further improve vegetation carbon monitoring with dual-frequency radar.

In agricultural landscapes, multispectral imagery is used to predict crop types and even specific cultivars, which can be tied to known carbon sequestration potentials (e.g. a field of legumes vs. a field of wheat plants will sequester different amounts of carbon into the soil (Khalofah, 2025). Thus, for many landscapes, remote sensing is instrumental in quantifying carbon stocks and flows to verify carbon credit systems and inform climate strategies.

For soil organic carbon, remote sensing can be more challenging due to difficulties in the ability to take a direct soil reading. However, hyperspectral imagery can, through chlorophyll reflectance, detect certain soil properties (like organic matter content or moisture) that correlate with soil carbon (Jiang et al., 2024). Still, this often requires region-specific calibration. Notably, ground-based technologies are emerging to fill the soil carbon data gap. Companies are developing portable soil scanners and *in situ* probes. For instance, Canadian firms like ChrysaLabs and SoilOptix provide handheld or towed sensors (using infrared spectroscopy and gamma radiation) that can measure soil carbon along with nutrients and pH in real time. In practice, as in other focus areas of this report, these ground-based measurements are used to validate and refine the remote sensing models.

Validation and local calibration are of specific concern in carbon sequestration monitoring via remote sensing. Many commercial carbon sequestration estimator tools have been developed overseas and may not directly apply to A-NZ conditions. Soil types, mineralogy, and vegetation all affect soil carbon and can differ markedly from country to country (Reddy & Shwetha, 2024). So a carbon sequestration prediction model trained on, say, North American prairie soil might incorrectly estimate carbon in an A-NZ Northland dairy pasture soil. This has highlighted the need for A-NZ-specific calibration datasets, essentially ensuring that remote sensing predictions of carbon content are checked against actual field measurements from A-NZ. The central government and researchers are working on this. For example, the New Zealand Agricultural Greenhouse Gas Research Centre, MWLR, and the Ministry for Primary Industries (MPI) have jointly supported trials comparing remotely sensed international estimates with national soil carbon data (Roudier et al., 2015).

Encouragingly, emerging academic research in carbon sequestration remote sensing shows some clear directions. First, there is a push to extend analysis to global scales with platforms like GEDI or ESA's BIOMASS missions which map biomass and soil carbon worldwide at high resolution (30 m or better). Second, analysis methods are diversifying. Older studies often used simple regressions (e.g. relating NDVI to biomass in a bivariate, linear fashion; le Maire et al., 2011), but newer work employs neural networks and multi-sensor data fusion, allowing more complex relationships to be determined. For example, deep learning models can integrate optical images, LiDAR metrics, and even climatic variables to improve carbon stock predictions (Poudel et al., 2025). Third, there is growing interest in identifying agricultural practices that influence carbon stocks positively. Remote sensing is being used to identify where regenerative agriculture techniques are applied (i.e. continuous ground cover, diverse crop rotations), since these practices affect soil carbon sequestration. If those practices can be mapped (e.g. via classification algorithms on satellite time series), then over time monitoring has the potential to show whether areas under regenerative management show increasing soil carbon compared to conventional fields. Finally, research is addressing soil carbon mapping coverage. At the time of this report, only 44.3% of A-NZ's land had soil data available (MWLR Soils S-Map). New soil mapping projects are underway through MWLR as well as projects utilising the inclusion of soil sensors on aircraft (e.g. Rongowai programme).

Who is conducting remote sensing of carbon sequestration in Aotearoa New Zealand?

In A-NZ a range of companies offer forest carbon inventory services using third party aerial imagery, or offering aerial imaging services that may be applied to forest carbon assessments. In the private sector, demand for carbon sequestration services is dictated mostly by the Emissions Trading Scheme (ETS), which typically only requires traditional aerial imagery paired with carbon look-up tables. As a result, the number of emerging companies collecting remote sensing data to provide carbon sequestration reporting is limited due to difficulties of integrating into a somewhat inflexible system.

Key examples of A-NZ companies operating in this space include Interpine Innovation and CarbonCrop. Interpine Innovation is a Rotorua-based forestry consultancy that combines traditional forest inventory methods with remote sensing technologies for ETS compliance applications. Interpine has contributed to the LUCAS programme for over 20 years. Their remote sensing capabilities include airborne LiDAR systems using sensors and UAV-based mapping services. The company has developed machine learning algorithms for automated forest carbon assessment and provides satellite imagery analysis for large-scale carbon sequestration monitoring for carbon accounting. CarbonCrop has built a forest restoration platform utilising AI and remote sensing technologies to measure, monitor, and monetise newly-planted forest carbon sequestration. They have a focus on encouraging native forest restoration for biodiversity benefits alongside carbon capture (i.e. for carbon+ credits). The company's remote sensing approach integrates high-frequency satellite imagery from Planet Lab's satellite constellation, which captures the entire global landmass nearly daily with space-based LiDAR data from NASA's GEDI[22] mission deployed on the International Space Station.

Other A-NZ organisations offer specialised services in the carbon sequestration domain alongside their core aerial imaging and land cover analysis services. Software companies Orbica and Lynker Analytics interact in the carbon sequestration monitoring space as part of their broader geospatial analytics and land use monitoring capabilities. Orbica offers software platforms with vegetation indices (like NDVI) specifically to track forest status, including percent canopy cover, which are proxies for carbon sequestration status and can be used to support carbon credit projects. Lynker Analytics includes forest loss detection and replanting mapping among their range of services, using machine learning and remote sensing techniques to support forest carbon sequestration applications.[23]

Consultancies like Indufor Asia Pacific provide AI-based monitoring of forest establishment in A-NZ by using satellites to verify if new forests are planted properly and track native forest areas for conservation purposes. Indufor also reviews remote

[22] GEDI provides 3D forest canopy measurements including canopy height, vertical structure, and surface elevation.

[23] Using AI to identify areas of deforestation and replanting; Remote-Sensing Indices in 5 Minutes: NDVI, NBR & NDWI Basics

sensing tech for regulatory compliance, for instance under the Resource Management Act, ensuring that carbon monitoring methods meet required standards.

Large management companies like PF Olsen incorporate remote sensing into their operational workflow, from using satellite data to plan harvests to employing LiDAR for carbon inventory in permanent native forest reserves. Aerial survey firms (e.g. Aerial Surveys Ltd) also contribute by flying LiDAR missions across regions. Through a national LiDAR mapping initiative (led by LINZ), over 80% of A-NZ's terrain (including forests) has been captured. Mapping coverage is planned to continue until June 2027, ultimately providing a nationwide baseline for carbon stock assessments. However, without continual data capture of this type, single time step measurements will have limited use as land changes.

Scion has been developing a digital twin of forests, combining drone-collected LiDAR, multispectral imagery, and even video feeds to monitor growth of commercial harvest pine tree stands. By calibrating these data with field plot measurements, it is possible to model carbon accumulation annually and detect any issues (like storm windthrow or tree disease outbreaks) that might reduce carbon stocks.

There are established methods for quantifying aboveground carbon, e.g. in the parts of trees aboveground like trunks and branches. However, there are not well-established methods for quantifying belowground carbon, e.g. in roots or soil organic matter itself, and especially lacking methods for large scales (i.e. regionally). Satellite methods for soil carbon assessment are still in development, but overseas work has shown promise through using proxies like soil moisture and texture (Cui et al., 2025). Using high-resolution soil moisture data as a proxy (like that from GNSS-R flights or NASA's SMAP mission) is relevant as soils with higher organic carbon tend to retain more moisture. By tracking changes in soil water holding capacity via remote sensing, it may be possible to infer changes in soil carbon over time.

Currently, such methods are not operationally available in A-NZ, as the processes and algorithms developed internationally are often proprietary or not validated for A-NZ soils. However, with programmes like Rongowai underway (providing detailed soil moisture maps from aircraft), researchers anticipate that adapting international models to A-NZ will soon be possible. This development will enable monitoring of soil carbon under various land uses and verification of management change impacts (e.g. soil carbon increases after a switch to regenerative farming practice).

Remote sensing has become an indispensable approach for tracking carbon sequestration. It provides transparent, scalable, and repeatable measurements that inform both domestic policy (like setting carbon credit allocations or conservation funding priorities) and international reporting (under the Paris Agreement, for instance). By knowing where and how carbon is being stored, carbon sinks can be better predicted (e.g. by detecting deforestation or degradation early) and enhanced (e.g. identifying ideal areas for reforestation or soil restoration). For these reasons, it is also a crucial element for data collection for verification purposes in carbon markets.

Spotlight Box 5: Remote Sensing in Action - Carbon Sequestration in Aotearoa New Zealand

The Organisation
Dragonfly Data Science is a private science consultancy specialising in statistical analysis and AI to power environmental monitoring through remote sensing. The company combines expertise in machine learning, computer vision, and geospatial analysis.

The Technology
Dragonfly has established a partnership with NASA for forest mapping and monitoring initiatives, developing systems that integrate space-based remote sensing with AI. They develop machine learning models, particularly neural network architectures adapted for tree height estimation, to create synthetic canopy height models from satellite imagery (where LiDAR coverage is unavailable).

The Application
Dragonfly's forest monitoring capabilities utilise NASA's GEDI spaceborne LiDAR system alongside multispectral satellite imagery from Landsat and other Earth observation platforms to generate forest canopy mapping and biomass estimation. Their analysis of LiDAR data from native forests helped demonstrate, for example, how reduction in non-native possum populations increases forest canopy density (hence more carbon stays sequestered). This data fusion methodology enables high-resolution forest monitoring for carbon stock assessment, ecosystem services evaluation, and recovery monitoring following disturbance events (i.e. wildfires, cyclones, non-native invasive species outbreaks).

As technology advances, even more granular carbon monitoring is anticipated. Perhaps one day mapping not just forest carbon as a whole, but differentiating carbon in trunks versus leaves, or active versus stable soil carbon. Such detail will improve climate modelling and land management. For now, the combination of LiDAR, multispectral imaging, and ground-based innovation is giving A-NZ an idea of its carbon landscape, highlighting sequestration opportunities and risk areas where stored carbon could be lost (wildfire, non-native invasive species, land use change). Capture and integration of new data (soil moisture) will strengthen A-NZ’s position.

Who is conducting remote sensing of carbon sequestration internationally?

International companies improving the quality and accessibility of carbon sequestration information are addressing simultaneous challenges of expanding geospatial coverage, increasing resolution, and integrating data.

Planet Labs, TraceX, and CarbonSpace are international companies which represent three distinct technological approaches. Planet Labs, with its extensive satellite constellation, provides an off-the-shelf carbon monitoring product called Forest Carbon Diligence (See Spotlight Box 6). TraceX uses satellite imagery analysis, GIS technology for precise monitoring, and real-time data collection through IoT devices to track soil health, moisture levels, and environmental factors affecting carbon sequestration. CarbonSpace combines satellite GHG data[24] with Fluxnet station ground truth data to measure net ecosystem-atmosphere exchange (above and below-ground biomass) and provide monthly global carbon maps at regional and smaller resolution.

Improvements in temporal and spatial resolution have been made possible through the combination of Planet Lab's quarterly 30 m measurements, CarbonSpace's weekly monitoring cycles, and TraceX's real-time data collection systems by combining multiple satellite data sources together. Each company employs multi-sensor integration approaches. Planet Labs combines satellite imagery with LiDAR, TraceX IoT sensors and ground-truthing, and CarbonSpace combines space-based measurements with ground-based data.

Spotlight Box 6: Remote Sensing in Action - Carbon Sequestration Internationally

The Organisation
Planet Labs is a company which operates the world's largest constellation of commercial Earth-imaging satellites. With imagery from these, the company has created the Forest Carbon Diligence product which provides comprehensive forest carbon monitoring services globally.

The Technology
Planet Labs' satellites deliver quarterly observations (starting 2013) of global forest change and above ground carbon sequestration estimates at 30 m resolution. Quarterly observations represent the most frequent data commercially available in terms of comprehensive tracking of forest canopy height, canopy cover, and aboveground carbon density changes through time.

The Application
Planet Labs' approach combines deep learning models trained on over 14 million km^2 of airborne LiDAR data from NASA's GEDI to produce forest carbon estimates. Their platform utilises advanced cloud masking, pixel selection, multi-sensor fusion incorporating PlanetScope, Sentinel-2, Landsat, and ALOS-PALSAR-2 data, along with temporal harmonisation techniques to minimise measurement variability and enable detection of subtle forest changes including selective logging and early-stage reforestation.

[24] from GOSAT-1 and Landsat, with multispectral MODIS Satellites' role in tracking the carbon footprint of land use

Soil Condition

In an environmental monitoring context soil condition refers to the health and quality of soils, understood by measuring some basic attributes (i.e. moisture content, nutrient levels, organic matter like carbon content, pH, structure, and biological activity). Remote sensing applications in this focus area aim to assess these variables over large areas and to track changes caused by drivers like land use practices, droughts, or erosion.

While some soil attributes (like chemical composition) are difficult to measure remotely, many can be derived or monitored through proxies like physical properties. One example is soil moisture, which serves as an important indicator because it affects plant growth, drought risk, and erosion potential (Abdulraheem et al., 2023). Nutrient levels (e.g. nitrogen, phosphorus) can be estimated by observing vegetation colour reflectance. Certain crops which reflect the yellow-edge multispectral band can indicate where nitrogen levels are suboptimal (Li et al., 2025). Remote sensing provides a way to map soil condition continuously, supporting precision agriculture (adjusting fertiliser inputs to match soil needs exactly) and land management (identifying degraded soils or areas needing remediation) without requiring constant sampling by hand.

Several remote sensing data approaches can be used to monitor soil condition. Satellite radar sensors like ESA's Sentinel-1, ESA's BIOMASS mission, NASA's SMAP or NISAR satellites measure soil moisture by emitting microwaves and analysing the returned signal through a backscatter measurement. Wetter soils reflect the signals differently than dry soils, allowing quantitative moisture estimates down to 20 m resolution (Tola et al., 2025). The Rongowai programme has continued data generation efforts through the use of reflected GNSS signals measured from an Air New Zealand aircraft. Similar to satellite radar, these GNSS-R measurements allow national-scale soil moisture mapping, but with much higher resolution than satellite data. This work has the potential to capture soil moisture data at a local scale multiple times a day (flight dependent) and therefore could indicate how quickly different soils dry out or re-wet, which is key to agricultural, drought and flood monitoring.

Ground-based technologies like the CropScan 3300H, place a near-infrared spectrometer onto farm harvesters and rapidly sample the soil every few seconds during harvesting. This provides spatial data on grain protein (which correlates with soil nitrogen) (Nurgaliyeva et al., 2024) or soil organic matter levels across a field. Drones can also survey fields with special sensors. For example, drones can be equipped with GNSS-R sensors or ground-penetrating radar and have been tested to map soil moisture patterns at 5 m resolution (Farhad et al., 2025). Some drones carry hyperspectral cameras that can pick up subtle differences in soil colour and vegetation stress, which, with appropriate models, can inform on soil organic carbon or nutrient hotspots (Y. Yan et al., 2023). Combining these technologies (satellites for broad moisture patterns, aircraft for medium scale, tractors or drones for fine detail) represents a move toward multi-scale soil condition monitoring that can guide decisions from the farm level to the regional level and identify emerging drought areas or soil health trends.

Integrating research from other fields is especially powerful for understanding soil condition, given a single measurement cannot tell the whole story (e.g. soil moisture data combined with terrain data and land cover can aid in predicting erosion risk). Remote sensing data (LiDAR for topography, and lack of vegetation or saturated ground) are used to create models which forecast landslide probable areas (MWLR; Zhao et al., 2023) , which are a dominant erosion process in A-NZ's hill country. In fact, studies since the 1990s have used satellite-derived indices like NDVI (indicating vegetation cover) and NDSI (soil indices) to map soil exposure and infer erosion status (Bing & Lei, 2022; Nait-Taleb et al., 2025)

Frequent imaging allows for quick identification of erosion such as after a cyclone. Multi-temporal satellite images can directly identify new landslide scars (light soil patches where vegetation was stripped) and sediment deposition in river valleys (Hughes et al., 2021; Satriano et al., 2023). Remote sensing thus provides both preventive indicators (areas of low vegetation cover on vulnerable soils) and reactive mapping (post-event erosion extent). A-NZ benefits from a wealth of elevation data via the national LiDAR program, which provides high-resolution DEMs, and extensive satellite coverage. Resolution can be a limitation as freely available satellite imagery at 10 m resolution will only detect larger areas of change, underscoring the need for high-resolution data in detailed erosion mapping.

Who is conducting remote sensing of soil condition in Aotearoa New Zealand?

The array of current soil condition monitoring in A-NZ is a mix of international products and local innovations. Soil Scout (from overseas) offers wireless underground sensors farmers bury to continuously measure moisture, temperature, and salinity, transmitting data via radio to a central hub. FarmSense is a A-NZ based software product solution providing real-time soil moisture monitoring, which has been adopted by growers to fine-tune irrigation. Remote Networks NZ partners with a Dutch company, Sensoterra, to supply connected soil moisture probes that can cover large farms with minimal power usage. Service providers such as Adroit design and install complete IoT monitoring systems (from soil moisture to weather to water level) as well as handle the data analytics and alert-based systems (e.g. a field becomes waterlogged). Vantage NZ specialises in precision agriculture solutions and designs systems to integrate tools such as AquaCheck soil moisture probes and the Metos range of soil sensors.

Collectively, these services mean land managers can choose from many options, from a user-friendly sensor to a fully managed solution, or a hybrid approach. However, many of these are only ground-based so remote sensing from satellites and drones still plays a crucial role in spatially extrapolating those point measurements across large areas like entire farms. A-NZ has yet to see local private companies step into the space of aerial and satellite imagery for soil condition monitoring, however international companies are advancing this.

GNS have been taking the approach of combining ground based measurements and modelling to extrapolate and predict landslides through their programme and tools (MBIE-funded Endeavour programme Sliding Lands). This information will help prevent damage from future extreme weather events. There is also research on drone-mounted sensors that can be deployed on-demand to map soil conditions in real time during farming operations (De Ocampo & Montalbo, 2024). This would augment the ground validation data needed to scale.

Spotlight Box 7: Remote Sensing in Action - Soil Condition Internationally

The Organisation
The Rongowai programme is an international collaboration led by the University of Auckland and University of Canterbury's Geospatial Research Institute, working in partnership with Air New Zealand, the University of Michigan, Ohio State University, and the University Corporation for Atmospheric Research (UCAR). The mission is part of NASA's Cyclone Global Navigation Satellite System (CYGNSS) mission and is supported by MBIE's Catalyst Fund, the University of Auckland Vice-Chancellor's Strategic Development Fund, and NASA. The University of Auckland's Centre for e-Research hosts the Science Payload Operations Centre (SPOC), which was purpose-built to manage the data processing and make findings publicly available.

The Technology
Rongowai utilises a Global Navigation Satellite Systems Reflectometry (GNSS-R) sensor mounted on an Air New Zealand Q300 aircraft, which records both direct and reflected signals from up to 20 GNSS satellites simultaneously during flight. These GNSS signals use L-band radio spectrum that can penetrate clouds, rain and vegetation, allowing the system to infer properties of the ground surface from reflected signals. During routine scheduled operations, Rongowai autonomously records reflected GNSS signals and transmits data via cellular connection once the aircraft has landed.

The Application
The primary application of Rongowai is to provide significantly improved observations of soil moisture and flood dynamics across A-NZ at high spatial and temporal resolution. Since its first flight on 13 September 2022, Rongowai has been recording reflected GNSS signals across much of the country with around 50 flights per week, including observing floods in the Auckland and Northland regions. The data generated aims to have real-world impact across research and industry, helping A-NZ make informed decisions regarding environmental policy and practice, including monitoring regenerative agricultural practices.

Within the public research space, MWLR has progressed soil mapping capability in their S-map tool which provides detailed soil properties for about half the nation's agricultural land. There is a need for scaling up predictions to a full national coverage, which can be done with machine learning. Models are able to learn from measurements in well-sampled areas to predict soil properties in un-sampled areas but will need to account for regional differences by incorporating some ground validation.

Who is conducting remote sensing of soil condition internationally?

Globally, remote sensing of soil condition is advancing through the three main platform types: space, air, and ground-based. Planet Labs provides near-daily 3–5 m imagery that can show soil moisture patterns after irrigation or rain. New hyperspectral satellite missions (e.g. the upcoming Environmental Mapping and Analysis Program (EnMAP); PRISMA) offer hundreds of spectral bands, which have been shown to improve detection of soil organic matter and even certain mineral deficiencies. Companies such as Taranis and Ceres Imaging fly drones over crops at ultra-high resolution (sub-cm) to detect issues like soil nutrient stress (through leaf discolouration patterns). These companies also merge their drone data with satellite data to give both detail and contextual information over an entire farm. On the ground, newer entrants like ChrysaLabs provide handheld spectrometers that when inserted into the soil can instantly estimate soil nutrients like N,P and K and C. SoilGrids by ISRIC provides a global map at a spatial resolution of 250 m for various soil properties such as nitrogen, soil carbon and pH derived by combining various global datasets into one portal for anyone to use. International companies such as Perennial Earth, Seqana and Downforce Technologies are combining machine learning and AI integration, with satellite data combined with ground-based sampling, to solve the traditional limitations of expensive, time-intensive sampling for soil organic carbon, pH, moisture and temperature at scale.

To summarise, remote sensing has capability to monitor soil condition, giving early warning and broad surveillance. It's now possible to see patterns of wet and dry soils across the landscape as weather changes, identify fields that consistently show soil nutrient deficiencies, and detect where erosion is likely or has occurred. Challenges remain though, such as detecting soil contamination like heavy metal pollution. Some progress has been made using hyperspectral indices (Lovynska et al., 2024) but applying that to low-level diffuse contamination is not yet routine and usually requires manual soil sampling. The overall trajectory is integration of remote and *in situ* sensing, powered by AI, will improve the resolution, reliability, and scope of soil condition monitoring. This will empower agricultural practitioners, help regulators and councils identify emerging issues (declining organic matter or rising salinity) and ensure efforts to improve soil (central to both climate mitigation and water quality goals) can be quantitatively tracked over time. Remote sensing of soil condition supports kaitiakitanga (land stewardship) ensuring that soil is managed sustainably for future generations.

Water Quality and Hydrology

Water quality and hydrology pertain to water movement through landscapes and the often subsequent transport of pollutants (e.g. runoff from land). Understanding both supports better water management and land-use practices. Runoff may consist of excess nutrient leaching from agricultural land leading to algal blooms or soil erosion leading to sedimentation (Hunt et al., 2019). Changes in hydrological flows (rivers, groundwater, drainage patterns) can affect both ecosystems and human water use (Esteban et al., 2021). Remote sensing provides a way to monitor large catchments for nutrient hotspots and to model hydrology in data-sparse regions by filling in spatial and temporal gaps between ground sensors.

Tracking nutrient flows is critical for freshwater ecosystem health. Key remote sensing variables for water quality are turbidity, chlorophyll-a, and optical indicators of nutrient enrichment or pollution. These data are used to assess freshwater, estuarine and marine condition, identify trends over time, and support early-warning systems signalling environmental degradation (Jaywant & Arif, 2024). The majority of nutrient modelling research is at local or catchment scale with process models (like Overseer) relying on linear modelling and lacking remote sensing input. However, global research indicates that hyperspectral imagery combined with neural networks can detect subtle changes in plant chlorophyll that reflect soil nitrate availability (Jaywant & Arif, 2024). If pasture in one paddock consistently shows a spectral signature of nitrogen richness (dark green, high chlorophyll) versus an adjacent paddock with a lower nitrogen signature (visually light green, lower chlorophyll), hyperspectral remote sensing data with combined modelling can correlate those differences beyond what the human eye sees (Qi et al., 2025). Such “nutrient signatures” from reflectance patterns are enabling landscape-scale nutrient monitoring without needing thousands of physical sensors.

Deeper leaching, where nitrates that have percolated below the root depth toward groundwater, won’t be directly visible in crop reflectance. Research proposes combining soil moisture sensing (like GNSS-R derived maps of where water is moving through the soil) with hydrological modelling to estimate how nutrients could be moving with that water beyond the root zone. This is an active research frontier to integrate remote sensing of the water cycle with models of solute transport (Dwivedi et al., 2025).

Multispectral satellite imagery can reveal threats to water quality e.g., exposed soil prone to erosion or aquatic plant health (through "greenness" colouration). When nutrients like nitrogen and phosphorus leach into surface waters, they often promote algal growth (Kong et al., 2025), which satellites detect via increased chlorophyll concentrations (a phenomenon clearly visible in lake colour change) (Phetanan et al., 2025). SAR data from Sentinel-1 provides soil moisture measurements which can be interpreted to understand where soils are saturated and likely to leach or generate runoff.

Calibration of remote sensing data with targeted ground measurements can allow for scalability across larger areas. For example, catchment managers may use satellite-derived maps to identify sub-catchments that appear prone to high runoff (indicated by frequently saturated soils and low vegetation cover in winter). The managers would then install *in situ* sensors to directly measure nutrient concentrations in identified potential hotspots to validate the satellite indication of a problem area.

Increasingly, affordable optical sensors are being installed *in situ* such as Lincoln Agritech's HydroMetrics unit, a small probe for wells that gives real-time nitrate readings. Having such devices in groundwater or tile drains provides point data that satellite data can't detect but by correlating those ground measurements with what satellites *can* detect (like vegetation content or soil properties), models can be built to estimate nitrates across similar unmonitored fields (Sarkar et al., 2025).

The monitoring of hydrology can include precipitation, river flows, flood inundation, wetland dynamics and subsidence caused by groundwater drawdown. Frequent data about hydrology reveals the hydrological response of entire catchments under different land use and climate change scenarios (Shadmehri Toosi et al., 2025). Hydrological remote sensing technologies include NASA's Surface Water and Open Topography satellite (SWOT) (Ka-band SAR interferometry to obtain spatial maps of surface water level from which discharge can be derived), altimetry (to assess water levels such as river stage, used to estimate flows if a rating curve is available), ESA's Gravity Recovery and Climate Experiment (GRACE) to observe changes in groundwater through differences in gravity, SAR imagery for flood extent, L-band SAR imagery for mapping forested wetlands (e.g. in Amazonia) and soil moisture.

Understanding hydrological flows is key to improving resilience to floods and droughts. Satellites can map flood extents in real time (through radar imaging of inundation), contributing to emergency response, and monitor groundwater-related land subsidence in areas of heavy extraction. The KIPs report noted that combining high-resolution sensing technologies can give Māori agribusiness and communities unprecedented information on how their land management affects water in their rohe (Reid et al., 2025). This empowers local decision-making in line with kaitiakitanga, ensuring that both economic and environmental success are balanced.

Data analysts using hydrological remote sensing have embraced advanced machine learning more so than other environmental fields. Published studies are showing frequent use of neural networks (both Long Short-Term Memory (LSTM) and CNNs) to interpret time series data and spatial correlations for river flow and flood predictions (Waqas & Humphries, 2024). Neural network modelling is appropriate for the highly dynamic and non-linear behaviour of water flow, and these models often better predict stream response to rain. In A-NZ, neural networks have been used to predict stream flow in ungauged basins by training on climate and terrain data from gauged basins (Samarasinghe, 2010).

Who is conducting remote sensing of water quality and hydrology in Aotearoa New Zealand?

Domestic capabilities for remote sensing of water quality and hydrology are spread across public institutions and private firms, with public research quite prolific. For example, MWLR developed SedNetNZ, a model to predict sediment (and attached nutrient) transport in rivers, which relies on land cover data to estimate where erosion will send sediment into waterways. However, there are over a dozen sediment models included in the PCE's freshwater modelling report. Such models benefit from continuous land cover monitoring (e.g. detecting plantation felling causing higher erosion risk; refer to Land Cover and Land Use section for more).

Some water quality indicators, like chemical concentrations, have measurement limitations when it comes to remote sensing. Nutrients like nitrate and phosphate are not optically visible (but can manifest visually through proxies e.g. algae growth, water clarity). Remote sensing methods typically measure these proxies, the outcomes of nutrient exposure. This means ground-based sampling and sensors remain essential to measure indicators like chemical concentrations and calibrate the remote sensing observations. The integration of these ground-based and remote sensing data into models (like 3D hydrodynamic models by MetOcean Solutions) allows for cross-validation. A multi-pronged approach is critical for accuracy. For example, combining satellite rainfall data, ground-based soil nutrient levels, and land cover type through watershed modelling can predict how much nutrient runoff a storm will generate and where it will travel. Later, satellites can also confirm the impact via aquatic sediment plume observations.

Topography data can be used to predict water flow across landscapes. For example, A-NZ's Land and Water Science consultancy uses LiDAR-derived high-resolution DEMs to model farm-scale water flow patterns, identifying where overland flow will carry nutrients to streams. At a larger scale, NIWA's satellite-based Satellite Coastal and Estuarine Water Quality (SCENZ) products track sediment through changes in colour of coastal waters, which can infer river plumes carrying nutrients and sediment out to sea.

Spotlight Box 8: Remote Sensing in Action - Water Quality and Hydrology in Aotearoa New Zealand

The Organisation

Xerra Earth Observation Institute is an Otago-based regional research institute specialising in Earth observation and remote sensing technologies. Their work applies satellite imagery to improving coverage and resolution of lake and marine water quality monitoring. Xerra has been supported by MPI to develop a Centre for Space Science Technology in 2015, and then to develop the more commercially-focused Starboard Maritime Intelligence in May 2021, a cloud-based platform providing comprehensive views of maritime activity.

The Technology

Xerra has delivered water quality monitoring by combining multiple layers of satellite data, scientific models, and machine learning. This includes using Sentinel-2 data to track lake colour changes throughout the year across A-NZ's 3,800 of lakes, where lake colour is used as a proxy for phytoplankton levels (green colour from chlorophyll) and sediment (brownish hues), both of which relate to nutrient levels.

The Application

Xerra and the University of Waikato collaborated on analysing satellite imagery for the Rotorua lakes over an 18-year period. By merging satellite observations with decades of manual Secchi disk measurements (water clarity readings by human observers on boats), they could retrospectively assess trends and identify that nine lakes showed statistically significant water clarity improvements. In 2019, they launched the Xerra Gateway as a satellite data repository for A-NZ, but it was discontinued in July 2020 as the uptake was insufficient to continue as a stand-alone product.

Who is conducting remote sensing of water quality and hydrology internationally?

Global trends suggest an increasing commercialisation and democratisation of water monitoring via remote sensing. This anticipated growth is driven by the urgent need for better water resource management under climate change and nutrient pollution control. Techniques such as thermal infrared imaging from satellites or drones locate springs or seepage zones (as cooler or warmer spots) which indicate groundwater discharge areas, and possible nutrient pathways (C. L. Watts et al., 2023). Some key challenges persist in large scale water monitoring. For example, atmospheric interference (like clouds and variable sunlight) compromise data capture, and algorithms often need site-specific calibration to relate reflectance to actual concentration values. Continual ground truthing through water sampling and sensor buoys is indispensable (e.g. Cawthron's TASCAM buoy, which measures real time water quality).

There are several noteworthy international companies operating in the water remote sensing area. Utilis (now part of ASTERRA) is an Israeli company using satellite-based radar to detect underground pipe leaks and similar technology is being adapted to detect wet soil areas that could indicate nutrient-laden groundwater seepage (C. L. Watts et al., 2023). Another international company focusing on these applications is Water Insight (Netherlands), which produces satellite-based algal bloom maps and also makes a portable device (WISP) for on-site spectral water quality readings.

In terms of research collaborations, Australia's Commonwealth Scientific and Industrial Research Organisation (CSIRO) has built the AquaWatch initiative, using constellations of satellites to support an integrated ground-to-space water quality monitoring system through collaborations with international technology demonstration partners. This system is focused on real-time data and predictive analysis of water quality, for example in detecting toxic algal species. Hyperspectral imaging is particularly powerful in this context as different types of algae and dissolved substances have unique spectral signatures. This allows hyperspectral sensors like on the upcoming NASA Plankton, Aerosol, Cloud, Ocean Ecosystem (PACE) mission or existing PRISMA imagery to distinguish between a diatom bloom versus a cyanobacteria bloom by spectral shape. This differentiation informs whether a bloom is likely toxic.

Spotlight Box 9: Remote Sensing in Action - Water Quality and Hydrology Internationally

The Organisation
Gybe is a technology startup company that provides automated water quality monitoring for lakes, rivers, and coastal areas. They integrate automatic and up-to-date monitoring with more comprehensive spatial coverage.

The Technology
Gybe's offers satellite imagery analysis to deliver real-time measurements of parameters like chlorophyll-a, turbidity, and cyanobacteria in an accessible, integrated way. This includes time series data for any point in a water body, which expands the spatial coverage and resolution typical of ground-based monitoring. Their GybeMaps platform turns complex remote sensing data into an accessible web-based dashboard that enables water utility providers, conservation organisations, and researchers to monitor entire water bodies continuously without expertise in satellite data processing.

The Application
GybeMaps has been used to monitor algal blooms in drinking water reservoirs, monitor impacts of up-stream ecosystem conservation actions on down-stream water quality, and track nitrate quality along river catchments. Gybe is also working on expanding capabilities to detect *E. coli* bacteria and other contaminants to target real-world water quality challenges.

In summary, remote sensing is increasingly enabling a whole-of-catchment perspective on water quality and hydrology. It's now possible to observe how rainfall turns into runoff, carries nutrients through soil, enters streams and effects on water bodies. The use of remote sensing tools can greatly help identify critical source areas of pollution, track improvements or deteriorations over time, and provide accountability (e.g. whether the efforts in a certain catchment are yielding better water clarity). Aotearoa New Zealand can leverage the commercial examples overseas and focus on integrating data sources via commercial products and services that increase accessibility and practical applications.

As technology and research advances, research tools may soon be easily publicly accessible to see near-real-time nutrient monitoring from constellations of mini-satellites and dense ground-based sensor networks. Currently tools such as Hydro3DJS are making "digital twins" of watersheds into a reality (Sajja et al., 2025). Managers could then simulate interventions (like a wetland installation) and immediately see the predicted outcomes. Remote sensing will be the backbone of such systems, observing the flows of wai and providing the knowledge to protect and restore A-NZ's precious freshwater.

Marine Condition

Marine condition monitoring is required to manage the health of the ocean including coastal ecosystems. Aotearoa New Zealand has an extensive coastline and a vast marine exclusive economic zone. Typical environmental conditions monitored include coastal saltwater quality, algal blooms, sea surface temperature, animal habitats (e.g. reefs and seagrass beds), shoreline dynamics and sediment plumes. These could not be assessed efficiently without remote sensing technologies, *in situ* measurements, and modelling to interpret the data. Remote sensing technologies are transforming how we understand these conditions, providing synoptic and repeatable views of marine environments that are often difficult to access but which many depend on (e.g. coral reef management, fisheries, marine carbon sequestration).

There are several core remote sensing technologies in use. Satellite-based ocean colour sensors such as NASA's MODIS, Visible Infrared Imaging Radiometer Suite (VIIRS), and ESA's Sentinel-3 Ocean and Land Colour Instrument enable near-global, frequent observation of chlorophyll-a concentrations, suspended sediments, and coloured dissolved organic matter. These indicators help track phytoplankton biomass, water quality, and runoff impacts across vast areas. Complementing these optical sensors are SAR systems (e.g. Sentinel-1, RADARSAT, TerraSAR-X). SAR provides key data for mapping sea surface roughness, detecting oil spills, identifying algal slicks, and contributing to coastal landform classification in the intertidal zone.

More recently, hyperspectral imaging missions such as PRISMA and EnMAP, and emerging commercial platforms have expanded what's possible in marine monitoring enabling:

- Early detection of harmful algal blooms by distinguishing pigment signatures between phytoplankton species (e.g. toxic dinoflagellates vs diatoms) (Hamed et al., 2025)
- Stress signals in coral reefs before visible bleaching, based on shifts in fluorescence and symbiotic algae health (Alevizos et al., 2025)
- Tracking terrestrial runoff and pollutants through spectral signatures of coloured dissolved organic matter (Wu et al., 2025)
- Monitoring seagrass health via subtle changes in leaf pigmentation, biomass, or nutrient stress (L. Zhao et al., 2025)
- Detecting sediment source and composition changes tied to land-use shifts or coastal infrastructure development (Oh et al., 2025)

These capabilities enable early warning of environmental changes before they become visible or irreversible, providing a critical advantage for marine management. Here too, there is a degree of multi-platform integration for optimal data collection. Surface monitoring from space is now being augmented with data from drones, ocean gliders[25], and moored sensors. Moored sensors collect detailed subsurface data, such as temperature, salinity, pH, nutrients, or acoustic signals from marine life, that satellites cannot measure. Companies and research programmes integrate these complementary platforms, offering multi-layered views of marine systems.

Marine condition monitoring is increasingly utilising hybrid analytical approaches that combine statistical and machine learning techniques. Traditional regression models remain important for deriving relationships (like between chlorophyll concentration and fish stock health, or turbidity and shellfish growth rates) (Gernez et al., 2025). However, convolutional neural networks (CNNs) are increasingly being applied to detect patterns like algal bloom extents or identify features such as coral reefs and kelp forests in imagery (Nasios, 2025). CNNs can be trained on multispectral or hyperspectral images to pick out the unique spectral/spatial signature of phenomena. For example, certain harmful algal blooms have a distinct colour and texture in satellite images that a CNN can learn to identify automatically (Phetanan et al., 2025).

In summary, to manage the massive, multi-source datasets generated in marine condition monitoring, researchers are increasingly relying on AI-driven analytics for interpretation and predictive power (Giménez et al., 2025). These tools recognise patterns across time series, classify habitat types, and support forecasting (e.g. of algal bloom events or identifying bleaching-vulnerable coral reefs). The field is evolving rapidly, and A-NZ is well-positioned to benefit from global momentum, particularly through collaborative research and integration of international data sources.

Who is conducting remote sensing of marine condition in Aotearoa New Zealand?

Remote sensing in A-NZ works hand-in-hand with *in situ* marine condition monitoring. For example, Cawthron Institute has developed monitoring buoys like TASCAM, which uses inductive telemetry to bring data on temperature, salinity, turbidity and chlorophyll up from sensors in the water column, in real-time. These monitoring buoys provide validation for satellite observations and provide information below the ocean surface that satellites cannot directly measure (such as subsurface chlorophyll maxima or bottom water conditions). The CawthronEye platform processes NASA satellite imagery (e.g. from MODIS or VIIRS) and delivers it to users within 3 hours of satellite overpass, demonstrating the rapid turn-around now possible.

Another data provider, MetOcean Solutions (a division of A-NZ organisation MetService) creates global high-resolution 3D ocean models using assimilation of satellite and *in situ* data. Their models simulate sea conditions like currents, temperature, and can track particles, useful for predicting oil spill movement or larval dispersal. Once again, when these models use satellite data, they can create a more

[25] "An ocean glider is a type of autonomous underwater vehicle (AUV) that uses a buoyancy engine to passively sample the ocean"

complete picture for ocean monitoring. For example, because satellites detect surface expressions and models predict sub-surface features, together they can help interpret whether a drop in chlorophyll detected by satellite was due to actual decline in algae or instead from water mixing shown by the model.

The domestic marine condition monitoring community utilises international data sets such as NOAA's sea surface temperature or the Integrated Marine Observing System (IMOS, Australia) ocean colour products as baseline references for A-NZ's waters. The European Digital Twin Ocean, also has potential application for A-NZ. This initiative is building a virtual ocean where all available data (satellite, model, float, etc.) are integrated, with frameworks and tools that could be adopted in A-NZ. The FathomNet project is more specialised and provides a demonstration of AI application. It has compiled a large, labelled image database for training algorithms to identify marine life in underwater imagery. It complements remote sensing by enabling analysis of ROV/drone imagery from beneath the surface, which can then be connected to satellite-observed conditions.

Random forest models and other ensemble methods are also used to merge data layers such as land-based data (e.g. river nitrogen loads from catchments) and marine observations (e.g. coastal algal blooms) to understand their relationships (Gao et al., 2025). A common approach in A-NZ is to blend rule-based models with machine learning. For example, a rule might classify any pixel near the coast with very high turbidity as a river plume, while a machine learning model refines the classification of the plume content (e.g. sediment type). Integration of particle tracking and eDNA data can be included for comprehensive analysis. For instance, particle tracking models (numerical) can simulate how larvae or pollutants move (Prants, 2025); remote sensing can provide the environmental context such as temperature fronts that affect larvae survival (Dunn et al., 2025). If eDNA sampling is added, it is possible to detect traces of certain fish or kelp in water samples that confirm what the models and satellites suggest about species distribution. Each provides a line of evidence for monitoring marine ecosystem health.

There are the usual remote sensing challenges when it comes to marine condition monitoring. Cloud cover is a major issue in some regions (e.g. West Coast of the South Island) - weeks of cloudy weather can hamper satellite observation, which is where SAR or gap-filling by models can be utilised. Spatial resolution of many ocean colour sensors (300 m to 1 km) can also mean that small fjords or estuaries are pixelated or mixed with land signals, so high-resolution options such as PlanetScope Dove satellites with a coastal band, offer potential solutions.

Spotlight Box 10: Remote Sensing in Action - Marine Condition in Aotearoa New Zealand

The Organisation
Discovery Marine is a company which integrates traditional benthic surveys with modern remote sensing technologies to specialise in comprehensive marine monitoring. Their work is focused on increasing monitoring coverage across A-NZ's marine environments to enhance understanding and ecosystem management.

The Technology
The company operates a suite of marine sensors and technologies such as their multibeam systems, which acquire backscatter data that provides information on seafloor hardness and roughness and sediment grain-size. These characterise habitats and reveal spatial patterns of seafloor biodiversity.

The Application
Their technology has been applied to water column measurements for three-dimensional mapping of fish schools and other mid-water marine organisms, facilitating biological abundance assessments, species identification, and habitat characterisation. This technology is also able to map underwater freshwater, gas and oil seeps. One of the most significant environmental monitoring projects undertaken by this company was the comprehensive seabed survey of Queen Charlotte Sound/Tōtaranui and Tory Channel/Kura Te Au, in collaboration with NIWA. The survey included characterisation and mapping of sea beds, benthic terrain modelling to classify ecosystems, and identification of habitats important for biodiversity. This represented the largest nautical charting and science survey completed in A-NZ waters, covering areas last surveyed in the 1940s. The project delivered dual objectives: providing validated data for updating nautical charts, while generating essential datasets for sustainable management of natural resources in the Marlborough Sounds.

Marine condition monitoring via remote sensing in A-NZ is becoming increasingly integrated and applicable for environmental management. It can detect harmful algal blooms from space and corroborate them with ground-based toxin tests before they impact shellfish farms or beaches and monitor sediment plumes after heavy rains, linking them to specific river catchments and predicting their impact on coastal ecosystems. Further, it records coastal habitat changes like the expansion or decline of seagrass beds and kelp forests, by analysing time series of satellite, aerial and drone images. Finally, it tracks ocean warming and acidification proxies using thermal infrared sensors for sea surface temperature and satellite-detected changes in marine chemistry.

Crucially, the data from marine environmental monitoring is increasingly accessible in near-real-time and in formats useful to decision-makers. Web-based dashboards fed by remote sensing data are already in use, for example, to monitor chlorophyll concentrations or the status of coastal turbidity. These interfaces allow resource decision-makers to monitor environmental changes and respond accordingly, such as imposing a temporary shellfish harvest closure if a bloom is detected.

From a Te Ao Māori perspective, the ability to observe the oceans, Tangaroa's domain, from the sky, Ranginui's domain, and integrate that with mātauranga Māori (e.g. traditional indicators of marine health) holds strong potential for the practice of kaitiakitanga. The Kaitiaki Intelligence Platform envisions using remote sensing technologies to gauge the balance between human activities and ecosystems in a way that resonates with concepts of mana, mauri and utu. For instance, remote sensing combined with kaitiaki insights of historical and current species abundance, might show changes in the health of a coastal ecosystem.

Who is conducting remote sensing of marine condition internationally?

Many private companies servicing the international market have developed technological approaches for marine condition monitoring that integrate satellite remote sensing with AI and autonomous platforms. For example, Planet Labs has analysed satellite imagery to remotely identify sources and pathways of plastic pollution in the Caribbean Sea. Marine protected area monitoring is being addressed through OceanMind's development of AI algorithms that integrate satellite data, vessel transmissions, and oceanographic information to support conservation compliance. The company's approach combines Electro-Optical and SAR satellite data with AI to identify vessel activities and detect potential environmental violations in marine protected areas.

CLS Telemetry provides a comprehensive suite of remote sensing-enabled marine monitoring solutions, addressing ocean physics, sea ice, marine pollution, wildlife and vessel movement, and real-time incident response via satellite, *in situ* and drone-based systems. They support a range of platforms that provide actionable ocean intelligence. Coral reef monitoring has been advanced through the Allen Coral Atlas, a collaboration including Planet and National Geographic, which released a satellite-based global coral reef monitoring system in May 2021. The system uses high-resolution satellite imagery with algorithms to detect coral bleaching events globally at bi-weekly intervals.

Hyperspectral satellite technology has been developed by multiple companies for marine applications. Pixxel's Firefly satellites are capable of coastal/inland water quality monitoring including chlorophyll, total suspended solids, coloured dissolved organic matter, and harmful algal bloom detection. They support coastal pollution tracking and habitat health analysis such as mangrove stress detection.

Nonprofit organisations are also involved in the international scene. Remote kelp forest monitoring has been addressed collaboratively by the Nature Conservancy, Woods Hole Oceanographic Institution and Kelpwatch, which apply machine learning to map kelp canopy extents from satellite imagery (since 1984). This is with coverage from the US West Coast to Southeast Alaska, Peru, and the Falkland Islands. Monterey Bay Aquarium Research Institute (MBARI) has deployed high-resolution camera-equipped UAVs for marine community surveys in Monterey Bay, documenting kelp forest canopy surface area and observing underwater life. Ulysses Ecosystem Engineering are utilising marine drones to collect seagrass seeds from donor meadows and replant them in degraded areas while monitoring growth. GeoNadir provides platforms for drone-based seagrass mapping coupled with machine learning, offering fine-scale sampling capabilities that can integrate with satellite imagery.

Spotlight Box 11: Remote Sensing in Action - Marine Condition Internationally

The Organisation

Sofar Ocean is an international company who has developed ground-based remote sensing technology to enable large-scale remote ocean monitoring for weather, maritime shipping, and marine research applications.

The Technology

Their technology includes *in situ* hardware, and visualisation and analytics dashboards, allowing them to offer multi-modal data integration by combining satellite remote sensing with a network of ground-based spotter buoys and smart mooring cables. Their Spotter Platform brings together this technology into an ocean sensing system designed for real-time data collection across a range of ocean metrics including sound, waves and current, water quality (salinity and dissolved oxygen), water levels such as tidal or storm surges, and temperature. Data is transmitted via satellite or cellular networks to support applications in conservation, aquaculture, shipping, and offshore industries. This approach allows for both surface and underwater parameters relevant to marine environments to be brought together for analysis.

The Application

The Sofar Spotter Platform was utilised near Tawhiti Rahi - Poor Knights Islands marine reserve off the coast of A-NZ to collect and transmit real-time observations required for management of a non-native invasive sea urchin species. By enabling more consistent, reliable, and granular data collection, the Sofar Ocean’s technology has improved the data quality available to researchers to understand hazards such as heatwaves, and pinpoint conditions where species flourish and enable long term predictions of change. Sofar Ocean’s technology is suitable for scaling up to a regional approach, which they describe as a ‘strategic shift’ in ocean monitoring, to improve data collection and decision-making on larger and more impactful scales.

Section 4: Current Environmental Data Systems Supporting Decision-Making

Harnessing remote sensing data to empower environmental decision-making requires both technology and a supporting data system. This involves connecting the institutional, infrastructural, and governance arrangements that manage data collection, sharing, analysis, and usage. This section examines A-NZ's existing environmental data systems in the context of remote sensing. First, it defines environmental data systems, then reviews their current situation in A-NZ. It highlights strengths to build on and some critical challenges. Inspiration from overseas models is suggested for managing environmental data, as they offer ideas for improvement and local implementation. This will set the stage for the subsequent recommendations on creating a more collaborative, optimised, and accessible system for A-NZ.

Defining Environmental Data Systems

An environmental data system refers to the end-to-end network of data generation, storage, processing, and dissemination for environmental decision making (Figure 12). It is comprised of five main elements:

- **Data Sources** - all satellite, aerial and ground-based platforms that provide remote sensing data.
- **Data Infrastructure** - databases, cloud storage, web portals, application programming interfaces[26] (APIs) through which data is stored and accessed.
- **Standards and Protocols** - common formats (e.g. GIS shapefiles, NetCDF for climate data), metadata[27] standards, and data quality frameworks that ensure datasets can work together.
- **Governance and Policies** - who owns or stewards data, how data sharing is governed (open data policies versus proprietary data), privacy and sovereignty considerations (especially for Indigenous Peoples' data), and funding.
- **People and Organisational Capacity** - the experts, analysts, and institutions that maintain the data system and translate data into insights; also the users (policy makers, scientists, public) who interact with data products.

[26] An API is a standard data communication protocol. It creates a consistent method of acquiring data from a single data source. They are often used in automated data systems where the same type of measurement is being captured at a regular interval. An example is weather data published daily through an API for other applications to share with users.
[27] Metadata is a description of the dataset which is attached to help sort and understand the data better. The Dublin Core metadata standard is often used: Dublin Core™ Metadata Element Set, Version 1.1: Reference Description.

Figure 12. Environmental Data Systems are composed of five main elements which together enable end-to-end networks of data generation, storage, processing, and dissemination for optimal decision-making.

An integrated, accessible environmental data system might look like: remote sensing and other types of data streaming into centralised repositories, being processed consistently (e.g. all satellite imagery orthorectified[28] and calibrated to standards), and made available through an online platform where stakeholders can query or download. It would include documentation (i.e. metadata, data collection methods) and perhaps analytic tools or dashboards for non-technical users to obtain processed information (e.g. real-time water quality alerts).

[28] Orthorectification is the process of aligning an image from an aerial source to the ground. This is often done by creating alignment points called ground control points (GCP) and using a program which aligns the GCP's with accurately measured points on the ground.

Existing Environmental Data Systems in Aotearoa New Zealand

In A-NZ, various components of an environmental data system exist, but they are distributed and disconnected across organisations. The PCE has previously reviewed A-NZ's environmental reporting system, identifying fragmentation and lack of coordination as major issues. Rather than operating a single unified environmental data system, the country relies on various domain-specific and scale-specific systems that serve different purposes. The component of the environmental data system relating to remote sensing data signifies a particular challenge to integration within a theoretical unified system, given the rapid pace of technological change, data complexity and volume of data.

Land Information New Zealand operates the LINZ Data Service (LDS), which hosts extensive geospatial data openly. The service includes basemap imagery layers like aerial photos and Sentinel-2 image mosaics, national LiDAR datasets[29] (when released openly), and topographic maps. This LDS serves as a key distribution node but focuses largely on static datasets rather than real-time sensor feeds. LINZ previously led the NZ Geospatial Strategy, which recognised the need for better data integration and developed a spatial data infrastructure to facilitate easier remote sensing data sharing between organisations. LINZ has made over 1,000 datasets openly available within their data service. However, many satellite based datasets, especially dynamic ones like daily satellite observations or continuous sensor data, are not yet part of the service.

All of A-NZ's 11 regional councils collect environmental data including rainfall, water quality, and air quality, typically storing them in separate databases. The Environmental Monitoring and Reporting initiative aims to standardise and centralise some of this data through the Land Air Water Aotearoa (LAWA) website. LAWA provides public access to certain datasets like swimming water quality and river levels aggregated from councils both as raw data and in dashboard format. Individual councils may use remote sensing like satellite imagery for land use analysis, but variation in data collection methods and a lack of shared data systems leads to inconsistency and disconnection at national scale. Initiatives such as the National Environmental Monitoring Standards (NEMS) are poised to address these issues.

Many research institutions host their own substantial environmental databases. NIWA operates DataHub for climate, freshwater and ocean data. The NIWA-SCENZ (Seas, Coasts and Estuaries NZ) portal provides satellite-derived coastal water quality data from MODIS at 500 m resolution for all A-NZ coasts. GNS operates GeoNet for seismic and volcanic data. The LUCAS and LRIS portals hosted by MfE and MWLR respectively, offer satellite-based land use change data used in carbon accounting and other land use decision-making. OurEnvironment, developed by MWLR, provides the NZ Land Atlas and NZ Landcover Explorer. These initiatives provide value but tend

[29] LiDAR datasets are also hosted on opentopography.org alongside other global topography data.

to be use-specific and not fully integrated outside of the institutions. Users must know each portal and fetch data separately, often dealing with different data formats.

Aotearoa New Zealand operates under the Environmental Reporting Act 2015, which mandates regular reporting covering air, atmosphere and climate, freshwater, marine, and land systems, as well as synthesis reports. These reports draw on a range of data sources that are primarily held by research organisations along with data from Regional Councils and other providers. The Our Atmosphere and Climate 2020 report used satellite temperature data for some indicators; however, satellite data is not always used in the mandated reports (but see Our Marine Environment 2022, StatsNZ Sea-Surface Temperature, and Satellite indicators of phytoplankton and ocean surface temperature for New Zealand as some exceptions).

Many initiatives to encourage public release of datasets in A-NZ have shown positive progress including the LDS, Data.govt.nz open data catalogue, A-NZ signing of the International Open Data Charter, the New Zealand Data and Information Management Principles and the Declaration on Open and Transparent Government. Many regional councils, including Taranaki and Wellington operate open data portals featuring environmental layers, including satellite-derived maps. Publicly funded research datasets are now expected to be available unless containing sensitive information. This aligns with global shifts toward open science. Canterbury's LiDAR data release on LDS immediately sparked multiple uses from flood modelling to urban tree canopy analyses (Pedley & Morgenroth, 2025). The growth of open science policies in research institutions amplifies data sharing, as demonstrated by New Zealand's Biological Heritage Data Repository and the Aotearoa Genomic Data Repository.

While several platforms referenced earlier are aspiring to more unified environmental data systems (e.g. LDS, LAWA, OurEnvironment, Regional Environmental Data Hubs), more progress is required. Inspiration may be taken from the KIPs conceptual prototype of a unified data system. This system suggests a Māori-led environmental sensor network with an online data platform accessible to iwi and communities, using governance structures honouring indigenous data sovereignty. While still conceptual, KIPs highlight the need for systems that incorporate co-governance between Māori and the Crown for data management. Such prototypes show potential but scaling them to national level remains challenging without sustained funding and institutional mandates.

In summary, A-NZ's current environmental data system for remote sensing is fragmented with disparate parts curated for bespoke purposes. Some A-NZ data systems with a narrow domain focus are world-class in quality and accessibility (e.g. national topography and aerial imagery data via LINZ, or the robust climate station network data via NIWA), but others are patchy or hard to obtain (e.g. near-real-time water quality across the country, or national biodiversity observations). There is no one-stop national platform for all environmental data (including remote sensing data), but rather a mosaic of portals and systems. Users often must possess significant expertise to find and combine data.

Gaps & Barriers in Aotearoa New Zealand's Environmental Data System

Challenges remain in A-NZ's environmental data system, consisting of both gaps and barriers limiting use of remote sensing data. These are summarised at a high level in Figure 13. The cumulative effect of these gaps and barriers is that A-NZ is not recognising its potential when it comes to environmental monitoring.

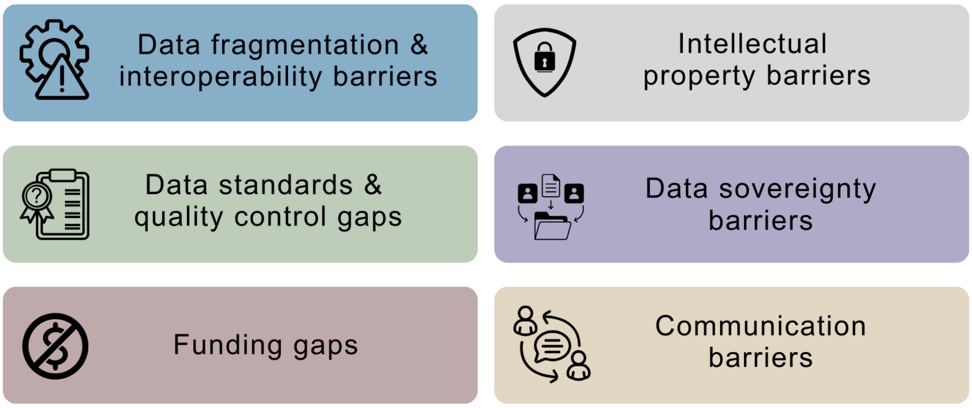

Figure 13. Challenges to overcome: the six main gaps and barriers within Aotearoa New Zealand's environmental data system.

Data fragmentation and interoperability barriers. Fragmentation often occurs when multiple agencies obtain data without coordination. One council might buy high-resolution satellite images for their region in year X, while a neighbouring council does the same for year Y, preventing a consistent national picture. Information fragmentation also plagues attempts to understand nationwide water quality trends. Data is gathered by individual councils, however there are barriers to creating a master combined dataset due to misaligned interoperability capabilities. This barrier ultimately prevents data discovery and access by users and stops comprehensive interoperability and analysis across organisations and research domains.

Intellectual property barriers. These are being mitigated in part through the move towards open research and open access data. Historically, organisations collecting data often retained control over it due to commercial imperatives or lack of incentive to release it. Research institutions might embargo datasets until published in academic journals (a lengthy and uncertain endeavour), while councils may not release raw data due to resource constraints or privacy concerns. When coupled with episodic funding and capacity constraints, data release has not been planned for or prioritised, resulting in limited sharing of technological development between organisations. Typically, when technology to advance data collection emerges from sectors where there are intellectual property concerns, a data hoarding mentality prevails as default. Even within government funded public value projects, outputs rely on static interpretive information in reports rather than raw data being published. This limits the ability to continue the research outside of the organisation which initially developed it. To mitigate this, MBIE's Open Research Policy is mandating open access publications and strongly recommending the release of data for publicly funded research. Progress is occurring through commercial satellite providers offering public-good licenses like Planet Lab's Norway International Climate and Forest Initiative (NICFI) which provides high resolution multispectral data for others' work combatting climate change, conserving and restoring biodiversity and forests, and facilitating sustainable development (non-commercial use).

Data standards and quality control gaps. Different organisations use varying data formats and classification schemes, making integration laborious. One council might measure a lake's chlorophyll monthly while another measures only bacteria *E. coli* levels on a weekly basis. This leads to issues with variation of ground truth data needed for validating satellite-based detections for quality control. A lack of data collection purposes and recording standards compounds the issue (e.g. see Appendix 1 of the PCE's report Focusing Aotearoa New Zealand's environmental reporting system). Inconsistent metadata standards hamper development toward a central platform, then forming a data discovery barrier to users. Gaps in data standards and quality control create integration barriers even when data is available, e.g. remote sensing data often has inconsistent geo-referencing and imagery calibration. Inconsistencies, or ambiguity in class definitions (e.g. land use classifications) compound these problems. Without agreement on what constitutes "forest" in a land cover map, combining maps from various sources requires significant manual input. Missing or non-uniform information about collection methods, accuracy, dates and quality assurance checks create difficulty in reusing data for new research.

Data sovereignty barriers. Indigenous data sovereignty must be a foundation of any centralised environmental data system. Data sovereignty is about access and technical management but also should ensure Indigenous Peoples (i.e. Māori in A-NZ) retain rangatiratanga (right to exercise authority) over data relating to their people, lands, and taonga species. The Māori Data Governance Model (Kukutai et al. 2023) and Principles of Māori Data Sovereignty (Te Mana Raraunga, 2018) together provide a vision, principles, guidance and examples for Māori to be active decision-makers in data governance and to ensure rights and obligations under Te Tiriti o Waitangi are upheld. Many iwi and hapū are generating environmental data but may be reluctant to contribute to national systems without guarantees of culturally appropriate governance and respect for mana motuhake (Māori self-determination). The KIPs programme demonstrated that gaps in cultural appropriateness create barriers when it comes to interconnected data systems. Embedding Māori data governance principles and best practice from the outset is therefore essential to building an inclusive, equitable environmental data system that supports public good while honouring data sovereignty.

Funding gaps. The creation of a unified environmental data system is funding-limited, particularly for small organisations. The creation and maintenance of data systems is expensive and continuous, and funding gaps exist due to data often being tied to time-capped project or agency-specific allocations. Organisations prioritise their mandated data needs while cross-agency infrastructure ends up neglected. Many A-NZ organisations cannot commit to costed initiatives beyond the fiscal year, showing funding gaps, or uncertainty at least, prevents a sustained unified system. Dataset updating and maintenance requires ongoing resourcing which most projects won't fund in the proposal stage, locking out long term data stewardship from the outset. Keeping long term datasets current (e.g. managing large scale, updated satellite data archives) requires dedicated funding.

Communication barriers. Several factors contribute to lack of data uptake by decision-makers. A key factor is the communication step, which is necessary to translate data analysis for understanding by a wide audience. Without proper translation, decision-makers can't use data as actionable information. An example is council planners who can plan to protect wetland areas but require satellite-derived soil moisture data translated into maps and interpreted by ecologists. Often decision-makers aren't intended to directly interpret modelling data, so without a secondary translating step by other specialists (e.g. ecologists in example above), they cannot incorporate into their planning or use data to justify decisions. This exemplifies reliance on excellent communication of remote sensing environmental data to galvanise actual change and highlights the need for data user interfaces with interpretive services built in.

Environmental Data Systems Internationally

Many countries have built unified environmental data systems that integrate remote sensing data along with other environmental data, processing pipelines, and user-access services. These systems demonstrate solutions to the technical and organisational challenges of coordinating environmental data at national or even continental scales. Each approach offers insights about investment strategies, governance models, and technical architectures. Examining these real-world implementations of environmental data systems reveals elements that A-NZ might adapt. The focus in this report is on the remote sensing data aspects of these systems. A summary of these international data systems is in Table 3.

Europe

European remote sensing initiatives demonstrate strong integration between research, policy, and operational services. The European Union operates Copernicus, which provides satellite data through its Sentinel missions and delivers Copernicus Services including ready-to-use public environmental information like land cover maps and atmospheric composition analyses (Spotlight Box 4). The EU's Destination Earth programme represents the most ambitious digital twin project globally. It combines data from Copernicus Sentinels, ESA satellites, and The European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) systems to create highly accurate Earth system models. The European Centre for Medium-Range Weather Forecasts implements the Destination Earth Digital Twin Engine technology in their weather predictions. The system is targeted towards climate adaptation and extreme weather prediction. The Copernicus Data Space Ecosystem, essentially a cloud hub where users can access and process data with provided tools, operates at the continental scale providing data for comparisons between countries. The continental scale approach creates a centralised data system and offers "Analysis-Ready Data" and thematic services, including drought monitoring through integration of remote sensing and ground data. The system requires significant ongoing investment[30], to produce a user-friendly platform supporting over 780,000 registered users (Apicella et al. 2022), including from multiple A-NZ initiatives.

The European Environment Agency coordinates environmental monitoring across 39 member countries through established frameworks. It utilises Copernicus satellite data and Coordination of Information on the Environment (CORINE) Land Cover mapping[31] for policy development. The ESA Climate Change Initiative (CCI) operates as a major science programme focused on Essential Climate Variables. This system leverages a 40-year satellite archive from multiple international partners. It produces datasets that directly support IPCC climate assessments and global climate research. The CCI programme has contributed to over 650 peer-reviewed research papers.

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[30] Investment until 2013 was €2.4 billion, funding for 2014-2020 was €4.3 billion and funding for 2021-2027 is €5.4 billion.

[31] CORINE land cover maps are generated on a 6 yearly interval from 1990 to 2018. They have a resolution of 100 m from and have 44 land cover classes.

The United States of America

The United States of America (USA) operates multiple environmental data systems, with an emphasis on operational weather services and open data access through large-scale federal programmes. NASA Earthdata provides a repository of Earth science data, incorporating observations from MODIS, Landsat, Geostationary Operational Environmental Satellites (GOES), and specialised missions like Surface Water and Ocean Topography (SWOT), all processed through Science Investigator-led Processing Systems. The open access policies for all Earth observation data accelerates scientific research and supports diverse applications ranging from agriculture to disaster monitoring across both public and private sectors.

The National Oceanic and Atmospheric Administration (NOAA) operates two complementary data systems that serve different user communities while maintaining consistent quality standards. The Open Data Dissemination programme makes over 24 petabytes[32] of environmental data available through partnerships with commercial cloud platforms including Amazon Web Services, Google Cloud, and Microsoft Azure. Meanwhile, the National Centers for Environmental Information manages a large environmental data archive, housing climate data records, weather observations, and historical datasets spanning decades and informing a range of sectors from transportation to fishing. Together, these systems support data requests from users worldwide, reflecting the global reach of USA environmental data systems.

In addition, NASA operates the Earth Observation System Data and Information System (EOSDIS) archives and distributes data from many satellites at no cost. The system uses discipline-specific data centres for atmosphere, oceans, and land data, ensuring information is well-curated and accessible. The USGS contributes through EarthExplorer and LandFire portals, which provide nationwide vegetation and fire risk datasets that are continuously updated through remote sensing. All Landsat data and many commercial datasets purchased by the government, like National Agriculture Imagery Program (NAIP) aerial imagery, are released freely. Aotearoa New Zealand has benefited significantly from the USA's open access stance, using Landsat open data since 2008 and increasing its usage since release. The USA maintains federal coordination of climate data and research through the US Global Change Research Program (USGCRP).

Australia

Led by Geoscience Australia and CSIRO, Australia has made significant investments[33] in computing infrastructure to handle large datasets and create derived products. This includes a national fractional cover dataset from Landsat that with daily updates. Another Australian system, the Terrestrial Ecosystem Research Network (TERN), aggregates nationwide ecological data, integrating remote sensing and field data to

[32] A petabyte is equal to 1 million gigabytes or 1000 terabytes.
[33] For example $36.9 million was invested in Digital Earth Australia in 2018 and $14.5 million in a CSIRO high-performance computing cluster in 2022.

produce national soil grids and vegetation indices. Australia operates under multiple state and territory jurisdictions, and some national datasets, such as TERN, have been developed through coordination of common methods and co-funding arrangements, while others are produced centrally using satellite data and national programmes.

Australia also operates continental-scale environmental monitoring through data cube[34] technologies that have influenced global approaches to satellite data management. The Australian Earth Observation Data Cube, known as Digital Earth Australia, processes Landsat and Sentinel satellite data using the Open Data Cube framework to produce analysis-ready data covering the entire Australian continent since 1986. The system allows users to easily analyse regional trends like water extent changes across three decades. The Australia Research Data Commons extends this capability by integrating traditional satellite data with emerging ground-based technologies including camera traps and acoustic sensors, creating biodiversity research infrastructure that supports ecosystem monitoring and climate adaptation studies.

Africa

Digital Earth Africa adapts the Australian data cube technology to address African environmental challenges including food security and water scarcity. The South African Environmental Observation Network conducts long-term environmental research, offering open-access data via an online system integrated with the Global Earth Observation System of Systems (GEOSS).

Pacific

Digital Earth Pacific also adapts the Australian data cube technology to address Pacific environmental challenges including mapping ecosystem and coastline changes. The Pacific Environment Portal connects 14 national environment portals, providing tools for environmental monitoring, evaluation and analysis. The Tuvalu Coastal Adaptation Project's hazard and risk dashboard provides information and tools (including remote sensing data) to support climate change adaptation strategies.

Japan

Japanese organisations provide specialised monitoring capabilities that serve both regional needs and global environmental coordination. The Japan Meteorological Agency operates Himawari geostationary satellites equipped with Advanced Himawari Imagers that provide high-resolution weather imagery and support disaster risk reduction across the Asia-Pacific region. Data from these satellites are used by Metservice in A-NZ for their forecasting (see Metservice's blogs on A Close Eye on the Weather and Himawari Satellite Data). Data is shared through partnerships including with the Australia Bureau of Meteorology for integrated regional forecasting.

[34] Data cube technology is used for organising, storing, and analysing large volumes of multi-dimensional spatiotemporal data. It allows efficient access and processing of data across space, time, and data variables.

Global environmental data systems

The UN Environment Programme coordinates global environmental data through partnerships with space agencies. It utilises satellite data for tracking sustainable development goals, methane emissions (UN Environment Programme), and ecosystem monitoring. The data are also used to support international environmental policy and climate action initiatives that require coordinated observation (European Space Agency). Global environmental data platforms include the UNEP World Environment Situation Room, which integrates satellite, aerial, and ground-based data in near real-time, and the Group on Earth Observations' GEOSS platform, which aggregates datasets to support environmental analysis and decision-making.

Global environmental data systems are increasingly benefiting from public-private partnerships. Some countries negotiate with private companies to obtain licensed imagery. For example, the Norwegian government purchased Planet Labs imagery for tropical regions to combat deforestation and made it openly available through the NICFI program. A-NZ is a member of the International Charter: Space and Major Disasters which provides access to Earth-observation satellite data for disaster response (Land Information New Zealand, 2023). Aotearoa New Zealand could further explore public-private partnerships and collaboration with global systems such as those in Table 3.

Table 3. International Organisations and their Environmental Data Systems

System	Remote Sensing Technologies	Data Types Generated/Used	Environmental Application
Europe			
Copernicus Data Space Ecosystem	Copernicus Sentinel data, Copernicus Contributing Missions	Continent scale, ocean, atmosphere, climate, and emergency monitoring data available as raw satellite imagery and value-added products	Range of applications including assessment of land cover, soil moisture, soil erosion, oil spills, algal blooms, ocean turbidity, sea ice loss, air pollution, deforestation, biodiversity loss, water scarcity, ocean pollution, climate, natural disasters, urban expansion
ESA Climate Change Initiative (CCI)	ESA satellites, Copernicus data, partner satellites (NASA, NOAA, JAXA, EUMETSAT), 40+ year satellite archive	27 Essential Climate Variables (ECVs), long term climate data records, sea surface temperature, land cover, atmospheric composition	Climate change research, IPCC assessments, global climate monitoring, carbon cycle studies, sea level monitoring, atmospheric chemistry
EU Destination Earth (DestinE)	Copernicus data, ESA Earth observation satellites, EUMETSAT data, ECMWF model data, Digital Twin Engine	Digital twins for climate adaptation and weather extremes, high-resolution Earth system models, machine learning enhanced datasets	Climate change adaptation, extreme weather prediction, environmental disaster preparedness, policy impact assessment, carbon neutrality planning
European Environment Agency (EEA)	Copernicus Sentinel data, CORINE Land Cover mapping, High Resolution Layers, NASA remote sensing data	Land cover and land use datasets, environmental indicators, air quality data, biodiversity assessments, climate change indicators	Environmental policy development, biodiversity monitoring, air and water quality assessment, climate change tracking, land use planning
The United States of America			
EarthExplorer	Landsat series, Sentinel-2, Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), MODIS, Shuttle Radar Topography Mission (SRTM), LiDAR, Aerial photography, NAIP, DEMs, land cover classifications, water and vegetation indices	Imagery, elevation, land cover, vegetation, water, climate, and historic datasets from satellites, aircraft, and declassified missions	Monitoring of land, water, climate, ecosystems, and hazards
LandFire	Landsat, MODIS, Sentinel-2, LiDAR, aerial photography, DEMs, vegetation indices, historical fires perimeter datasets, climate layers	Vegetation, fuels, and fire regime data	Wildfire risk reduction, ecological restoration, habitat conservation, and climate resilience planning
NASA Earthdata	MODIS,Landsat,GOES satellites, Terra/Aqua platforms, airborne instruments,Surface Water Ocean Topo	Multispectral imagery, atmospheric data, ocean data, land surface data, weather/climate models, fire detection products	Weather forecasting, climate research, disaster monitoring, air quality assessment, agricultural applications, water resource management

System	Remote Sensing Technologies	Data Types Generated/Used	Environmental Application
NASA Earth Observation System Data and Information System (EOSDIS)	Archives and distributes major remote sensing technologies: optical, multispectral, hyperspectral, radar, lidar, microwave, atmospheric sounding from both satellite and airborne platforms	Wide range of land, ocean, atmosphere, cryosphere and natural hazard data	Range of applications including climate change monitoring, ecosystem and land use management, water resources and hydrology, atmospheric monitoring, disaster management, oceans and coastal applications, biodiversity conservation, policy
NOAA National Centers for Environmental Information (NCEI)	Satellite radiometers, weather stations, ocean buoys, paleoclimate proxies, radar systems	Climate data records, weather observations, ocean/coastal data, geophysical data, historical climate averages	Climate research, environmental baseline establishment, long-term climate monitoring, extreme weather analysis, climate services
NOAA Open Data Dissemination (NODD)	GOES-16/17/18/19 satellites, Joint Polar Satellite System (JPSS), weather radar, ocean buoys, atmospheric sensors	Weather imagery, climate data records, ocean databases, atmospheric observations, radar data, 24+ petabytes of environmental data	Weather prediction, climate monitoring, marine forecasting, disaster response, agricultural planning, aviation safety
Rest of World Systems			
Australia Bureau of Meteorology	Himawari satellite data, weather radar networks, automatic weather stations, ocean buoys, lightning detection	Weather forecasts, satellite imagery, radar precipitation maps, climate observations, oceanographic data, water information	Weather prediction, flood monitoring, drought assessment, marine forecasting, climate services, water resource management
Australia Research Data Commons (ARDC) - Planet RDC	Machine-based observation (camera traps, acoustic sensors, drones), satellite remote sensing, environmental sensor networks	Eco-acoustic data, camera trap imagery, environmental monitoring datasets, biodiversity occurrence records, agricultural data	Biodiversity conservation, biosecurity, ecosystem monitoring, climate adaptation, environmental decision-making, ecological research
Digital Earth Africa	Landsat, Sentinel-2, SAR	Continental-scale environmental products, land cover mapping, water body detection, agricultural monitoring products	Food security, water scarcity, deforestation monitoring, agricultural planning, environmental change assessment across Africa
Digital Earth Australia (DEA)	Landsat 5 TM, Landsat 7 ETM+, Landsat 8/9 OLI, Sentinel-2A/B/C MSI satellites; Open Data Cube (ODC) infrastructure	Analysis Ready Data (ARD), geometric median composites, fractional cover, water body mapping, coastal change detection, intertidal elevation models	Coastal erosion, water resource management, land cover change, agricultural monitoring, environmental impact assessment
Digital Earth Pacific	Landsat, Sentinel-2, SAR	Regional environmental data including water dynamics, mangrove ecosystems, land use change and coastline changes	Informing climate change, agriculture, disaster management and resource management decision making across multiple Pacific nations

System	Remote Sensing Technologies	Data Types Generated/Used	Environmental Application
Global Earth Observation System of Systems (GEOSS)	Sentinel-2, Landsat, MODIS, LiDAR, SAR, in-situ sensors, atmospheric data, multispectral & hyperspectral	Land cover, vegetation health, water quality, terrain and seafloor mapping, meteorological data, air and water quality, seismic and GPS and more	Disaster management, climate change monitoring, biodiversity conservation, water resource management, agricultural monitoring, urban planning
Japan Meteorological Agency (JMA)	Himawari-8/9 geostationary satellites with Advanced Himawari Imagers (AHI), ground-based radar, seismic networks	High-resolution weather imagery, atmospheric motion vectors, sea surface temperatures, precipitation data, earthquake monitoring	Typhoon tracking, tsunami warning, weather forecasting, climate monitoring, disaster risk reduction across Asia-Pacific region
Pacific Environment Portal	Landsat, Sentinel-2, SAR	Land cover and land use, coastal, marine and biodiversity	Urban monitoring, coastal management, disaster response and risk, biodiversity conservation
SERVIR Global Collaborative	Landsat, Sentinel, MODIS, SAR, LiDAR, ground-based sensors	Vegetation indices, land cover, surface temperatures, first biomass, flood extent, topographic information, climate variables	Disaster management, agricultural monitoring, water resource management, biodiversity conservation, climate change adaptation, urban planning
South African Environmental Observation Network	Landsat, Sentinel-2, airborne & drone-based multispectral & hyperspectral, SAR	Vegetation indices, soil moisture & temperature, water quality parameters, land cover and land use, climate variables	Biodiversity monitoring, land degradation assessment, water resource management, climate change impact studies, disaster risk management
Terrestrial Ecosystem Research Network (TERN)	Landsat, Sentinel-2, LiDAR, hyperspectral imaging	Vegetation, soil, landscape, climate and flux data alongside field calibration data	Ecosystem monitoring, biodiversity assessment, soil health and carbon storage, climate change research, land management and policy development
Tuvalu Coastal Adaptation Project's Hazard and Risk Dashboard	LiDAR, Sentinel-2	Inundation modelling, shoreline change detection, damage and loss assessment, marine hazards exposure	Coastal resilience planning, risk-informed development, community preparedness, policy and decision support
UN Environment Programme (UNEP)	Multi-satellite remote sensing, Methane Alert and Response System (MARS), partnership with ESA/NASA data	Land cover and land use, methane emission detection, ecosystem monitoring, SDG indicators, freshwater ecosystem data and more	Global environmental monitoring, pollution tracking, biodiversity conservation, climate action, sustainable development goal tracking

Opportunities for Learning from International Environmental Data Systems

International examples include several organisational models and policy approaches that could inform Aotearoa New Zealand's (A-NZ's) development of a more unified environmental data system. This includes strategies for governance, technical architecture, and incentive structures to address A-NZ current gaps and barriers.

Environmental data system organisation varies. Some countries centralise everything into a single large online portal while others federate through interconnected but separate nodes. As recommended by the PCE in a note to the minister, A-NZ could adopt a federated model given its small size and distributed governance structure. This approach would maintain regional portals while ensuring they feed into a searchable, unified national system. However, it would take significant investment and coordination to implement the shared standards and governance structures across the current disparate regional systems. Although not federated, Australia's success in producing national datasets despite multiple state jurisdictions demonstrates how shared standards and co-funding arrangements can overcome these barriers.

Formal standards committees play crucial roles in many successful environmental data systems. In the United States of America, formal bodies set data standards for federal agencies and discipline-specific data centres called Distributed Active Archive Centers (DAACs). This ensures data for atmosphere, oceans, and land are well-curated and accessible. In Europe the INSPIRE Directive ensures interoperability of spatial data infrastructure across Member States. Aotearoa New Zealand could benefit from a similar mandated standards framework to address the current fragmentation in data formats and quality protocols. Some standardisation work is currently organised through the Spatial Information Council (ANZLIC) and NEMS to align with larger standard organisations such as the Open Geospatial Consortium, but these initiatives need more awareness and uptake from researchers.

Not-for-profit consortium models[35] offer another governance approach to consider. This approach is based on multi-sector oversight to manage environmental data and provides balanced governance to prevent domination by any single agency. Aotearoa New Zealand's Environmental Monitoring and Reporting network could evolve into a more formal entity of this sort that includes government, academia, industry, and iwi representatives overseeing data sharing in a formal consortium. This model ensures diverse stakeholder input while maintaining focus on public benefit.

[35] A not-for-profit consortium model involves multiple organisations (often government agencies, research institutes, NGOs, or industry bodies) joining together to collaborate on a shared goal, without aim to profit. It differs from a federated approach that aligns organisations but there is no formal collaboration.

Data sharing incentives and enforcement represent critical policy tools for encouraging awareness and participation in a more unified data system. Many countries use legislative tools like freedom of information laws or open records legislation to enforce data sharing. For example, the US open data policy, which makes all Landsat data and many commercial datasets freely available, demonstrates how government policy can overcome intellectual property barriers. Funding conditions and financial incentives are also effective mechanisms for compliance. Aotearoa New Zealand could make stronger requirements for open data outcomes from public funding. Incentives for private sector data sharing, such as tax benefits or procurement preferences for companies that contribute data, could encourage broader participation.

Technical approaches from overseas could address A-NZ's issues with lack of decision-maker engagement and interoperability. For example, Europe's Copernicus Data Space Ecosystem provides a cloud hub where users can access and process data with in-built digital tools. Copernicus' thematic services, such as drought monitoring that integrates remote sensing with ground-based data and models, demonstrate how suitable technical support can translate raw data into actionable information. Both Copernicus and Digital Earth Australia apply an "Analysis-Ready Data" approach that would be beneficial if transferred to the A-NZ context.

Australia's analysis-ready stacks of satellite data allow users to easily analyse regional trends over time while the integration of remote sensing with field data through their TERN demonstrates how to overcome data fragmentation. Adopting similar approaches would empower A-NZ users to undertake more comprehensive data analyses.

In summary, A-NZ can adopt organisational models from overseas to improve environmental data systems in the areas of coordination, governance, infrastructure and incentives. A-NZ has growing strengths in open data ethos and technical skills that form some critical parts of an integrated, user-friendly national system. In the next section, there are concrete recommendations for adding missing parts to promote an optimised environmental data system – essentially charting a path forward that draws from both domestic experience and international best practice.

Section 5: Recommendations for an Optimised Environmental Data System

This report provides five key recommendations to improve Aotearoa New Zealand's (A-NZ's) collection, integration, and use of remote sensing and related environmental data to inform environmental decision-making. Each recommendation is described below with suggestions for implementation.

1. Improve Computational Capability, Capacity and Infrastructure

Modern environmental datasets, especially from remote sensing, are large and require significant computing power to store, process, and analyse. A-NZ's research and government agencies must be skilled and equipped to handle this "data deluge" effectively, otherwise even if procured, valuable data will remain underutilised.

Build technical capacity and capability

Investment in educational programmes and technical training to upskill scientists, analysts, and data managers in using advanced computational tools is needed. For example, workshops and online courses (for council data scientists and researchers alike) about cloud-based geospatial analysis could harness ESA's Copernicus Data Space Ecosystem, NASA's Earthdata platforms or Google's Earth Engine, as used by the EnviroSat Tools project. Training should cover how to leverage APIs, cloud computing, and big data workflows for environmental applications. By improving skills nationwide, data will be more effectively accessed and translated to inform decision-making.

Leverage international cloud platforms through partnerships

Aotearoa New Zealand could forge partnerships with major cloud service providers like Amazon Web Services, Microsoft Azure, or Google Cloud to obtain scalable computing resources for public-good environmental data improvements. This could take the form of credits or dedicated programmes enabling A-NZ scientists to run data-intense analyses (e.g. processing decades of satellite imagery) without prohibitive cost. Partnerships might also involve co-developing infrastructure, for instance hosting a copy of relevant global datasets (e.g. Sentinel archive) in existing A-NZ data centres for faster access. Leveraging international cloud platforms can remove computational bottlenecks such as large download requirements or local server limitations and allow users to work more efficiently.

Invest in local infrastructure for sensitive data and sovereignty

While international clouds are useful, personal data and Indigenous Peoples' data (i.e. relating to whenua Māori or iwi, hapū and whānau-led kaupapa) should not be moved offshore. Aotearoa New Zealand therefore needs robust onshore computing infrastructure for cases where data sovereignty or privacy is a concern. This could mean upgrading the National eScience Infrastructure (NeSI) or similar A-NZ based high performance computing (HPC) facilities and ensuring government agencies have secure cloud options (perhaps through an all-of-government cloud framework) that comply with indigenous data governance principles. This could also mean incentivising private companies to build their own or purchase onshore storage (e.g., Catalyst Cloud).
Data concerning taonga species or Māori land use could be processed within a platform that aligns with guidance from Te Mana Raraunga - the Māori Data Sovereignty Network and Te Kāhui Raraunga, including the Māori Data Governance Model (Kukutai et al., 2023). Engaging Te Mana Raraunga, Te Kāhui Raraunga and Māori tech experts in designing such infrastructure will help to ensure it aligns with Kaupapa Māori values for handling and controlling data.

Enable real-time processing and automated reporting systems

A critical aspect of computational improvement is speeding up data-to-decision pipelines by designing for continuous updates rather than static annual reporting. Where possible, A-NZ should develop near-real-time environmental data collection capabilities that can trigger fast-response management actions. Cawthron Institute has made progress in this space with CawthronEye, which delivers coastal images in ~3 hours. Expanding this capability would aid detection of many time-sensitive issues, for example toxin-producing algal blooms in drinking water reservoirs, wildfires or forest loss. Near-real-time monitoring requires automating data ingestion, processing (typically with machine learning), and dissemination (via dashboards or alerts).

2. Encourage Cross-organisational Collaboration and Data Sharing

No single entity can collect or analyse all relevant data and therefore collaboration between government, academia, iwi, and the private sector is essential. Breaking down silos through standards, incentives, and shared initiatives, will foster an environmental data system where data flows more freely for informed decision-making and collective benefit.

Establish and enforce consistent data standards

A collaborative environmental data system requires everyone to speak the same language. Developing common data formats, metadata standards, and API specifications for environmental data is a necessary. For instance, a national standard for how to format time-series sensor data or how to classify land cover typologies (as currently being led by MfE) would enable easier and more frequent data merging. An example of formatting standards is the Australian Bureau of Meteorology's Water Data Transfer Format which applies to more than 240 organisations who submit specified water information. In A-NZ a similar unifying effort could be led by a multi-agency working group including central and local government agencies, Māori organisations, research institutions and private initiatives. This could be coordinated by an expanded ANZLIC or a new environmental data governance entity.

The standards must align with international best practices (like using Open Geospatial Consortium (OGC) standards for geospatial APIs), but also incorporate A-NZ-specific needs (e.g. bilingual metadata including Māori place names and space for integration of Mātauranga Māori, by Māori, where applicable). Once established, the standards should be embedded as requirements in funding contracts and procurement to get mass uptake. For example, any publicly funded project should be required to deliver open access data according to these standards, and all systems should adhere to them (e.g. council databases). Over time, this would yield interoperable data building blocks across the country.

Further promote open science and data accessibility policies

Strengthening policies that mandate or encourage open access to environmental data is recommended, especially when data is collected with public funding. This includes requiring research methodologies and all results (code, models, processed datasets) be made publicly available in a timely manner. Mechanisms to promote this can include government directives, incorporating open data clauses in research grants, and establishing repositories for data deposit, for example, expanding the A-NZ Government's data portal, Genomics Aotearoa, or partnering with international data archives (when appropriate).

Compliance should have recognition (e.g. public recognition like awards or media releases), and non-compliance should have consequences (e.g. funding loss). The principle is that taxpayer-funded data is a public good and should be accessible to fuel further innovation and national benefit. An immediate step could be a policy similar to the EU's: after a short proprietary period, all data and tools from publicly funded environmental projects must be released publicly. This requires a change to current funding frameworks, which allocate funding for research itself, but rarely for archiving, curating, pre-processing or publishing data. A plan for how to achieve these steps should be required in funding bids with funding dedicated to this purpose.

Transparency and reproducibility benefits will follow, as others can validate and build on existing work.

Refine funding and procurement requirements to incentivise cross-sector collaboration

To broaden environmental data collection and sharing, funding mechanisms (e.g. via MBIE's Endeavour Fund or other environment-related funding programmes) could be adjusted to require lead bidders to partner with other sectors, e.g. research institutions, iwi organisations, local councils, private companies and NGOs. Further, a specific contestable funding round from a dedicated funding pot could encourage collaboration of this nature. Government contracts for environmental data collection could include evaluation criteria that awards points to bidders who include cross-sector partnership and data sharing. Similarly, procurement reform could favour companies that commit to partnering to deliver outputs. This creates a financial incentive for cross-sector collaboration in a broader environmental data system.

Strengthen existing cross-Tasman and Pacific data collaborations

Aotearoa New Zealand should foster the existing data sharing agreements with Australia and Pacific Island nations. This is to mutual benefit, for instance, sharing ocean data improves climate resilience planning for all parties involved. There is strong potential in further developing data collaboration into a fully-fledged Trans-Tasman and Pacific environmental data commons. While existing initiatives like the Copernicus Australasia Regional Data Hub and Digital Earth Pacific (see Table 3 for more) provide foundational infrastructure for satellite data access and environmental monitoring, A-NZ can build upon these efforts in three ways.

First, federating data platforms by integrating A-NZ's environmental data systems with Australian and Pacific nation's platforms to create a cohesive data system that enhances accessibility and usability. Second, developing joint analytical tools to inform shared decision-making. Third, enhancing capacity-building initiatives like expanding training programmes for Pacific Island nations to build local expertise in remote sensing and data analysis for optimal management. By proactively engaging in these areas, A-NZ can not only contribute to filling data gaps but also demonstrate its commitment to regional environmental leadership and support for Pacific neighbours.

3. Improve Availability and Discoverability of Environmental Data

Collecting data is not enough, it must be available to those who need it for decision-making. This set of recommendations focuses on the infrastructure and policies to make environmental data as easily available as possible, while respecting necessary protections.

Align data storage locations for efficient computing and user access

A hybrid approach could be utilised to establish interoperating international platforms for global datasets that bolster a domestic system for local environmental data. For non-sensitive data that can be processed offshore, A-NZ should lean on international repositories like ESA's Data Hub, NASA Earthdata, or commercial cloud storage. For example, instead of duplicating all Sentinel satellite data storage in A-NZ, the Copernicus Data Space or Amazon Web Services could be used, accessing them via high-speed internet. This gives immediate access to a vast user community and proven infrastructure.

For sensitive or sovereign data, A-NZ should develop robust domestic platforms that mirror the storage and processing functionality of the aforementioned international repositories. These platforms could include an expanded Koordinates/LDS system or a new cloud hosted by an onshore provider such as Catalyst Cloud. This domestic platform should adhere to Te Mana Raraunga and Te Kāhui Raraunga guidelines and principles (Kukutai et al., 2023) for any data that intersects with whenua Māori or iwi, hapū or whānau-led kaupapa. Crucially, both international and domestic systems should be interoperable, meaning metadata from one can be discovered via the other and linking is seamless. The user experience should involve entry via a national data portal that then retrieves data from domestic or international servers, depending on the dataset and the user's access rights.

Account for data sensitivity and privacy

Not all data can be fully open. Ethical, inclusive environmental data systems require clear guidelines for managing sensitive data. This includes environmental data for which the right to govern, access, and control rests with Indigenous Peoples (e.g. Māori), as well as data that might reveal private information (e.g. a high-resolution satellite image with private property details). Engagement with iwi/hapū for the development of data sharing agreements or Māori-led data repositories will be important. A tiered access model is recommended to facilitate necessary privacy restrictions, potentially drawing on models like the Stats NZ 'Five Safes' and 'Nga Tikanga Paihere' frameworks. This model could be organised into public data (open to all), restricted data (available to accredited users or with certain safeguards), and confidential data (limited to data owners and specific use-cases). For example, detailed water quality at farm level might be restricted to avoid farmer identification, but aggregated catchment-level data can be public. Organisations will likely be more willing to release data when such privacy safeguards are in place.

Create incentives for private sector data contribution

A great volume of environmental data is collected by private companies (e.g. forestry LiDAR scans, agricultural sensor networks, mining environmental impact data). To improve overall data availability, the government can use financial or regulatory incentives to encourage these entities to share relevant data in public repositories. Potential incentives include tax credits for companies that openly share datasets, procurement preferences for companies willing to share data, or data purchase agreements where the government buys data rights for use in the public domain. One example of incentives for data submission is the USA National Agriculture Imagery Program which acquires aerial imagery from vendors and releases it into the public domain. Another option is establishing a data donation recognition program – akin to Corporate Social Responsibility, where companies are publicly acknowledged or awarded for sharing environmental data, thus improving their social license to operate. An example is CDP's widely-used disclosure platform where companies that publicly disclose high-quality environmental data can earn public credibility through placement on the CDP A-List. Any incentive to support public environmental data should ensure that the benefit of the submitted data is clear.

4. Promote Publicly Available Data for Decision Support

To provide tangible benefits, data must be actively used in decision-making across all sectors. This recommendation focuses on ensuring impact from open environmental data.

Integrate data into early warning and response systems

Environmental data, especially from remote sensing, should feed public early warning systems for hazards and threats. This requires institutionalising data flows into agencies responsible for emergencies. For example, automatic alerts could be established from satellite fire detections for Fire and Emergency NZ and regional authorities. This approach is being demonstrated using Himawari-8 data in some countries (Zeschke et al., 2019). Similarly, remote sensing of harmful algal blooms or water quality issues could trigger health alerts or water treatment adjustments. A dedicated entity could be established to monitor environmental indicators such as flood, drought, air quality, wildfire, biosecurity incursion (via vegetation anomalies), and coordinate warnings and response. This approach would ensure active data sharing that protects communities and infrastructure, demonstrating public value and justifying sustained investment in a unified environmental data system.

Develop user-friendly tools and platforms for data interpretation

Decision-makers who need environmental data are often not proficient in raw data analysis or aware of the disparate sources of environmental information. Investing in centralised, intuitive dashboards, maps, and decision-support tools will increase the application and impact of collected data (Le Lec & Hill, 2024). These could be thematic portals, e.g. a water resources portal, building on the functionality of LAWA, where a user can see current and historical flow, water quality, ecology, and catchment land use data (all drawn from the integrated datasets). Or a climate risk tool that brings together NIWA's daily climate maps and climate projections (hosted by MfE), NZ SeaRise, Our Changing Coast sea-level rise projections and other climate-relevant remote sensing data. Involving decision-makers in co-design of these user interfaces is critical, as user-friendly tools will encourage data use, improve cross-sector understanding, and can be public-facing to boost community awareness. One international example is from the National Environment Agency in Singapore who provide the "myEnv" app with environmental information including weather, air quality, water levels, floods and water disruption.

Demonstrate and publicise the benefits of data sharing

To sustain momentum, it is important to continuously highlight success stories made possible by having a unified environmental data system. For example, the UK's Friends of the Earth developed a woodland restoration opportunity map and clearly communicated how it was built, emphasising the importance of open LiDAR data. This kind of communication is important for showing contributors how their data has led to positive change, and for the public to see how investment in data systems results in safer, healthier environments and communities. This, in turn, can benefit political and social support, which is crucial for continued funding and collaboration.

Foster a data-informed culture in environmental policy

Central and local government staff should be encouraged to routinely utilise high-calibre data and adopt new analyses in their planning and policy processes. This could be achieved through guidelines and regulations that identify the best available data and how to utilise it with the latest technical approaches. For instance, implementation guidance for National Policy Statements relating to the environment (e.g. fresh water or biodiversity) could encourage use of remote sensing data in council monitoring programmes. Another example could be a requirement for remote sensing to be used for land-use verification in ETS carbon accounting, as some private companies are already doing. Mandating data use into policy frameworks and audit processes will lead to greater data literacy, better policies and advances in environmental data collection, sharing and management.

5. Establish Robust Governance, Validation, and Innovation frameworks

Sustaining an effective environmental data system will require appropriate governance structures and continuous improvement through research and validation.

Set up an inclusive data governance body

The establishment of a national environmental data council or working group is recommended to oversee data system development, maintenance, and governance. This body should include central government (e.g. MfE, Stats NZ, DOC, LINZ), local government (e.g. Local Government New Zealand or regional council Special Interest Groups) Māori representatives (possibly nominated by Te Kāhui Raraunga or Te Mana Raraunga), research institutions, and private sector representatives. Its role would be to develop and maintain standards, prioritise data investments, resolve cross-agency issues, and ensure alignment with Te Tiriti o Waitangi obligations. This group could be a formal committee under the Government Chief Data Steward and might eventually become an independent entity managing a unified environmental data system with funding from multiple sources (government, grants, industry contributions).

Invest in systematic ground-truthing and calibration infrastructure

A recurring theme in this report is the need for validation of environmental remote sensing data. Many global models (for biomass, soil carbon, etc.) are built for international conditions and often do not directly transfer to A-NZ's unique ecosystems. Local calibration ensures remote sensing outputs are credible. Establishing a network of long-term validation sites across representative ecosystems, and with sustainable funding is recommended. For example, reference plots in forests where carbon is measured on ground while satellites pass overhead. This could build on existing networks such as Forest Flows plots (hosted by Scion) or catchments monitored by NIWA, and include a range of ecosystems and landscapes.

Bridge high-resolution local data and broad-scale monitoring

As noted, significant gaps exist between fine-scale monitoring (farm or regional) and national or global assessments. It is recommended that funding is targeted to research on multi-scale data integration techniques. This R&D should develop methods, likely AI-based, to incorporate high-resolution drone or field data together with satellite data to improve models. One example is using machine learning to learn relationships between 10 cm resolution drone images and 10 m satellite images so that satellites can effectively provide similar insights as drones in areas where there is no drone coverage (Carbonneau et al., 2020). By investing in such innovation, A-NZ can maximise the information gleaned from all scales, including exploring upcoming technologies like super-resolution algorithms (to synthetically enhance satellite imagery using training from higher-res data) and data assimilation techniques in models (like incorporating satellite and ground data into one consistent model). The outcome could be that local detail informs national models, and national context informs local analysis, thus enabling decision-makers to drill down from a national picture to on-the-ground specifics.

Continue addressing research gaps within Aotearoa New Zealand

Finally, it is vital to recognise and fill research gaps where A-NZ's environment has unique characteristics. For instance, developing locally tuned climate models that incorporate A-NZ's complex terrain and oceanic context, creating biodiversity monitoring frameworks suited to high rates of endemism, and improving natural hazard models for seismic and volcanic activity. Many of these require targeted studies and integration of different data types. Funding agencies should earmark resources for environmental data-related research questions that are specific to A-NZ. This would ensure our environmental data system stays current and adaptive as new opportunities or challenges arise. Critical research needs currently include:

- achieving full soil carbon mapping coverage
- refining methane accounting methods for pastoral agriculture
- developing coastal ecosystem monitoring for sheltered estuaries
- monitoring emerging tech like new satellite missions and sensor types

Conclusion

By implementing these recommendations, A-NZ can transform its environmental data landscape into a cohesive unified system that empowers decision-makers, respects and involves kaitiakitanga by Māori, and harnesses technology and community. The path forward requires coordination, investment, and cultural change, but examples around the world show it is feasible and worth the investment. The recommendations in this report align with the PCE's ongoing focus on "environmental information systems", and the MfE-commissioned report, which called for better alignment of reporting, research, and investment (environment.govt.nz). These works serve as a roadmap for turning environmental remote sensing and related innovations into robust environmental benefits, ensuring A-NZ's decision-makers are equipped with the best possible information.

Appendices

Appendix A: Analytical Techniques for Remote Sensing Data

This appendix explains in non-technical terms some common analysis methods mentioned in the report, to aid understanding for people who may not have a data science background. It also underscores why different methods are used and how they relate to the trustworthiness of insights.

In essence, the analytical toolbox ranges from simple to cutting-edge: choosing the right tool often involves a trade-off between interpretability and complexity/accuracy. A collaborative environmental data system should support multiple approaches, enabling straightforward analyses for routine monitoring and more complex ones for advanced research, and crucially, link them so that insights are cross validated. By combining human expertise with these analytical techniques, remote sensing data can be translated into credible, actionable environmental knowledge.

Intersection over Union

Intersection over Union (IoU) is a metric for evaluating the spatial accuracy of predictive models, particularly in tasks like object detection, land cover classification, and change detection. IoU measures the overlap between predicted and ground-truth regions by calculating the ratio of the intersection area (where predictions and ground truth overlap) to the union area (the total area covered by both). A value of 1 indicates perfect alignment, while lower values signal misalignment. However, IoU has limitations, such as sensitivity to class imbalance and data resolution, which can skew results if not addressed through weighted calculations or combined with other metrics like the F1 score - a performance metric commonly used in machine learning. Despite these challenges, IoU remains an important tool for validation due to its intuitive interpretation and direct relevance to spatial precision

Confusion Matrices

Confusion matrices provide a detailed breakdown of classification model performance in remote sensing, showing how well a model distinguishes between different land cover or land use classes. Structured as a table where rows represent actual classes and columns represent predicted classes, confusion matrices reveal misclassification patterns by counting true positives, false positives, and false negatives. Metrics like precision, recall, and the F1 score, derived from confusion matrices, offer class-specific evaluations, enabling targeted improvements. When combined with metrics like IoU, they provide further insight into prediction power, ensuring both spatial and categorical accuracy.

Table A. Overview of Analytical Techniques Commonly used in Remote Sensing				
Analytical Technique	**Description (Non-Technical Explanation)**	**Example Use Case**	**Strengths / Advantages**	**Limitations / Considerations**
Data Assimilation (model-observation blending)	The process of continuously integrating real-world observations into a running predictive model to keep the model's simulation aligned with actual conditions. Often used in environmental forecasting (weather, hydrology, climate) with formal statistical methods (like Kalman filters) to combine model and data.	NIWA's weather models in NZ assimilate satellite observations (e.g. cloud cover, moisture readings) at regular intervals so the forecast stays on track and errors are corrected with real data. Similarly, global carbon cycle models assimilate CO_2 measurements from stations and satellites to constrain and improve their estimates of emissions and uptake.	- Merges the strengths of models and observations: produces more accurate and robust outputs than using the model or data alone. - By correcting model trajectory with real data, it improves forecast reliability and helps models handle unexpected changes. - Assimilation frameworks rigorously account for uncertainties in data and model, increasing confidence in results.	- Technically complex and computationally demanding to implement. - Depends on a steady stream of quality observational data and a well-calibrated model; if data are sparse or errors aren't handled properly, benefits diminish. - Requires expertise to tune and maintain, but when done well it greatly enhances the trustworthiness of model predictions.
Data Fusion (multi-source integration)	Combining multiple data sources or sensor types in analysis to enrich information or improve accuracy. Different datasets (e.g. optical imagery, LiDAR, radar) are merged or used together to leverage their complementary strengths.	For example, LiDAR elevation data can be fused with aerial imagery to better distinguish vegetation types (tall forest vs short scrub by adding height information). Another example is pan-sharpening, where a high-resolution panchromatic image is combined with lower-resolution multispectral images to produce a single high-detail colour image.	- Leverages complementary information: integrated data can provide a more complete picture (one dataset can fill gaps of another). - Can improve accuracy and detail – e.g. adding LiDAR's 3D structure to imagery improves classification, and merging images of different resolutions yields sharper results. - Allows analysis of features not visible in a single source alone e.g. detecting features only when height and colour data are both considered).	- Data integration can be complex: requires aligning (co-registering) different datasets and dealing with differences in resolution or format. - Relies on availability of multiple datasets for the same area/time; these might be costly or hard to obtain for all regions of interest. - If not carefully calibrated, differences between data sources (noise, resolution, timing) can introduce errors or inconsistencies in the result.
Machine Learning (algorithmic modelling)	Uses data-driven algorithms to learn patterns without a pre-defined equation. Can model complex, non-linear relationships using multiple input variables. Includes methods like decision trees, random forests, and neural networks.	A random forest model can be trained on many satellite bands and terrain data to predict a biodiversity index; the algorithm automatically finds which combinations of inputs (and any thresholds or interactions) best predict the index.	- Highly flexible: can capture complex, non-linear patterns that simple models might miss. - Often achieves higher predictive accuracy on complex datasets. - Can incorporate many variables and large datasets, leveraging more information for better predictions.	- Less interpretable ("black box") – it's not always clear why a particular prediction is made. - Generally requires more data for training; if data are limited or biased, the model may overfit or learn spurious patterns. - Typically more computationally intensive than simple regression.

Table A. Overview of Analytical Techniques Commonly used in Remote Sensing				
Analytical Technique	**Description (Non-Technical Explanation)**	**Example Use Case**	**Strengths / Advantages**	**Limitations / Considerations**
Neural Networks & Deep Learning (advanced machine learning)	A subset of machine learning using multi-layered neural networks to automatically learn complex features from data. Especially effective for high-dimensional inputs like images. For example, Convolutional Neural Networks (CNNs) progressively detect edges, textures, and shapes, building up to recognise objects or land-cover types.	CNNs (a type of deep learning model) have been used to analyse imagery – for example, scanning satellite images to detect ships at sea or to classify land cover in fine detail (even distinguishing similar crop types). Deep learning has also been applied to time-series data: for instance, in A-NZ some hydrological models use Recurrent Neural Networks (a deep learning approach) to predict complex stream flow patterns.	- Very powerful for complex tasks: can outperform traditional methods in image recognition and pattern detection, capturing fine details and subtle differences. - Able to fuse multiple data types (e.g. ingesting imagery + weather data together) within one model for richer predictions. - Learns features automatically from raw data, reducing the need for manual feature engineering.	- Data-hungry and computationally intensive: requires large labelled datasets and significant computing power for training. - Lacks transparency: essentially a "black box" – difficult to interpret why it makes specific predictions, and it doesn't inherently provide uncertainty estimates. - Due to these challenges, adoption in NZ's environmental applications has been limited so far (with some exceptions like specialised hydrological models); thorough validation with independent data is needed to trust results.
Regression Analysis (statistical model)	Fits a simple equation to relate a known independent variable to a dependent variable based on observed data. Assumes a specific relationship shape (often linear). Yields a clear formula for the relationship.	Linear regression can predict water clarity from satellite-measured reflectance at certain wavelengths, yielding an equation (Y = aX + b) relating reflectance to clarity.	- Straightforward and transparent: produces an explicit mathematical formula that is easy to interpret. - Provides uncertainty estimates (confidence intervals) for predictions. - Can work with relatively small datasets if assumptions (like linearity) hold.	- Assumes a fixed relationship form (e.g. linear), so it may miss complex non-linear patterns. - Less flexible if multiple factors or interactions affect the outcome (can underfit complex data).
Supervised Classification (with training data)	Image classification guided by examples of known categories. The analyst supplies labelled training pixels/areas for each class (e.g. forest, pasture, urban), and the algorithm learns from these to classify the rest of the image into those categories.	A-NZ's national land cover maps are produced with supervised classification: analysts provide training samples for each land-cover class, and algorithms (e.g. random forest or SVM) then classify the entire satellite imagery. Human experts review and adjust results to ensure consistency with defined classes.	- Can produce accurate, reliable thematic maps when quality training data is available. - Ensures the map aligns with specific classes of interest (and definitions) provided by the user. - Tends to have high accuracy for well-represented classes since the model is "taught" with real examples.	- Requires good representative training data for each class, which can be time-consuming to collect. - Cannot identify classes that were not included or adequately represented in the training dataset. - Some manual effort (for training data collection and validation) is needed, which can introduce human bias or error.

Table A. Overview of Analytical Techniques Commonly used in Remote Sensing

Analytical Technique	**Description (Non-Technical Explanation)**	**Example Use Case**	**Strengths / Advantages**	**Limitations / Considerations**
Unsupervised Classification (cluster analysis)	Image classification without prior labels. The algorithm (e.g. k-means clustering) groups pixels into clusters based on statistical similarity alone, without knowing what those clusters represent. The analyst must then interpret and label each cluster by comparing it with reference information or field knowledge.	Analysts might run unsupervised clustering on satellite imagery to see natural groupings in the data. For instance, pixels might be grouped into several spectral clusters that the analyst later identifies as different land cover types (perhaps revealing a category that wasn't pre-defined).	- Does not require any pre-labelled training data – useful for exploring new or unknown patterns when ground truth data is unavailable. - Can highlight unexpected or subtle categories in the data that a pre-defined classification might overlook (may reveal "unknown" classes or variability).	- Clusters may not correspond cleanly to real-world categories (one cluster might mix multiple land types, or a single class might split into several clusters). - Results need manual labelling and interpretation, which can be subjective. - Generally yields less accurate or useful maps than supervised methods when reliable training data is available.
Accuracy Assessment & Validation (Confusion Matrix, RMSE, R^2)	Techniques to evaluate the accuracy of remote sensing outputs by comparing them to reference "ground truth" information. For classified maps (categorical data), accuracy is measured with a confusion matrix comparing predicted vs actual classes (yielding metrics like Overall Accuracy, and per-class User's and Producer's Accuracy). For continuous estimates (numeric data), metrics like Root Mean Square Error (RMSE) indicate average error magnitude, and R^2 (R-squared) indicates the proportion of variance explained by the model.	For instance, a national land cover map validated against field survey sites might show around 85% overall accuracy and high user's accuracy for major classes – giving confidence for broad land-use policy. Meanwhile, a continuous-model output (e.g. a soil carbon map) could have RMSE around 2% and R^2 about 0.70 when tested against soil samples, meaning predictions are on average within ±2% of actual values and explain about 70% of observed variation. That level is suitable for regional planning, but not exact enough for farm-level accounting.	- Provides quantitative confidence measures for maps and models, helping decision-makers gauge how much to trust the data. - Identifies strengths and weaknesses: e.g. which classes are well mapped or which areas have high errors, guiding improvements. - Essential for transparency and credibility – shows that remote sensing products have been rigorously tested against reality.	- Requires high-quality validation data (ground truth), which can be costly and time-consuming to collect at scale. - Metrics need interpretation in context: an "acceptable" accuracy level varies with the application (e.g. 80% might suffice for national monitoring but not for enforcement on individual properties). - Ongoing validation is needed as new sensors or models are introduced (to verify, for instance, that a new satellite's claimed precision holds true under local conditions).

Appendix B: Spotlight Box Organisations - Desktop Survey Methodology

The survey that informed the Spotlight Boxes in this report focussed mainly on private corporate sector organisations. It was conducted via desktop internet search of company websites and public-facing descriptions of their services and offerings. This was supported by conversations with the Eco-index industry network to identify and/or qualify companies of interest to include. A long-list of companies was identified from this desktop research, and this was subsequently short-listed. Short-listed companies were selected to include those who offered remote sensing data collection services, remote sensing hardware, software for accessibility or analytics (e.g. interpretation platforms).

The first step of the short-listing process was to include companies directly relevant to the focus areas of this report. This process required Eco-index professional and expert judgement due to the diversity of business models within this private corporate space, language used, and publicly facing material companies make available. Notably, website resources are often intended for marketing rather than technical purposes and interpretation of this information in the context of the report's focus areas was required. Eco-index recognises that alternative expert judgement may have resulted in an alternative selection of Spotlight companies. Areas of judgement and selection include making the following distinctions:

- Between companies who provide data that is possibly applied to the focus areas in question, and companies who actively and/or explicitly focus on servicing these focus areas. This includes identifying companies offering products and services with the potential to be relevant to environmental monitoring (such as generalised landscape imaging for planning, infrastructure or military purposes) but are not directly and explicitly stated by the company as being currently directed to environmental monitoring in their business. Companies actively and/or explicitly servicing the focus areas were included in the shortlist.
- Companies focusing primarily on consulting or planning services which includes making use of 3rd party remote sensing data and technology, and companies offering generalised aerial imaging services. Such companies were excluded from the short list.

The second step was to identify companies within each focus area. This step involved a binary scoring of Y or N for companies' coverage of the focus areas in this report: biodiversity monitoring, GHGs and climate change, land cover and land use, carbon sequestration, soil condition, water quality and hydrology, and marine condition. Companies which provide a wide range of remote sensing services or provide services that are or could be applied to a wide range of focus areas (such as satellites that provide imagery applicable to a range of applications) were subsequently scored with 'Y' across a range of focus areas.

Shortlisting outcomes:

- From a long-list of 36 A-NZ companies identified, a short-list of 17 that offered products or services specific to one or more focus areas was developed. The 19 excluded from the shortlist offered products and services related to remote sensing (such as mapping and GIS services) but were not directly or explicitly focused on environmental monitoring.
- Internationally, the survey identified a short list of 57, from a long list of 83 companies.

From these short lists, companies were selected for inclusion in the Spotlight Boxes and discussion within the wider report.

Final selection considered representation of the range of remote sensing applications to fill data gaps or increase coverage extent, improve temporal and spatial resolution, provide novel integration with other sensors (remote or *in situ*), or apply novel environmental domains/cross domain use. Spotlight companies were selected for their illustrative purposes and are not intended to represent a comprehensive analysis of the many industries engaging with remote sensing technologies relevant to environmental monitoring. Note that this desktop and internet-based survey did not extend to engaging companies directly to verify or augment their information available online and thus, selection of one company over another does not represent an exhaustive or academic overview of all long-list companies.

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