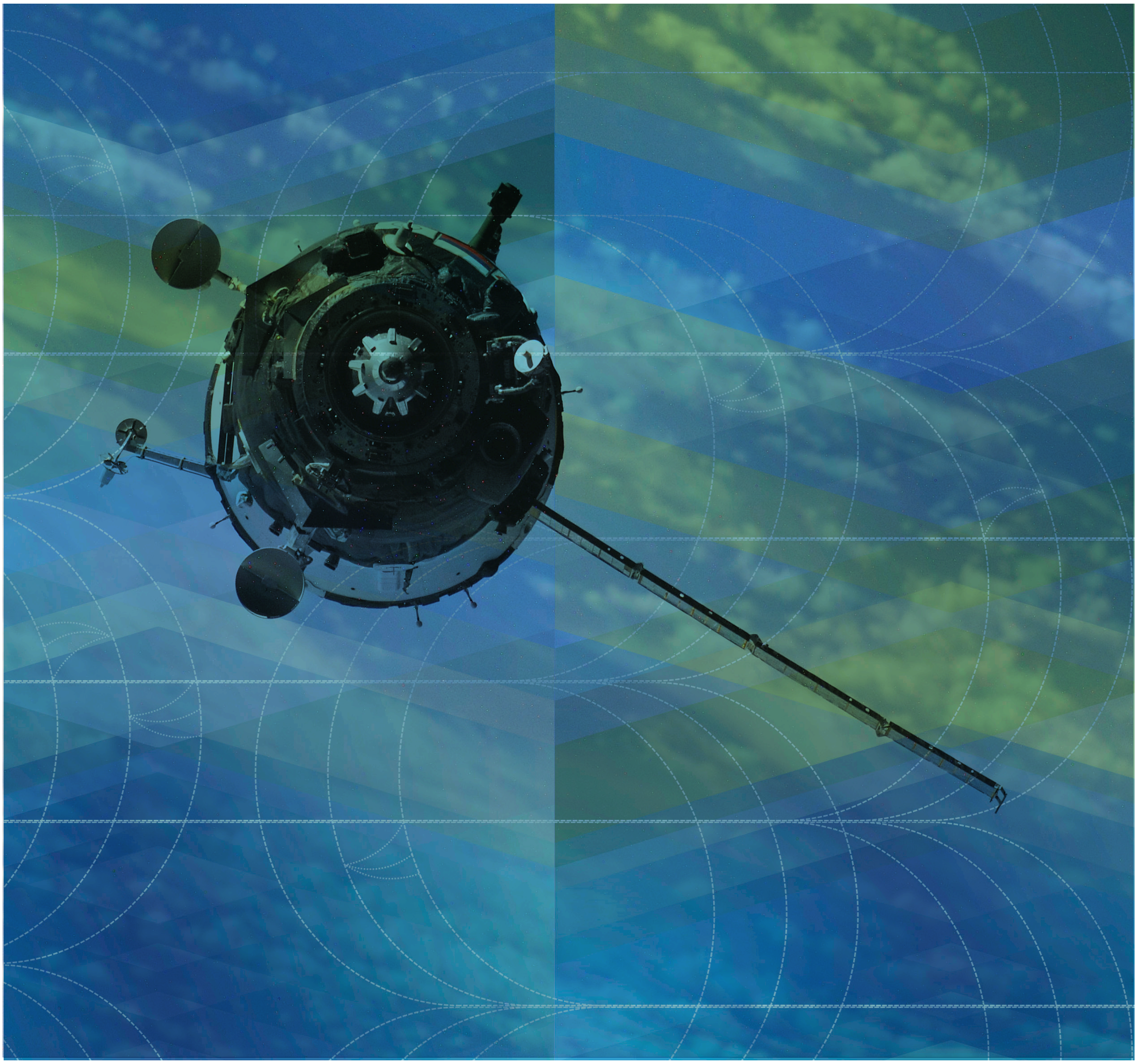
Kaitiaki Intelligence Platforms

Earth Quotient



The Kaitiaki Intelligence Platform: An automated sensor network design for meeting the environmental intelligence needs of Māori Agribusiness Collectives and Iwi

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The Kaitiaki Intelligence Platforms (KIPs) project aims to position Māori at the forefront of cutting-edge remote environmental sensing in Aotearoa.

Leveraging the latest and emerging technologies, this project is designing a robust tech platform that will empower iwi to access real-time and precise information about the environmental condition of their rohe (territories). Furthermore, it will equip Māori farming collectives with the essential data to confidently manage their farms in alignment with their kaitiaki principles. Additionally, the platform will facilitate Māori farms in verifying their sustainable production to markets, regulators, and assurance bodies. Simultaneously, it will provide invaluable data to iwi for informed decision-making regarding their environmental management plans and policies

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Content

05 Quick Summary

08 Introduction

10 Māori need quality environmental intelligence with cultural fit

13 How to build Māori values into next-generation environmental intelligence platforms

16 Based on the Māori knowledge structure, what types of environmental data should be incorporated within the platform

18 Adding extra functionality to the environmental intelligence platforms

26 Types of metrics sought by MACs, iwi, assurance systems, sustainable finance and markets

30 Explaining and defining the technology

30 In-situ Sensors

30 Remote Sensors

32 Combining In-situ and remote sensors

32 Making sense of data – warehousing and analysing data

33 Communicating data

36 Technology to generate and communicate the data MACs and iwi need

36 Detecting Biodiversity

37 Detecting Nutrients and Microbial Diversity in Soil and Water

39 Detecting erosion

39 Detecting sediments in water

40 Detecting Carbon Emissions and Sequestration

43 Detecting Water Availability and Excessive Extraction

44 Detecting Heavy Metals in Soil

44 Detecting species biodiversity in surface water

46 Combining technologies to generate a Kaitiaki Intelligence Platform

49 The Kaitiaki Intelligence Platform – a modular design

54 The Kaitiaki Intelligence Platform Design

55 Figure 1: Whakapapa structure underpinning the Kaitiaki Intelligence Platform design.

57 Figure 2: Process for using mātauranga Māori to guide AI

58 The costs of building the Kaitiaki Intelligence Platform

61 Conclusions and recommendations

63 Citations

71 Glossary

70 Acronyms

Disclaimer

The environmental sensor network design outlined in this report is conceptual and based on current technological standards and methodologies. It represents an experimental approach to environmental monitoring and is intended to serve as a preliminary framework for further development. Given the rapidly evolving nature of sensor technology and environmental monitoring practices, the specifics of this design may be subject to change as new technologies emerge or as more detailed project requirements are defined. The design is provided for informational purposes and should be viewed as a starting point for discussion and planning. It does not guarantee specific performance outcomes or compatibility with all potential environmental conditions and monitoring needs. Stakeholders should conduct a detailed and comprehensive analysis, including field trials and technology validation, to adapt and refine the design to meet the specific objectives and operational conditions of the intended deployment. The implementation of this sensor network design will require careful consideration of technical, environmental, and logistical factors, and it should be undertaken with flexibility to accommodate necessary modifications and improvements based on ongoing research and development in the field.

The cost estimates provided herein are preliminary and based on current market analysis, intended as a general guide for initial budgeting purposes. They are not definitive and may vary significantly depending on actual project conditions, technological advancements, market fluctuations, and specific implementation challenges encountered. Before proceeding with project implementation, a comprehensive financial assessment must be conducted. This detailed cost analysis should account for all capital and operational expenses, including installation, maintenance, potential research and development, and any contingency planning. This thorough financial planning is essential to ensure that the project is financially viable and to prepare for any budgetary adjustments that may be required during the course of the network's development and deployment.

Quick Summary

Māori possess profound whakapapa connections to the lands and waters of Aotearoa New Zealand (A-NZ), with a strong commitment to protecting and enhancing the environment. This commitment extends into organisations, with Māori agribusiness collectives (MACs) seeking enhanced environmental intelligence for farming operations and iwi seeking data for environmental management and resource issues.

Environmental sensing technology is advancing rapidly, offering significant opportunities for MACs and iwi to develop and deploy environmental sensor networks that provide continuous and comprehensive environmental data. Historically, Māori have been quick to embrace and integrate new technologies into their culture, all while maintaining their core values.

There is a high demand for quality environmental data across various sectors. The sustainable finance sector is in search of reliable environmental data to ensure that their investments remain secure amidst tightening environmental regulations. Similarly, the agriculture and forestry assurance sectors require such data to prove the sustainability of their practices to the market and regulators. However, integrating this high-quality data into their systems poses challenges due to issues with their data infrastructure and the challenges they face in establishing data standardisation. By developing and deploying environmental sensor network, Māori have the chance to lead in supplying detailed environmental data to these sectors, which could help finance the development of a sensor network.

This environmental data will also enable MACs to command higher prices for their products because of the growing international demand for sustainably produced goods. These market segments will pay a premium but require verification that the environmental claims are real.

Based on a detailed review of Māori, iwi, and MAC environmental reporting frameworks, alongside workshops with iwi and MACs, it was determined that these entities are seeking environmental intelligence that is framed from Māori worldview and draws upon both scientific biophysical indicators and local indigenous experiential knowledge and awareness.

This report details a design for an environmental sensor network that can meet these aspirations and generate the types of data that iwi and MACs seeking, while also generating data that would meet the needs of the sustainable finance sector, markets, and regulators. This network is referred to as the Kaitiaki Intelligence Platform (KIP).

Four Pillars

1

The first pillar of the network is a range of new sensing technologies combined with local mātauranga (indigenous knowledge). In terms of technology, data would be generated by satellite, plane, or drone mounted remote sensors, such as LiDAR, hyperspectral imaging, and GNSS-R reflectometry, in combination with on-ground sensors, for example lysimeters (measuring water quality) and eDNA (measuring biodiversity). In terms of mātauranga, sources of data may include, for example, knowledge of changes in environmental patterns, such as species abundance or migrations. Mātauranga can guide remote and in-situ sensors in terms of where and what biophysical data is gathered.

2

The sensors would gather significant quantities of data that needs to be organised. Making sense of the data is the second pillar of the KIP, and is referred to as taputapu, or pattern recognition. Following significant advances, Artificial Intelligence (AI) is a technology that enables rapid pattern recognition within data to identify signatures of environmental health. However, to become accurate AI needs to be trained through ground truthing. Mātauranga Māori alongside field research can be used to do this to ensure that the patterns being recognised match the science and experience on the ground.

3

The large quantities of data analysed, modelled, and processed by AI needs to be stored. This is third pillar of the KIP, with the need for a data warehouse that stores and protects the data. Special consideration needs to be given to indigenous data sovereignty, with emphasis on protecting valuable environmental data generated through the prompting and guidance of mātauranga Māori – including AI algorithms.

4

The fourth pillar of the KIP is the user interface. This frames and communicates the environmental information generated by the KIP. Drawing on a range of Māori, MAC, and iwi environmental reporting systems, a whakapapa (genealogical) structure has been suggested, which organises the information into different atua domains, for instance Tāne-mahuta (forest and vegetated areas), Rongomātāne (cultivated areas), Hinemoana (water bodies), and Tūmatauenga (human society). This grounds the KIP in a relational worldview, with the relationship between humans and the environmental atua being gauged in terms of utu (relationship balance), and more particularly whether humans are acting in ways that enhance or diminish the mauri (vitality) or mana (dignity) of environmental atua.

It is envisioned that a user interface will communicate the state of the environment for MACs or iwi through this relational framing. However, it would also need to communicate information in biophysical formats that are crucial for MACs and iwi to engage with governments, markets, and regulators – and to potentially sell data to clients. The biophysical data prioritised by MACs and iwi in the design include: biodiversity; water quality, quantity, and use efficiency; soil quality; greenhouse gas emissions (GHGs) and sequestration; and stock management. The mediums for communicating this range of environmental information might include data reports, geospatial mapping, and virtual reality. A schematic of the full design of the KIP can be found in Figure 1 of the report.

The KIP has adopted a modular design, which would enable the KIP to be built using a staged approach, that is module-by-module according to priority and resourcing. However, there are efficiencies that can be gained through a complete build. A hybrid approach, which considers the entire system while developing individual modules, may offer the best of both worlds, combining efficiency with resource-driven development and tailoring each module to local conditions for improved predictive accuracy.

It is estimated that a full KIP build, following a hybrid approach, would cost approximately NZ$50million, with NZ$12m in maintenance costs – primarily associated with the purchase of satellite data.

It is concluded that building KIPs would require a consortium approach amongst MACs and iwi, with select involvement of the public sector in terms of funding and research investment, and private sector in terms of accessing data and technology.

Introduction

The purpose of the Kaitiaki Intelligence Platform (KIP) project is to position Māori as first movers in environmental intelligence. Environmental sensing technology is advancing rapidly, offering significant opportunities for Māori agribusiness collectives (MACs) and iwi. Māori have a strong history of rapidly adopting and incorporating new technologies into their culture, whilst still retaining core values. In fact, mātauranga Māori can be used to shape how this technology develops and how it is applied. As part of this knowledge system, Māori have their own methods and techniques for environmental sensing based on long-standing relationships with, and experiences of, place. This includes knowledge of changes in the abundance of plants, birds, insects, fish, across land and waterscapes. There is deep mātauranga on the underpinning rhythms of nature, based on the maramataka and whakaaro on seasonal changes, and how humans and non-humans move according to these patterns - whether the migration of fish, or the arrival or departure of birds in the spring and autumn. Deep insights into methods of environmental management are also pervasive, with the capacity to predict the impacts and consequences of specific actions on the environment.

On a wairua level, there is knowledge of the representatives of the ancestor communities that make-up the non-human world - the atua, and the spirits of nature including taniwha and patupaiarehe that exist between the material and non-material, dwelling in our rivers and on our mountain tops and valleys. Drawing on this knowledge many āhika can sense and know the changes happening to our environment and often acting as the environmental conscience of their tribal territories to draw attention to what is happening to the mauri and mana of our environment and how to respond.

In conjunction with the deep environmental awareness, Māori have also adopted scientific methods and technologies to supplement and augment their indigenous environmental sensing capabilities. While mana whenua can tell that the mauri of a river, forest, or wetland has declined or improved, pinpointing the specific origins and causes can at times be difficult when there may be multiple factors at play. It is for this reason that many MACs and iwi adopt scientific testing and monitoring, using their knowledge and insights to guide the scientific process, interpret results, and communicate them to audiences using their own cultural framing. In this way there is complementary interchange between science and mātauranga Māori. Māori also operate in a political environment where there is a strong emphasis on using knowledge generated via scientific evidence to make decisions. Consequently, generating scientific knowledge in an interchange with mātauranga Māori provides a powerful means for Māori to influence decisions concerning the environment by councils and central government.

In this report, we introduce MACs and iwi to the latest environmental sensing technology. We review this technology and look at the various technologies that can be brought together to build a platform that can provide comprehensive environmental monitoring and intelligence - we refer to this as Kaitiaki Intelligence Platform. We explore how such a platform might be framed using mātauranga Māori, and how such a platform could be used by MACs and iwi to enhance their farming and forestry practices, while generating insights to help them monitor the environmental health of their tribal lands and make informed resource management decisions.

We also outline how this type of environmental intelligence is in significant demand in the assurance sector and sustainable finance sector - where regulators, industry, investors, and consumers are looking for hard data and evidence that agricultural and forestry businesses are sustainable. Such data can be sold to generate income and be used by MACs and iwi to verify the sustainability and indigenous authenticity when selling their products in premium markets.

In this report, the emphasis has been placed on exploring the new and innovative technologies, how they might be applied and bundled into a KIP to generate types of environmental intelligence that MACs and iwi are seeking, and how much it might cost to build a platform. However, the way in which mana whenua may wish to adopt and use the new technologies will differ depending on context and the tikanga specific to each hapū or iwi grouping. Consequently, the focus in the report is on a general framing of how a platform might be deployed. In conclusion, KIPs offer iwi and MACs the opportunity of becoming the innovators and leaders in the adoption and utilisation of novel environmental sensing technologies generating comprehensive insights into the environmental changes across their whenua and awa.

Lastly, this report is the product of six 'feeder reports' which have been conducted across several objectives, bringing together desktop research and expert interviews, and where relevant the hyperlinks to these feeder reports have been provided.

Māori need quality environmental intelligence with cultural fit

Over the past three decades, Māori have gained prominence in the primary sector. Numerous Māori agribusiness collectives (so called as the land is governed for the benefit of a broader group of owners - hereafter 'MACs'), including land trusts, incorporations, and iwi-owned corporations, have established successful farming and forestry enterprises. These enterprises are recognised for their profitability and commitment to Māori environmental values. While many MACs utilise platforms, such as Overseer and FARMAX, to evaluate their environmental performance, these systems are typically designed to meet regulatory, market, and production demands rather than the needs of trustees, directors, managers, and collective owners. These constituents require detailed, customised environmental intelligence to guide their farming and forestry activities to ensure they are operating in alignment with their indigenous values.

In addition to their role in the agricultural sector, iwi have also become politically prominent, securing a degree of influence over the environmental governance of their tribal territories. Regional and district councils are legally required to consult with local iwi when developing their plans and policy statements. Local iwi also have the authority to express concerns or opposition to the granting of resource consents for activities they believe may negatively impact the environment from their cultural perspective. Furthermore, the current resource management legislation is undergoing reform, with the Māori input and influence set to become even more robust. However, when consulted, iwi often operate in an information vacuum. They have limited access to the type or quality of environmental data required to develop environmental plans and assess impacts from their cultural perspective. Many environmental monitoring frameworks have been developed by Māori for broader catchment and regional scales to target specific species and ecosystems such as kauri and rivers. These frameworks have largely emerged because of the growing role iwi have in environmental and resource management and are generally built on a foundation of indigenous values and gather a range of data. Yet, the collection of this data is costly and incomplete.

Most MACs and iwi also have an explicit values framework. These frameworks are generally developed as part of broader charter or constitution, and usually cover a broad range of environmental, social, cultural, and economic parameters. However, while these frameworks are used to both to guide decision-making and assess outcomes in annual reports, they are rarely monitored or measured in any systemic or rigorous fashion. Like corporate values more generally, they are often presented as aspirational goals or ambiguous objectives rather than quantifiable targets or baseline goals. This is not because MACs and iwi do not want to be able to monitor and measure these parameters but rather because obtaining this data has been beyond their capacity. As entities that strategise in long-term, often intergenerational, time periods the focus of many MACs and iwi is to operationalise their values frameworks, as Māori values are action-oriented, functioning as ethics that must be assiduously and actively upheld.

In summary, MACs and iwi need quality environmental intelligence that meets their cultural needs. Previously, the construction of technology platforms capable of delivering the necessary level of environmental data required by MACs and iwi was either prohibitively expensive or technically infeasible. However, recent advancements in environmental sensing, artificial intelligence (AI), and data warehousing combined with dramatically falling costs have made this both financially and technically viable. It is plausible that the existing farm platforms MACs use may soon become obsolete or be integrated into new, next generation, dynamic systems. A combination of affordable in-situ and remote sensors will generate vast amounts of real-time, high-fidelity environmental data. AI will structure this data, creating digital twins of farm environments that can guide on-farm management decisions to achieve desired environmental outcomes. Similarly, this technology can be used to generate digital twins of iwi tribal territories. Existing environmental monitoring systems and models administered by local and central government that currently provide data to iwi may also become obsolete or the data they produce may be integrated into these next-generation platforms. However, if Māori are not involved in the design of these systems they risk having to use one that enforces a Western-centric worldview onto their operations[1,2].

Broader internal and external drivers

MACs and iwi face numerous, sometimes conflicting, internal and external pressures including collective owner demands, economic performance, environmental sustainability, regulatory requirements, and cultural obligations. These pressures are exacerbated by a broader national imperative to transform the economy in the face of environmental limits. Similarly, for landscapes recognised as legal persons, innovative restoration and management is required to realise Māori community aspirations with respect to kaitiakitanga (guardianship) at scale. Culturally-framed, environmental intelligence platforms can help overcome many of these pressures.

As outlined, MACs and iwi are beholden to their collective owners, who want reassurance that their lands are being managed in a way consistent with their values, whilst also delivering economic returns. These owners are often geographically dispersed and have varying connection to their culture and land, requiring communication - and the underpinning environmental data - that has a high degree of transparency and clarity. High quality, comprehensive, and reliable environmental data is of fundamental importance to MAC owners and iwi, particularly when it is gathered, presented, and acted upon in ways that align with Māori environmental values. It will also help increase economic outcomes whilst simultaneously conserving and enhancing the environment.

Externally, MACs and iwi face a range of pressures to provide environmental data and maintain the highest environmental standards. These pressures come from markets, regulations, public opinion, policy, and finance. In terms of markets, consumers and retailers are increasingly seeking products made sustainably, with demands for these claims to be verified through tracing and assurance schemes. MACs also face many regulatory requirements around environmental standards and reporting that require environmental data. More nebulous, but Māori have also long campaigned for higher environmental standards, creating a burden of proof on Māori primary producers

to ‘walk the talk’. The Aotearoa New Zealand (A-NZ) government has indicated a transition to a low emission, carbon neutral primary economy in the coming decades, with numerous government policies and roadmaps outlining the need for improved environmental outcomes and also increased monitoring. The finance sector is also increasingly interested in the environmental credentials of loan applicants, particularly due to these other pressures and the consequent ongoing economic viability of the operation.

How to build Māori values into next-generation environmental intelligence platforms

To ensure that KIPs deliver environmental intelligence that aligns with indigenous values and guides decision-making, it is essential that they are shaped according to Māori cultural perspectives.

This involves a four-stage process:

1. The indigenous knowledge structure must be made explicit.
2. This structure needs to be used to determine the types of environmental sensing data that should be incorporated into the platform.
3. The structure should guide the training of AI to model environmental data.
4. It must influence how the generated information is communicated to support decision-making.

A report on stage one has already been completed. This four-stage process is outlined on p14 (overleaf).

Making the Māori knowledge structure explicit

Māori environmental values are shaped by mātauranga Māori and Te Ao Māori. Together, these are guided four key underlying axioms: reality is holistic, in that humanity and nature are nor separate, nor are the material and immaterial worlds; relationships are central, placing process over substance and dynamism over materiality; balance is the most important dynamic in these relational processes; and that reality is cyclical, which places importance on both the past and future as well as the present[3].

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A simplified Māori knowledge structure for developing KIPs may be built on five fundamental Te Ao Māori concepts that emerge from these axioms:

1

Whakapapa

The genealogical framework that outlines the history, relationships, and interconnections between entities, which, from a Māori perspective, include both humans and non-humans[4,5,6]. Through this lens, all entities in the world are related and part of an extended kin-group or 'cosmological family'. For instance, entities may include: Papatūānuku, Ranginui, Tangaroa, Tāwhirimātea, Tāne-mahuta, Rongomātāne, and Tūmatauenga etc[7].

2

Mauri

From a Māori cosmological perspective, mauri is a central animating principle[8,9]. It can be used for understanding and assessing the vitality of both human and non-human entities[10]. Entities in a state of high health and vitality are considered to have abundant mauri, while those with compromised health and vitality have low mauri. Negative actions by one entity can diminish the mauri of another. For instance, pollution of a river by humans will diminish the river's mauri[11].

3

Mana

The concept has a rich array of meanings and in this context, mana refers to the inherent dignity and intrinsic value of an entity, whether human or non-human[12,13,14]. Like mauri, the negative actions of one entity can diminish the mana of another. For example, harm inflicted by a human on another human, or a river, will diminish the mana of the
affected entities.

4

Utu

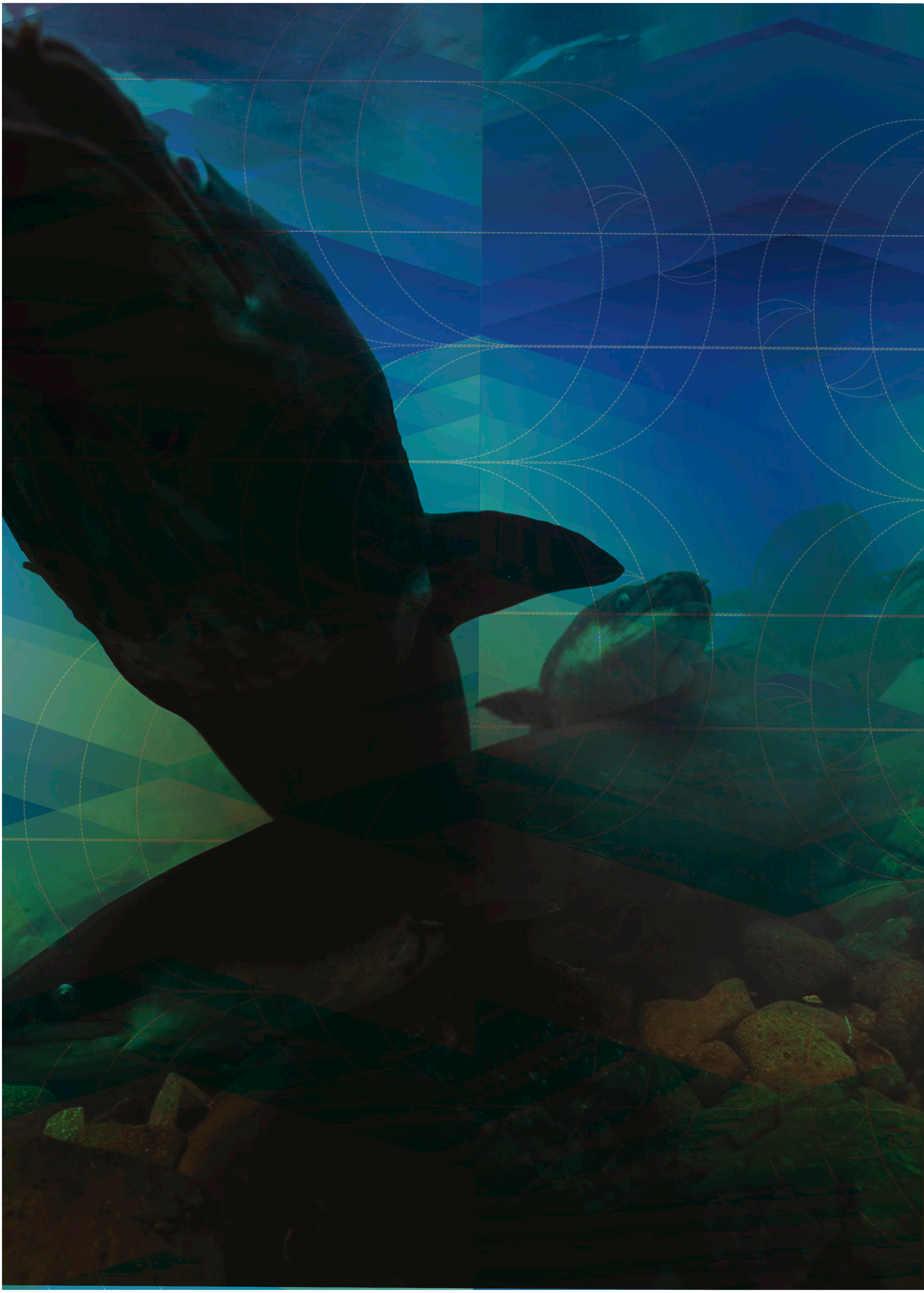
A concept with many meanings and in this context, utu refers to the natural tendency of relationships between entities to establish equilibrium in response to imbalances[15]. For instance, pollution by a human community that diminishes a river's mauri creates a negative imbalance. This imbalance may be redressed by the river no longer providing clean water or harvestable foods. Positive imbalances can also occur, such as when pollution entering a river is addressed, allowing the river to provide clean water.

5

Tauutuutu

The ethical obligation to create positive imbalances between humans, and between humans and the environment, to encourage reciprocating relationships between entities[16].

Together these five concepts work together to form a holistic worldview and environmental ethic. Whakapapa defines the different human and non-human entities that are in a relationship with each other. Mana and mauri gauge the current vitality and status of the entities, while utu conceptualises the relationships balances and imbalances. In terms of environmental ethics, tauutuutu encourages the formation of reciprocal relationships between entities and ascending cycles of growth.



Based on the Māori knowledge structure, what types of environmental data should be incorporated within the platform

The concept of whakapapa defines the domains of interest, determining whose mana and mauri gets measured. For instance, for MACs, this might include the mauri of Papatūānuku, Tangaroa, Tāwhirimātea, Tāne-mahuta, Rongomātāne and Tūmatauenga. In terms of gauging the mauri and mana of these entities, Māori authorities typically use a combination of standard scientific indicators and indigenous knowledge, providing a comprehensive understanding of local environments. For instance, the mauri of a waterway might be gauged using standard scientific measurements such as nitrate, phosphate, pH, and sedimentation levels. Simultaneously, indicators derived from mātauranga, such as changes in the behaviour or abundance of certain species, seasonal cycles, and areas known as sensitive to environmental change, may also be used. Qualitative indicators may also be incorporated, such as intuitive sensing of an environment's vitality. The use of both objective and subjective metrics has shown to be critical to sustainability endeavours to capture the broad reality of 'nature' and seizing the attention of an array of stakeholders. It is often found that hard scientific metrics overly reduce complex systems, universalise different contexts, and are often not as accurate. Furthermore, through numerous projects and initiatives, Māori have shown they are able to enfold both qualitative and quantitative metrics into their worldview without compromising the core values. In most cases, when done properly, this hybrid approach is able to enhance human-environment relationships and strengthen Te Ao Māori.

Using a Māori knowledge structure to guide the training of AI to model environmental data

The interconnectedness of 'Whakapapa' can help guide the development of AI models that better capture the complexity and interconnections between atua domains, as well as mapping the relative value and significance of different relationships. The concepts of mauri, mana, and utu can guide AI to model human-environment relationships in terms of relational and ethical balance – with particular regard to maintaining and enhancing vitality and dignity across atua domains.

Although all Māori share a common knowledge structure, individual hapū possess detailed local knowledge, refined over centuries. This knowledge can be used to train and validate AI models. For instance, knowledge of weather cycles can calibrate AI generated weather models. Furthermore, mātauranga can establish ethical guidelines in the use of AI. For example, tauutuutu could guide AI modelling to identify to identify processes that optimise human-mana/mauri enhancing relationships. Finally, mātauranga can guide the prioritisation of specific cultural values into AI models. For example, an AI model could be designed to prioritise environmental outcomes that align with indigenous values, such as the preservation of specific species or habitats. Incorporating AI into environmental monitoring platforms gives them the intelligence required to harness these information flows, turning them into adaptive and predictive systems that can guide decision-making grounded in wisdom.

Using a Māori knowledge structure to influence how the generated information is communicated to support decision-making

The data generated through the modelling process needs to be communicated to end-users, and in ways that will help them make informed decisions and to learn from the data as effectively and efficiently as possible. Drawing on the Māori knowledge structure, the entities involved, and the quality of the relationships between them, in terms of utu, mana, and mauri would appear to be important considerations when it comes to presenting the data. There are many ways to represent these relationships including GIS mapping systems which provide an interface for viewing numerous environmental datasets, environmental digital twins that create virtual representations of the environment with ongoing data inputs, and virtual reality that provides immersive 3D representations or augmented reality which enables graphic overlays when users move through landscapes. For instance, an iwi wanting to know the state of mahinga kai (food-gathering place) in their takiwā might be provided maps indicating the location and mauri of mahinga kai. While a virtual digital twin might visually show the mahinga kai areas, how they have changed over time, and how they are predicted to change in the future. A virtual reality representation might visually fly you through the areas showing the current state and what future changes might look like, while an augmented reality representation might be used to show landowners what effects different environmental strategies might have on their land as they walk through the landscape.

The use of both objective and subjective metrics has shown to be critical to sustainability endeavours to capture the broad reality of 'nature' and seizing the attention of an array of stakeholders. It is often found that hard scientific metrics overly reduce complex systems, universalise different contexts, and are often not as accurate. Furthermore, through numerous projects and initiatives, Māori have shown they are able to enfold both qualitative and quantitative metrics into their worldview without compromising the core values.

Adding extra functionality to the environmental intelligence platforms

KIPs would be distinct given the primary intent of such platforms would be to support MACs and iwi to act as kaitiaki of their whenua, which means operating according to Māori environmental values. Other elements could be built into any design to provide data and environmental reporting for a range of additional purposes. As noted, there are numerous external requirements driving the need for Māori to develop and implement these KIPs, and while the data will be primarily centred around fulfilling Māori environmental values, it can also be utilised to fulfil these requirements. Specifically, the following three sections will outline how the data generated by KIPs can be used for assurance reporting, sustainable finance reporting, and accessing premiums from markets through the verification of product environmental attributes. Feeder reports exploring each of these have been conducted and hyperlinks for each are provided in the text.

Broadening the design to include assurance reporting (see feeder report here)

As part of A-NZ farming and forestry industries, MACs already need to gather environmental data to meet various reporting standards, including regulatory standards imposed by the government. The NZ Freshwater Farm Management Program is an example – a standard implemented by regional councils that aims to address freshwater degradation. It requires MACs to develop Farm Environment Plans (FEPs) that detail their environmental strategies for improving water quality and to undertake water quality monitoring.

Gathering environmental data for assurance purposes is also sought by some industries - usually to demonstrate compliance with standards required by markets (e.g., supermarket chains) and overseas regulators. An example is the NZ Farm Assured Programme (NZFAP), developed by processors in the red meat sector to demonstrate their commitment to sustainable farm practices. It requires participating farmers to have detailed farm plans for protecting water quality, preserving biodiversity, managing effluent, and mitigating greenhouse gas emissions. It is accompanied by regular on-farm audits. Another example, from the dairy sector, with similar features is the Synlait's "Lead with Pride" assurance programme.

There are internationally recognised assurance systems that some MACs use that require environmental information to be gathered. For instance, the Global Reporting Initiative (GRI), operates as an independent international non-governmental organisation (NGO) and has a standardised framework for sustainability reporting. Reporting covers greenhouse gas emissions, water management, biodiversity conservation, environmental compliance, and energy consumption. Another international example is GlobalGAP, originally established by European supermarkets, which requires reporting on pest management, soil conservation, efficient water use, waste management, biodiversity protection, energy efficiency, and safe chemical usage.

It is noteworthy that the regulatory and non-regulatory (i.e., voluntary) assurance systems outlined are often interlinked. For example, Synlait's "Lead with Pride" system is used to satisfy Environment Canterbury requirements for farm environment plans. There is a drive to further integration of systems to reduce the compliance burden on farmers when they may be required to provide the same environmental information to multiple assurance systems. In A-NZ initiatives like the NZ Farm Data Code of Practice and the associated Farm Data Accreditation Ltd are examples of attempts at integration. The need for improved integration is illustrated by the International Trade Centre Standards Map which documents over 300 assurance standards related to farming.

Integration and standardisation are also being facilitated at an international scale by the emergence of guidelines for standards setting in recent years. Notable examples include the United Nations Sustainable Development Goals (SDGs), the Food and Agriculture Organisation Sustainability Assessment of Food and Agriculture systems, and the International Social and Environmental Accreditation and Labelling Alliance, which establishes best practice processes for building standards.

Currently, these assurance systems have low levels of digitalisation. There remains a reliance on traditional or manual methods for data gathering and reporting, relying on paper-based documentation, basic spreadsheets and word processing tools, or simple deterministic software. This approach contrasts with more advanced, integrated digital platforms that offer automated, real-time, and comprehensive data management, analytics, and reporting capabilities. In addition, assurance systems primarily use practice-based indicators to determine the environmental sustainability of farming enterprises – assessments are based on how the farmer farms rather than on the environmental outcomes of their operations. For instance, how they manage water, cultivate land, ecologically restore areas, or dispose of waste. There is little focus, or perhaps ability, to measure the direct impacts of a farmer's practices on their farm environment, for example, detecting changes in water quality, biodiversity, or carbon sequestration. This is largely due to the significant expense, historically, of undertaking such detailed on-farm environmental monitoring.

This situation creates opportunities for MACs and iwi with an interest, or intent, to build new generation environmental sensing platforms. Firstly, they could automate their data gathering to report against assurance standards that they currently need to meet. For instance, satellite imagery of a farm could be analysed by AI to show changes on farm (e.g., riparian planting) and demonstrate how farm management plans are being implemented to meet FEP or NZFAP requirements. Secondly, the types of environmental data created by comprehensive platforms utilising remote sensing, that cover broad areas, could be sold to assurance systems providers such as government, industry, and NGOs, to ascertain the impact of farming practices. This would permit these entities to understand the actual impacts of the farming practices that they advocate for and assess farmers by, allowing them to accurately determine the connection between action and outcome in a process of continual learning and improvement.

Although there is significant potential to incorporate advanced environmental sensing technologies into assurance systems, there are also several challenges. One primary obstacle is the need for the validation of any new methods, that is the need for validation via peer reviewed research - as well as acceptation by international assurance governance bodies. Apprehension also arises from concerns about the disruption of traditional methods and practices that have become institutionalised. Further complicating the landscape are the regulatory and procedural delays inherent in the sector. Certification bodies, accreditation agencies, and standard owners play crucial roles in the authorisation of new monitoring technologies. Their scheduled review timetables can introduce significant delays, preventing the swift integration of innovative methodologies. Additionally, some entities have reservations about the efficacy of remote sensing, especially in contexts like food safety audits. Without clear evidence supporting these technologies' benefits, their widespread adoption becomes challenging.

Stakeholder acceptance is another critical factor. Key value chain operators, such as supermarkets, need to be on-board. While many of these actors are enthusiastic and keen to demonstrate the sustainability of their value chains to retain their brand value, the adoption of assurance innovations by retailers has, more recently, been relatively limited. This indicates a potential reluctance to fully embrace these new methods. As technology evolves, the expertise required of auditors also expands. Introducing new technologies often means additional training, presenting challenges for both auditors and those being audited. A further constraint is the sector's slow pace in embracing advanced technologies, often attributed to a low level of digitalisation and a reliance on older, pre-internet era processes. This sluggishness is further exacerbated by challenges related to the harmonisation of standards and processes. Inconsistencies and variations in these standards can create barriers for new technologies, hindering their mainstream acceptance.

The sector's hesitancy in investing in new technologies is another concern. Even as innovative solutions in farming emerge, their adoption rate in the assurance sector remains low, affecting stakeholders' perception of the potential benefits.

Lastly, the increasing complexity of assurance systems, especially for small and medium-sized enterprises, introduces a range of cultural, capacity, and trust issues. These complexities can create significant barriers, affecting market access and the overall sustainability of operations.

Broadening the design to include sustainable finance reporting

KIPs data could be utilised to attract sustainable finance investments for MACs and iwi land ventures or to offer expansive data for to sustainable finance reporting companies. While the first approach resonates with investors interested in risk and positive outcomes, particularly those drawn to MACs' unique attributes, the second approach is challenged by the intricacies of the sustainable finance realm.

An increasing number of investors, including banks, asset managers, and entities like sovereign wealth and pension funds, are showing a preference for investing in eco-friendly companies. This shift is driven by growing environmental consciousness, potential regulatory changes, and consumer advocacy. Companies that negatively impact the environment are likely to face significant challenges in the future. For example, in A-NZ, banks with major agricultural investments are under scrutiny for the environmental effects of their financial choices, with a focus on issues like water quality and climate change. Recognising these challenges, investors are keen to understand the environmental implications of their investments. This has led to a demand for companies to disclose their environmental impact, a process that currently relies on manual and time-consuming data collection. Often, the quality of this data is compromised, and there is a tendency to focus on company practices rather than actual impact. KIPs present an opportunity to bridge this gap, offering companies a way to provide live, accurate and traceable environmental data to their investors.

Like the assurance sector, various frameworks guide reporting practices. Some of these are transitioning to mandatory requirements as they become embedded in regulations. High-level principles serve as general guidelines or value sets that outline the essence of responsible or ethical investment. These principles are typically broad, offering a philosophical or ethical base rather than detailed action points. Prominent examples are the United Nations (UN) Principles for Responsible Investment and the UNSDGs. In A-NZ, the Stewardship Code for Responsible Investors is the predominant framework. While it aligns with international principles, it also integrates local nuances, including Te Ao Māori values.

Global environmental, social, and governance (ESG) reporting frameworks and standards, grounded in high level principles, offer businesses detailed guidelines on environmental disclosures to lenders, investors, and insurers. These frameworks specify metrics, indicators, and disclosure norms. For instance, the Taskforce on Climate-related Financial Disclosures, an industry-driven international framework adopted in A-NZ, recommends climate-related financial disclosures. This is now expanding to include biodiversity and other environmental factors through the Taskforce on Nature Related Financial Disclosures. The Global Impact Investing Network introduced the Impact Reporting and Investment Standards Plus, standardising impact measurement in sustainable finance. On the inter-governmental front, the UN Global Biodiversity Framework Target 15 sets nature-related disclosure guidelines, urging global governments to mandate reporting by 2030. The GRI is another framework popular among A-NZ companies, including iwi corporations. Drawing on international frameworks, A-NZ's External Reporting Board has expanded from setting financial auditing standards to incorporate ESG codes suited to A-NZ conditions – including the incorporation of Te Ao Māori concepts.

Secondary verification frameworks and ratings entail third-party evaluations of ESG performance. In A-NZ, the Responsible Investment Association Australasia (RIAA) Product Certification Standard benchmarks responsible investment products, emphasising transparency and ESG integration. Certified entities can display the RIAA certification symbol, denoting their commitment to responsible investment. The Gold Standard is another prevalent certification for climate mitigation projects in A-NZ, ensuring genuine and verifiable carbon credits.

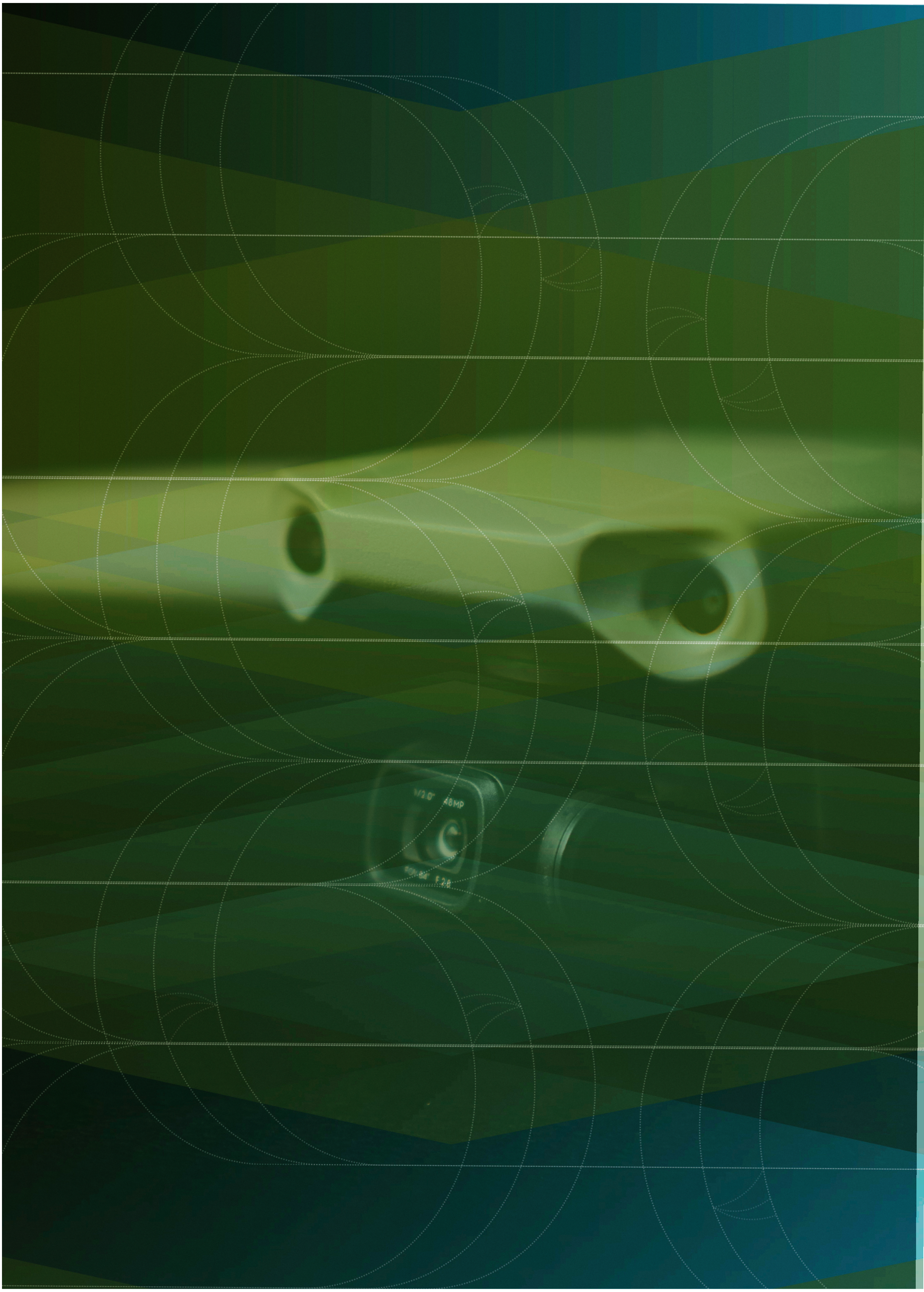
Niches and market creation pinpoint specialised ESG sectors, often birthing new investment avenues. In A-NZ, several niches could benefit from a Māori-led environmental intelligence platform. For example, the Sustainable Agriculture Finance Initiative, developed by A-NZ banks, guides sustainable agriculture and structures Sustainable Linked Loans. The A-NZ Climate Innovation Market, overseen by Toha, promotes sustainable farming investments, with farmers sharing environmental data for financing. New Forests is a global investment manager focusing on nature-based assets. Tahito integrates Māori values into its ESG investment strategy, mainly for positive screening in the Te Tai o Rehua Fund. The voluntary carbon market in A-NZ features entities like Ekos and Toitū Envirocare, offer carbon certifications and broker carbon credits. Platforms such as Carbon Crop and Carbonz also specialise in native carbon credits and facilitate their trading.

Based on interviews with different stakeholders in the sustainable finance sector it has been determined that there is demand for the types of data that environmental intelligence platforms could provide for disclosure purposes. Furthermore, such demand is likely to grow. A-NZ banks' lending to farmers see the potential data generated as a tool that could determine the transitional or physical risk of their investments and to monitor business operation improvements, especially in the context of 'sustainability linked loan' products. Direct equity investors could also leverage data to understand risks associated with land, water, and climate impacts, aiding in investment decisions, and facilitating engagement with the businesses they invest in. Impact investors, focused on specific environmental outcomes, could also use the data to quantify their investment impacts. While these environmental intelligence platforms would primarily offer environmental data, entities using it would still need to address social and governance reporting for comprehensive ESG performance. A-NZ is a signatory of the Global Biodiversity Framework, the demand for nature-sensitive production systems, verifiable by KIPs monitoring, is anticipated to grow, underscoring the platform's significance in the evolving landscape of sustainable finance.

However, realisation of the full potential of these platforms in the finance sector faces several challenges. The evolving nature of data infrastructure necessitates interfaces that can handle high-resolution data across various scales, from individual farm levels to entire supply chain footprints. Globally, there is an inconsistency in ESG measurements, with certain environmental data, such as biodiversity and nutrient emissions, still in nascent stages of standardisation. Research across frameworks show that few have reporting requirements at the metric level, focusing at the higher indicator level. This poses barriers to the automation of data flows crucial for financial decision-making. Stakeholders have also expressed concerns about potential 'data overload', emphasising the need for data that provides actionable insights. Furthermore, the rapid evolution of the ESG sector introduces uncertainties about future finance-related decision frameworks. While there is an anticipated increase in demand for transparent, high-resolution data, the exact nature of future demands and the frameworks to address them remain in development.

Broadening the design to meet the needs of consumers wanting the credence attributes of indigenous products

Gathering precise information about the environmental condition of their farms and forests could allow MACs to add value to their food and fibre products. Many consumers are willing to pay more for products with certain 'intangible' credence attributes - e.g., sustainable production, food safety, fair trade etc. – that are not immediately apparent from the product itself. A platform based on indigenous values also adds a cultural point of difference which emphasises the environmental and social ethics underpinning Māori production practices. Such cultural attributes have been



identified as factors that can command premiums in certain markets alongside environmental and social attributes. By communicating these attributes in a verified and authentic manner to the right consumers, Māori producers can potentially achieve higher prices for their products. There are three critical components to adding value in this way: establishing the credence attributes that emerge from tauutuutu production and aligning these with international analogues; understanding how these attributes can be communicated in a verified and authentic way; and identifying the consumer markets that are willing to pay the most for these credence attributes and what premiums they would pay.

There are several important credence attributes that emerge from Māori production guided by tauutuutu values. These are based on the core principles of Te Ao Māori and mātauranga, with the most critical being kaitiakitanga (actively guarding and enhancing ecosystems), rangatiratanga (showing leadership and self-determination), and whanaungatanga (nurturing wellbeing and relationships). The focus of these both being the maintenance and growth of mana and mauri of humans and ecosystems through the relational interactions. Through analysis, a range of similar or proximate, internationally recognised, credence attributes were determined that would enable the identification of the best markets and the premiums they would pay. These include: kaitiakitanga – sustainable production, organics, animal welfare, and food safety; rangatiratanga – food sovereignty, country of origin, local foods, alternative food networks; whanaungatanga – fair trade and human values.

The demand for credence attributes has grown significantly in recent decades, driven by the industrialisation of food production, cases of food adulteration and duplicitous marketing, and resulting food scares and environmental crises. Many consumers now seek healthy, safe, ethical, and sustainable products. At the same time, most people have lost connection with their food as it has become a commodity 'from nowhere' that simply appears in their supermarkets. This has led consumers to look for authentic associations with food types, geographical locations, production methods, and producers, particularly producer cultures. Knowing where your food comes from and trusting this information have become increasingly important for both practical and emotional reasons. Critically, because of the loss of trust amongst consumers and the fact that credence attributes are not distinguishable at point of purchase, ensuring consumers believe these claims requires verification. This can be achieved using either: 1. tracing schemes, which enable the consumer to track the product back to its origin; or 2. assurance schemes, which are trusted third party actors that can verify the accuracy of claims. These both require the collection, verification, and communication of salient data, making the collection of comprehensive on-farm environmental data of high value for MACs. Both these fields are undergoing several improvements. Advanced technologies like the blockchain, Internet of Things, and radio-frequency identification allow food producers to record every step of the production process for tracing schemes, though as noted in the previous section, assurance schemes have not adopted new technology as quickly. Environmental data collected with a cultural frame can deliver practical and emotional authentication.

Willingness-to-pay (WTP) studies are the most common mechanism for determining the possible premiums paid for credence attributes, though these are more frequently deployed in an academic setting than by commercial actors and are often focused on a single credence attribute for a single product in a single market. WTP studies generally involve surveying population segments, and thus measuring hypothetical rather than actual WTP, reducing their accuracy. Still, WTP studies can help Māori enterprises identify the best markets and the key attributes that resonate with these markets and align their products accordingly to achieve a price premium. A thorough review of WTP studies, found in the feeder report, provides a range of insights. The data highlights differences in WTP for credence attributes across various regions, with consumers from Southern and Western Europe exhibiting higher WTP compared to other regions, including North America and Asia. The data also provide other demographic insights, showing for example, that younger female consumers generally display higher WTP values for credence attributes. The data offers a range of insights regarding possible premiums paid for different credence attributes, with some such as food safety accessing up to 64% premiums.

However, the analysis shows significant variation across studies for the same credence attribute, which suggests that the data gleaned from these is indicative at best. Also, because these studies are often very specific in terms of products/credence attributes but also very broad regarding demographics they are not necessarily easily translatable or targetable, respectively. For this reason, a number of complementary methods for determining WTP have been proposed, including: collecting and analysing transaction data from retailers and e-commerce platforms selling Māori products; analysing social media data for insights into consumer sentiments, emerging trends, and popular product attributes; examining online reviews and ratings of Māori products on various e-commerce platforms, blogs, and forums; using market basket analysis to determine the purchasing patterns of consumers who buy Māori products in conjunction with other products; and, conducting a comprehensive review of existing studies and databases (other than WTP studies) related to consumer preferences for food products.

Numerous indicator frameworks could be used by enterprises to measure and communicate MACs performance against credence attributes. The precise metrics to be used would depend on the context of the enterprise; for example, a dairy farmer would require different metrics to a dryland farmer. At a high level, several well regionalised frameworks, some of which have been outlined above, could be used, such as: GRI Standards; SDGs Indicators; International Organization for Standardization Standards; B Corporation Certification; Fair Trade Certification; Rainforest Alliance Certification; SA8000 Standard. These standards face the same issues outlined in the assurance system section above.

There is a current need for higher quality and more reliable data to communicate and verify credence attributes. The data gained from the environmental intelligence platforms can be aggregated in ways needed to suit what might be termed different ‘credence clusters’ of specific market segments and can provide a highly verifiable form of traceable information that can be communicated with authenticity to the consumer. Likewise, it can be aligned with the different national and international frameworks needed to deliver assurance through the variety of different schemes. The key is accurately determining these credence attributes and markets, so the alignments can be made with a high fidelity.

Types of metrics sought by MACs, iwi, assurance systems, sustainable finance and markets

Earlier, it was outlined that many MACs and iwi organisations use a combination of traditional knowledge and modern scientific methods to evaluate environmental health and changes on their lands. Mātauranga, which is holistic knowledge accumulated over generations through observation, hands-on experimentation, and intuitive insight, is focussed on the relationships and interconnectedness between the different elements that make-up the environment. In comparison, scientific methods isolate and measure the biophysical properties and components of environmental systems, using scientific instruments, to reveal changes in their health. Mātauranga also may not identify specific environmental signs, such as the absence or presence of a species, to determine environmental health, it is just that this is done in reference to broader environmental patterns, flows, and cycles using a whakapapa orientation and relational values and not isolated variables. While science can look at parts of the system it has difficulty measuring and explaining, it is missing all the complex interactions between the parts. MACs and iwi find scientific measures useful, however, they are used within a broader frame of cultural reference. Understanding what biophysical measures these entities find useful is crucial to determining which environmental sensing technologies are incorporated within a KIP, and more broadly what metrics can be incorporated into mātauranga Māori oriented frameworks.

MACs and iwi from literature review and analysis

In the feeder report to this report, 'Determining the environmental intelligence needs of Māori Agribusiness Collectives (MACs) and iwi to inform the design of a Kaitiaki Intelligence Platform', (see feeder report here) a detailed review and textual analysis was undertaken of Māori Environmental Frameworks, Māori Wellbeing Frameworks, and MACs and iwi strategic documentation. Based on this analysis a set of biophysical indicators and metrics commonly used by Māori authorities were identified. In total, seven indicators (Table 1) were distinguished under which 25 metrics were categorised. Qualitative indicators were excluded from this analysis, given qualitative methods are required to generate this data, which environmental sensors are unable to capture. However, this is not to dismiss qualitative data, such data may be incorporated and built into reporting systems to augment quantitative data as is commonly done by Māori authorities.

Table 1: MACs and Iwi biophysical data needs: Indicator and Metric categories (*Agricultural production specific).

Indicators	Terrestrial Biodiversity	Water Quality and Quantity	Soil Quality	Water use Efficiency/ Management*	Stock Management*	Greenhouse Gases	Nutrient Loading
Metrics	Native Habitat Species diversity Taonga Species Presence/ absence of pest and weed species Riparian Planting	Nitrates Phosphates Turbidity pH Species diversity E. coli Taonga Species Surface flow rates	Erosion Compaction Moisture Levels PH Heavy metals Microbial density and diversity Levels of N and P	Soil moisture levels Ground water quantity Surface water flows	Paddock lines Stock numbers	Emissions Sequestration	Levels of N and P in soils and groundwater

Collaboration partners' metrics

In addition to the literature review, the KIPs research also engaged with iwi and MACs collaboration partners (CPs) to identify the key metrics to be incorporated within a KIP platform design through a series of workshops. The CPs reiterated the findings of the literature review identifying the same set of metrics. The agricultural CPs emphasised the need for environmental data that also acted as operational data for improving farming practice and performance, while measuring any environmental improvements. This included data on soil nitrate and phosphate levels in conjunction with soil moisture to optimise fertiliser regimes and minimise environmental impact. In relation to soil, there was interest in accessing data on soil microbial density and diversity. In terms of stock management, CPs wished to be able to count and monitor stock movements remotely as well as locate and measure paddock lines. Finally, data on pest management was sought, in particular, detecting wildling pines and being able to determine the presence and absence of possums and deer based on the health of native ecosystems – for example, being able to measure the density of forest canopies and understorey. Beyond iwi, CPs also sought unique measures including data concerning flood risk to land and communities, wāhi tapu, and wāhi taonga, and archaeological sites.

Metrics from assurance, sustainable finance, and markets

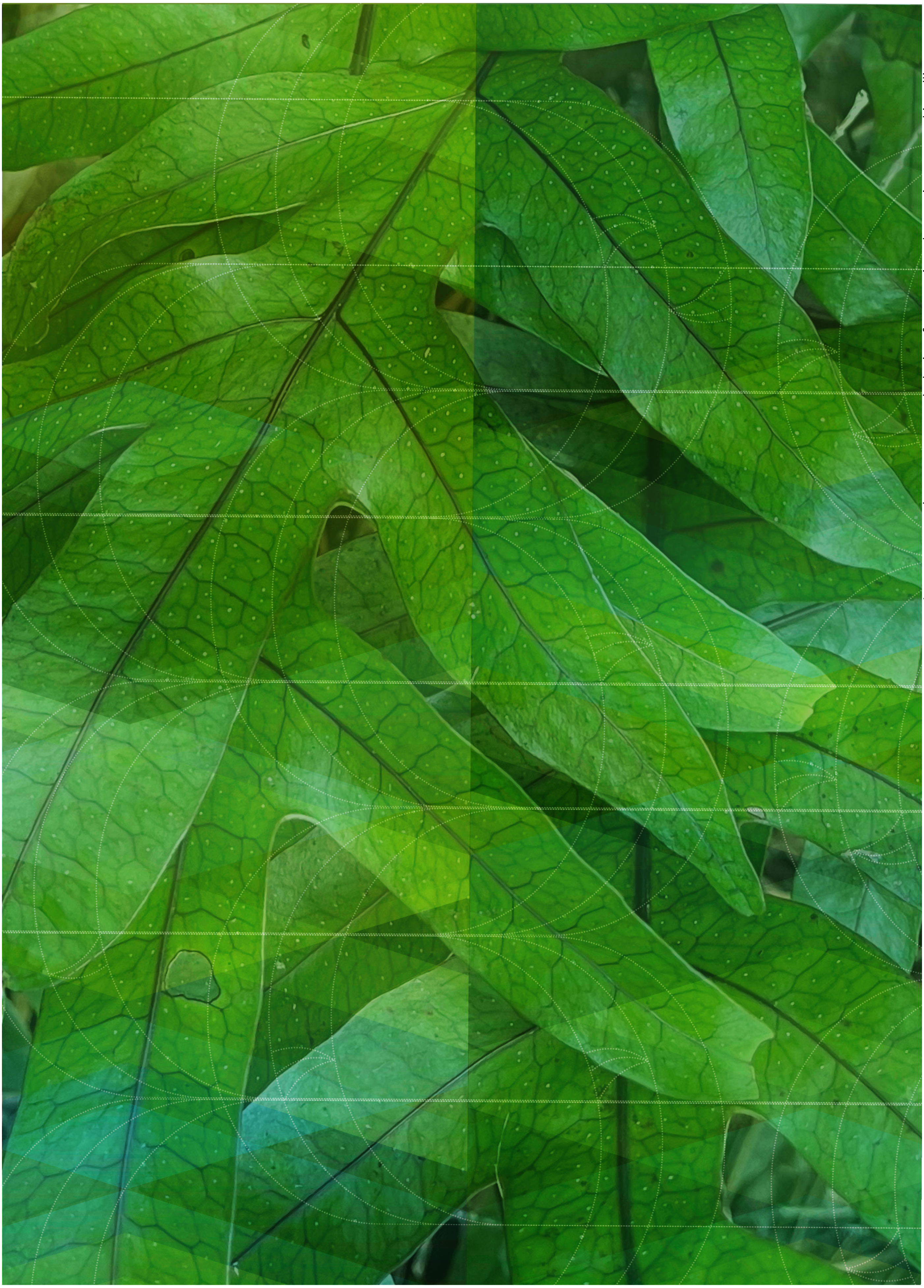
As outlined in previous sections, there is an opportunity for MACs and iwi to provide assurance and sustainable finance sectors with biophysical data, first as a commercial opportunity to provide verification services and access favourable financing, and second as a means for MACs to automate their own environmental reporting to these entities. Consequently, a detailed literature review, and 40 interviews with a wide range of stakeholders across the assurance and sustainable finance sectors was undertaken to identify the types of biophysical impacts metrics these sectors are seeking (see feeder reports for assurance here and sustainable finance here). However, few hard environmental metrics were identified as being sought or prioritised by these sectors – apart from GHG gas emissions. Most environmental auditing and reporting systems used in these sectors rely upon practice-based indicators – that is, relatively subjective assessments of the practices farmers, foresters, or other land managers are employing that are known to generate positive environmental outcomes on the ground. Generally speaking, there is a lack of direct objective environmental impact monitoring across these sectors. However, the analysis also revealed that there is potential to integrate direct environmental impact monitoring into these systems. This integration, however, comes with certain challenges due to institutional rigidity and a resistance to adopting new approaches within these sectors. Furthermore, many auditing systems in this sector only offer overarching guidelines and general environmental indicators. Nonetheless, the general environmental indicators identified align closely with the indicators sought by MACs and iwi (Table 2). Overall, there appears to be opportunities for a KIPs platform to generate data against these indicators using the biophysical metrics considered important by MACs and iwi.

Summary of biophysical metrics applicable across organisation type and sectors

Based on the analysis above, Table 2, outlines the types of biophysical metrics that are sought MACs and Iwi. Table 2 also indicates that these same metrics have the potential to be incorporated into market assurance and sustainable finance auditing systems.

Table 2: Biophysical indicators sought by sectors

	MACS	IWI	ASSURANCE	SUSTAINABLE FINANCE
ENVIRONMENTAL INDICATORS				
Terrestrial biodiversity	Y	Y	Y	Y
Water quality and quantity	Y	Y	Y	Y
Soil quality	Y	Y	Y	
Water use efficiency/management	Y	Y	Y	Y
PRODUCTION INDICATORS				
Stock management	Y		Y	Y
Greenhouse gases	Y		Y	Y
Nutrient loading	Y		Y	Y



Explaining and defining the technology

In this section, the technologies designed to generate the types of environmental data sought by MACs and iwi is explored. Understanding these technologies, and the terminology surrounding them is needed, which is provided below, before exploring the application of these technologies in a sensor network tailored to Māori authorities.

In-situ Sensors

An in-situ sensor is a type of environmental sensor deployed directly at the location where data needs to be collected[17]. Types of in-situ sensors include soil moisture sensors, nutrient sensors, water quality sensors, air quality sensors, weather stations, and biodiversity sensors. The cost of these sensors has fallen dramatically due to technological advancement and economies of scale. Now many of these types of sensors are solar powered and connected to the internet and transmit real time data regarding environmental conditions. Together these are referred to as Internet of Things (IoT) sensors[18].

Soil moisture sensors are crucial tools for improving environmental outcomes by aiding in water conservation, preventing over irrigation, and mitigating drought impacts[19]. By measuring soil moisture levels, farmers can optimise irrigation practices, reduce water wastage, and promote sustainable water use. Integrating these sensors with nutrient sensors helps minimise nutrient runoff and groundwater contamination. Overall, maintaining optimal soil moisture levels enhances crop and pasture health, preserves soil structure, and reduces soil degradation[20].

Water quality sensors monitor key indicators such as pH, dissolved oxygen, nutrients, suspended sediments, and other pollutants in water bodies. By identifying potential sources of contamination, land managers can take appropriate measures to reduce runoff and prevent harmful substances from entering waterways thus minimising water pollution[21].

Weather stations produce real-time weather data that allows farmers to optimise irrigation, crop planning, and pest management, promote water conservation and reduce pesticide use. Long-term weather trends inform climate-resilient practices, while monitoring weather patterns helps with erosion control[22].

Air quality sensors monitor air pollution levels, enabling better environmental management and safeguarding human and animal health. A range of polluting gases can be sensed including carbon dioxide and methane – both of which are greenhouse gases[23].

On-ground biodiversity sensors play a crucial role in biodiversity monitoring and conservation efforts. These advanced technologies include camera traps to study animal behaviour and population dynamics, acoustic sensors for assessing species presence, environmental DNA (eDNA) sensors for identifying species presence and abundance in water bodies, soil, forests, and farmland[24].

Remote Sensors

Remote environmental sensing involves the use of various technologies to collect data about the health of land, water, and air from a distance, without direct physical contact. There are a range of remote environmental sensors that are mounted to unmanned aerial vehicles (UAVs or drones), manned aerial vehicles (planes and helicopters), and satellites. The cost and availability of this remote sensing technology, particularly regarding UAVs and satellites, has dropped dramatically in recent years. In terms of UAVs, the emergence of smaller and more efficient sensors, cameras, batteries, and processors, combined with advances in AI and economies of scale, has driven this change. Similarly, satellite technology has improved dramatically through miniaturisation, alongside cheaper manufacturing and launch options – seeing a ubiquity of 10 cm2, 2 kg3 satellites produced. Moreover, sensor improvement and AI advancements have greatly increased data resolution. Additionally, longer satellite lifespans and increased government and private funding have contributed to cost savings and affordability[25]. The use of planes and helicopters remains expensive, or is increasing in expense, though there are options to utilise existing commercial flights to house remote sensors which cuts costs significantly. However, they can carry larger, heavier sensors than UAVs and satellites that generate higher resolution data[26].

There are various types of sensors carried by these vehicles that generate different types of useful data. Optical sensors capture visible and infrared light, enabling land cover classification and monitoring vegetation quantity and health[27]. There are two main types of optical sensor: multispectral and hyperspectral. Multispectral sensors provide data in specific non-contiguous wavelength bands, with band combinations varying depending on requirements. Hyperspectral sensors allow detailed spectral analysis across contiguous spectral bands. Multispectral imaging can be thought of as a reduced subset of hyperspectral imaging. Optical data permits assessment of plant biodiversity, plant health and stress (including early signs of disease and nutrient deficiencies) and algae levels in water bodies[28].

Thermal cameras measure the heat signature of different objects by detecting the amount of infrared energy they produce. These cameras can be particularly useful to see below forest canopies at potential animals below; more so when an optical camera cannot see through the canopy. Providing data on the temperature patterns of vegetation enables areas of stress or damage caused by pests, diseases to be identified[29].

Synthetic Aperture Radar (SAR) sensors utilise microwave radar to produce high-resolution images, crucial for all-weather and day-and-night imaging. This makes SAR essential for monitoring land use changes, agriculture activities, and detecting surface deformations, supporting precision agriculture and disaster management in rural areas[30].

Microwave and Radiometer sensors estimate soil moisture levels and monitor ice conditions, essential for rural land managers to manage water resources efficiently, particularly during droughts, and assess potential frost damage to crops[31].

LiDAR (light detection and ranging) sensors employ laser pulses to create precise 3D elevation maps of the Earth's surface, enabling terrain mapping and biomass analysis. Data generated from LiDAR can be used for optimising land use planning, implementing contour farming, and analysing vegetation structure in hilly or forested areas to determine levels of biomass, carbon, and canopy thickness[32].

GNSS-R (global navigation satellite systems reflectometry) sensors use reflected signals from navigation satellites to gather information about soil moisture and vegetation. This data enables assessments of soil moisture levels, water availability, and making informed decisions for irrigation and water management, especially in regions with limited access to ground-based monitoring[33].

GPS Radio Occultation (GPS-RO) sensors measure the refractivity of Earth's atmosphere, providing valuable data for weather forecasting and climate studies. In rural areas, accurate weather predictions are crucial for planning agricultural activities, optimising resource use, and mitigating weather-related risks[34].

Combining In-situ and remote sensors

In environmental sensing, both in-situ and remote sensors play crucial roles, each offering advantages and working together to generate a comprehensive understanding of the environmental conditions. In-situ sensors serve a pivotal role in calibrating remote sensors, refining their accuracy and improving data quality over time[35]. Analogous to tuning a musical instrument to a specific key, in-situ sensors fine-tune remote sensors to enhance their performance. Generally, in-situ sensors produce more accurate data since they are positioned at the source, providing high-resolution measurements at specific locations. However, remote sensors can rapidly cover vast areas, generating data over entire landscapes, which would be impractical to be done with in-situ sensors without significant investment costs. To maximise data coverage and resolution, both in-situ and remote sensors are valuable tools that should be viewed as complementary[36]. Data from both types of sensors can be integrated and fused to create comprehensive datasets, harnessing the strengths of each method. Nonetheless, as technology advances, remote sensors are becoming increasingly accurate, and there are many situations where they could eventually replace in-situ sensors. However, it is important to recognise that in-situ sensors may remain indispensable for localised studies and long-term monitoring efforts, which may not be practical with remote sensing alone.

Making sense of data – warehousing and analysing data

The range of sensors outlined above can collect a prodigious amount of environmental information. Storage of such large quantities of unstructured data can be problematic, however, the exponential growth in data warehouses that store data is managing to keep up with this challenge. The data also needs structuring, where it is cleaned and transformed into a standardised format to ensure its quality and consistency. Data warehouses are optimised for querying and analysis, allowing users to perform complex queries and generate meaningful insights from historical and current data[37].

Māori data sovereignty is also an important consideration. Generally speaking, this recognises that Māori data should be subject to Māori governance[38]. Māori data sovereignty supports tribal sovereignty and the realisation of Māori and iwi aspirations. As data collection has grown in size and scope, the issue of how this is managed and governed has grown for indigenous peoples. Many iwi and hapū have developed policies, governance structures, and warehousing capacity, with layers of encryption protecting this data. More broadly, there is the Māori-operated network, Te Mana Raraunga[39], formed in 2016 to advocate for Māori rights and interests in data to be protected, while references to the Treaty of Waitangi have been incorporated into the Data and Statistics Act 2022[40]. It will be up to each participating MAC and iwi to develop their own warehousing and analysis protocols and practices, though the project will also seek to provide a range of potential solutions that align with the broader Māori data sovereignty principles.

The rapid development in AI is revolutionising data analysis. AI excels at mining raw data, spotting intricate patterns, and uncovering hidden insights that may elude human analysts, and in far shorter time periods. AI can also automate the data structuring process through classification, feature extraction, and predictive modelling, providing valuable insights for environmental monitoring, climate modelling, biodiversity analysis, and resource management[41,42,43]. Additionally, AI-powered data analytics can facilitate real-time decision-making to address environmental challenges with more precision and effectiveness. Finally, AI systems continually learn from new data, progressively enhancing their analytical abilities over time[44]. As big data volumes expand, AI algorithms become more accurate and efficient in their analyses.

Communicating data

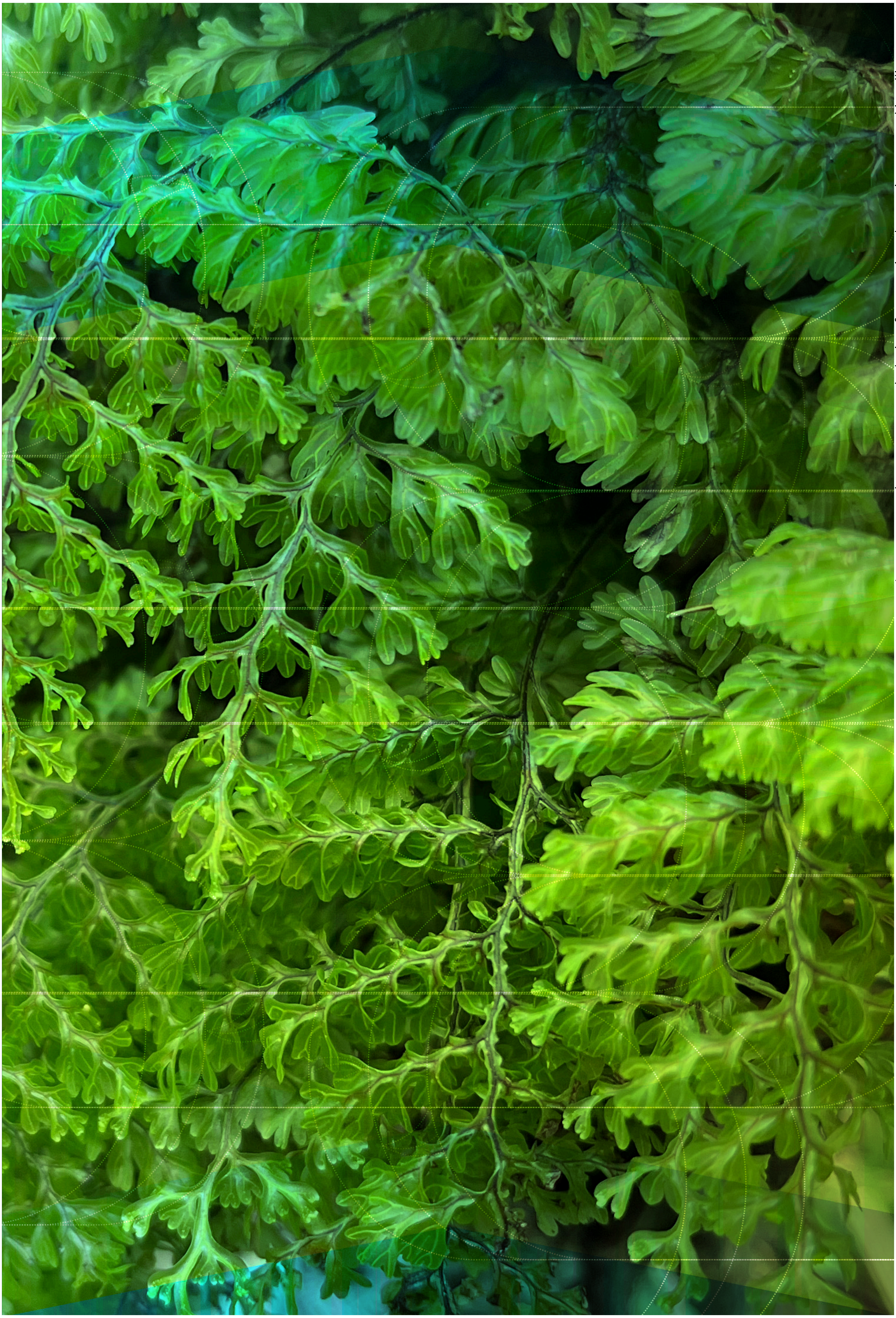
There are a number of current and near horizon methods of communicating this data in ways that are able to condense the preponderance of information into easily comprehend forms, and offer a range of potential visualisation methods that can be aligned with Te Ao Māori. These are presented in order of cost, ease of deployment, and current viability, from cheapest, easiest and viable first.

Geographic Information Systems (GIS) are computer programmes that create, manage, analyse, and map geographically referenced information, using layers of data that are attached to unique locations to build a tailored interface the user can explore and alter[45]. Generally speaking, GIS overlays these different datasets onto some form of 2D or 3D map, though only the terrain data is usually displayed in three dimensions. GIS can show many kinds of data on one map, such as biodiversity levels, water quality, and nitrate levels. This enables the user to not only explore each dataset in isolation but also to identify and understand patterns, relationships, and geographic context between the different datasets. GIS can be used to identify problems, monitor changes, manage and respond to events, perform forecasting, set priorities, and understand trends. As a well-established system, GIS has numerous existing datasets, interfaces, and plugins that can be relatively cheap, or freely, utilised to enhance communication to specific stakeholders46. There are also a number of geospatial data sources of high relevance for a wide variety of kaupapa Māori GIS mapping projects available.

An environmental digital twin Is a digital replica of a physical entity or system. It is like GIS in many respects, with GIS technology foundational to the development of an environmental digital twin. The key difference is that the digital twin is dynamic, merging as many individual datasets as possible into a singular representation that aims to mirror its real-world twin as effectively as possible not just spatially but also chronologically, covering processes and relationships[47]. Digital twins go beyond simulation, as they replicate a system's various processes, creating a virtual environment that has a greater alignment with reality than a simulation. They are even more sophisticated than traditional environmental models, as while models only use environmental data to calibrate digital twins have data inputted in either an ongoing basis or constant feed. The digital twin concept is newer than GIS, emerging out of engineering and manufacturing, with the 'twin' concept coined during the Apollo programme – in this case, literally a second physical copy left on Earth – and the 'digital' element being added in the 2000s[48]. Nevertheless, much like GIS, there exists several off-the-shelf resources that can be utilised for the construction of a digital twin for MACs and iwi.

Extended reality (XR) has been around for a long time though the technology is only just coming to maturity, with the latest generations of visors and their underlying software delivering on its long-held promise. XR encompasses both virtual and augmented reality, where virtual reality replaces your vision with 3D graphics, augmented reality adds 3D graphics over the top of your field of view. The immersive nature of XR can help bring the environmental data to life in a visceral and emotional way that other methods cannot. People can move through and interact with the data, experiencing in a range of ways from an on-the-ground first person experience to a god-like third person view high above. Research has shown that this type of experience can deepen the impact and understanding of environmental data for users, helping connections with nature, increasing awareness of sustainability issues, and guiding decision-making. Currently, it is one of the more costly options for communication, both in terms of headsets and software, though prices will drop over time[49]. While there are less general and specifically Māori resources for XR than the other methods, these will grow over time.

The rapid development in AI is revolutionising data analysis. AI excels at mining raw data, spotting intricate patterns, and uncovering hidden insights that may elude human analysts, and in far shorter time periods. AI can also automate the data structuring process through classification, feature extraction, and predictive modelling, providing valuable insights for environmental monitoring, climate modelling, biodiversity analysis, and resource management. Additionally, AI-powered data analytics can facilitate real-time decision-making to address environmental challenges with more precision and effectiveness.



Technology to generate and communicate the data MACs and iwi need

This section outlines how the technologies explored above are applied in practice to meet the environmental data needs of MACs and iwi. Many of these approaches have been tested and developed overseas, however some are not yet available in A-NZ or are yet to be applied. Consequently, it is also discussed whether the technology is available, or applied in the A-NZ context. For a detailed and referenced version of available technologies, please see the Kaitiaki Intelligence Platform report: 'Designing a comprehensive sensor network to provide Māori Agribusiness Collectives and iwi environmental intelligence'.

Detecting Biodiversity

There are different types of in-situ sensors that have been developed to detect the presence, absence, and numbers of species in a location – this includes desirable native species as well as pests. Acoustic sensors are instrumental in monitoring animal vocalisations, sounds, and even microbial activity in soils[50]. In parallel, camera traps, which are motion-activated cameras, have gained prominence for their ability to capture images of animals as they traverse their habitats. Complementing these are thermal imaging cameras, which harness the capability to detect the heat signatures emitted by organisms. This feature renders them invaluable for identifying animals during night time or within densely vegetated areas[51]. These detection options are useful as the presence (or lack thereof) of wildlife is an indicator of a healthy ecosystem, or successful ecosystem regeneration. Another innovative approach to biodiversity detection is the use of eDNA sensors. These devices are unique in that they can provide in-situ, real-time monitoring of organism presence in a specific environment; they have been shown to be successful in mediums such as water and soil24. Lastly, the assessment of soil health and microbial diversity is indirectly facilitated by soil sensors. These devices gauge various parameters, including soil moisture, temperature, and pH that are indirectly indicative of the underlying diversity in microbial activity[52].

There are various remote sensors designed for biodiversity detection, with a primary emphasis on vegetation. Optical, multispectral, and hyperspectral cameras record the spectral reflectance of vegetation across the visible and invisible spectrums–- including both desirable and undesirable plant species (i.e., weeds)[53]. Different ecosystems have their own spectral signatures; for instance, forests, wetlands and grasslands can be differentiated[27]. Combining such data with LiDAR, allows for plant species identification, as the 3D approach incorporates canopy height and underbrush density[32]. In turn, this combination can help to identify stages of ecological succession. GNSS-R sensors that pick-up reflected signals from navigation satellites offer an additional layer of identification data; these aeroplane mounted sensors detect soil moisture levels and water availability, which make this data source particularly useful for detecting wetland ecosystems[54].

Since applications for data are so varied, most sensors output data in a raw format that then requires some level of processing. While historically such analysis has been challenging, advancements in AI have revolutionised the process of ecosystem identification and species differentiation. AI models are now trained to identify specific features, leading to the creation of what are termed "biodiversity signatures"[55]. In such applications, and where data sources like LiDAR and spectral sensors are used, the model efficacy is improved with increased data resolution. Typically, this resolution is inversely proportional to the distance of the sensor from the Earth; sensors closer to the surface, such as drones, capture higher resolution data in comparison to satellites at greater distance[56]. Such high-resolution data facilitates AI in crafting signatures for individual species more accurately. While high-quality satellite images can also serve this purpose, they are optimally utilised for training AI to recognise broader ecosystem signatures. The latter is also less computer-resource heavy, thus there is merit in combining data sources with various resolutions, particularly if analysis is sought on a large area of land[57].

The ability to detect ecosystems and species across vast landscapes offers multifaceted insights into biodiversity assessment. One primary advantage is the capability to monitor changes in the size and extent of ecosystems over time–-identifying whether they are expanding or contracting[58]. The latter can be an indicator of biodiversity loss, since specific ecosystems provide habitat for specific species, and their success is closely linked to ecosystem size. Another benefit of the AI modelling approach is the ability to evaluate the connectivity between different ecosystems. This connectivity is crucial as many species' survival rely on corridors
for their natural behavioural patterns[59]. Additionally, understanding the structure of ecosystems, such as the density of forest canopies and understories, provides valuable information about the ecosystem's health. For example, over-browsing in a forest might indicate the presence of pests, while under-browsing could suggest the absence of a certain beneficial species.

Lastly, the absence or presence of specific flora, or lack thereof, serves as an indicator of an ecosystem's overall health. The absence of a signature species, perhaps identified through its unique annual flowering pattern, could signal that an ecosystem is facing challenges[60].

Availability of technology in Aotearoa New Zealand

The Eco-index in A-NZ operates a platform (nearing completion in 2024) that can detect changes in ecosystems extent over time utilising optical and hyperspectral satellite imagery, plane mounted GNSS reflectometry, and LiDAR. It is building a range of biodiversity signatures for vulnerable ecosystems and species; that enable assessments of biodiversity presence and status at farm and catchment scales.

Detecting Nutrients and Microbial Diversity in Soil and Water

In terms of determining microbial diversity and quantity in soil and water, eDNA sampling is currently the most detailed approach with the ability to find thousands of unique DNA variants in a single sample[24]. In regard to nutrient detection there are a range of in-situ sensors designed for this purpose, principally for detecting nitrogen and phosphorus in soils and water, offering insights into nutrient cycling and environmental health. Ion-Selective Electrodes (ISEs) respond selectively to specific ions, such as nitrate or phosphate, making them popular in portable metres for field measurements[19]. Optical sensors, leveraging light absorption or fluorescence properties, can detect these nutrients, with UV absorption being particularly effective for nitrate detection in water[61]. Colorimetric sensors identify nutrients based on their colour-changing reactions with specific reagents, while techniques like Near-Infrared (NIR) and Mid-Infrared (MIR) spectroscopy assess organic and inorganic nutrient forms by analysing light absorption and reflection patterns[21]. Lysimeters, which collect water from soils, offer insights into nutrient movement within the soil profile. Automated samplers, stationed in water bodies, periodically collect samples for nutrient analysis[62]. Additionally, microbial biosensors utilise microorganisms, such as bacteria, that produce measurable signals when exposed to target nutrients[63]. Some Time Domain Reflectometry (TDR) probes, primarily used for soil moisture, can also detect nitrates based on their impact on soil dielectric properties[64]. Lastly, absorption and fluorescence probes in water bodies detect nutrients based on their specific light-related characteristics[65]. While these sensors provide valuable real-time data, they often benefit from validation through laboratory analyses.

The ability to detect nutrients remotely is more challenging; however, a suite of techniques and approaches have emerged in recent years that are showing similar levels of accuracy to in-situ sensors. In a similar manner to biodiversity detection, hyperspectral cameras can reveal subtle changes in the chlorophyll of vegetation, which indicate the levels of nitrates and phosphates within the root zones of plants[66]. AI is then used to pick-up on these patterns and generate soil nutrient signatures based on the reflectance patterns of different plant species, such as pastures and crops. These patterns change over seasons, which also needs to be factored into analysis and can be accommodated with a temporal AI model[67]. The benefit of using remote sensing is that it enables nutrient detection across whole landscape areas and does not require the significant number of expensive in-situ sensors that would be required to achieve the same task. Furthermore, such broad scale monitoring enables nutrient 'hotspots' to be identified. This approach can also be used to detect soil pH as the reflectance and types of vegetation can change with soil acidity or alkalinity by using remote sensing to pick up on the vegetation indices generated by a change in pH and merge the finding with soil maps of an area[68]. This combination of data can create a prediction map of soil pH.

The limitation of the technology is that it can only detect nutrients within the root zone of soil, and cannot reveal nutrient movement into deeper layers, or into aquifers in the way that lysimeters can[62]. However, this constraint may be potentially addressed through a combination of GNSS-R and hydrological modelling. GNSS-R can generate detailed data on soil moisture levels across landscapes, and when combined with sophisticated hydrological modelling, could estimate the movement of nutrients in the shallow layers of soils into groundwater and waterways[69].

Remote sensing can also be used to detect nitrates and phosphates in surface water bodies, like lakes and streams. When high nutrients are present in these waterbodies different types of algae are produced. These nutrients can be detected in the same way that nutrients are detected in soil by picking up the signatures of the algae which correspond to changes in the reflectance of chlorophyll in the algae[28].

Availability of technology in Aotearoa New Zealand

Currently a range of in situ sensors are available. The hyperspectral imaging and GNSS-R technologies are available for remote sensing, however, AI methods for analysing this data have not been developed for A-NZ conditions but have been developed abroad[70] . eDNA technology for assessing soil microbial diversity is available and advanced in A-NZ.

Detecting erosion

In-situ soil monitors provide insights into potential soil erosion, but these are limited by scale and cost, however, remote sensing offers a valuable and effective method for detecting erosion and has been used since the 1990s. Data from plane and UAV-based LiDAR systems and a broad range of satellite scanning technologies provides information about a set of erosion factors - the topography, soils, vegetation, and land use. Terrain characteristics are able to be obtained through digital elevation models generated by satellite image processing, such as Advanced Land Observing Satellite (ALOS), Shuttle Radar Topography Mission (SRTM), ASTER Global Digital Elevation Map (GDEM)71. Vegetation cover is also a critical input for soil erosion detection. Satellite-based spectral indices, including the Normalised Difference Vegetation Index (NDVI), Normalised Difference Soil Index (NDSI), Tasseled Cap Transformation (TCT), along with Linear Spectral Unmixing Analysis (LSMA) are often used to estimate soil erosion processes, to investigate soil exposure, to measure soil reflectance, to evaluate soil erosion status and assess soil properties[72]. Remote sensing data gathered via plane, UAV, and satellite is used to directly identify erosion areas and sediment accumulation sites[73]. Most landslides in A-NZ are rapid, shallow slides and flows that occur in soil and regolith in response to storm rainfall, these shallow landslides are considered the dominant erosion process[74]. For these types of erosion events, scans covering time periods are considered the best source of information for statistical landslide susceptibility modelling with variation of the colour or structure of soil as a subsidiary indicator of soil degradation and impending erosion[75]. Even while rainfall is generally the triggering event, using individual storm inventories is not optimal because of their dependency on the pattern and extent of rainfall triggering events[76].
In a similar analysis, the vegetation indices used for soil exposure measurements can be used to pick up on overgrazing and pugging that has occurred in paddocks[77]. All of these measurements rely on frequently collected data of which satellites are poised perfectly to capture.

Availability of technology in Aotearoa New Zealand

These technologies and datasets are available in A-NZ. LiDAR scanners are available for both commercial and (some) recreational drones and several companies offer LiDAR scanning services across the country. Land Information New Zealand's (LINZ) National Elevation Programme provides LiDAR-based elevation open data for much of A-NZ. Data on topography, soils, vegetation, and land use from the different satellite's is also available for most of A-NZ, though often the free or cheap data is of low resolution while high-resolution data is more costly. The Ministry for the Environment provides satellite data with a resolution of between 10-15 m, licensed as a Creative Commons, where the required resolution for detecting soil erosion is in the ~0.5 m range[78].

Detecting sediments in water

In-situ sensors play an important role in directly detecting and measuring sediment levels in water, often providing real-time data. Turbidity metres, or turbidimeters, gauge the cloudiness or haziness in water due to suspended particles, offering insights into sediment concentration79. Similarly, suspended solids probes, which often

operate based on optical or laser diffraction principles, measure the concentration of these suspended sediments[80]. Optical Backscatter Sensors (OBS) determine sediment concentration by measuring the intensity of light scattered back to the sensor from these particles[81].

Remote sensing offers a powerful approach to detecting and monitoring sediments in waterways, which can arise from sources like soil erosion and urban runoff. The presence of sediments can alter the colour and turbidity of water, and optical sensors on satellites can detect these changes by measuring the light reflectance from the water's surface[82]. The specific colour or appearance of the water can indicate the concentration and type of sediments. Different water particulates, such as sediments, phytoplankton, and dissolved organic matter, possess unique spectral signatures[84,85]. Analysing these signatures, especially in the visible spectrum from green to red wavelengths, allows for the determination of sediment concentrations[86] Turbidity, which describes the cloudiness of a fluid due to particles, can also be estimated using remote sensors, providing insights into sediment levels. Use of the empirical, generic equation allows for the estimation of turbidity without prior derivation of a reflectance and turbidity relationship, which requires in-situ, site-specific measurements[87] Use of fine resolution satellite imagery (e.g., PlanetScope from Planet) across different light spectrums can reveal water turbidity in narrow streams and rivers, with the green band producing the most accurate estimates[86.] In some instances, the thermal properties of water, which can be influenced by sediments, can be assessed using thermal imagery[82] Additionally, radar systems, including SAR, can detect changes in water surface roughness caused by sediments[89].

Availability of technology in Aotearoa New Zealand

These technologies are currently available. A-NZ companies provide turbidimeters with a number of sensors, including pH, temperature, and turbidity, and both cellular and satellite connectivity, though the costs of these can be prohibitive. Similarly, the required satellite imaging is also available, though for narrow waterways the resolution needs to be well below 5 m for accurate spectral analysis, requiring access to the latest generation satellites, with the recommended resolution being 4-5 pixels across the width of the waterbody[90].

Detecting Carbon Emissions and Sequestration

Detecting carbon emissions of farming activity at a fine scale is difficult. This is because there are so many sources of greenhouse gas emissions to the atmosphere, particularly regarding agriculture. Ruminant livestock produce methane during digestion, while manure decomposition can emit both methane and nitrous oxide. Soil management practices, such as tilling and fertilisation, can release carbon dioxide and nitrous oxide. Burning agricultural residues post-harvest, using fossil fuels for machinery, and removal of native ecosystems, such as wetlands and forests, for agricultural expansion further add to GHG emissions[91]. Additionally, the transportation of farm products and inputs, energy-intensive irrigation, and the use of certain soil amendments and chemicals indirectly contribute to the farm's carbon footprint.

Currently, determining the emissions from a farm requires the use of a range of methods, often involving expensive technologies that are brought on site to undertake measurements. Adding to the complexity is that emissions can change due to a range of biophysical factors, such as season, temperature, wind conditions, and soil type[92]. Gas Chromatography is a laboratory technique employed to measure specific GHG, such as methane and nitrous oxide , extracted from farm soil or manure samples[93]. The Tunable Diode Laser Absorption Spectroscopy (TDLAS) uses optical methods to identify gases by assessing the absorption of laser light at distinct wavelengths, with its portable versions being especially useful for direct field measurements from sources like livestock or manure heaps[36]. Fourier Transform Infrared Spectroscopy (FTIR) can simultaneously detect multiple gases by analysing their unique infrared absorption patterns, and its portable variants facilitate on-site assessments[94]. Flux Chambers, containers positioned over soil or water surfaces, trap emissions for subsequent GHG content analysis[23].

In terms of carbon sequestration, a combination of LiDAR and spectral imaging can be used to make reasonably accurate assessments of carbon capture within vegetation on both farms and in forests using satellites[95]. As outlined previously LIDAR can detect changes in the density and height of vegetation over time, which can be used to determine how much carbon is being stored. The imaging generated by satellites and drones can be used for this purpose. It is, however, more challenging to detect levels of carbon sequestration within soils using remote sensing. Typically soil sampling and subsequent laboratory analysis is used to determine the amount of carbon stored in the soil, giving insights into a farm's role as a carbon sink or source[96]. Although remote sensing methods using satellite data have been developed overseas for determining soil carbon sequestration, the processes they use are not publicly available in A-NZ. However, it appears that changes in soil carbon levels can be deduced based on knowledge regarding soil water holding capacity and according to soil type. Soils with more carbon can hold more water, consequently, changes in the water holding capacity of soil over time can indicate changes in soil carbon[97]. Detailed data on soil moisture levels across landscapes and could be used for this purpose. This approach also applies to detecting soil organic matter - which is effectively a measure of soil carbon levels.

In terms of in-situ sensors the Eddy Covariance System can be used to detect both GHG emissions and carbon sequestration[98]. This system gauges gas exchanges between the land or pasture/crops and the atmosphere using high-frequency measurements. Two instruments are attached to a mast, or tower, on-farm. Firstly, an anemometer measures the three-dimensional wind several times per second, capturing tiny vertical wind movements (eddies) that transport gases to and from the ground. Secondly, a gas analyser measures the concentration of the target greenhouse gas at equally high frequencies. The rapid measurements capture the fluctuations in gas concentration associated with each eddy. Advanced software tools are used to clean, process, and analyse the data to arrive at GHG flux estimates between the land and atmosphere.

Apart from the Eddy Covariance System there are software tools and models that predict GHG emissions based on diverse farm parameters, drawing from empirical data and extensive research using the techniques outlined above. However, the disadvantage with modelling is relation to the GHG balance on farms in particular is that there is significant variance in the way individual farmers farm, leading to large variations that may not be captured in deterministic models.

Availability of technology in Aotearoa New Zealand

While in-situ sensors for measuring GHG are available, the ability to do these measurements remotely is currently being developed. The MethaneSAT project[99] (a satellite aimed specifically at measuring GHG) is a partnership between the New Zealand government and NASA and is aimed to launch at the start of 2024. The data from this satellite will greatly expand the ability to measure GHG without in-situ sensors.

The ability to measure sequestered carbon using remote sensing has not been made publicly available in New Zealand as mentioned above. Local Crown Research Institute, Scion, has done research in this area with plantation forests[100], however, the ability to measure beyond the tree canopy has not been available. Having the Rongowai programme's soil moisture data available will provide critical information that current models are missing for predicting soil carbon. Moving the modelling done overseas into an A-NZ context will then be a much more trivial task.

Detecting Water Availability and Excessive Extraction

The primary source for water as well as measuring excessive extraction lies within the knowledge of the amount of water in the underground aquifers. The traditional way to measure aquifer volume is with geographical knowledge of an area. Water can lie in predictable areas (such as between rock layers) and knowing the geography of a specific area can increase the likelihood of finding water. Newer methods of detection involve using a seismic mapping technique. The measuring process sends a percussion sound wave into the ground and analyses the returning sound wave[101]. The changes in density of the contents (soil, rock, water, hollow area) show up as different sound wave frequencies on their return. While this method allows for depths of up to 100m into the ground, this method requires multiple measurements per farm to obtain a map of potential water.

When we look at remote sensing methods, we are generally limited to surface water measurements. GNSS-R and SAR technologies have the ability to penetrate into the soil and with the Rongowai programme[26] mounting the sensor to an aircraft and bringing the measurements closer to the earth surface they have the possibility to measure up to 100 mm depth. SAR measurements vary depending on the specific band they are using but with L-band there is a potential penetration depth of 100 to 250 mm depending on the ground conditions[102]. While these measurements will not reach any underground water sources, we are able to get an insight into the surface water flow of an area. When these measurements are combined with traditional modelling techniques for water flow using AI, we have the ability to estimate the status of ground water in an area[103]. Furthermore, with the access to frequent high resolution satellite imagery, we can measure various vegetation indices to determine areas of wetter conditions.

Availability in of technology in Aotearoa New Zealand

Water drilling experts and engineers will have local knowledge of an area and be a good first indication of water sources within an area. There are many experts across A-NZ in all regions. Seismic water measurements are also available in parts of the north island from a small company in Gisborne. The remote sensing modelling has been done overseas but not in an A-NZ context.

Detecting Heavy Metals in Soil

Technology for detecting heavy metals (As, Cd, Co, Cr, Cu, Fe, Hg, Mn, Mo, Ni, Pb, Sb and Zn) comes primarily from the mining industry. Being able to pick up on contamination beyond a mining site is critical. Techniques have been developed to pick up on a variety of heavy metals by using indices developed for their detection. These indices rely on the use of Visible and Near-Infrared and Short Wave Infrared to pick up the metal traces[104]. The current research has focused on mining activities as this is a high likelihood of future issues, but the research has not made its way into a farming practice, or broader environmental monitoring yet.

Availability in of technology in Aotearoa New Zealand

While these techniques are developed for mining activities overseas, they have not been developed in an A-NZ land management context. Instead, standard soil sampling techniques are used.

Detecting species biodiversity in surface water

Conventional methods such as water sampling are primarily used, however eDNA, and associated databases, are providing an excellent source of in-situ data for taonga species and species diversity[105]. It is not currently possible to detect these species using remote sensing, however; species diversity can be correlated to other measures of water quality such as low nutrient concentrations, low turbidity, high oxygen levels, and appropriate pH106.

Availability in Aotearoa New Zealand

eDNA sources are increasingly popular within A-NZ and even have open data for the public to view and use. Sensors are currently cost prohibitive for smaller operations, but as the technology becomes easier to manufacture more data will be available for use.

Combining technologies to generate a Kaitiaki Intelligence Platform

Technologies capable of high-resolution environmental sensing offer a comprehensive means to detect shifts in biodiversity, native land cover, soil nitrates, and phosphates, their migration into water, erosion patterns, waterborne sediments, and the dynamics of GHG emissions and sequestration. These tools could equip MACs with in-depth insights into the environmental repercussions of their agricultural and forestry operations and guide continual improvement. Addressing iwi environmental concerns, these technologies can pinpoint areas within a rohe or tribal territory where freshwater sources are compromised due to agricultural and forestry runoff. They also highlight regions susceptible to drought or excessive water extraction. The technologies can identify zones experiencing land degradation, whether from soil quality deterioration, erosion, or suboptimal agricultural and forestry practices. Furthermore, they can detect the decline of taonga species resulting from habitat loss, invasive threats, and alterations in the health and extent of native ecosystems. This intricate terrestrial monitoring also sheds light on pollutants, such as sediments, entering coastal marine zones. Having access to such comprehensive data would bolster the ability of iwi to participate actively in resource management discussions, ensuring their rights and interests receive due recognition and respect.

Utilising live in-situ sensors, along with traditional sampling and lab analysis techniques, can be costly and challenging to implement on a large scale. In contrast, emerging remote sensing technologies, powered by AI, present a cost-effective solution for extensive monitoring to the benefit of MACs and iwi. However, as previously mentioned, in-situ and remote sensing methods are not mutually exclusive; they can complement each other. Specifically, areas with detailed in-situ monitoring can serve to calibrate remote sensors. This, in turn, can inform AI development, refining and enhancing remote sensing techniques over time.

Furthermore, there is a relatively high degree of crossover in terms of remote sensing technologies and different metrics needing monitoring. For example, LiDAR and spectral imaging can provide data on both erosion and carbon sequestration, while the same in-situ metres are often modular and can provide data on a range of different factors. For instance, water metres can measure turbidity, temperature, pH, dissolved oxygen, conductivity, trace metals, chlorophyll-a, oxidation reduction potential, biochemical oxygen demand, flow rates, nitrates, and coliforms. Given the significant potential and advantage of remote sensing to provide detailed and comprehensive low-cost environmental data at both farm and rohe scales, an emphasis has been placed on these technologies in the design of a KIP. However, where such technologies are not available or someway away from being developed in-situ monitoring or modelling approaches have been drawn upon.

Yes	Maybe	No
🟢	🟡	🔴

Table 3: Kaitiaki Intelligence Platforms technology input

Metric Detection Categories	Possible using remote sensing?	What detector types?	How?	Research & Development needed?
BIODIVERSITY INDICATORS				
Native Habitat **Riparian planting** **Species diversity** **Presence/absence of pest and weed species**	🟢	Optical, multispectral, and hyperspectral cameras LiDAR GNSS Reflectometry	AI generated biodiversity signatures from vegetation reflectance and structure, and soil moisture for wetland identification. Calibrated with in-situ sensors and biodiversity databases that store data	🟢
Taonga Species	🟡	AI generated biodiversity signatures can detect some individual taonga plant species. The presence of other species may possibly be inferred from the presence, extent, and health of ecosystems revealed by AI generated signatures. ≠≠≠Calibration with in-situ sensors and biodiversity databases would be necessary (e.g., eDNA databases)		🟢
Detection of native and pest fauna	🟢	Optical, multispectral, and hyperspectral cameras LiDAR	AI generated biodiversity signatures from vegetation reflectance and structure can detect levels of browsing pest fauna indicating presence and abundance	🟢
	🔴	There are no remote sensing options for detecting many species of fauna	In-situ sensors and sampling methods are required such as camera traps, acoustic sensors, and eDNA	🟢 🔴
SOIL QUALITY INDICATORS				
Erosion	🟢	Optical, multispectral, and hyperspectral cameras	AI generated erosion signatures (i.e., landslips) from ground reflectance	🟢
Compaction	🟢	Optical, multispectral, and hyperspectral cameras	AI generate signatures from vegetation and soil ground reflectance	🔴

In Table 3, the various indicator and metric detection categories are outlined and based on the analysis and discussion throughout this report, it is indicated whether remote sensing is possible for the detection categories, what types of detection technologies is needed, how it would occur, and whether research and development is required to implement.

Metric Detection Categories	Possible using remote sensing?	What detector types?	How?	Research & Development needed?
WATER QUALITY AND QUANTITY				
Excess Nitrates and Phosphates in soil		Multispectral, and hyperspectral cameras	AI generated soil nutrient signatures from pasture and crop vegetation reflectance to reveal nutrients within rootzone. Calibrated with in-situ nitrate and phosphate sensors	
Ground water quantity Surface water flows		Remote GNSS Reflectometry in combination with sophisticated water modelling	GNSS reflectometry reveals surface and soil moisture levels and sophisticated water modelling predicts migration to below ground	
Nitrate and Phosphate migration to ground and surface water		Remote GNSS Reflectometry in combination with sophisticated water modelling	GNSS reflectometry reveals soil moisture levels and sophisticated water modelling predicts nutrient migration from plant rootzone to ground and surface water. Calibrated with in-situ lysimeters and in-situ stream sensors	
Nitrate and phosphate surface water concentration		Multispectral, and hyperspectral cameras	AI generated nutrient signatures using algal chlorophyll reflectance Calibrated with in-situ nitrate and phosphate sensors	
Species diversity		Conventional sampling methods and eDNA	Using mobile or in-situ eDNA sampling	
GHG INDICATORS				
Emissions		There are no remote sensors that can do this at a local scale. The in-situ Eddy Covariance System can be employed at farm scale, but expensive. Modelling required.	There are various forms of software based on input-output models that can be used to estimate the likely GNG footprint of farms and regions. They are however static and deterministic models and may not capture local nuance	
Carbon sequestration in soil / Soil Organic Matter		Remote GNSS Reflectometry	AI generated signatures that detect changes in soil carbon via soil moisture holding capacity	
Sequestration in vegetation		LiDAR	Detecting changes in vegetation structure indicating above ground carbon storage	
STOCK MANAGEMENT				
Paddock lines **Stock numbers**		Optical, multispectral, and hyperspectral cameras	AI generated stock and fence line signatures from ground reflectance	

The Kaitiaki Intelligence Platform – a modular design

Building a platform that is capable of monitoring and reporting across each of the indicator–metric detection categories outlined above would be a significant undertaking. Two approaches could be taken to build this, a staged approach, or a complete build approach. Each of the indicator–metric detection categories may be considered a module, making 17 modules (illustrated in Table 4), each of which could be built separately in a sequential way, or all built simultaneously together. The strength of the staged approach is that it would permit modules to be built based on the level urgency and ease of development. This allows for the gradual construction of the KIPs over time, depending on the availability of resources and investments from MACs and iwi, and other stakeholders. However, many of these modules rely on the same data source, typically remote sensing data, often obtained from satellites. For example, both native habitat biodiversity and soil stability detection depend on multispectral imagery. In such cases, the purchase of imagery can be a one-time investment that covers the development of multiple modules. Consequently, there can be efficiency gains from pursuing a complete build approach where modules are developed simultaneously, considering their data interdependencies. Nevertheless, a combination of these two approaches is likely to be the most effective. In this hybrid approach, the entire system or complete build is kept in mind while designing and building individual modules. This allows for capturing efficiencies wherever possible while permitting modules to be developed as resources become available.

The module building process

Many of the modules mentioned have been successfully developed and tested in other regions, but they have not yet been tailored to the specific conditions of A-NZ, including its unique ecology, geology, soils, crops, pastures, and land management practices. Adapting these modules to the local context requires two essential sets of data. Firstly, it necessitates high-quality, locally ground-truthed environmental data specific to a particular area (which may include mātauranga-derived data), along with relevant remote sensing data (such as optical, multispectral, or radar satellite imagery) covering the same region. This ground-truth data serves a dual purpose: it is initially used as training data for the models, allowing them to adapt to the new landscapes and signatures observed in the satellite data; additionally, it is employed to validate the model's outputs and assess its accuracy. The process of constructing these models is iterative. Initially, a selected model is run using the training data, and the results are compared against the ground-truthed data. This process may be repeated multiple times until a satisfactory result is achieved – a process through which mātauranga can be built into models. Furthermore, additional input data may be introduced into the model to better distinguish specific signatures from their surroundings.

As these modules are developed, there is an opportunity for interoperability between them, which can enhance their predictive accuracy. For instance, if a biodiversity module is in development, it may benefit from integrating information from modules related to soil erosion and heavy metals detection. These modules can provide complementary data that, when combined using a neural network approach, enhances the predictive capabilities of the biodiversity module. A full outline of the modules underpinning the KIP are outlined in Table 4 (p52) and includes the underpinning category the module is gathering data and reporting against, the data needed to develop the module, and a description of the process for module build.

The overall development sequence of the modules would be influenced by three factors:

1. Demand: The priority is given to areas with the highest interest from MACS and iwi. A strong interest in a specific area strengthens the case for developing those modules first.
2. Existing Developments: Efforts and time can be significantly reduced by adapting existing research or products that are close to deployment. This approach avoids the need to start research from scratch.
3. Data Sharing: If there are modules that can use the same input data, such as satellite imagery, this can lower both the initial costs of data research and the effort required to integrate the data into the KIPs framework. If a module already developed uses the same data a new module needs, it streamlines the process.

Warehousing data

The development of modules will require the retrieval, analysis, management and storage of significant quantities of data. With the costs associated in acquiring data (primarily satellite) being relatively high, the data becomes an asset which needs proper storage. Depending on the type of data and its area coverage, this can be a very large amount of data to store as well (hundreds of terabytes). Both points lend the project to rely on a data streaming structure. This structure means that the data is not stored permanently on servers owned by the platform but instead is downloaded from the data host (i.e., Planet Labs) when needed for analysis. Most data providers will account for the purchasing of data within their system so to redownload does not pose extra costs. This allows for an initial download of the data, then the data can be stored locally while the model is being built. Once the models have been built and ready for further analysis the data used to build those models can be discarded. If there is a need to get the data back, then it can be re-downloaded from the supplier. This significantly reduces the cost of storage and archiving of data. At the time that a user is wanting a new output from the already built models, the latest imagery will be pulled down for analysis, run through the models and the model outputs will be passed to the user. The imagery will once again be discarded after it has been run through the model as it is no longer needed. This user interaction is described as a data streaming structure where only the outputs are held onto by the end user.

A user interface

While most of the discussed platform features up to this point lie within the backend of the platform, the user interaction is of great importance as well. There are three ways in which we intend to have user interaction:

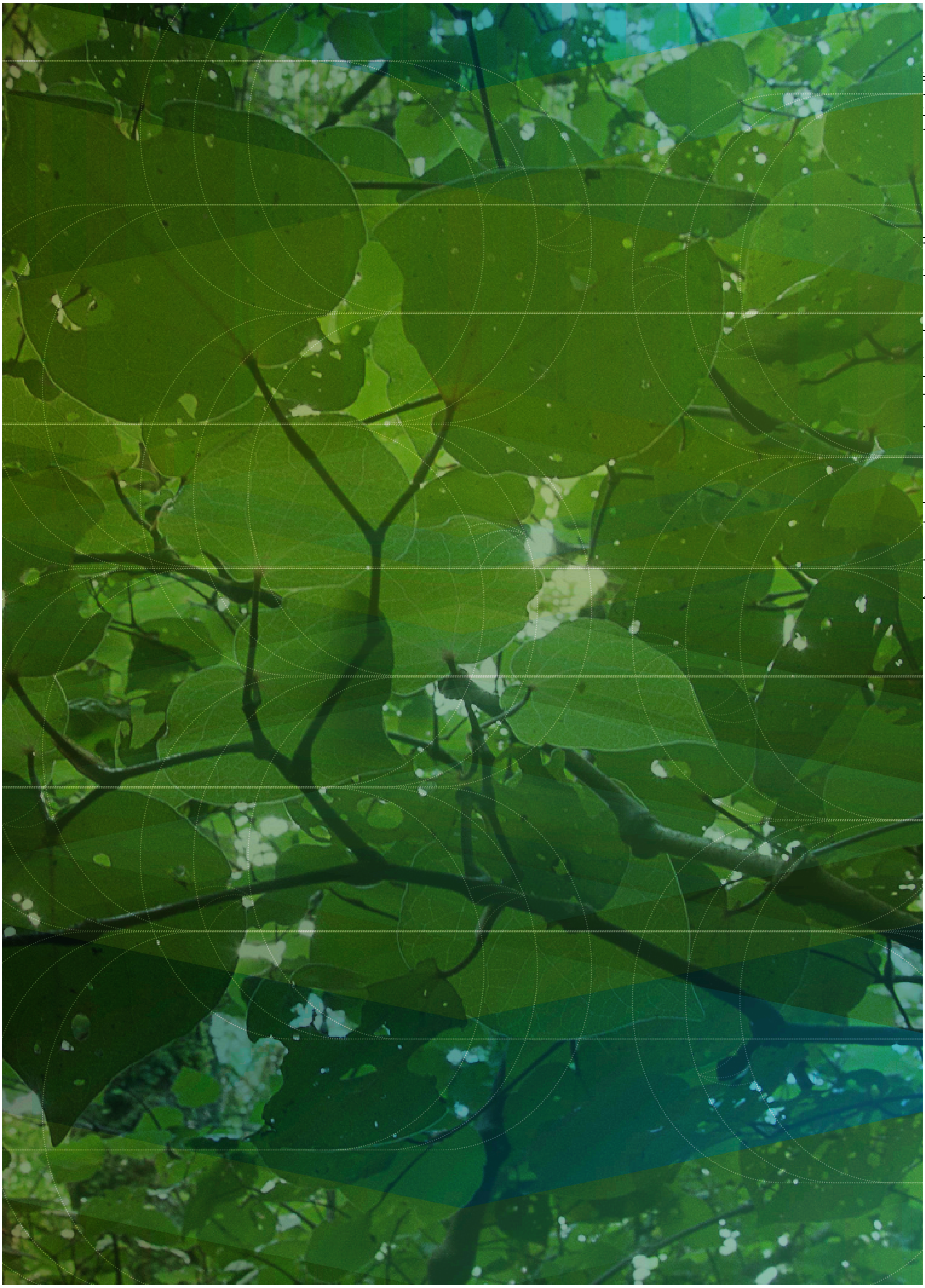
1. Summarised data document,
2. GIS maps,
3. Virtual user experience.

The summarised data will be for a user who is needing the information provided by the platform to pass onto further analysis or to be integrated into a larger report. This output will involve taking the model output data (e.g., total area of native habitat) and summarising it for the user (e.g., total area across regions). The GIS output will allow further integration and visualisation by a user who is familiar with working inGIS maps. This output could allow further analysis of the model outputs such as changes over time or simply to visualise the outputs overlaid on a map such as Google Earth. The virtual user experience is intended to provide a subversive experience for the end user. Amongst many potential users, an end user might be a trustee or shareholder of a MAC or an iwi decision maker forming an environment plan. The user would be able to see an animation of the output (e.g., prediction of soil erosion areas and the predicted land change).

Adapting these modules to the local context requires two essential sets of data. Firstly, it necessitates high-quality, locally ground-truthed environmental data specific to a particular area (which may include mātauranga-derived data), along with relevant remote sensing data (such as optical, multispectral, or radar satellite imagery) covering the same region. This ground-truth data serves a dual purpose: it is initially used as training data for the models, allowing them to adapt to the new landscapes and signatures observed in the satellite data; additionally, it is employed to validate the model's outputs and assess its accuracy. The process of constructing these models is iterative.

Table 4: Kaitiaki Intelligence Platform modules

Module	Detector Category	Module	Data Source	Build Description
1	Terrestrial Biodiversity	**Ecosystem type by area: Native vegetative biodiversity**	RGB, Multispectral, SAR, GNSS-R, LiDAR, Hyperspectral	AI-generated biodiversity signatures from vegetation reflectance structure and soil moisture for wetland identification. Calibrated with in-situ sensors and existing biodiversity databases.
2		**Taonga Species**	RGB, Multispectral, SAR, GNSS-R, LiDAR, Hyperspectral, eDNA	AI-generated biodiversity signatures can detect some individual taonga plant species. Other species' presence may be inferred from the presence, extent, and health of ecosystems revealed by AI-generated signatures. Calibration with in-situ sensors and biodiversity databases would be necessary.
3		**Native and pest fauna**	Optical, multispectral, and hyperspectral cameras, eDNA, LiDAR	AI-generated biodiversity signatures from vegetation reflectance and structure can detect levels of browsing pest fauna, indicating presence and abundance. In-situ sensors and sampling methods, such as camera traps, acoustic sensors, and eDNA.
4	Soil Stability and Quality	**Erosion**	Optical, multispectral, and hyperspectral cameras	AI-generated erosion signatures (i.e., landslips) from ground reflectance.
5		**Pugging and Compaction**	Optical, multispectral, and hyperspectral cameras	AI-generated ground disturbance signatures.
6		**pH**	Multispectral and hyperspectral cameras	AI-generated biodiversity signatures from vegetation reflectance and species presence, case study ground-truthing.
7		**Microbial Diversity and Quantity**	eDNA	Using mobile or in-situ eDNA sampling, and existing eDNA databases.
8	Water Quality and Quantity	**Excess Nitrates and phosphates in soil**	RGB, Multispectral, Hyperspectral	AI-generated soil nutrient signatures from pasture and crop vegetation reflectance to reveal nutrients within rootzone calibrated with in-situ nitrate and phosphate sensors.
9		**Surface and ground water flows & associated nitrate and phosphate migration**	Remote GNSS Reflectometry, RGB, in combination with hydrological modelling	GNSS reflectometry reveals soil moisture levels and surface water, modelling predicts migration to groundwater. Modelling also predicts nutrient migration from plant rootzone to ground and surface water. Calibrated with in-situ lysimeters and in-situ stream sensors.
10		**Nitrate and Phosphate surface water concentration**	Multispectral and hyperspectral cameras	AI-generated nutrient signatures using algal chlorophyll reflectance Calibrated with in-situ nitrate and phosphate sensors.
11		**Species diversity**	Conventional sampling methods and eDNA	Using mobile or in-situ eDNA sampling, or existing eDNA databases where available.
12	GHG	**GHG emissions to air**	There are no remote sensors that can do this at a local scale. The in-situ Eddy Covariance System can be employed at farm scale but is expensive. Modelling required.	Using mobile or in-situ eDNA sampling, or existing eDNA databases where available.
13		**Methane Emissions**	Satellite - MethaneSAT	Various forms of software based on input-output models can be used to estimate the likely GNG footprint of farms, rohe, and regions. They are, however, static, and deterministic models and may not capture local nuance.
14		**Carbon Sequestration in soil/ soil organic matter**	Remote GNSS Reflectometry	AI-generated signatures that detect changes in soil carbon via soil moisture holding capacity. Existing data on soil type is required.
15		**Sequestration in vegetation**	LiDAR	Detecting changes in vegetation structure indicating above-ground carbon storage.
16	Stock Management	**Paddock lines**	Optical, multispectral, and hyperspectral cameras	AI-generated fence line signatures from ground reflectance.
17		**Stock numbers**	Optical, multispectral, and hyperspectral cameras	AI-generated stock signatures from ground reflectance.



The Kaitiaki Intelligence Platform Design

The modules outlined above are designed to generate the biophysical environmental data sought by MACs and iwi. However, it is important to orientate and place this technology within a Māori value system and mātauranga frame. Drawing on the discussion in earlier sections of this report, it was outlined how the environment, from a mātauranga perspective, is divided into different atua domains. Although there are many atua, which vary between hapū and iwi across A-NZ, there are a group of atua that are commonly referenced within a range of Māori environmental reporting frameworks that represent - in Western terms - the natural world. However, from a Māori worldview, humans are not separate from nature, and as such have their own atua domain, Tūmatauenga. These atua are descendants of two primordial parents, Papatūānuku and Ranginui. The schematic in Figure 1 (p55) illustrates how this whakapapa structure underpins the KIP design, with Ranginui and Papatūānuku represented two poles of the design - containing all domains. Each KIP module is placed within, or across, the atua domain/s associated most strongly associated with it. For example, modules designed to generate data concerning the health of terrestrial biodiversity are situated within Tāne's domain – the atua of forests, forest creatures, and many plants. Table 5 below outlines the different atua domains and the modules associated with them - noting that more than one atua is mentioned for the same atua domain to illustrate how hapū and iwi have either different names for the same atua, or a different atua for a specific domain.

The data that remote sensing technology gathers, is represented by atua Hinekōrako (lunar rainbow). This atua represents the optical phenomenon of a rainbow when light from the moon refracted through tiny droplets of water. Very rare, Hinekōrako represents the accumulation of trillions of droplets that usually cannot be seen by the human eye, and therefore if seen, appears white. However Hinekōrako can be captured by a long exposure camera.

Table 5: Atua domains linked with the Kaitiaki Intelligence Platform modules.

Atua	Domain	Modules
Tāne-mahuta	Forests, forest creatures, many plants	Native habitat, Species presence or absence, Taonga species
Tangaroa or Hinemoana	Water bodies and creatures	N & P Migration to groundwater, Aquatic species presence or absence, N & P surface water
Rongomaraeroa or Rongomātāne	Cultivated lands	Paddock lines, Stock numbers
Hine-ahu-one	Soils and earth	N & P Concentrations, pH, Pugging & Compaction, Erosion, Microbial diversity
Parawhenuamea	Wetlands	Species presence or absence, N & P concentrations
Tāwhirimātea	Wind and air	GHG emissions, GHG sequestration
Tūmatauenga & Hine-tītama	Humans - Te Ao Turoa - the natural world	Taututuutu reporting: Mauri-ora or Mauri Mate

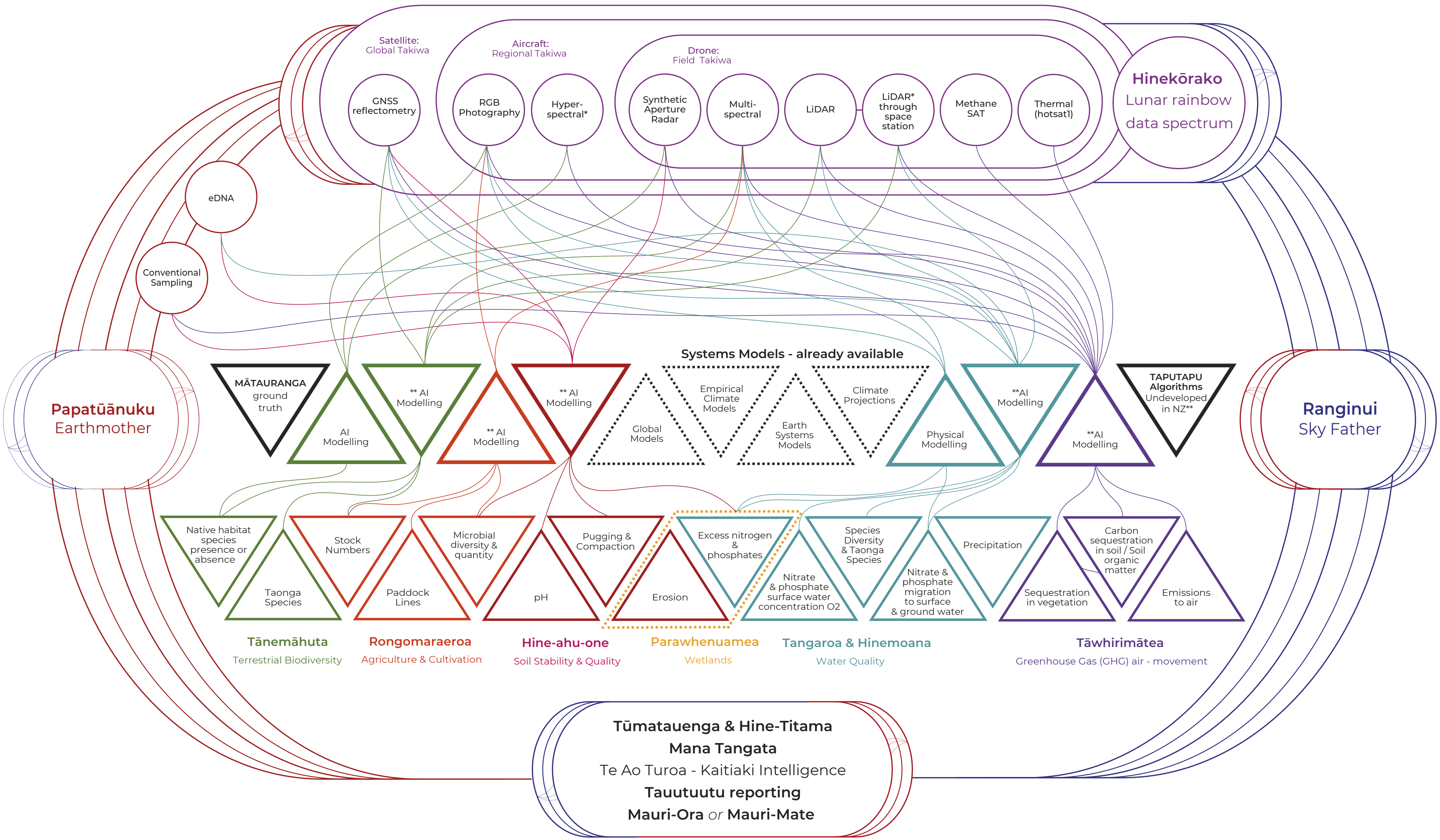


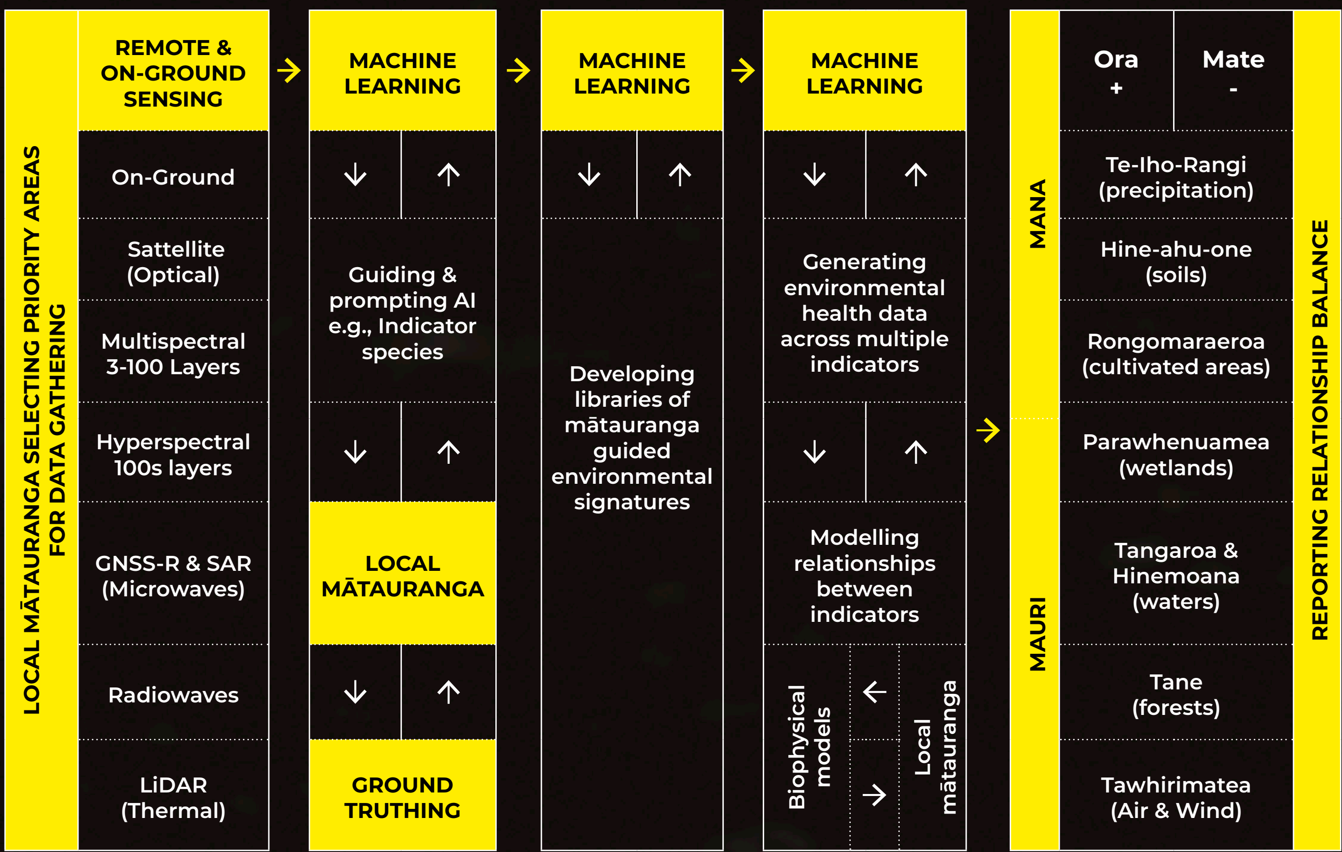
Figure 1: Whakapapa structure underpinning the Kaitiaki Intelligence Platform design. (undeveloped in Aotearoa New Zealand)**

Remote sensing detectors, are represented in as residing in the domain of Ranginui, given their association with the sky and space. Data flows from the sensors and are combined, where required, with data from in-situ sources (i.e., conventional sampling, or eDNA) and earth system models. AI is then used to identify taputapu in the data, that can reveal the health and wellbeing of the various environmental atua domains. It is then illustrated how this intelligence may be used to support MACs and iwi to gauge whether relationship balance (utu) between Tūmatauenga and the other atua domains is mauri and mana enhancing (ora) or diminishing (mate).

In Figure 1 it is also illustrated how MACs and Iwi (the users) may build local mātauranga into modelling processes through ground-truthing. As outlined previously, there are limitations with relying solely on biophysical data generated by environmental sensors to understand environmental changes – particularly when attempting to gauge changes in mauri and mana - which cannot be fully captured quantitatively. This is communicated in more detail within Figure 2, where it is shown how local mātauranga can guide and prompt the AI to create libraries of environmental signatures/ algorithms. For instance, AI trained to identify changes in the abundance of a particular tree species from satellite imagery may be correlated with local knowledge of the decline in abundance of that species, or other associated ecological changes. Many algorithms can be built for different environmental features, generating libraries of environmental signatures. Once built, these libraries can be used to scrape large quantities sensing data to detect broad environmental changes and examine correlations between different environmental indicators. For instance, relationships between indigenous ecosystem land cover and water quality. Through this approach detailed environmental reports can be generated concerning the mana and mauri of different atua domains. Moreover, Figure 2 also illustrates how local mātauranga Māori may be used to guide where remote sensors are directed, or in-situ sensors are placed, to gather data considered most relevant by MACs and iwi. How this mātauranga is built into KIP would need to be done carefully and with consideration to data sovereignty.

In addition, Figure 2 also refers to the user interface. As outline previously, the user interface would allow MACs and iwi to access relevant data in useful formats. Clearly, a primary role of the user interface would be to communicate the status of atua, and particularly the state of balance, or imbalance, between humans and the environment in an iwi territory, or on the whenua managed by MACs. The types of formats, as mentioned might include data documents, dashboards, GIS maps, and a virtual user experience. The design of the user interface provides an opportunity to include qualitative and intuitive expressions concerning the state of the environment and human relations with it. Multiple mediums include mātauranga inspired art, design, waiata, and karakia, which could be interwoven throughout the user experience. Such expressions, deeply rooted in local knowledge and the sense of place, help convey the personal experiences mauri and mana degeneration or regeneration. Any design, however, would need to be developed with mana whenua to ensure that cultural sensitivities and data sovereignty rights are respected.

Figure 2: Process for using mātauranga Māori to guide AI..



The costs of building the Kaitiaki Intelligence Platform

Below an estimate is provided of the costs associated with developing the 17 KIP modules (see feeder report here). Estimating costs is quite challenging given that many the technologies and methods have not been applied in A-NZ, and furthermore research and development that entails risk and uncertainty. For instance, while data from hyperspectral imaging and GNSS-R technologies are accessible, AI techniques for analysing this data to assess environmental health are still in early development stages in A-NZ - despite being more advanced overseas. Cost estimates for each module cover labour, software, hardware, data, overheads, scalability, external consultation, and research and development. The estimate also considers potential cost savings from 'experience curve' efficiencies gained through development experience.

As outlined above the development of the KIP can proceed via a staged or a complete build approach. The staged approach involves developing modules sequentially, such as a water quality module, based on their urgency and development ease, allowing for phased construction aligned with available resources and investment. However, as many modules share common data sources, like remote sensing data, a complete build approach—developing multiple modules simultaneously with consideration for their data interdependencies—could be more efficient. A hybrid approach, which considers the entire system while developing individual modules, may offer the best of both worlds, combining efficiency with resource-driven development and tailoring each module to local conditions for improved predictive accuracy.

The cost estimates in this report lay the groundwork for future financial planning, depending on the chosen development approach. Costs can be adjusted based on shared data sources or technologies across modules, and efficiencies from similar development approaches can further reduce costs. Thus, this report establishes a baseline for the development of independent modules, which can be refined with additional future information.

The cost estimates encompass 17 modules, categorised into five groups. In addition to these, Modules 1 (Native Vegetative Biodiversity Detection) and 2 (Taonga Species) include additional sub-modules. In total, 39 distinct but interconnected developments are considered in this analysis.

The methodology for cost estimation follows a five-stage process, including identifying key roles and resources, assessing difficulty levels, estimating time, calculating proportional allocations, and summarising total costs. Technical experts provided primary information on development needs, estimating the time required by data scientists, and the relative difficulty of developing each module. The report delineates other costs such as software, hardware, data, overheads, scalability, external consultation, research and development, and marketing and outreach.

The total development cost for all modules amounts to approximately $50 million (Table 6).

This figure of $50m is considered a high-end estimate and is intended to establish a baseline for developing independent modules. The report also highlights

Table 6: Cost estimates for each module to be developed for the Kaitiaki Intelligence Platform.

MODULE		COSTS	NOTE
1	Ecosystem type by area: Native vegetative biodiversity detection	$6,888,243	**14 Signatures**
2	Taonga Species	$4,525,347	**7 Signatures**
3	Detection of native and pest fauna (Indicator species)	$7,601,752	
4	Erosion	$867,418	
5	Pugging and Compaction	$867,418	
6	pH	$7,601,752	
7	Microbial Diversity and Quantity	$7,601,752	
8	Excess Nitrates and phosphates in soil	$867,418	
9	Nitrate and Phosphate migration to ground and surface water	$867,418	
10	Nitrate and Phosphate surface water concentration	$867,418	
11	Species Diversity	$7,601,752	
12	Emissions to air	$182,752	
13	Methane Emissions	$182,752	
14	Carbon Sequestration in soil/ soil organic matter	$867,418	
15	Sequestration in vegetation	$867,418	
16	Paddock lines	$867,418	
17	Stock numbers	$867,418	
TOTAL COST		**$49,992,865**	

the possibility of deriving more precise estimates for any combination of multiple modules through an iterative approach as more information becomes available.

In providing the cost for developing KIP modules, we have considered only each module's development and maintenance costs. The use of eDNA, however, requires field sampling that may add additional costs to a module, particularly if a widespread annual sampling regime were implemented. We estimate a national eDNA sampling method might involve taking 4,455 samples per annum across 94 habitats for a cost $1,291,950 per annum.

The report also considered maintenance costs of $30,765 p.a. for each module or $523,011 p.a for all 17 modules. As in the development costs, each module is treated independently, and no synergies or efficiency gains from crossovers have been considered. If an annual eDNA sampling regime is included, it is estimated to cost $1,814,961 p.a. to operate the KIP system. Moreover, cost for purchasing satellite imagery is estimated at $10M p.a. It is consequently estimated that the annual maintenance cost would be approximately $12M.

The cost estimates provided in this report can form the basis of future financial analysis depending on the development approach. Where data sources or technologies complement multiple modules, these costs can be removed from the estimates. Additionally, where modules take a similar development approach, efficiencies generated through experience will likely reduce the cost of each next module. Therefore, this report should be understood as having established a baseline for developing independent modules that can be refined based on future additional information.

Conclusions and recommendations

This report outlines a process by which MACs and iwi may become pioneers in environmental intelligence by leveraging advanced modular sensing technology, guided by deep environmental knowledge. The report outlines the necessity for enhanced environmental data collection, and how this data can support not only informed decision-making but also meets reporting requirements, enables sustainable financing, and improves market positioning. It describes the required metrics for different stakeholders, details the sensor technologies for these metrics, explains the modular system for data integration, storage, and visualisation, and offers a financial overview for setup and operational costs.

This project serves as a foundational step for developing a Kaitaiki Intelligence Platform (KIP), focusing on environmental ethics, stakeholder data needs, and the necessary technology and infrastructure. The research presents several recommendations for the platform's conceptual and practical development.

1

Modules: It is recommended that a modular approach be taken to the development of a KIP. This allows for the options of both a staged build, based on priorities, level of technical difficulty, and resources, or a complete build. However, as many modules share common data sources, like remote sensing data, a complete build approach—developing multiple modules simultaneously with consideration for their data interdependencies— would be the most efficient. A hybrid approach, which considers the entire system while developing individual modules, may offer the best of both worlds, combining efficiency with resource-driven development and tailoring each module to local conditions for improved predictive accuracy.

2

Mātauranga Māori: It is recommended that mātauranga Māori be put at the forefront in any build. This includes:

- Guiding what biophysical data is gathered by remote and in-situ sensors.
- Ground-truthing AI generated environmental signatures and models through the local knowledge of mana whenua.
- Using indigenous sovereignty principles in the warehousing and management of data.
- Using whakapapa, to underpin the generation and framing of information created by the platform. This would involve gauging the relationships between humans and the environment in terms of utu, and more particularly whether humans are acting in ways that enhance or diminish the mauri or mana of environmental atua.

3 **Product accreditation:** It is concluded that there is an opportunity for a KIP to offer indigenous product accreditation, providing verification for consumers interested in purchasing genuine environmentally sustainable indigenous products.

4 **Biophysical Data:** It is also recommended that the KIP generate data in biophysical formats to assist Māori Agribusiness Collectives (MACs) and iwi in their engagement with government, to support environmental reporting according to regulatory requirements, and generate data for the sustainable finance and market assurance sectors. Income from data sales could support ongoing KIP development; however, the capacity of these sectors to integrate high-quality data into their systems is currently limited due to issues with their data infrastructure and the challenges they face in standardising data.

5 **Partnerships:** It is concluded that the development of the platform would require partnerships with data, technology, and research providers (i.e., satellite companies, data analytics platform providers, and science institutions). Data would need to be brought together, warehoused, analysed, and processed, and communicated through multiple mediums. It should be noted that the technology in this area is rapidly advancing and that the market, or ecosystem, of technology providers is fluid and changing. Consequently, partnerships with technology companies most likely to survive in this dynamic environment should be carefully selected and prioritised.

6 **Consortium:** It is recommended, that for a KIP build to be successful, leadership of an iwi or MAC, or a consortium of these entities under a common governance structure, would be required. Such a structure would be needed to attract the necessary resources and investment and partnerships with the public and private sectors.

7 **Investment, ownership and management:** It is concluded that the build of the KIP is technically feasible and not overly complex, with the modules outlined having been successfully developed in other contexts outside of A-NZ. However, the complexity in the build lies in the development of structures for investment, ownership, and management of data.

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Glossary

Atua: Deities / Sentient eco-systems

Hapū: Subtribe

Hine-ahu-one: First woman created from soil by Tāne / Sentient eco-system

Hinekōrako: The lunar rainbow

Hinemoana: Female deity of the sea

Hine-tītama: Daughter of Hine-ahu-one, who was formed from the earth

Iwi: Tribe

Kaitiaki: Guardian, keeper, preserver, conservator, foster-parent, protector

Kaitiakitanga: Guardianship, obligation, arising from kin relationship, to nurture or care for a person or thing. It has a spiritual aspect, to nurture well-being and mauri

Karakia: Chants, prayers, oral artform

Kaupapa: Topic, matter for discussion

Mahinga kai: Food-gathering place

Mana: Authority, prestige

Mana whenua: Māori people with authority for the land

Maramataka: Māori lunar calendar

Mātauranga: Māori knowledge system

Mate: Mana diminishing, unwell

Mauri: Life essence

Ora: Mana enhancing, wellbeing

Papatūānuku: Mother earth / Sentient eco-system

Parawhenuamea: Wetlands, rivers, streams and flood waters deity

Patupaiarehe: Fairy folk, forest or mountain dwellers

Rangatiratanga: Showing leadership and self-determination

Ranginui: Sky Father / Sentient eco-system

Rongomaraeroa: Deity of cultivated food

Rongomātāne: Deity of cultivated areas

Takiwā: District, area, region

Tāne-mahuta: Deity of the forests

Taniwha: Water spirit, guardian, can indicate area with a natural hazard

Tangaroa: Water and water creatures deity

Tapu: Sacred

Taputapu: Patterns

Tāwhirimātea: Wind and air deity

Tauutuutu: Reciprocity

Te Ao Māori: Māori worldview

Te Ao Tūroa: The natural world, light of day

Tikanga: Correct procedure, custom

Tūmatauenga: War and humans deity / Sentient eco-system

Utu: Repaying to restore balance

Wāhi tapu: Sacred place

Wāhi taonga: Sacred possesions

Waiata: Songs, singing

Wairua: Spirit, soul - spirit of a person which exists beyond death

Whakapapa: Genealogy, knowledge organising principle

Whakaaro: Thought, opinion, plan, understanding, idea, intention, gift, conscience

Whanaungatanga: Nurturing wellbeing of relationships

Whenua: Land, placenta

Acronyms

A-NZ: Aotearoa New Zealand

AI: Artificial Intelligence

ALOS: Advanced Land Observing Satellite

ASTER: Advanced Spaceborne Thermal Emission and Reflection Radiometer

CP: Collaboration partner

eDNA: Environmental DNA

ESG: Environmental, Social, and Governance

FEP: Farm Environment Plan

GDEM: ASTER Global Digital Elevation Map

GHG: Greenhouse Gases

GIS: Geographic Information Systems

GNSS-R: Global navigation satellite systems reflectometry

GPS-RO: GPS Radio Occultation

GRI: Global Reporting Initiative

IoT: Internet of Things

ISEs: Ion-Selective Electrodes

KIP: Kaitiaki Intelligence Platform

LiDAR: Light detection and ranging

LSMA: Linear Spectral Unmixing Analysis

MACs: Māori agribusiness collective

MIR: Mid-Infrared

NDSI: Normalised Difference Soil Index

NDVI: Normalised Difference Vegetation Index

NIR: Near-Infrared

NGO: Non-governmental Organisation

NZFAP: NZ Farm Assured Programme

RIAA: Responsible Investment Association Australasia

SAR: Synthetic Aperture Rada

SDG: Sustainable Development Goals

SRTM: Shuttle Radar Topography Mission

TCT: Tasseled Cap Transformation

TDR: Time Domain Reflectometry

UAV: Unmanned aerial vehicles

UN: United Nations

WTP: Willingness-to-pay

XR: Extended reality

National SCIENCE Challenges

OUR LAND AND WATER

Toitū te Whenua, Toiora te Wai