A METHODOLOGY TO ASSESS RIVER HABITAT QUALITY

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THESIS ABSTRACT

Declines in the ecological health of rivers and streams worldwide have led to a range of policy responses from environmental protection organisations and government departments. However, while policy has often provided specific direction on issues such as nutrient and sediment pollution, over-abstraction of water, flow regulation, and (increasingly) the impacts of climate change, direction to protect the condition of physical habitat in rivers and streams has been vague at best—despite its wide recognition as a core component of ecosystem health. In Aotearoa New Zealand, protection of the 'natural character' of rivers and the 'habitats of indigenous freshwater species' is required under the Resource Management Act (1991) and National Policy Statement for Freshwater Management (2020), however, very few regional authorities effectively manage physical habitat, and regulations have so far not stopped ongoing declines in habitat condition.

While a range of methods have been developed to assess and monitor the condition of physical habitat in rivers and streams, many are complex or conflate variables and there is little to suggest any have been effectively applied in resource management to reverse ongoing habitat degradation. This thesis explores this issue, considering what makes a robust and effective ecological assessment of physical habitat, reviewing a range of existing assessment techniques against those criteria, exploring the opportunity to improve habitat quality assessment through the integration of readily available drone technology, and testing the efficacy of drone integration in the field. I find that Death et al.'s 'Habitat Quality Index' (HQI) has considerable value as an assessment of change in habitat quality, evaluate the efficacy of visually assessing fine sediment cover and substrate composition using a drone, present a comprehensive hybrid HQI assessment of native fish habitat in a reach of river subject to in-stream engineering works, and discuss the implications of using drones for physical habitat assessment.

CONTENTS

INTRODUCTION

Background

Declines in the ecological health of rivers and streams worldwide have led to environmental protection organisations and government departments developing a range of policy responses to address the issue, including the widely cited European Water Framework Directive (Rouillard et al., 2018; Latinopoulos, 2018). However, while policy has often provided specific direction on issues such as nutrient and sediment pollution, over-abstraction of water, flow regulation, and (increasingly) the impacts of climate change, direction to protect the physical condition of rivers and streams has been vague at best. In Aotearoa New Zealand, protection of the 'natural character' of rivers and the 'significant habitat' of indigenous fauna is required under the Resource Management Act (1991), however very few regional authorities (if any) effectively manage physical habitat through rules or consenting processes, and—despite the availability of at least one localised method designed exclusively for quantifying and monitoring habitat condition (Harding et al., 2009)—it has not stopped ongoing declines in physical habitat. Recent changes to Aotearoa New Zealand's National Policy Statement for Freshwater Management (2020) mean it now includes more specific direction that "the habitats of indigenous freshwater species are protected" (p. 9) and recognises and protects habitat as a key component of ecosystem health, though whether this will result in reversing the declining trend in the condition of physical habitat in rivers and streams is yet to be seen.

One suggestion for the lack of monitoring and protection of physical habitat quality in resource management is "the lack of a simple and effective method to quantify the quality of that physical habitat" (Death et al., n.d., p.1). A review of international literature (below) suggests this is a fair conclusion, with numerous authors developing parallel and overlapping methods for physical habitat assessment at various levels of complexity—with little in the way of evidence to suggest they have been effectively applied in resource management. Whatever the problem, if we are to effectively deliver on policy directions and ultimately protect and restore the ecological condition of rivers and streams, a simple and readily applicable method for quantifying physical habitat is critical.

Substantial improvements in the quality and capability of consumer-grade and professional drones[1], as well as significant reductions in their cost, have led to an increasing interest in the potential for drones to overcome limiting factors across disciplines (Toffanin, 2019). In ecology and environmental management, drones are now an accessible technology at all levels of research—from citizen science projects to academic studies—and have substantially increased the accessibility of high-resolution geospatial data (Woodget et al., 2017; Hentz et al., 2018). Drones are already used in ecology to effectively assess numerous components of river habitat, including flow types, vegetation, and erosion (Casado, et al., 2015); channel width (Hentz, et al., 2018); water temperature (Wawrzyniak et al., 2013); sinuosity and riparian habitats (Langhammer, 2019); and substrate characteristics (Arif et al., 2017; Bind et al., 2018;

[1] Also referred to as Unmanned (though it should be 'Unpersonned') Aerial Vehicles (UAVs) or Remotely Piloted Aircraft Systems (RPAS).

Woodget & Austrums, 2017; Woodget et al., 2017, 2018), with many of those studies using now out-dated drones (see Woodget et al., 2017 in particular). Despite this, there is very little work (at least, very little that I have been able to find) on the integration of these developments in drone-based monitoring with a simple technique for assessing physical habitat quality in applied resource management.

Aims

In light of the ongoing decline in the condition of physical habitat in rivers and streams worldwide, the increased (and hopefully increasing) policy direction to protect and restore habitat, the lack of uptake of existing habitat quality assessment methods, and the potential opportunities in the rapidly-increasing use of drones in ecology and environmental management, this thesis aims to:

1. Establish the fundamental measures of physical habitat required for a robust ecological habitat assessment, as well as the key characteristics and abilities of an effective assessment technique
2. Review a range of existing physical habitat assessment techniques against these requirements and ascertain what factors might be limiting their application in applied ecology and resource management
3. Explore the opportunity to improve a habitat quality assessment technique by integrating the use of readily available drone technology
4. Test and review the efficacy of any drone integration in the field

Thesis Structure

This thesis is presented as three chapters in the style of discrete journal articles. As a result there is some duplication in content and references between chapters. It is prefaced by an abstract (above) and introduction (which you are now reading) to provide the context and aims of the work, and is followed by a synopsis evaluating the outcomes of the work.

In Chapter 1, I consider what makes an effective assessment of physical habitat quality, review a range of existing assessments against those criteria, and discuss the opportunity to integrate the use of drones with Death et al.'s (n.d.) 'Habitat Quality Index' (HQI), which stands out as having considerable value as an assessment of change in habitat quality. I test the feasibility of integrating drones into HQI assessment in part in Chapter 2, by evaluating the efficacy of visually assessing fine sediment cover and substrate diversity using a drone—two variables that I considered would be difficult to adapt to drone-based assessment. I found that while some estimates of substrate composition using a drone were highly correlated with observations made on-the-ground, others varied significantly, and there was not enough confidence to rely entirely on drone-based estimates in an HQI assessment. In Chapter 3, I present a comprehensive hybrid HQI assessment of native fish habitat in a reach of the Waiohine River subject to in-stream engineering works, utilising the benefits of ground- and drone-based measurements. Finally, I review my findings and conclusions against the aims of this thesis in a synopsis, in which I discuss the benefits and limitations of drones for HQI assessment.

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CHAPTER ONE: HABITAT QUALITY ASSESSMENT IN RIVERS: A REVIEW

ABSTRACT

Despite an increasing recognition of the importance of river and stream systems in providing life-supporting services to communities and biota, the condition of these environments continues to decline. In response, a range of indices have been developed to assess physical habitat in rivers. However, despite ample choice of method, habitat quality indices have been widely criticised as a result of their tendency to focus solely on the condition of either geomorphological or biological components of a river system, rather than the assessment of how physical habitat condition connects the two. This review sets out the characteristics, abilities, and fundamental measures of robust ecological habitat assessment, before examining currently available habitat indices against these requirements. In closing, it considers how habitat quality indices might be developed to better reflect these requirements and how such development will lead to better outcomes for riverine species through more accurate, resource-efficient, and context-appropriate assessments of river habitat quality.

INTRODUCTION

Despite an increasing recognition of the importance of functioning ecosystems in providing life-supporting services for communities and biota, the condition of the environment continues to decline. Pressure on freshwater systems, and in particular river and stream systems, continues to rise as a result of human activity (Maddock, 1999). With the frequency of extreme climatic events increasing there is a perception that further modification to river systems will be required, as communities attempt to alleviate the resultant effects of climate change on agriculture, human health, or infrastructure (Death et al., 2015; Vaughan et al., 2009). While there has been some recognition of the effect of these changes on biota, attention has generally been directed towards measuring the impact of changes in water quality, water quantity, or the biotic assemblages themselves (Death et al., n.d.b; Harding et al., 2009; Maddock, 1999; Raven et al., 1997). It has, until relatively recently, been ignored by many that without the provision of adequate physical habitat many riverine species will continue to trend toward extinction (Death et al., n.d.b; Elosegi et al., 2010; Elosegi & Sabater, 2013).

In response to the increasing recognition of the importance of physical habitat for riverine species, environmental protection organisations and government departments have developed a range of indices for the quantification of physical habitat in rivers (Table 1). Depending on the context each was developed within, assessments are available for a range of purposes, including to provide detailed descriptions of river habitat; to assess changes in habitat quality through time; to quantify the effects of river modification or restoration projects; to assess the value of habitat for a particular species; or to map or predict habitat quality or valuable habitat remnants across a landscape; among many others. However, despite ample choice of method, habitat quality indices have been widely criticised as a result of their

Table 1: Comparison of habitat assessment methods. Components of physical habitat measured in each method included substrate (fine sediment cover, D_{50}, particle compaction, stability, etc.), instream cover (undercut banks, instream wood, macrophytes, etc.), channel form (pattern, sinuosity, braiding index, channelisation, etc.), geomorphic units (runs, riffles, pools, etc.), floodplain function (width, connection, etc.), and riverbank condition (riparian vegetation, erosion, shading, bank slope, etc.). Additional components, that aren't explicit measures of physical habitat (marked as ^), are also required for some assessments: flow (regime, depth, velocity, extraction, etc.), water chemistry, and invertebrate community composition. *marks a variable for which assessment is optional or independent of the physical habitat assessment.

			Indication of variables measured:									Developed to measure habitat for:			
Habitat assessment	**Developed in:**	**No. variables measured:**	**Substrate**	**Instream cover**	**Geomorphic units**	**Riverbank condition**	**Floodplain function**	**Channel form**	**Flow ^**	**Chemistry ^**	**Invert. Community ^**	**Fish**	**Macroinvertabrates**	**Overall / other**	**References**
Habitat Assessment Protocol	AUS	28 control + 47 response	✓	✓	✓	✓	✓	✓	✓	✓	•	•	•	✓	Parsons et al. (2004)
Habitat Predictive Modelling	AUS	28 predictors + 35 predicted	✓	•	✓	✓	•	•	✓	✓	•	•	•	✓	Davies, Norris, & Thoms (2000)
Habitat Quality Index	USA	9	✓	✓	•	✓	•	•	✓	✓	•	✓	•	•	Binns & Eiserman (1979)
Habitat Quality Index [event] (eHQI) / Natural Character Index (NCI)	NZL	2 - 5 (NCI), < 19 (HQI)	✓	✓	✓	✓	✓	✓	•	•	•	✓	•	✓	Death et al. (n.d.a, n.d.b, n.d.c), Fuller et al. (2020), Pratt et al. (2018)
Hydraulic-habitat models (IFIM, WUA, PHABSIM, RHYHABSIM, etc.)	USA	3	✓	•	•	•	•	•	✓	•	•	✓	•	•	Bovee (1982), Spence & Hickley (2000), Kelly et al. (2015)
Hydromorphological Index of Diversity	CHE	2	•	•	✓	•	•	•	✓	•	•	•	•	✓	Gostner, Alp, Schleiss, & Robinson (2012)
Identification of Austrian rivers with high and good habitat quality	AUT	27	✓	•	✓	✓	✓	✓	✓	•	•	✓	•	✓	Muhar, Schwarz, Schmutz, & Jungwirth (2000)
Index of Stream Condition	AUS	18	✓	✓	•	✓	•	•	✓	✓	✓	•	•	✓	Ladson et al. (1999)
Morphological Quality Index	ITA	28	✓	✓	✓	✓	✓	✓	✓	•	•	•	•	✓	Rinaldi et al. (2013; 2015)
Overview (OVS) and On-site (OSS) surveys	GER	9 (OVS) – 25 (OSS)	✓	•	✓	✓	✓	✓	✓	•	•	•	•	✓	Kamp et al. (2007), Kamp et al. (2004), Raven et al. (2002)
Rapid Bioassessment Protocols (RBP)	USA	13 <	✓	✓	✓	✓	✓	✓	✓	✓	✓*	•	•	✓	Barbour et al. (1999)
Rapid Habitat Assessment Protocol	NZL	10	✓	✓	✓	✓	•	•	•	•	•	•	•	✓	Clapcott (2012, 2013, 2015)
River Habitat Audit Procedure (previously State of the Rivers Survey)	AUS	64	✓	✓	✓	✓	✓	✓	✓	✓*	•	•	•	✓	Anderson (1993a, in Parsons et. al., 2004)
River Habitat Survey (RHS)	GBR	> 200	✓	✓	✓	✓	✓	✓	•	•	•	•	•	✓	Raven et al. (1997; 1998), Environment Agency (2003)
River Styles	AUS	48	✓	•	✓	✓	✓	✓	✓	•	•	•	•	✓	Brierley et al. (1996)
Stream Habitat Assessment Protocols (SHAP)	NZL	28 <	✓	✓	✓	✓	✓	✓	✓	•	•	•	•	✓	Harding et al. (2009)
Systemes d'evaluation de la qualite physique (SEQ)	FRA	Unknown	✓	✓	✓	✓	✓	✓	✓	•	•	•	•	✓	Raven et al. (2002)

tendency to focus solely on the condition of either geomorphological or biological components of a river system, rather than the assessment of how physical habitat condition connects the two (Death et al., n.d.b).

This review sets out the characteristics and abilities required of an ideal habitat quality index, as well as the fundamental measures necessary to achieve robust habitat assessment, before examining currently available habitat indices against these requirements. In closing, it considers how habitat quality indices might be developed to better reflect these requirements and the complex systems they attempt to assess.

CHARACTERISTICS AND ABILITIES OF AN IDEAL INDEX

An index of river habitat quality should provide an accurate assessment of current physical habitat quality as it relates to biodiversity. However, an ideal method should far exceed this standard to meet a number of additional criteria in terms of its application. With this in mind, it is considered that an index of habitat quality should:

Provide accurate assessments: Provision of an accurate assessment of habitat condition as it relates to biodiversity is the primary objective of habitat assessment. Results should be robust, consistent between samplers, and interpreted easily by ecologists, non-specialists, and environmental managers (Harding et al., 2009; Parsons et al., 2004).

Utilise some form of a reference condition: Using the reference condition approach provides an easy-to-interpret 'natural' benchmark against which sample sites can be measured. It is considered that habitat quality indices should utilise this technique in some form, as it clearly illustrates the degree to which a site reflects its expected condition without degradation (Davies et al., 2000; Death et al., n.d.b; Parsons et al., 2004).

Be fast to complete: Rapid and user-friendly sampling and processing techniques should be used where possible, as this can significantly reduce inputs of time and cost, while still producing robust results (Harding et al., 2009; Parsons et al., 2004). Assessments should also minimise the number of variables measured where possible, provided the quality of results is not compromised.

Have an ability to integrate with other systems: Habitat quality assessment results should be able to be integrated with existing water quality, macroinvertebrate, fish assemblage, or GIS databases (Parsons et al., 2004). Integrative ability allows for impacts of degradation across different components of a system to be more readily understood, as well as allowing for any habitat index to be quickly introduced into existing sampling regimes.

Be adaptable: An ideal index should be able to be modified relatively easily for a variety of contexts or applications, while being consistent enough to allow for comparisons between those contexts or within the same context through time. In particular, assessments should be able to work at different scales (i.e. reach versus valley); work on different stream types (urban, rural, natural), flow regimes, or river systems (Harding et al., 2009; Parsons et al., 2004); assess habitat quality for different species; predict the potential impact of an engineering or restoration activity; and be usable by non-experts (Parsons et al., 2004).

FUNDAMENTAL MEASURES TO INCLUDE IN AN IDEAL INDEX

In order to provide an accurate assessment of habitat quality, an index must include some measure of those habitat variables most relevant to biodiversity (Parsons et al., 2004). Based on expert understanding and a review of the literature it was considered that a robust assessment of habitat quality should at least include some measure of substrate condition/composition, the availability of in-stream cover, the diversity of geomorphic units, riverbank condition, the degree of floodplain functionality, and general channel form (or the degree of modification to this). If a comprehensive description of an area is required or habitat for a particular species is to be assessed, the appropriate method may require the measurement of more variables, however it is considered the aforementioned would be the minimum to provide an accurate indication of overall habitat quality. Table 1 illustrates which of the 16 habitat assessment methods in this review measured at least some component of each of the identified variables. Rationale for the inclusion of these variables is set out below.

Channel form: Provides an indication of the degree of modification to a channel from its natural form, whether geomorphological (channel forming) processes are still functional, and whether other components of physical habitat are also likely to be degraded (Death et al., 2015; Fryirs & Brierley, 2000; McFarlane et al., 2011).

Floodplain function: Maintaining a connection between the floodplain and channel is critical for many stream organisms (Collier & Winterbourn, 2000; Maddock, 1999). Streams with functional floodplains tend to retain channel forming processes through an enhanced ability to avulse or meander, as well as having somewhere to deposit fine sediment, particulate matter, and nutrients picked up during high flows, which can negatively affect habitat if left in the main channel (Death et al., 2015, n.d.b; Storey et al., 2011).

Geomorphic units: Geomorphic features (runs, riffles, pools, etc.) provide habitat for many riverine species, but also indicate a more natural flow regime and a connection with the hyporheic zone (Storey et al., 2011). Diversity of geomorphic features is regarded as one of the most important factors in determining the suitability of habitat for biological communities (Harding et al., 2009; Maddock, 1999; Raven et al., 1998; Storey et al., 2011).

In-stream cover: Features such as woody debris, boulders, undercut banks, and macrophytes provide valuable habitat and refuge for various riverine species, as well as promoting the connection between a stream and its hyporheic zone (Binns & Eiserman, 1979; Petrove et al., in Death et al., n.d.c; Storey et al., 2011).

Riverbank condition: Riverbank condition includes a number of important components for determining habitat quality, such as the cover of riparian vegetation, provision of shading, and degree of erosion. In combination these components assist in the removal of contaminants in overland flow, provide an input of woody debris, provide habitat and flood refuge for macroinvertebrates and fish, prevent significant increases in water temperature and adverse changes to water chemistry, limit algal growth, and limit sediment contributions to the channel (Ballantine, 2012; Parkyn et al., 2003; Petrove et al., in Death et al., n.d.c; Storey et al., 2011).

Substrate: Is an indicator of habitat suitability for many riverine species (e.g. Petrove et al., in Death et al., n.d.c). In particular, fine sediment is a key stressor on stream communities, with its deposition driving detrimental changes in macroinvertebrate and fish communities (Ballantine, 2012; Burdon et al., 2013; Clapcott et al., 2011; Death et al., n.d.b).

INDICES FOR FISH HABITAT

Binns & Eisermann's (1979) Habitat Quality Index (HQI), the widely utilised hydraulic-habitat models[2], Muhar et al.'s (2000) method, and Death et al.'s (n.d.a, n.d.c) 'event' Habitat Quality Index (eHQI)[3] were the only indices identified that were developed explicitly for the assessment of habitat as it relates to fish (Table 1). While Binns & Eiserman's (1979) HQI provides a simple framework for the identification (and prediction) of relationships between habitat and biota, any further potential as a usable assessment of habitat quality can be ruled out relatively quickly because the technique (1) identifies habitat associations for only a few species of Salmonidae in a narrow range of locations, (2) utilises out-dated modelling techniques (Olden & Jackson, 2002), and (3) doesn't offer any sort of reference condition approach against which to assess habitat quality, not to mention any failings in terms of its usability. Similarly, despite their wide usage in the assessment of in-stream habitat (Death et al., n.d.b), hydraulic-habitat models should be ruled out early as a useful index of habitat quality too. Having been developed to quantify the habitat available to a given species under different flow regimes (Kelly et al., 2015), these techniques primarily assess flow metrics, and only assess one of the six habitat components identified here as important in providing for biota (viz. substrate, see Table 1). If anything, these techniques provide an indication of how accessible an area of habitat might be, and very little in the way of how suitable that habitat actually is, to particular species. Further, these techniques are time consuming, costly, and out-dated, and their narrow focus often leads to poorly informed management decisions (Beecher, 2017; Railsback, 2016, 2017; Spence & Hickley, 2000). Despite an acknowledgement and acceptance of these failings, hydraulic-habitat modelling continues to be used as a proxy for habitat quality in resource management decisions (Death et al., n.d.b).

Muhar et al.'s (2000) method offers some potential as a measure of habitat for fish. It includes five of the six important habitat components and uses a hybrid reference condition somewhere between having a 'library' of reference sites and

[2] e.g. IFIM, WUA, PHABSIM, RHYHABSIM (see references in Table 1)
[3] The eHQI is also referred to as the 'event based Natural Character Index (eNCI)' in Death et al. (n.d.a) or just as the 'HQI' in Pratt et al. (2018)

using a site's historical condition. However, possibly as a result of the scale it was developed at, the method fails to measure any component of in-stream cover, a critical element for many fish species, and is useful only in quantifying the habitat of ecosystems with 'high’ or ‘good' habitat quality, ignoring the potential assessment of anything more degraded.

Death et al.'s (n.d.a, n.d.c) eHQI differs significantly from that of Binns & Eiserman's (1979) HQI and the hydraulic-habitat techniques, and builds on Muhar et al.'s method (2000), offering the greatest potential as an index of habitat quality for fish. Developed to quantify the impact of a management activity or 'event' on native fish species in Aotearoa New Zealand rivers, the technique is a variant of the ‘higher-level’ Natural Character Index (NCI)[4] (Death et al., n.d.a, n.d.b; Fuller et al., 2020). It includes all habitat variables identified in this review as important for biodiversity (Table 1) and readily allows for the addition or removal of variables as required. In addition, the method assesses habitat condition only against its own pre-event 'reference' condition, rather than a 'library' of sites, and includes the assessment of a control reach, so any assessment provides an extremely accurate indication of changes in habitat quality and can be truly context specific. However, there are limitations in attempting to apply this event-based approach to the assessment of a site against its historical 'natural' condition, as measures of many habitat components, such as sediment, might not be available. A hybrid technique using modelled data and LiDAR assessments might be able to fill data gaps and overcome some of these issues, or a ‘step back’ to the higher-level NCI assessment could be used if appropriate. Regardless, it is the eHQI’s unique use of the reference condition, its ability to adapt to various contexts, and its independence from biological or water quality assessments that make it such a promising index for physical habitat assessment, particularly in applied management settings.

INDICES FOR INVERTEBRATE HABITAT

None of the habitat indices are purported to explicitly assess habitat for macroinvertebrates. However, several of the more comprehensive indices, i.e. those that measured most or all of the seven variables in Table 1, would be suitable for this purpose because cause and effect relationships with invertebrates have been recognised for each of the variables listed (e.g. river bank condition, Parkyn et al. (2003); or floodplain function, Thompson & Townsend (2000). See 'Fundamental measures in an ideal index' above). With this in mind, it is no surprise that measures of macroinvertebrate community health are often used as proxies for habitat quality (e.g. the MCI in Aotearoa New Zealand (Storey et al., 2011)). While in isolation this 'proxy' approach can be useful, the consideration of macroinvertebrate health as a component of habitat quality leads to a rather circular definition, where measures of macroinvertebrate health both define and are defined by habitat quality.

An assessment of habitat quality for macroinvertebrates should therefore be capable of isolating the biological from the physical or chemical components of a system. Anyone wishing to determine the cause of poor macroinvertebrate

[4] Also referred to as the ‘overall Natural Character Index’ (oNCI) in Death et al. (n.d.a), the Natural Character Index (NCI) in Fuller et al. (2020), and just as the HQI in Death et al. (n.d.b)

community health can then be confident in identifying whether issues with water quality or physical habitat are of primary concern. Only two techniques in this review encounter the potential issue of a 'circular definition' for macroinvertebrate communities (and it would be relatively easy to isolate these 'sub-indices' if required), however when water chemistry is also considered the number of indices of concern rises to six (see Table 1), contributing to the ruling out of most of these methods for invertebrate habitat assessment.

With further consideration given to the criteria identified above for an 'ideal' assessment index, the eHQI (Death et al., n.d.a, n.d.c) and Stream Habitat Assessment Protocols (SHAP) (Harding et al., 2009) offer the greatest potential for assessing habitat quality for macroinvertebrates. These methods measure appropriate variables, are simple and relatively adaptable, and achieve a good balance between being comprehensive while limiting the number of variables measured. While the eHQI offers a substantial benefit in its unique use of the reference condition approach (discussed above)—making it very effective at measuring *changes* in habitat quality, the SHAP provide a useful, but less quantitative tool for the immediate on-site assessment of the *state* of habitat quality for invertebrates. Clapcott's Rapid Habitat Assessment Protocol, a refined version of the SHAP, is not as comprehensive but provides a faster assessment of key in-stream habitat variables, which can be validated with other SHAP data (2012, 2013, 2015).

OVERALL INDICES

Fifteen of the 17 habitat indices reviewed were developed as overall assessments of habitat quality or could perform overall assessment with little modification. Despite this, only eight of the methods include some measure of all of the variables identified here as important (viz. substrate, in-stream cover, geomorphic units, riverbank condition, floodplain function, and channel form (Table 1)), with a further three including a measure of *almost* all (5/6) of these variables. While other indices offer some insights and may be useful in very specific contexts, it is these 11 that provide the most comprehensive and accurate assessments of overall habitat quality.

Many of these indices include a measure of flow or water chemistry (and in one case, the macroinvertebrate community). In a similar way to that discussed above for macroinvertebrates, these measures can complicate assessment results, making it difficult to isolate any cause and effect relationships between physical habitat, water quality, flow, and biological assemblages respectively (Raven et al., 1998). Further, these components are subject to regular fluctuation (e.g. day to day, between seasons, or following climatic events), while physical habitat might not experience any material change, potentially skewing the results of any assessment. It is considered that habitat quality indices are most accurate and useful with the exclusion of these measures. Only the River Habitat Survey (Raven et al., 1997, 1998), the Rapid Habitat Assessment Protocols (Clapcott, 2012, 2013, 2015), and the eHQI (Death et al., n.d.a, n.d.c) meet this criterion.

Variation in the number of measurements required within the most comprehensive indices is significant, ranging from around 10 to over 200 (column 3 in Table 1). While the input of time and resource required to complete any assessment will depend on the nature of a sample site and how measurements are made (i.e. what level of detail is needed, whether quantitative or qualitative metrics are used, and whether sampling is desktop- or field-based), those methods requiring fewer measurements are considered most desirable, provided they still produce comprehensive and accurate assessments. In general, such methods are more resource-efficient and produce results that are more readily interpreted and interrogated than those with a much larger number of components.

Considering the criteria identified and discussed in this review, the eHQI (Death et al., n.d.a, n.d.c) provides the greatest potential as an index of overall habitat quality, albeit with a focus on 'change in' rather than 'state of'. Its inclusion of all necessary variables (and its flexibility to add/remove variables as required, and to utilise different methods of measuring those variables); exclusion of flow, chemical, and biological measures; relative ease of application and integration with other data or systems; and its unique use of the reference condition approach make it an almost-ideal overall habitat quality index, particularly for applied ecology or resource management settings.

DEVELOPING AN IDEAL INDEX

The eHQI (Death et al., n.d.a, n.d.c) is an almost ideal index of habitat quality when measured against the criteria in this review. However, while its focus on change, its unique application of the reference condition, and the use of field-based measures offer substantial benefits, these characteristics also present several limitations.

Using a sample sites own pre-event condition as its reference results in extremely accurate and context-specific measures of changes in habitat quality. It also allows components assessment to be changed readily between applications based on what is important to resident species, even where a measure has not been made at a site before, because there is no need to call on data in a reference 'library'. It is an extremely valuable feature of the eHQI. However, the assessment of a site against its pre-event condition, rather than a fixed or 'natural' reference, means there is little to indicate whether the habitat should be regarded as degraded, good, or in excellent condition, and could contribute to a sort of shifting baseline syndrome—whereby the reference condition is regularly 'updated' to a new baseline without any consideration of long-term or cumulative impacts (Soga & Gaston, 2018). It is therefore an extremely good measure of *changes in*, rather than the general *state of*, habitat quality. There could also be issues in incorporating an historic or 'natural' condition to the eHQI because historic measures of many habitat components, such as sediment, might not be available. In these circumstances, the higher level NCI (Death et al., n.d.b; Fuller et al., 2020) technique might be more appropriate, but this could result in some important habitat variables being omitted. Hybrid techniques using modelled data, artificial intelligence, historical maps and records, and LiDAR assessments might offer a solution. This should be given further consideration in any development of the eHQI.

Measuring variables in the field presents challenges in assessing some variables at remote or difficult-to-access sites (including where there are issues with site access through private land), where there is difficult terrain, or where rivers are large or dangerous (Harding et al., 2009). While the eHQI (Death et al., n.d.a, n.d.c) can avoid these issues by flexing into the higher level desktop-based methods of its NCI variant (Death et al., n.d.b; Fuller et al., 2020), this omits important variables needing finer-scale field-based measurements. Drone technology may offer the means to overcome this limitation and has been tested once already with a variation of the eHQI (see Pratt et al., 2018). Drones have the potential to avoid difficulties with access and harsh terrain, allow users to sample significant lengths of river in a small amount of time (with the potential to be programmed to fly source-to-sea lengths of a river), and reduce the one-off and repeat costs of assessment. Drones are proving their worth in assessing elements of river condition already (e.g. Casado et al., 2015; Hentz et al., 2018; Langhammer, 2019; Wawrzyniak et al., 2013; Woodget & Austrums, 2017; Woodget et al., 2017, 2018), and many of the river habitat assessment methods reviewed here could be readily adapted to benefit from this technology.

CONCLUSION

Despite the development of a substantial number of habitat indices worldwide, few are able to meet the range of relatively simple criteria for accuracy and applicability identified in this review. The eHQI (Death et al., n.d.a, n.d.c) excels in a variety of contexts and stands out in this review as having considerable value as an index of changes in habitat quality. While it has several limitations, some minor modifications to its application, and development through the further incorporation of drone use, artificial intelligence, or other emerging technologies may overcome these. It is hoped such development will lead to better outcomes for riverine species through more accurate, resource-efficient, and context-appropriate assessments of river habitat quality.

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CHAPTER TWO: USING DRONE IMAGERY TO ASSESS SEDIMENT COVER AND SUBSTRATE COMPOSITION IN AOTEAROA NEW ZEALAND RIVERS AND STREAMS

ABSTRACT

Low substrate diversity and/or high levels of fine sediment cover can have a significant adverse effect on the physical habitat quality of a river or stream, with subsequent adverse effects on resident macroinvertebrate and fish communities. While bankside and in-stream visual assessments of substrate diversity and fine sediment cover are practical and relatively accurate, assessors are increasingly looking to assess components of river habitat more remotely, using drones and GIS to create visual records of change, validate on-the-ground measurements, or quickly survey large areas of a river or stream. In this study, I evaluated whether the visual assessment of substrate composition could be adapted for use with drones to confirm whether it could then be incorporated into existing drone-based assessments of river habitat quality. Expert estimates of substrate composition based on drone imagery were compared to observations made on-the-ground using bankside and in-stream assessments. Mean estimates of substrate composition using drone imagery were highly correlated with on-the-ground observations at five out of eight study sites ($r > 0.81$, $p < 0.05$). Mean estimates could also be used to correctly classify a site as having fine sediment cover above or below the 20% threshold at which biodiversity is adversely affected at seven out of the eight sites. Variation in drone-based estimates was not dissimilar to that recorded elsewhere amongst untrained observers using ground-based visual assessment methods to assess fine sediment cover. While some individual experts' estimates of substrate composition and fine sediment cover were highly correlated with observations, others varied significantly, suggesting that while assessments using a single expert can produce results consistent with on-the-ground methods, some experts are better than others. Any applied drone-based assessment of substrate composition or fine sediment cover should therefore train assessors to reduce potential errors.

INTRODUCTION

Effective assessments of the physical habitat quality of rivers and streams should include measures of substrate diversity and fine sediment cover, as these can have a significant effect on the health of resident macroinvertebrate and fish communities. Substrate diversity is a key component of habitat suitability for many species, while fine sediment can be a significant stressor on stream communities (Ballantine, 2012; Burdon et al., 2013; Death, 2000; Death et al., n.d.; Petrove et al., in Death et al., n.d.c). In Aotearoa New Zealand, the assessment and monitoring of these variables is regularly undertaken by regional authorities as part of their 'State of the Environment' reporting (Resource Management Act, 1991) using the bankside and in-stream visual assessment methods described in Clapcott et al.'s (2011) Sediment Assessment Methods. Assessments using such methods are strongly linked with many aspects of ecological health. Similar methods to that proposed in Clapcott et al. (2011) using percent sediment cover, Wolman pebble counts, sediment mass, median particle size, and embeddedness are widely used across the world to evaluate substrate condition. However, these techniques are limited in that they require direct physical access to a survey site, can be time consuming, provide low spatial representation (Chardon et al., 2020), and require numerous repeats when applied to extended lengths of river. As a result, researchers continue to look for alternative ways of measuring substrate characteristics in rivers and streams (e.g. Arif et al., 2017; Bind et al., 2018; Chardon et al., 2020; Dugdale et al., 2010; Woodget & Austrums, 2017; Woodget et al., 2017, 2018).

Drones are increasingly being used for the assessment of substrate composition and other components of river habitat. Substantial improvements in the quality and capability of consumer-grade and professional drones, as well as significant reductions in their cost, now make drones a realistic and accessible technology for environmental monitoring (Hentz et al., 2018; Woodget et al., 2017). Drones are already used to assess components of river habitat such as flow types, vegetation, and erosion (Casado, et al., 2015); channel width (Hentz, et al., 2018); water temperature (Wawrzyniak et al., 2013); sinuosity and riparian habitats (Langhammer, 2019); and substrate characteristics (Arif et al., 2017; Bind et al., 2018; Woodget & Austrums, 2017; Woodget et al., 2017, 2018), with many of those studies using now out-dated drones (see Woodget et al., 2017 in particular). Using drones to remotely assess components of river habitat allows researchers and monitoring agencies to undertake surveys at whatever intervals and scales suit their needs, to avoid challenges with river access or difficult terrain, to survey significant lengths of river in a small amount of time, to produce digital elevation models, and to reduce the resource and time costs of assessment (Hentz, 2018).

However, while many researchers are developing alternative techniques for the assessment of substrate characteristics and river habitat condition (see those examples cited above), these have largely been limited to exposed gravels (e.g. Woodget & Austrums, 2017; Woodget et al., 2017, 2018); or tended to rely on resource intensive, complex, or costly methods involving a combination of aerial and on-the-ground work (e.g. Bind et al., 2018; Chardon et al., 2020), expensive equipment and software (e.g. Wawrzyniak et al., 2013), or complex image classification techniques (e.g. Casado et al., 2015, 2016; Chardon et al., 2020). Given the known correlation between visual assessment methods of fine sediment cover and ecological condition, as well as Clapcott et al.'s (2011) suggestion that "guidelines developed for sediment cover can be assessed using *any* visual assessment method" (p. 32, emphasis added), I undertook to investigate whether a simple visual assessment method of substrate composition could be adapted for use with drones. This would provide a relatively fast and straightforward drone-based method for the assessment of substrate characteristics and fine sediment cover that could be readily incorporated into existing habitat quality assessments.

METHODS

Substrate composition and fine sediment cover were sampled at eight stream reaches across Aotearoa New Zealand's lower North Island (Fig. 1) using Clapcott et al.'s (2011) bankside and in-stream visual assessment methods. In-stream assessments were limited to measuring fine sediment (<2mm) and involved using a bathyscope to estimate percentage cover at 20 random locations within a run habitat. Bankside assessments involved making an estimate of the percentage cover of all seven substrate classes within a run habitat from the riverbank, with classes defined by Clapcott et al.—mud/silt (<0.06mm), sand (0.06-2mm), fine gravel (2-16mm), coarse gravel (16-64mm), cobbles (64-256mm), boulders (>256mm), and bedrock (layers of solid rock). Reaches varied significantly in length, width, and flow (Table 1). Surveys were generally completed within one hour.

Figure 1: Survey locations (red dots) labelled A-H (see Table 1 for corresponding stream names and site characteristics). Major catchment boundaries surrounding the sites have been included for context.

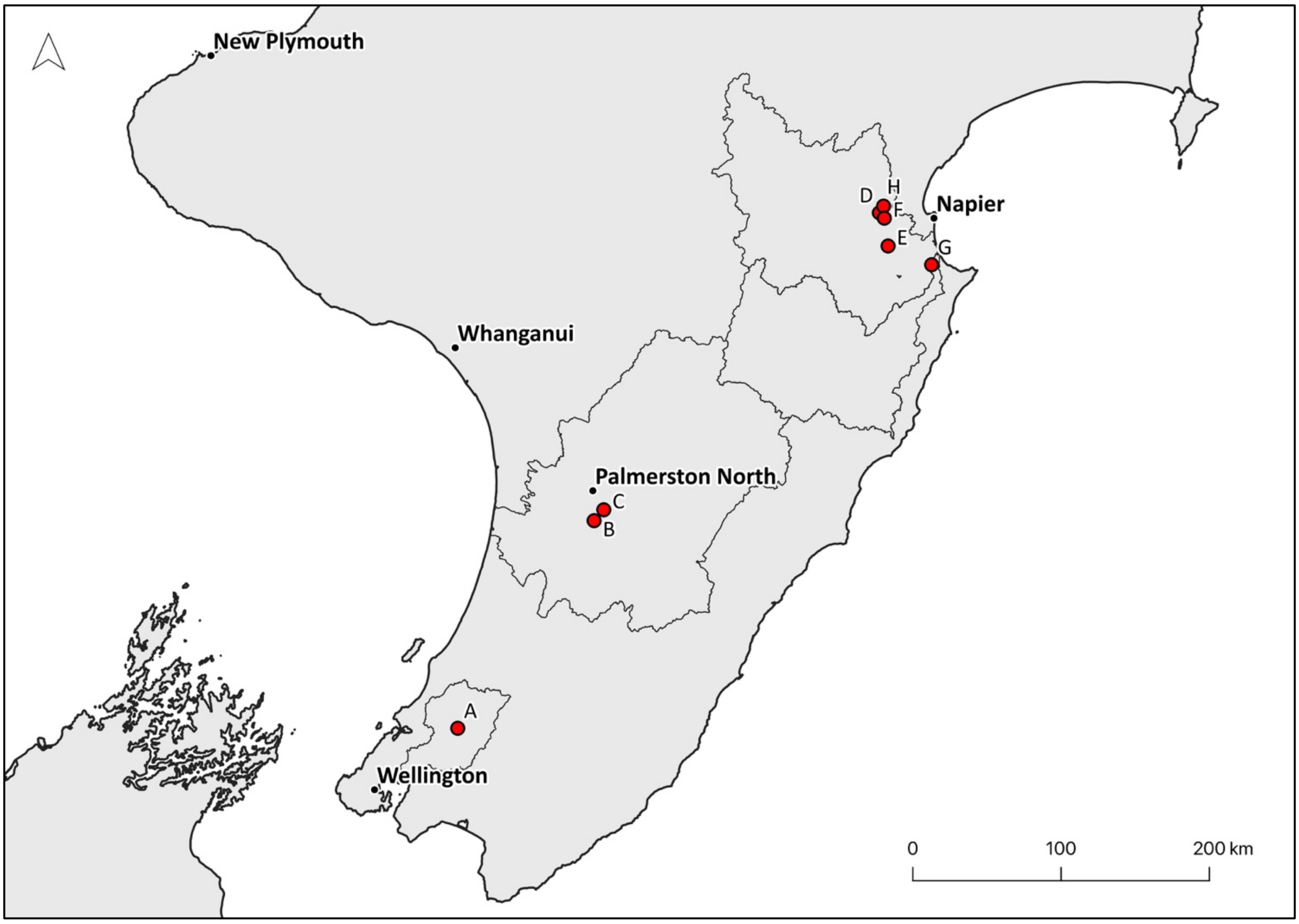


Table 1: Characteristics of study sites. Length and width measurements are approximate and given to the nearest metre. Flow measurements were taken from the closest monitoring station at the time of survey and are presented to the nearest 0.1 m^3/s. No flow data was available for the Ohiwia Stream (Site E), though it was estimated to be running at < 1 m^3/s, which appeared to be a normal flow for the time of year.

	Akatarawa River / Site A	**Kahuterawa Stream / Site B**	**Turitea Stream / Site C**	**Mangaone Stream / Site D**	**Ohiwia Stream / Site E**	**Tutaekuri River / Site F**	**Tukituki River / Site G**	**Mangaone Stream / Site H**
Length (m)	45	45	18	40	30	74	60	41
Average width (m)	16	17	7	30	4	13	29	15
Flow (m^3/s)	4.5	1.3	0.2	3.2	< 1 m^3/s	5.0	6.7	3.1

Aerial surveys of the wetted substrate in each reach were undertaken using a DJI Inspire 2 drone and Zenmuse X4S camera. In order to accurately capture the variation in substrate classes and fine sediment cover at each site (1) polarised filters were used to reduce glare and increase the visibility of the wetted substrate, (2) images were saved in DNG (RAW) format to capture as much detail in each image as possible, (3) photos were captured while the drone was stationary to avoid image blur (because the mechanical shutter on the drone was malfunctioning) (Toffanin, 2019), and (4) low flight elevations (of 15–20 m above ground level (AGL)) were used to achieve small Ground Sampling Distances (GSD) of approximately 4.1–5.5 mm (i.e. each pixel in the photos taken measures 4.1–5.5 mm in reality). Lower flight elevations generally decrease the quality of resultant orthophotos or photo mosaics (Toffanin, 2019), so this was as small a GSD as was considered possible without significantly compromising the quality of the mosaics produced while still trying to capture the detail of the smallest substrate classes (< 2 mm). Drone flights were undertaken manually at all but one site as (1) sites were often confined by cliff faces or had trees within the airspace that made automated flights difficult or dangerous and (2) this ensured control over the drone and camera settings if lighting conditions changed during the flight. Flights followed a grid pattern capturing overlapping nadir images. Each aerial survey was completed in around 20 minutes and was always undertaken after the bankside assessment of substrate composition to reduce the potential for the aerial view provided by the drone to influence observer estimates.

Photos were screened to remove those with excessive glare or poor focus and were then processed in Adobe Photoshop to correct colour and lighting before being exported as JPEG files. High-resolution photo mosaics of each site were then produced in Photoshop using the automated Photomerge function. The 'blend images together' and 'geometric distortion correction' functions were turned on and the spherical layout was used as per the recommendation of Song et al. (2016). This method was selected over the use of Structure from Motion (SfM) techniques (such as that used by Woodget et al., 2017, 2018; and others) as several test orthophotos produced using SfM methods[5] revealed SfM software could not sufficiently compensate for the selective removal of poor-quality images and did not preserve the same degree of detail from the original images as the mosaics produced in Photoshop. This was considered vital for the accurate identification of the smallest substrate classes within a reach. Processing times depended on the size and character of a reach, as well as the degree and quality of image overlap, but generally ranged from 5 minutes to over 1 hour. Processing was undertaken on a 15-inch 2012 Apple MacBook Pro with a 2.6 GHz Quad-Core Intel Core i7 processor, 16 GB of RAM, and a 1 GB NVIDIA GeForce GT 650M graphics card.

Red lines indicating the start and end of each study reach and a series of (scaled) 1000 x 1000 mm squares with an inset grain-size classification graphic were then superimposed over each mosaic. At most sites scale was approximated using large white 1000 x 1000 mm Ground Control Points (GCPs) that had been laid out at each reach during surveys as Photoshop does not have the capacity to utilise image location data to ascertain scale (whereas SfM software does). Scale at one site was calculated using a GSD calculator (Pix4D, n.d.) and at another using the known size of sampling equipment on the riverbank due to a lack of a GCPs at both sites**.** Processed photo mosaics for all sites are provided in Figures 2 and 3.

[5] In the open-source SfM program WebODM (Web Open Drone Map)

Mosaics were then provided to 11 professionals working in the fields of freshwater ecology and/or geomorphology, referred to herein as 'experts', who used the images to predict substrate composition in the wetted channel at each of the eight sites. Experts were independent, were not allowed to interact with each other (or other professionals) to make their estimates, and were not provided any information regarding the location or character of the sites. Substrate was divided into sand/mud/silt (< 2 mm), fine gravel (2–16 mm), coarse gravel (16–64 mm), cobbles (64–256 mm), boulders (> 256 mm), and bedrock. The experts' drone-based estimates were then compared to bankside and instream observations to determine whether drone-based visual assessment can produce estimates of substrate composition and fine sediment cover consistent with on-the-ground visual assessment methods.

Figure 2: Mosaics A-C as provided to experts for drone-based assessment of substrate composition. Red lines indicate the start and end of the survey reach. White 1000 x 1000 mm squares, inset with a grain-size classification graphic (difficult to see in these small images), provide an approximation of scale. River flow is top to bottom. Note that experts were provided high-resolution digital versions and could zoom in significantly to view details.

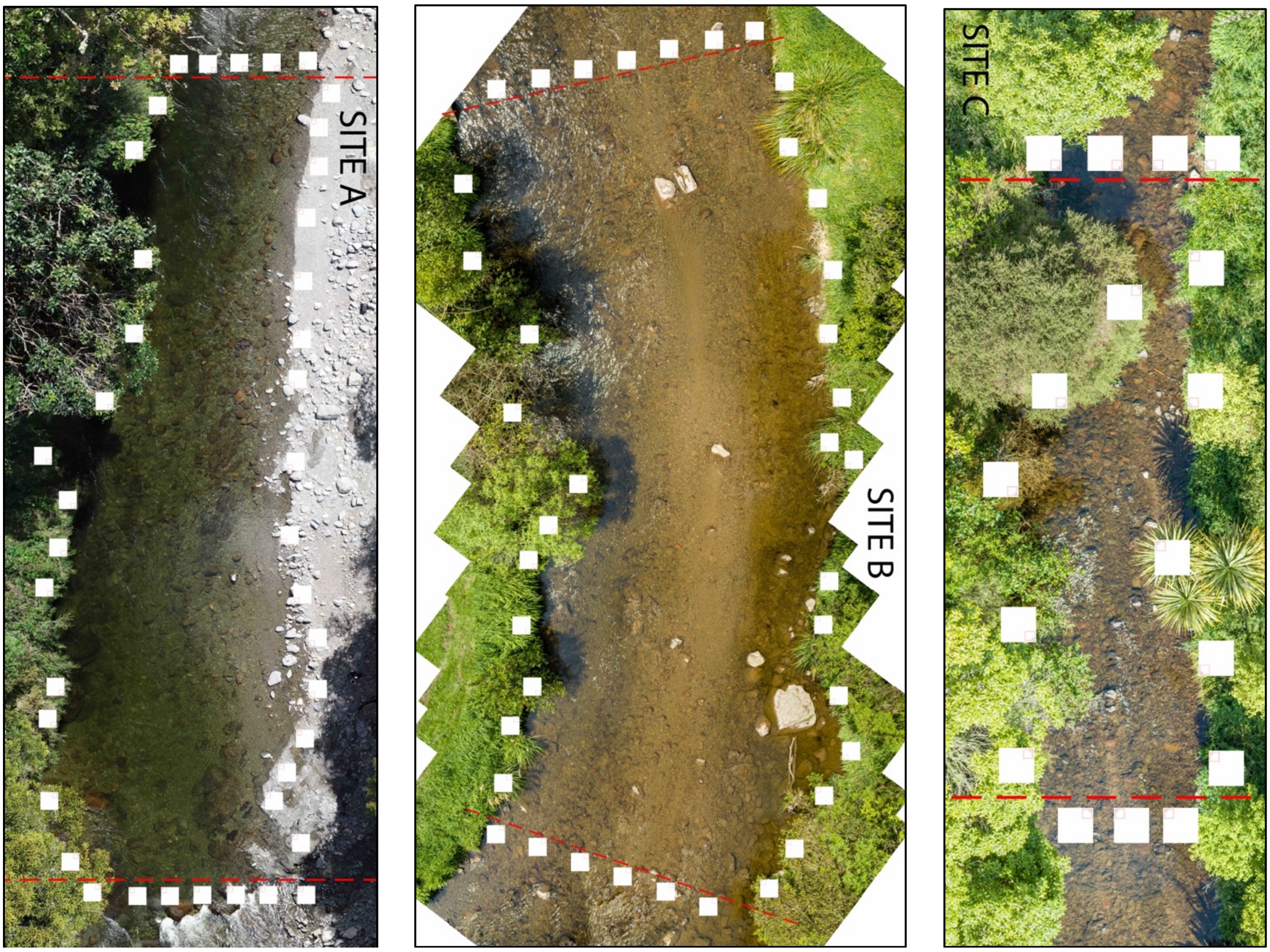
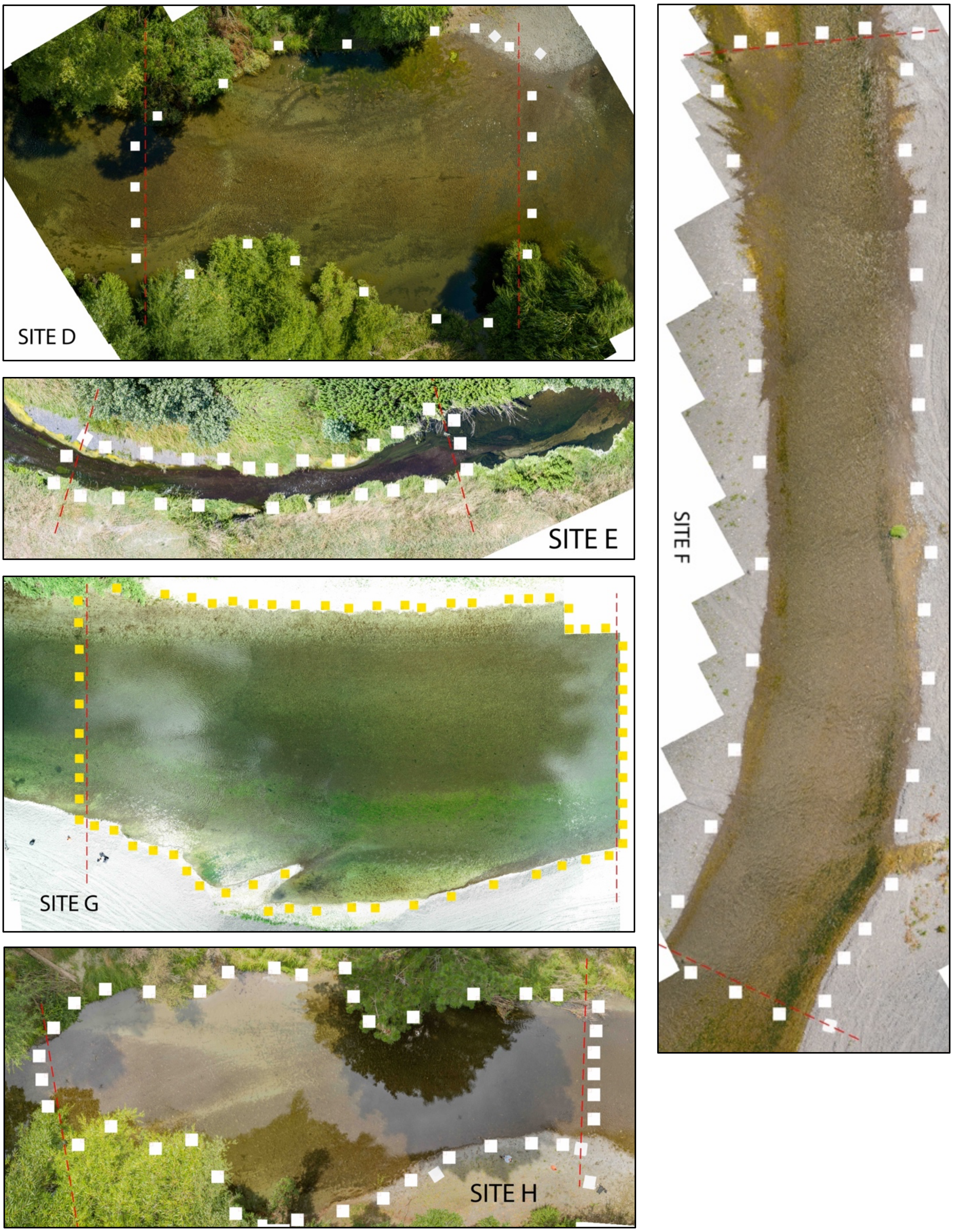


Figure 3: Mosaics D-H as provided to experts for drone-based assessment of substrate composition. Red lines indicate the start and end of the survey reach. White or yellow 1000 x 1000 mm squares, inset with inset with a grain-size classification graphic (difficult to see in these small images), provide an approximation of scale. River flow is left to right or top to bottom. Note that experts were provided high-resolution digital versions and could zoom in significantly to view details.



RESULTS

Substrate composition

Bankside observations and experts' mean estimates of substrate composition are presented in Figure 4. Mean estimates were most consistent with bankside observations at site A, with an average difference of only 3% and a Pearson's correlation coefficient of 0.93 (Table 2), indicating a strong positive relationship. Errors between mean estimates and bankside observations at site A were 8% for fine gravel, 4% for boulders, and below 2% for fine sediment, coarse gravel, cobbles, and bedrock respectively. Sites C and F also had strong correlations between mean estimates and bankside observations (Table 2). Site H had the lowest correlation between mean estimates and observations (Table 2). The predicted presence or absence of a substrate class was generally consistent with its observed presence or absence across all sites (Fig. 4).

Because visual assessments of sediment cover are known to vary between observers (Clapcott et al., 2011), the relationships between individual experts' estimates of substrate composition were assessed using a matrix of Pearson's correlation coefficients (Table 3). Correlation coefficients for the relationship between each expert's estimates and the bankside observations were also calculated (Table 3). Relationships between expert estimates ranged from zero or very weak, with a minimum correlation coefficient of 0.13 ($r(46)$, $p = 0.39$), to very strong, with a maximum coefficient of 0.90 ($r(46)$, $p < 0.001$). The average correlation coefficient for the relationship between expert estimates was 0.55, indicating a moderate positive relationship overall. The average correlation coefficient for the relationship between expert estimates and observed values was 0.56, also indicating a moderate positive relationship (this is the correlation coefficient across all 528 values—i.e. 8 sites x 11 experts x 6 substrate classes). Expert 8's estimates had the highest correlation with observed values, with a coefficient of 0.81 ($r(46)$, $p < 0.0001$), indicating a strong positive relationship, while expert 3's estimates had the lowest coefficient at 0.31 ($r(46)$, $p < 0.05$), indicating a weak positive relationship.

Table 2: Pearson correlation coefficients and p-values for the relationship between the six observed values and the six mean estimates of substrate composition for each site (i.e. one value for each substrate class). Red values returned a p-value > 0.05.

	Akatarawa River / Site A	**Kahuterawa Stream / Site B**	**Turitea Stream / Site C**	**Mangaone Stream / Site D**	**Ohiwia Stream / Site E**	**Tutaekuri River / Site F**	**Tukituki River / Site G**	**Mangaone Stream / Site H**
Correlation coefficient	0.93	0.81	0.89	0.77	0.65	0.89	0.84	0.59
p-value	< 0.01	< 0.05	< 0.05	0.08	0.17	< 0.05	< 0.05	0.22

Figure 4: Percent substrate composition at each of the study sites from visual bankside assessments (labelled 'Bankside') and mean estimates of substrate composition from experts using drone imagery (labelled 'Mean Pred.').

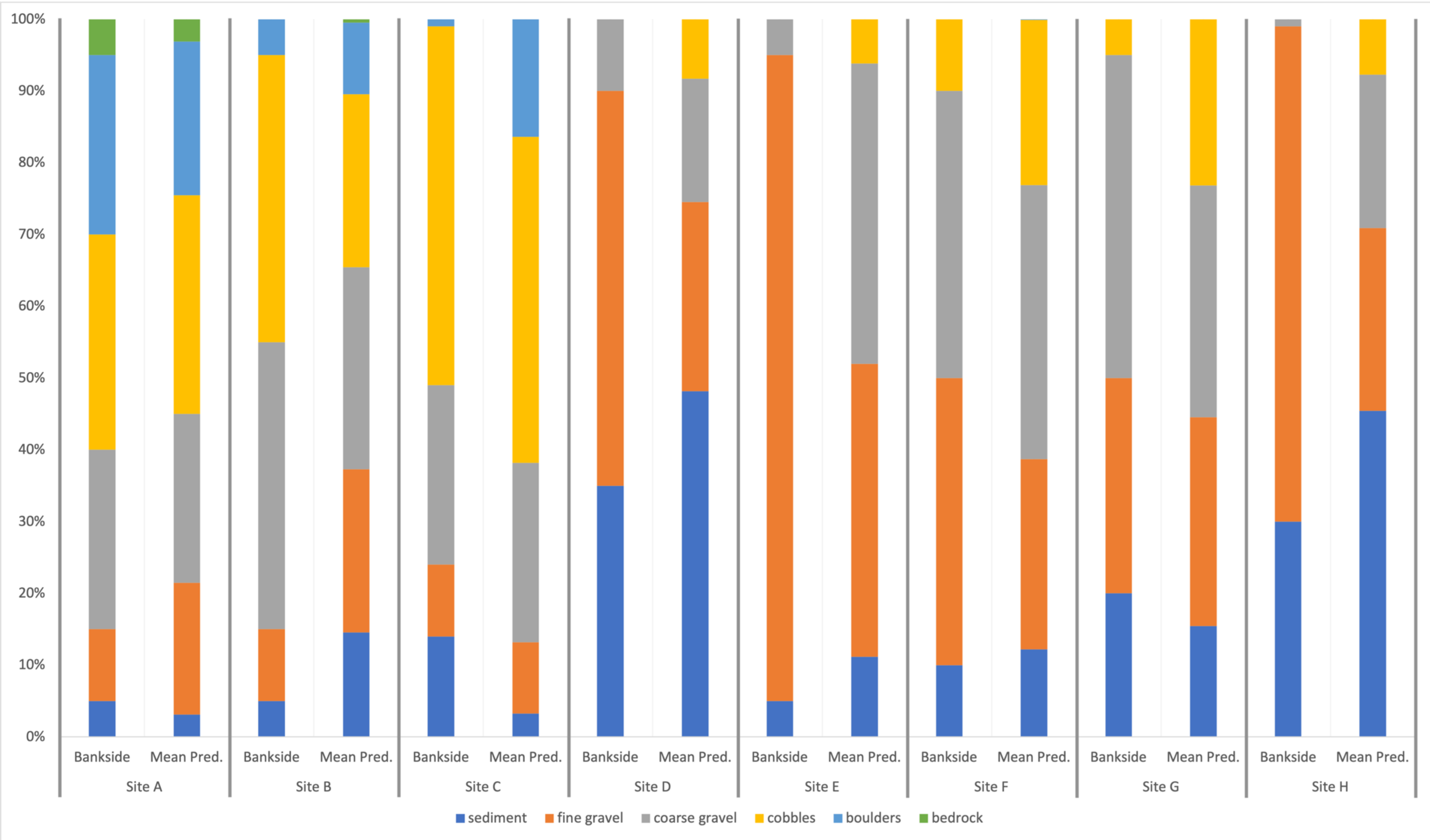


Table 3: Correlation matrix showing the Pearson correlation coefficients for the relationships between expert estimates (e.g. E1 against E2, E1 against E3, etc.), and the relationships between each expert's estimates and bankside observations (e.g. E1 against Bnk, E2 against Bnk, etc.), across all substrate classes and sites (48 values). The average correlation between expert estimates was 0.55. The average correlation between expert estimates and observed values was 0.56. Red values returned p-values > 0.05.

	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11	Bnk
E1		0.62	0.18	0.31	0.48	0.61	0.29	0.71	0.66	0.37	0.34	0.77
E2			0.54	0.48	0.81	0.90	0.51	0.79	0.65	0.82	0.62	0.59
E3				0.70	0.68	0.50	0.77	0.45	0.13	0.62	0.47	0.31
E4					0.49	0.46	0.68	0.65	0.17	0.62	0.40	0.53
E5						0.69	0.60	0.66	0.53	0.71	0.43	0.56
E6							0.56	0.76	0.54	0.85	0.66	0.65
E7								0.51	0.22	0.61	0.47	0.55
E8									0.63	0.66	0.63	0.81
E9										0.38	0.36	0.50
E10											0.60	0.51
E11												0.37
Bnk												

Fine sediment cover

Bankside and in-stream observations of fine sediment cover are presented alongside mean/median estimates in Table 4. Observations ranged from 5–35% in bankside assessments and 0–62% in in-stream assessments. Based on the descriptions in Clapcott et al. (2011), five of the sites had low (< 10%) or relatively low (< 20%) fine sediment cover, two sites had moderate levels of cover (20–40%), and one site had a moderate-high (< 35%) level of cover. Bankside observations were highly correlated with in-stream observations ($r(6) = 0.95$, $p < 0.001$) (affirming Clapcott et al.'s (2011) finding). Mean estimates also had strong positive correlations with bankside and instream observations, returning coefficients of 0.89 and 0.87 respectively ($r(6)$, $p < 0.01$).

Again, because observations of fine sediment cover vary between observers (Clapcott et al., 2011), the relationships between individual experts' estimates of cover were assessed using a matrix of Pearson's correlation coefficients (Table 5). The average correlation between expert estimates was 0.77. Correlation coefficients for the relationships between each expert's estimates and bankside and instream observations were also calculated (Table 5). The average correlation between expert estimates and bankside observations was 0.79, and the average correlation between expert estimates and in-stream observations was 0.78. Estimates from experts 5, 7, and 11 had the highest correlation with bankside observations ($r(6) = 0.90$, $p < 0.01$), while expert 7's estimates had the highest correlation with instream observations ($r(6) = 0.96$, $p < 0.001$).

Table 4: Visual bankside and in-stream observations, and mean/median expert estimates, of fine sediment cover at each site. Bankside observations had a significant positive correlation with in-stream observations ($r(6) = 0.95$, $p < 0.001$). Mean expert estimates had significant positive correlations with bankside ($r(6) = 0.89$, $p < 0.01$) and in-stream observations ($r(6) = 0.87$, $p < 0.01$).

	Akatarawa River / Site A	**Kahuterawa Stream / Site B**	**Turitea Stream / Site C**	**Mangaone Stream / Site D**	**Ohiwia Stream / Site E**	**Tutaekuri River / Site F**	**Tukituki River / Site G**	**Mangaone Stream / Site H**
Bankside observation	5%	5%	14%	35%	5%	10%	20%	30%
In-stream observation	3%	4%	7%	62%	0%	0%	31%	36%
Mean estimate	3%	15%	3%	48%	11%	12%	15%	45%
Median estimate	5%	15%	5%	40%	10%	5%	15%	35%

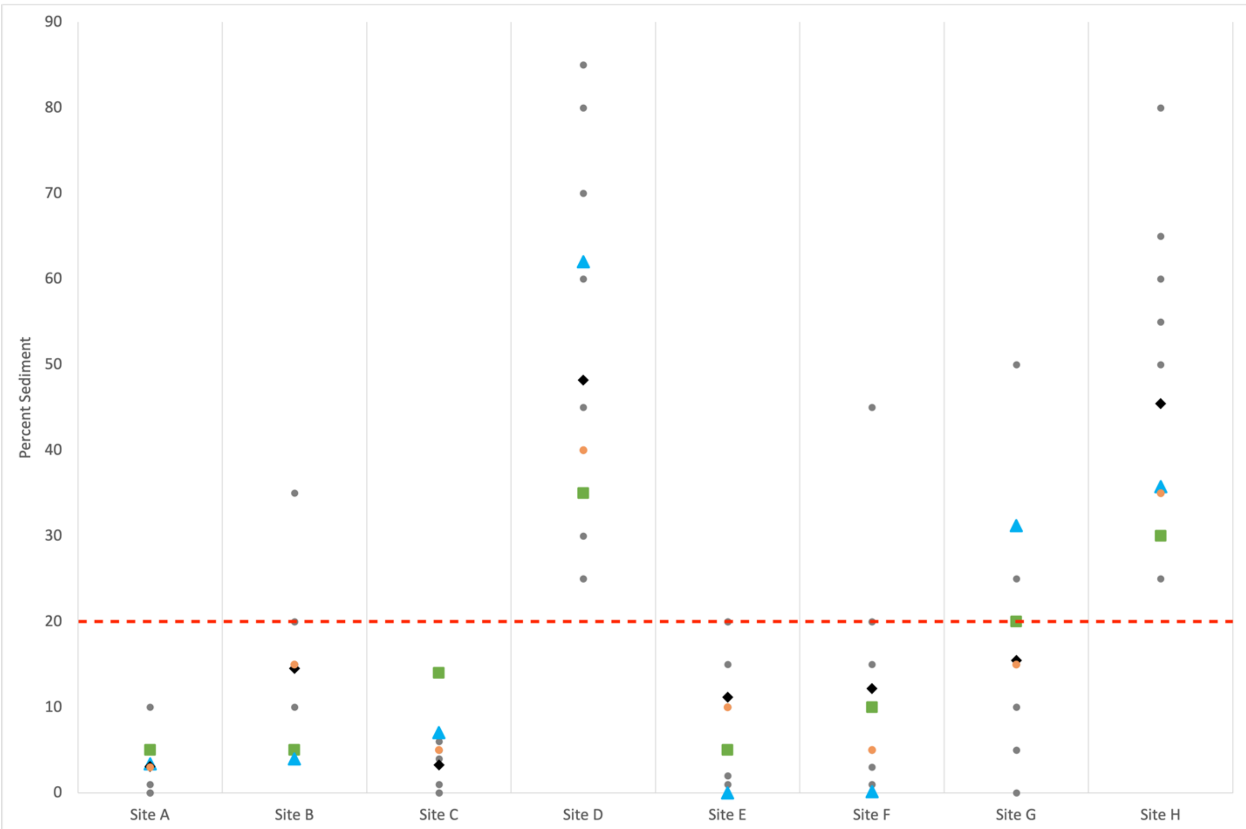
Table 5: Correlation matrix showing the correlation between expert estimates (E1, E2, E3…), visual bankside observations (Bnk), and visual in-stream observations, of fine sediment cover (Inst.). Red values returned p-values > 0.05.

	E1	**E2**	**E3**	**E4**	**E5**	**E6**	**E7**	**E8**	**E9**	**E10**	**E11**	**Bnk**	**Inst.**
E1		0.71	0.70	0.81	0.58	0.47	0.46	0.72	0.68	0.52	0.74	0.47	0.43
E2			0.99	0.92	0.82	0.90	0.93	0.84	0.65	0.95	0.91	0.86	0.85
E3				0.94	0.82	0.88	0.93	0.87	0.66	0.92	0.90	0.86	0.84
E4					0.85	0.70	0.81	0.96	0.78	0.75	0.91	0.86	0.79
E5						0.70	0.84	0.92	0.62	0.72	0.92	0.90	0.91
E6							0.95	0.59	0.28	0.97	0.82	0.75	0.85
E7								0.76	0.41	0.93	0.89	0.90	0.96
E8									0.82	0.66	0.87	0.86	0.79
E9										0.46	0.55	0.57	0.39
E10											0.82	0.78	0.81
E11												0.90	0.91
Bnk													0.95
Inst.													

Five sites (A, B, C, E, and F) had bankside and in-stream assessments with fine sediment cover below the 20% threshold at which biodiversity is adversely affected (Fig. 5) (Clapcott et al., 2011). The mean/median estimated cover at these sites was also below 20%. Two sites (D and H) had cover above the 20% threshold and mean/median estimates also above 20%. One site (G) was observed as having fine sediment cover equal to or above the threshold value, however the mean/median estimates at this site were below the threshold. In general, estimates were either equal to or on the same side of the biodiversity threshold as observed values, except at Site G where estimates were spread more evenly across both sides of the threshold. With the exception of Site G, only 2 estimates (of the remaining 77) were on the incorrect side of the threshold, and 7 (of the 77) estimates were equal to the threshold. Overall, 10% of all estimates (9/88) were incorrect with respect to breaches of a fine sediment threshold, 9% (8/88) were equal to the threshold, and 81% (71/88) were on the correct side of the threshold (assuming Site G has cover >20% based on the observed values).

The range of experts' estimates and their consistency with on-the-ground observations varied significantly between sites. For example, at Site A, where bankside and in-stream observations of fine sediment cover were 5% and 3% respectively (Table 4 and Fig. 5), all 11 expert estimates were between 0% and 10% (Fig. 5). However, at Site D, where bankside and in-stream observations of fine sediment cover were 35% and 62% respectively, estimates ranged from 25% to 85%. The range in experts' estimates appeared to increase with increased levels of fine sediment cover, as per the finding of Clapcott et al. (2011).

Figure 5: Visual bankside (green squares) and visual in-stream (blue triangles) observations of percent fine sediment cover at each site compared to individual experts' estimates (grey circles). A red line indicates the 20% threshold value at which in-stream biodiversity is adversely affected by fine sediment cover (Clapcott et al., 2011). Black diamonds show the mean estimate. Yellow circles show the median estimate.



DISCUSSION

Application of drone-based assessment

Mean estimates of substrate composition by experts using drone-based photo mosaics were highly correlated with observations at five of the eight sites (Table 2). Mean estimates at the remaining three sites were weakly linked to observations and not statistically significant. Mean expert estimates of fine sediment cover were highly correlated with observations at all eight sites (Table 4). At seven of the eight sites, mean estimates of fine sediment cover were also consistent with observations in identifying threshold levels of cover above or below 20%. The site that failed (G) appears to have been difficult to classify, as it was observed to have fine sediment cover just above the 20% threshold. Individual estimates at that site (G) were spread above and below the threshold, but favoured values below it, resulting in a mean (and median) estimate that was inconsistent with the observations. Overall, mean estimates using drone imagery appear to characterise overall substrate composition in a way that is highly correlated with observations at most sites and to accurately identify whether a site has low or high levels of fine sediment cover. However, any organisation looking to operationalise a drone-based technique for assessing substrate composition is unlikely to have the resource to produce mean estimates using multiple experts and is much more likely to use a single expert instead.

For that reason, analysis of the correlation between experts' estimates, and between each expert's estimates and the observations, was undertaken. That confirmed Clapcott et al.'s (2011) finding that visual assessments vary between observers, with some experts producing much more accurate estimates than others. While one expert's estimates of all substrate classes were highly correlated with observations (Expert 8, r = 0.81, Table 3), and another's estimates of fine sediment cover were very highly correlated with observations (Expert 7, r = 0.96, Table 5), other experts' estimates had low correlations with observations (e.g. Expert 3, all substrate classes, r = 0.31, Table 3). In practice, this meant that the mean observational error of a single expert across all sites and substrate classes could be as low as 7 (max. error 44, min. error 0), or as high as 15 (max. error 60, min. error 0), percentage points. Looking only at estimates of fine sediment cover, the mean observational error of a single expert could be as low as 5, or as high as 17, percentage points. Using the mean estimate of all 11 experts across all sites produced a mean observational error of 9 percentage points for all substrate classes and 8 percentage points for fine sediment. Overall, the variation in drone-based estimates was not dissimilar to that recorded by Clapcott et al. when they tested the variation in estimates from observers using ground-based visual assessment methods to estimate fine sediment cover (see Clapcott et al. Figures 4-7 and 4-8).

This suggests drone-based assessments of substrate composition or fine sediment cover using a single expert can produce results consistent with on-the-ground methods, though some experts are better than others. Some substrate classes might also be easier to predict than others, or experts might be most practised in assessing fine sediment over other substrate classes, which could explain the higher correlations between estimates and observations of fine sediment cover (r = 0.79 for bankside and r = 0.78 for in-stream) than between estimates and observations of all substrate classes (r = 0.55). Clapcott et al. (2011) found assessors using the bankside visual assessment method were able to correctly identify low, moderate, and high levels of fine sediment cover 'in general', which appears to also be the case for the aerial visual assessment method tested in this study. Several recent studies have demonstrated the use of drones and computer software to assess substrate composition can avoid the sorts of errors discussed above (Woodget & Austrums, 2017; Woodget et al., 2017, 2018), however they remain limited to assessing dry gravels and are relatively complex. Given that in this study experts were unfamiliar with the technique being used, were untrained (at least in the specific assessment of substrate using aerial imagery), and were unable to discuss their estimates with others, it is not surprising that some errors were present. It is expected that if experts were trained, errors would be lower and correlations higher, so training observers would be very important if a drone-based method of substrate assessment is used. Training was also recommended by Harding et al. (2009) and Clapcott et al. to reduce variability and error in visual substrate assessment techniques. It is expected it would make a considerable difference to drone-based assessment too.

Limitations of drone-based assessment and this study

Several other factors may have had a cumulative impact on experts' ability to assess substrate composition more consistently with on-the-ground observations and may limit the applicability of a drone-based assessment technique without further refinement. These have been broken down into sub-groups below for clarity:

Environmental factors

Several environmental factors are expected to have significantly affected the experts' ability to assess substrate composition using drone imagery. Where water was extremely clear (such as at Site A, Fig. 2), estimates are likely to have been much more accurate than where water was tannin-coloured, cloudy, or silty, which may have led experts to over-estimate the presence of fine sediment (given its usual brown colour), or to guess the cover of substrate classes. Deep water created darker patches in an image, while turbulent water (or water that had been disturbed by the wind) distorted the shape of the substrate below or created patches of the surface that couldn't be seen through (Fig. 2 and 3). Glare was also a significant issue faced at all sites regardless of whether surveyed in full sun or overcast conditions, regardless of the time of surveying and position of the sun (although reflections were worst around midday), and despite the use of a well-aligned polarised filter. Overhanging vegetation and shadows also obscured or affected the view of the substrate at some sites (Fig. 2 and 3). While many of these issues would face anyone undertaking a bankside assessment, the assessor would usually have some ability to move around a site to improve their view—something the assessor of a photo mosaic is unable to do.

Technical factors

Throughout the drone-based-assessment process there were numerous opportunities for the introduction of error as a result of technical factors. Inaccuracies in GPS and altitude data from the drone; distortion from the camera lens; the resolution of the camera's sensor; aperture, colour, ISO, and white balance settings; shutter speed; filter selection; focus; and image format all presented opportunities to diverge from what may have resulted in the 'optimum' results. Constant compromises were having to be made in all regards, such as between exposure settings (which could allow for darker substrate 'deeper' in the river to be seen more easily) and the shutter speed (which, if too slow, would result in blurred images obscuring any substrate anyway). Maintaining the ideal degree of detail, light, and focus in images was extremely difficult and was a point of significant frustration, and while the processing technique allowed for the removal of images that were substandard, this introduced another step in the processing workflow.

Every step in the image processing 'pipeline' presented a further opportunity to alter the quality of a photo mosaic or introduce error. The initial removal of images with excessive glare or blurring improved the clarity of substrate in the resulting mosaics but probably negatively affected their shape and scale (Toffanin, 2019). Adjusting exposure, white balance, and other image settings 'in post' was undertaken to improve the visibility of the substrate in images but could have equally skewed some experts' estimates towards certain substrate classes, for example if colours were adjusted to be duller or more brown, as fine sediment often is. Mosaics produced in Photoshop will also differ in shape and scale to those that would have been produced in the SfM programs used by other authors (Song et al., 2016), however, given its ability to retain image detail, cope with the selective removal of images from the dataset, and its relative performance in orthophoto production (Song et al., 2016), any error it may have introduced was considered secondary to the aforementioned benefits. Preserving the scale and shape of a site was also considered less important than preserving detail and clarity of substrate given that assessments of substrate composition are relative (i.e. % cover), rather than absolute (e.g. areal cover), measures.

Accuracy of on-the-ground observations

Using a single observer's assessments of substrate composition and fine sediment cover as the 'benchmarks' against which drone-based estimates were evaluated is also somewhat problematic. Assessments are prone to vary between techniques and individuals (as illustrated in this study; and Clapcott et al., 2011), and the accuracy of any one individual's assessment could be called into question. However, while it is possible that there are inaccuracies in the bankside and in-stream observations used in this study, it is likely they provide at least an accurate indication of the low, moderate, or high representation of a given substrate class at a site and provide a useful comparison for drone-based estimates. While conclusions on the 'accuracy' of drone-based assessment may be difficult to make as a result of this uncertainty, conclusions on the 'consistency' of drone-based assessment with bankside and in-stream observations can be made.

Resource costs

Drone-flight and image-processing times amounted to 1-3 hours of work per site assessed, including ‘unsupervised’ computer processing and not including time taken by experts to make estimates. This was exacerbated by a malfunctioning mechanical shutter on the drone camera, which meant photos needed to be captured while the drone was stationary to avoid any potential for image blur (Toffanin, 2019). While it is expected that these times could be significantly reduced now that a workflow has been developed, it would be difficult to bring them below the 5-30 minutes required for on-the-ground methods to assess a site. Surveys also came at a computing cost, requiring the storage and processing of 25 to several hundred high-resolution photos, and the storage of photo mosaics from around 300 MB to over 1 GB in size. Finally, while substantial financial investment in equipment was not required for this study, the combined cost of a drone, accessories, training, and image-processing software would not be insignificant to anyone looking to undertake drone-based assessments.

Opportunities for drone-based assessment

Drone-based methods for the assessment of substrate composition present a number of potential benefits over on-the-ground methods. Where site access is difficult or dangerous, or where visibility from the bank is limited, drones can be used to provide a largely unobstructed view of a site and its context; hundreds of images covering large areas can be captured in very little time, making the visualisation of long reaches of river possible; images can be used to create elevation and surface models; and resultant photo mosaics or orthophotos can be stored for future reference, to be assessed or cross-validated at a later date, or to be used in before/after comparisons—providing a visual record of substrate condition that paper records cannot. Mosaics produced during this study were of sufficient detail to allow for the assessment of a number of other important components of river condition too, including riparian vegetation, algae and macrophyte cover, and the extent of woody debris. Images captured at one site even revealed the presence of several trout, with a brief deviation from the flight lines providing for a count of about 20 individuals within the reach.

However, while the method of assessment presented in this study is able to provide ecologically relevant assessments of substrate composition, further refinement is recommended to increase its usability before it is widely adopted. Several minor adjustments to the technique, such as increasing image overlap, refining camera settings and filter use, and increasing flight elevations may improve the quality of mosaics or orthophotos produced, while reducing the time and resource costs of the process. It should be noted that increasing the flight elevations would reduce the GSD and therefore the detail of substrate visible, so experts’ ability to identify substrate composition should be validated with such changes, however, if combined with an increase in the resolution of the camera used, revalidation may be unnecessary.

Regardless of refinements in technique or developments in technology, drone-based assessments cannot yet substitute for on-the-ground assessments in many circumstances. On-the-ground methods remain efficient at the site/reach scale and can be combined with a number of rapid assessments for other habitat variables that cannot be completed with a drone, such as those used to quantify the D_{50}, suspended sediment, or substrate compaction (Clapcott et al., 2011, Harding et al., 2009). Drone-based assessments should not yet replace on-the-ground assessments, but instead offer a new range of benefits that can be leveraged to expand and improve on existing river habitat monitoring and assessment methods.

CONCLUSION

Results of this study suggest that a drone-based visual assessment method can provide estimates of substrate composition and fine sediment cover that are highly correlated with on-the-ground methods, with a degree of error between observers not dissimilar to that recorded elsewhere for ground-based estimates. However, there is not yet enough confidence to rely entirely on drone-based estimates in all circumstances, and some development of the method and establishment of an assessment protocol—including the use of trained experts in making assessments—would be useful. While many studies to date present drone-based methods for substrate classification using SfM and complex image-classification techniques, this study presents a simple and cost-effective approach using a high-end consumer-grade drone and inexpensive software. It builds on a well-established visual assessment method and forms a useful addition to ground-based assessments of substrate composition and river habitat quality, allowing assessors to create visual records of substrate composition (that can be checked by critics if required), and to check on-the-ground estimates with measurements taken from aerial imagery,

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CHAPTER THREE: USING DRONES TO ASSESS THE IMPACT OF IN-STREAM ENGINEERING

ABSTRACT

Although it is widely acknowledged that biophysical habitat is important for healthy freshwater communities, habitat condition continues to decline as rivers and streams are increasingly modified for human use or flood protection. Death et al. (n.d.a, n.d.b, n.d.c) developed the Habitat Quality Index (HQI)[6] as a method to identify and quantify changes in river habitat over time, assessing a river's 'current' physical condition against a previous or natural condition and presenting it as a measure of the change in condition. This study presents the first comprehensive HQI assessment of native fish habitat to incorporate aerial imagery collected with a drone. Using on-the-ground assessment methods in combination with an entry-level professional drone and open-source software, I present a hybrid drone/ground-based HQI assessment technique, illustrating that engineering works on a reach of the Waiohine River had no overall adverse effect on physical habitat condition. I found that drones present several benefits to HQI assessment, allowing assessors to create visual records of changes in physical habitat (that can be checked by critics if required), to check on-the-ground estimates with measurements taken from aerial imagery, to systematically identify areas of a river affected by change, and to produce Digital Surface Models (DSMs) useful to measure variables like floodplain width or streambank height. With minor adjustments to my application of the HQI, alongside continued improvements in drone technology and monitoring techniques, this hybrid drone/ground-based HQI assessment method forms a useful addition to the river management and HQI toolbox, and is ideal for the assessment of changes in habitat quality in response to activities such as engineering.

INTRODUCTION

Physical habitat quality in rivers and streams continues to decline despite its recognised value to ecosystem health (Death et al., 2015; Elosegi et al., 2010; Elosegi & Sabater, 2013; Maddock, 1999; Vaughan et al., 2009). With the frequency of extreme climatic events increasing there is a perception that further modification to rivers and streams will be necessary to alleviate resultant effects on agriculture, health, or infrastructure (Death et al., 2015; Vaughan et al., 2009). While a range of indices have been developed to assess and monitor changes in physical habitat in rivers and streams—and to prevent further declines in habitat quality, those used in applied ecology and resource management tend to focus on measuring impacts on water quality,

[6] The Habitat Quality Index (HQI) has been referred to in various applications as the 'event' Habitat Quality Index (eHQI), the 'event' Natural Character Index (eNCI), the 'overall' Natural Character Index (oNCI), and most recently in Fuller et al. (2020) as the Natural Character Index (NCI). Given that all of these are variants of the same technique, 'HQI' is used in this study to capture all definitions. Any differences in approach are described where relevant.

water quantity, or biotic assemblages in isolation (if they're used at all), and the adverse effects of ongoing catchment and channel modification on physical habitat continue to fall through the cracks (Death et al., n.d.b; Harding et al., 2009; Maddock, 1999; Raven et al., 1997).

In response to the lack of available tools to assess the quality of physical habitat in river ecosystems for instream fauna, Death et al. (n.d.a, n.d.b, n.d.c) developed the 'Habitat Quality Index' (HQI) to assess change in the condition of a river's physical habitat. The HQI quantifies and assesses changes in habitat variables important to the ecological health, or geomorphological condition, of a river over time or in response to a particular activity. It presents changes as a ratio of the current to previous condition, indicating any degradation or improvement over a particular timeframe. HQI assessment has largely relied on either GIS-based measurement of habitat variables for longer-term, larger-scale analyses of change in river habitat, such as channel and floodplain widths (e.g. Fuller et al., 2020), or ground-based measurement of habitat variables for shorter-term, smaller-scale assessments of change, such as substrate diversity and deposited fine sediment (e.g. Death et al., n.d.c). (See Death et al. (n.d.a) for a comparison of HQI assessment at the different scales.) Because GIS-based measurements rely on the availability of new aerial or satellite imagery between surveys, which is generally updated every few years (e.g. LINZ, 2020), GIS-based HQI assessments are not useful for activities with impacts occurring over days, weeks, or months, such as instream engineering works.

Drones are increasingly being used as a tool to overcome this shortage of GIS data for river habitat assessment, allowing people to undertake surveys at intervals and scales that suit particular purposes. Substantial improvements in the quality and capability of consumer-grade and professional drones, as well as significant reductions in their cost, now make drones a realistic and accessible technology for environmental monitoring at all levels of research—from citizen science projects to academic studies (Woodget et al., 2017; Hentz et al., 2018). Drones are already used to assess components of river habitat such as flow types, vegetation, and erosion (Casado, et al., 2015); channel width (Hentz, et al., 2018); water temperature (Wawrzyniak et al., 2013); sinuosity and riparian habitats (Langhammer, 2019); and substrate characteristics (Arif et al., 2017; Bind et al., 2018; Woodget & Austrums, 2017; Woodget et al., 2017, 2018), with many of those studies using now out-dated drones (see Woodget et al., 2017 in particular).

One recent application of the HQI incorporated aerial imagery collected with a drone, allowing habitat variables to be measured using either GIS- or ground-based assessment techniques (see Pratt et al., 2018; Fuller et al., 2020). Orthophotos from before and after engineering works were used to measure the area of the wetted channel and gravel bars, variables not readily measured on-the-ground. While this provided an example of the use of drones in HQI assessment, it centred on the geomorphological—rather than the ecological—value of the HQI, and didn't comprehensively apply the protocol for the assessment of habitat important to native fish, omitting some critical variables such as instream cover, flow types, and deposited fine sediment (Petrove et al., in Death et al., n.d.c).

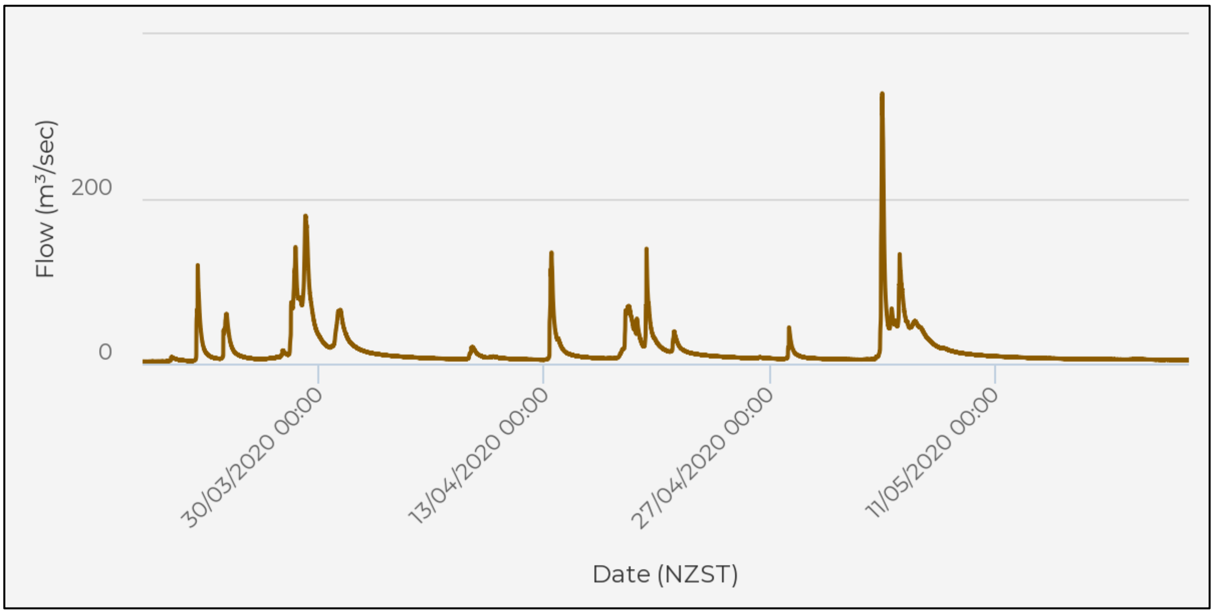
In this study I investigated the application of an HQI assessment for native fish incorporating drone imagery. Using on-the-ground assessment methods in combination with an entry-level professional drone and open-source software, I demonstrate the value of a hybrid drone/ground-based HQI assessment method to the river management and HQI toolboxes. A section of the Waiohine River in the Wairarapa region of Aotearoa New Zealand was surveyed before and after in-channel engineering works to assess the impact of the activity on native fish habitat quality.

METHODS

HQI assessment involves measuring components of physical habitat (relevant to fish likely to be present at a site) before and after a management activity, such as flood protection engineering, in a section of river and quantifying the changes caused by the activity. In this case, in-stream engineering was being undertaken to construct gravel groynes on the true left of a section of the Waiohine river, where the main stem had been threatening to undermine a stopbank (visible at the top right of Figure 1). The intention of the works was to prevent the main stem from re-establishing in this true left channel during high flows and further eroding the bank. Surveys of the reach were undertaken using the Habitat Quality Index (HQI) protocol in Death et al. (n.d.c) on 19 March 2020, several days before works at the site were intended to start, and again on 22 May 2020, several days after works were actually undertaken and completed. The delay between surveys (and in the completion of works) was a result of the restrictions of Aotearoa's COVID-19 lockdown, not the duration of the works. A hydrograph of the flows over this period is provided in Figure 2, illustrating flows were low and stable from the time of the works (mid-May) to the final survey (May 22). The survey section of the river was divided into upstream 'control' and downstream 'engineered' reaches (Fig. 1) of approximately equal length to ensure changes in the engineered reach could not be attributed to floods or other natural changes.

Figure 1: Aerial orthophoto of the Waiohine River study site before flood protection engineering. The upstream 'control' reach is on the left of the dashed line. The downstream 'engineered' reach is on the right.

Figure 2: Hydrograph covering the period between surveys on 19 March and 22 May 2020, as recorded at the monitoring location upstream of the survey site. Flows were around 2.5m^3/s on 19 March and 4.4 m^3/s on 22 May at the time of surveys (GWRC, 2020).



Native fish species likely to be present in the survey reaches were identified using the models of Crow et al. (2014) and the Department of Conservation's Freshwater Ecosystems of New Zealand (FENZ) database (DOC, n.d.). Habitat variables important for these species were then identified using the information collated by Petrove et al. as summarised in Death et al. (n.d.c). Three native species were predicted as likely to be present in the survey reaches, meaning 16 habitat variables needed to be measured. These are summarised in Table 1. Habitat variables were measured using a combination of aerial orthophotos and on-the-ground assessments. Each survey took about 3 hours of fieldwork plus several hours to set up image processing and undertake GIS analysis (noting that image processing time was idle). This could be reduced to about 2 hours of fieldwork and one hour of 'desktop' work now that an efficient workflow has been established.

Aerial surveys were undertaken using a DJI Inspire 2 drone equipped with a Zenmuse X4S camera. Flights were programmed and flown automatically using the DJI Groundstation Pro app. They followed a grid pattern capturing nadir images with 85% front and 60% side overlap using the 'hover & capture at point' setting. A flight elevation of 65 m above ground level (AGL) was used to achieve a Ground Sampling Distance (GSD) of approximately 1.8 cm (i.e. each pixel in the photos taken measures 1.8 cm in reality). Image settings were set manually to achieve a high shutter speed, no lens filters were used, and images were saved in JPEG format. This combination of settings reduced the likelihood of errors in sampling and processing (Toffanin, 2018). Four Ground Control Points (GCPs) were laid out at each site and their location was recorded for georeferencing, however these were not needed as the drone's onboard GNSS data was sufficient. Each flight captured about 260 images and was completed in around 20 minutes each using 2 sets of batteries.

Table 1: Habitat variables to consider for each of ten native species of fish from Petrove et al., in Death et al. (n.d.c). Species predicted as present at the survey site and the habitat variables important to each are in darker emboldened text.

	Longfin eel	**Torrentfish**	Giant kōkopu	Kōaro	Dwarf galaxias	Inanga	Shortjaw kōkopu	Lamprey	Bluegill bully	**Redfin bully**
Substrate										
Percent Deposited fines (100 – %x)	**x**	**x**		x	x	x	x	x	x	**x**
Particle compaction	**x**			x	x		x		x	**x**
Inorganic substrate diversity	**x**	**x**	x	x	x	x	x	x	x	**x**
D_{50} (mm)	**x**	**x**	x	x	x	x	x	x	x	**x**
Instream cover										
Total area of Instream cover	**x**		x		x	x	x	x		**x**
Undercut banks	**x**		x				x			
Instream wood	**x**		x		x		x	x		**x**
Macrophytes	**x**				x	x				
Flow types										
Deep pools	**x**		x				x			
Backwaters	**x**		x			x	x			
Side braids				x		x	x			
Riffles	**x**	**x**	x	x	x				x	**x**
Runs		**x**	x	x	x	x		x		
Riverbank										
Riparian vegetation			x		x	x	x	x		**x**
Overhanging vegetation	**x**		x				x			
Stream bank height			x			x	x			
Inanga spawning habitat						x				
Floodplain width	**x**					x	x			
Sinuosity	**x**					x			x	

Orthophotos of the survey reaches before and after engineering were then produced in the open-source Structure from Motion (SfM) software Web OpenDroneMap (WebODM). WebODM is comparable in its approach and performance to commercial SfM software such as Pix4D, DroneDeploy, and AgiSoft Photoscan used in similar studies (see Toffanin, 2020 for performance comparisons, and Woodget et al., 2017, 2018 or Pratt et al., 2018, for applications of other software). However, it can be downloaded for free by those familiar with command line coding, or for a small cost by those wanting a user-friendly installer, making it more accessible to independent researchers and small organisations. Orthophoto processing was undertaken using WebODM's 'Lightning Network' cloud processing service (https://webodm.net/) with the 'orthophoto resolution' set to 2 cm and the 'build-overviews' and 'dsm' options turned on. All other options were set to the default. Processing was reported as taking 4 hours and 32 minutes for the images from the March survey. A WebODM network outage prevented accurate reporting of the processing time for the May images but it appeared to be similar.

The methods used to assess each of the 16 habitat variables are described below:

Substrate

Deposited fine sediment was assessed using Clapcott et al.'s (2011) visual bankside method. It was estimated by an observer on the riverbank as the percent cover of fine sediment within several representative run habitats at each of the engineering and control reaches. 'Percent cover' values were converted to 'percent without cover' to ensure any decline in this metric was consistent with other HQI scores (Death et al., n.d.c). Particle compaction was assessed using Neverman's (2018) Bed Compaction Index (BCI), taking samples at randomised locations in a representative run reach to determine the final BCI. Substrate diversity (assessed using Simpson's diversity index) and the D_{50} were calculated based on phi class using data from a Wolman pebble count of 100 pebbles (Wolman, 1954) undertaken with a gravelometer, again in a representative run reach.

Instream cover

Undercut banks, instream wood, and macrophytes were visually estimated by an on-the-ground observer in terms of their percent cover of each survey reach. Total instream cover was the sum of these estimates.

Flow types

Pools, backwaters, riffles, and runs were assessed by tracing their extent in aerial orthophotos using the 'add polygon' tool in QGIS. The area of each was then divided by the total area of the wetted channel to provide a 'percent of channel' value. Delineation was based on the assessor's judgement, just as ground-based methods in many other habitat quality assessments are.

Riverbank

Riparian vegetation was assessed by tracing the extent of non-grass vegetation along the riverbank visible in aerial orthophotos using the 'add polygon' tool in QGIS. Overhanging vegetation was visually estimated in terms of its percent cover of a reach by an on-the-ground observer. Floodplain width was not measured as the engineering works had no impact on this. Sinuosity was calculated in QGIS by measuring the distance between the start and end points of each reach following the midpoint of the wetted channel, then dividing this by the straight-line distance between the two points.

RESULTS

Results of the HQI assessment are presented in Table 2. HQI scores < 1.00 indicate a decrease in habitat quality between surveys, while scores > 1.00 indicate an increase. The median HQI score of 1.00 for the control reach means any changes in habitat quality in the engineered reach can be attributed to the engineering activity and not a natural event (Death et al., n.d.a, n.d.c). Death et al. (n.d.c) suggest a decline of more than 15% in overall habitat quality (i.e. a median HQI score below 0.85) or more than 40% in the quality of any individual habitat component (a score below 0.60) is cause for concern and remediation, and, while these thresholds are likely to vary in different systems and contexts, this was considered a reasonable threshold to assess scores against for the purpose of applied management. An overview of the downstream reach after engineering is presented in Figure 3 and mapped orthophotos of both reaches before and after the engineering work are presented in Figures 4 and 5.

The median HQI score of 1.00 at the engineered site indicated the engineering activity had no overall adverse effect on habitat quality. However, the maximum individual component change indicated several variables were altered by more than 15% and one variable by more than 40%. Analysis of Table 2 shows that the D_{50} (0.62) and the areas of pools (0.54) and runs (0.64) were reduced at the engineered site. While the HQI scores based on changes in D_{50} need to be considered in the context of the logarithmic scales used to determine them (i.e. because small changes might be emphasised by final HQI ratio scores), the reduction in the D_{50} is of particular interest as the Wolman pebble count used to calculate this was undertaken in a section of run habitat clearly used numerous times by heavy machinery to cross the river (see Fig. 5). It is unclear how this vehicle 'traffic' could have been the cause given it is likely to have rearranged or compressed only the top layer of substrate. While the reduced D_{50} may be of consequence for resident fish at this specific location, it is difficult to know whether the D_{50} further downstream was also affected and whether the change will persist.

Table 2: Measurements of habitat variables and HQI scores for the control and engineered survey reaches. HQI scores are presented for the change in each habitat variable as well as overall through median, mean, and maximum-reduction scores. *floodplain width was not affected by the engineering works so has been assigned an HQI score of 1.00.

	Control (Upstream)			**Engineered (Downstream)**		
	Before	**After**	**HQI**	**Before**	**After**	**HQI**
Substrate						
Deposited Sediment (representative run habitat) (% without)	90	99	1.10	100	100	1.00
Particle Compaction (Bed Compaction Index)	0.27	0.36	1.33	0.46	0.47	1.02
Inorganic Substrate Diversity (Simpson's Diversity Index)	0.14	0.11	0.79	0.16	0.14	0.88
D_{50} (mm)	32	36	1.13	50	31	0.62
Instream Cover						
Total Area of Instream Cover (%)	6	6	1.00	6	6	1.00
Undercut Banks (%)	5	5	1.00	0	0	1.00
Instream Wood (%)	1	1	1.00	5	5	1.00
Macrophytes (%)	0	0	1.00	1	1	1.00
Flow Types						
Deep pools (% of channel)	54	41	0.75	18	10	0.54
Backwaters (% of channel)	9	14	1.46	24	37	1.53
Riffles (% of channel)	1	4	3.05	15	26	1.72
Runs (% of channel)	35	42	1.19	43	27	0.64
Riverbank						
Riparian Vegetation (non-grass) (m^2)	18,537	18,537	1.00	14,123	14,123	1.00
Overhanging Vegetation (%)	1	1	1.00	1	1	1.00
Floodplain Width*	n/a	n/a	1.00	n/a	n/a	1.00
Sinuosity	1.02	1.02	1.00	1.01	1.03	1.01
HQI (median)			1.00			1.00
HQI (mean)			1.18			1.00
Maximum individual component reduction			0.75			0.54

The reduced area of pools in the engineered reach (0.54) was also observed in the control reach (0.75), suggesting changes may be attributable to differences in flow between surveys (which increased from 2.5m^3/s on March 19 to 4.4 m^3/s on May 22 (GWRC, 2020)) rather than the engineering works. Increases in the area of riffles in both the control (3.05) and engineered (1.72) reaches suggest this is possibly also attributable to the increase in flow. There does appear to have been a reduction in runs isolated to the engineered reach (0.64), which is of concern given their importance for torrentfish (Table 1). Substrate diversity was slightly reduced in the engineered reach (0.88) however this was matched by a similar reduction in the control reach (0.79), suggesting a sampling error or natural change rather than any adverse effect of engineering.

Figure 3: Looking downstream over the engineered reach of the Waiohine River study site. Engineering work is evident in the three constructed gravel groynes seen in the centre of the image on the true left of the river. Heavy vehicle tracks are also evident throughout the reach.

Figure 4: Survey reaches before engineering. Flow is from top to bottom. The red dashed line indicates the divide between the control (upstream) and engineered (downstream) reaches. Red dots have been placed next to the sections of the runs where Wolman counts and BCI surveys were undertaken. Flow types are mapped in white (riffles), light blue (runs), medium blue (pools), and dark blue (backwaters).

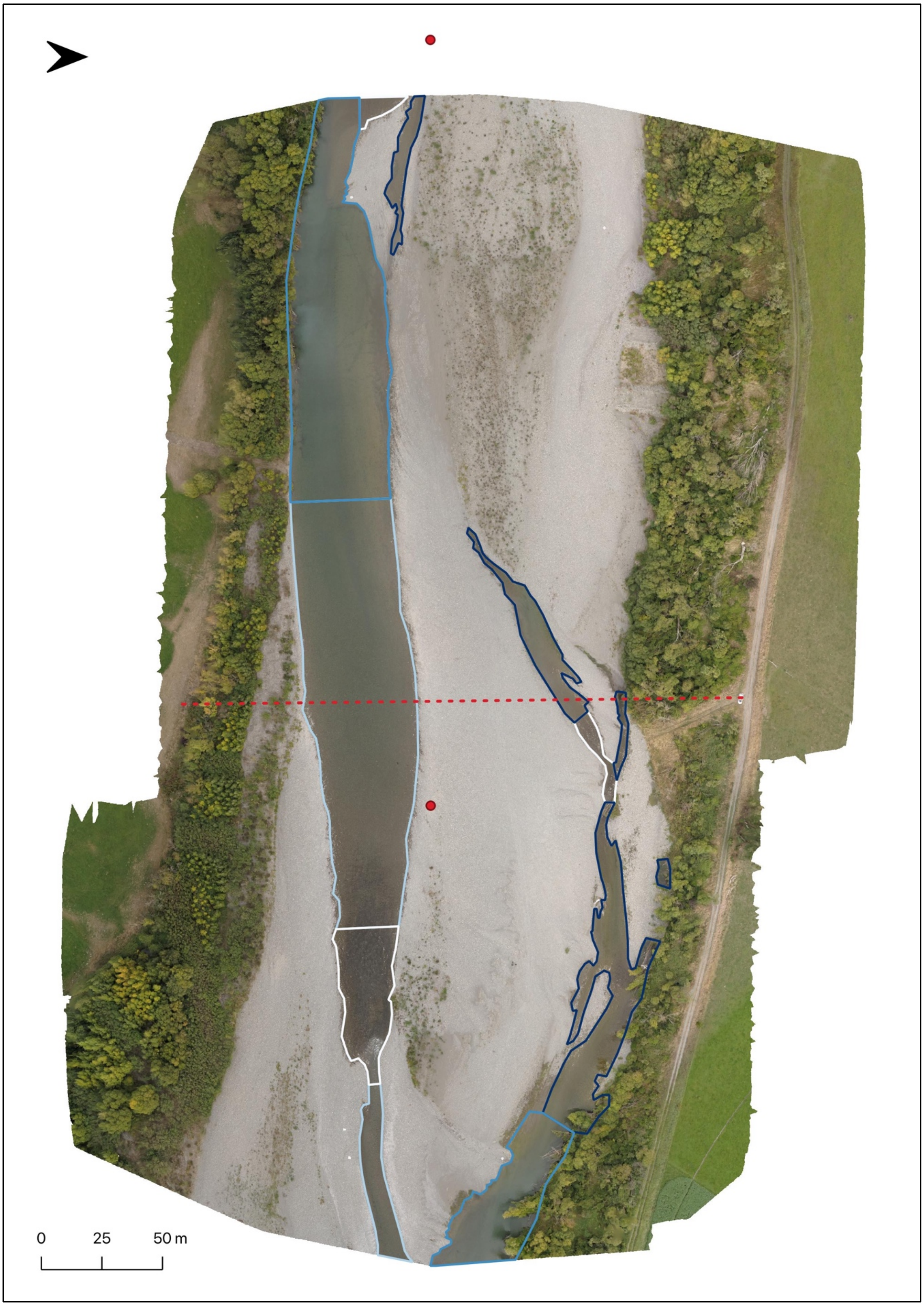
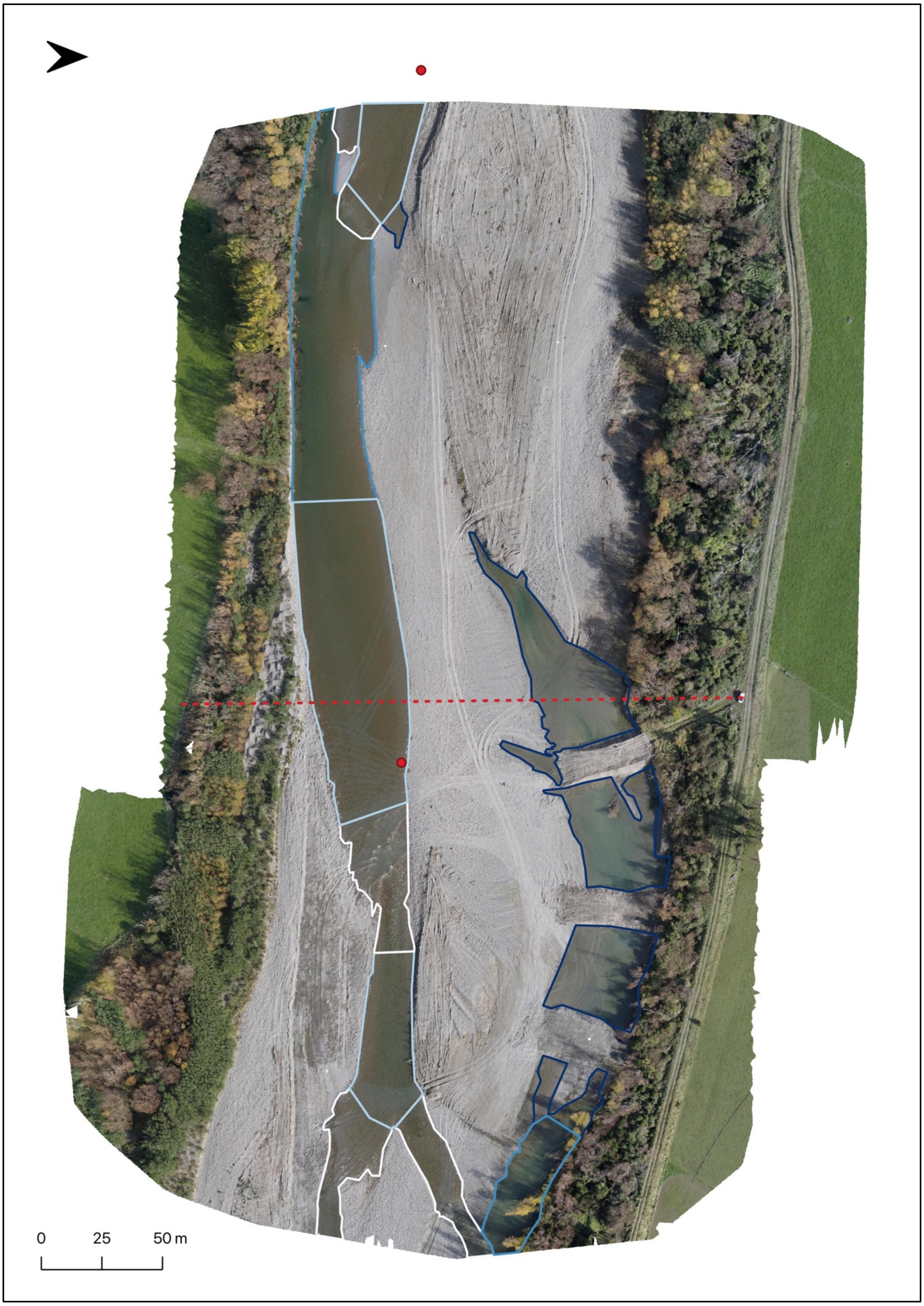


Figure 5: Survey reaches after engineering. Flow is from top to bottom. The red dashed line indicates the divide between the control (upstream) and engineered (downstream) reaches. Red dots have been placed next to the sections of the runs where Wolman counts and BCI surveys were undertaken (note the vehicle tracks at the downstream site). Flow types are mapped in white (riffles), light blue (runs), medium blue (pools), and dark blue (backwaters). Evidence of gravel raking at the control site can be seen in the centre of the upstream control reach.



DISCUSSION

Median HQI scores of 1.00 in both the control and engineered reaches indicate the engineering works had no overall adverse effect on habitat quality, at least not within the study timeframe, or over the length of river, measured. Post-engineering surveys were undertaken only 1-2 days after the works were finished, meaning the HQI assessment quantifies only its immediate impacts and not any changes that may have occurred in subsequent weeks or months as the river responded to the changes in the topography of its bed. Additional HQI surveys at regular intervals following the works would have been useful to assess potential longer-term impacts, such as effects on substrate characteristics, and whether the constructed groynes prevented an increase in sinuosity as a result of the river being unable to easily re-enter its true-left channel, where it had been flowing during recent high flow events (R. Graham, personal communication, March 19, 2020).

Data collected in this HQI assessment did not form an ideal basis for before/after comparison for several reasons. The survey reaches were short, at only 1.5 times the active channel width, making changes in sinuosity and the composition of flow types difficult to meaningfully detect and their HQI scores potentially unreliable. Having adjacent control and engineered reaches exacerbated these issues, as changes in one reach 'extended' into another. This was illustrated by the increase in the area of backwaters in the control reach as a response to the damming effect of the upstream groyne in the engineered reach (see Fig. 4 and 5). It also became apparent when surveying the reaches after engineering that some work had been undertaken in the control reach, albeit limited to gravel raking on a dry section of riverbed (see Fig. 4 and 5). Because surveying was undertaken almost immediately after the works were completed and the river hadn't been subject to a high flow (Fig. 2), the raking hadn't affected any of the measured variables in the control reach and it was still considered a suitable control. However, the riverbed was changed and habitat characteristics in the control reach are likely to respond to that change in future, making it unsuitable to use in any follow-up surveys. Potential changes in substrate characteristics between surveys might also have been missed because of the positioning of the Wolman pebble count and BCI surveys at the upstream end of the engineered reach (see Fig. 4 and 5). Somewhere further downstream would be preferable for these measurements, as changes in substrate characteristics would more reliably be picked up, and continue for, some distance downstream (Death et al., n.d.c).

Assessing fine sediment cover only in representative run habitats is likely to have further limited the HQI assessment. While the data in Table 2 indicates that fine sediment cover did not change in the engineered reach between surveys, if cover had been assessed across all flow types (not just runs) it is likely that an increase would have been detected in the backwaters, and possibly the pool, on the true-left side of the riverbed where heavy machinery had clearly loosened or exposed fine sediment while constructing groynes (see Fig. 3, 5, and 6).

Figure 6: An example of the fine sediment cover in one of the backwaters following engineering work. It was briefly agitated to illustrate the extent of cover.

HQI assessors can avoid these issues by (1) surveying appropriate lengths of river, (2) having significant gaps between control and engineered reaches, (3) positioning substrate survey sites at the lower ends of reaches or repeating them at several locations within each reach, (4) assessing sediment cover across all flow types, and (5) ensuring control sites remain 'untouched' by engineering activities between surveys. In regard to (1), the length of HQI survey reaches, Death et al. (n.d.c) suggest a length that 'appropriately reflects' the potential downstream effects of the activity to be undertaken. Harding et al.'s (2009) recommendation of 20 x the average wetted width, with a minimum length of 50 m and a maximum length of 500 m, for their quantitative habitat assessment protocol, provides a reasonable guideline for anyone unsure of how to interpret Death et al.'s suggestion.

I found that using a hybrid drone/ground-based method presented several benefits to HQI assessment, combining the advantages of previously used GIS- and ground-based methods. Orthophotos collected using the drone created a comprehensive visual record of changes in physical habitat between surveys that could be peer-reviewed or re-assessed in future. Using orthophotos and GIS software I could accurately measure, or cross-check ground-based measurements, of variables such as percent cover of flow types and riparian vegetation. I could also systematically identify areas of the river affected by change, including subtle changes like heavy vehicle tracks in the wetted channel, that I might not have identified otherwise. While not used in this study, DSMs were also created, which would be useful to measure habitat variables like floodplain width or streambank height had they been considered important for resident native fish species. Incorporating aerial imagery collected with a drone only added about 45 minutes of fieldwork to the assessment in total, including time to distribute GCPs across the site; and the image processing time, after a short setup, was largely idle time that could be used for other work. While some habitat variables, such as fine sediment cover, substrate diversity, or compaction, cannot yet be measured using aerial methods (although see Chapter 2 for developments in this area, as well as Arif et al., 2017; Bind et al., 2018; Woodget & Austrums, 2017; Woodget et al., 2017; 2018), measuring these on-the-ground was not difficult, and there is no doubt that drone imagery significantly improves the accuracy and applicability of the HQI when measuring the impacts of activities with short-term or small-scale effects, such as instream engineering works.

CONCLUSION

This study presented the first comprehensive HQI assessment of native fish habitat to incorporate aerial imagery collected with a drone. Using on-the-ground assessment methods in combination with an entry-level professional drone and open-source software, I presented a hybrid drone/ground-based HQI assessment technique, illustrating that engineering works on a reach of the Waiohine River had no overall adverse effect on its physical habitat condition. I found that using a drone presented several benefits to HQI assessment, allowing me to create a visual record of change in physical habitat that could be peer-reviewed or re-assessed in future; to accurately measure variables—such as percent cover of flow types—from aerial imagery; to systematically identify areas of the river affected by change; and to produce DSMs useful to measure variables like floodplain width or streambank height. With some adjustments to my application of the HQI, alongside continued improvements in drone technology and monitoring techniques, this hybrid drone/ground-based HQI assessment method forms a useful addition to the HQI toolbox, and is an ideal tool for the assessment of changes in river habitat quality in Aotearoa New Zealand rivers and streams in response to activities such as engineering.

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SYNOPSIS

If the question posed by this thesis was "does using a drone overcome the limitations of existing in-stream physical habitat assessments?" then the answer is probably no. Including drone-based measurements in an HQI assessment (or any other habitat assessment), while somewhat novel, is unlikely to revolutionise its application, and the assessment undertaken in Chapter 3 could have relied entirely on the ground-based methods used in previous applications of the HQI. However, that is not to say it was not *beneficial*, and if the question is "does using a drone *improve* in-stream physical habitat assessment?" or "can drones change the way people think about physical habitat in rivers?" then the answer is undoubtedly yes.

For a start, using a drone significantly improved the ease and accuracy of HQI measurement. Where previous applications of the HQI relied mostly on bankside estimates or measuring tapes, I could accurately map sinuosity and the areas of riffles, runs, pools, and backwaters using drone imagery in GIS. Drone imagery also allowed me to test the accuracy of the bankside estimates I had made of those variables (which were a back-up in case of any issues with the drone), as well as validate bankside estimates of percent instream cover and overhanging vegetation—all of which could be peer-reviewed using the imagery later if necessary. Web OpenDroneMap (WebODM), the photogrammetry software I used, also generated Digital Elevation and Digital Surface Models (DEMs/DSMs) that would have been invaluable for measuring floodplain width and stream bank heights had I needed to. And while drone imagery couldn't be relied upon for assessing sediment cover or substrate composition (though it appears to provide a good indication of these, see Chapter 2), the improvements in accuracy and ease of measuring these other variables was significant (Table 1).

Improvements beyond those above were less tangible, but no less valuable. With drone imagery I could understand the impact of change at a scale not visible from the ground. I could see a riffle in the context of a reach; a reach in the context of a river; and a river in the context of a landscape. I didn't need to traverse the three large gravel groynes constructed in the Waiohine riverbed (Chapter 3) at ground level and imagine the extent of change they had created—because with a drone they could be seen in context (Chapter 3: Figures 2, 3, and 4). Using a drone also allowed me to visually 'place' measurements within that context: I could map the exact location of Wolman pebble counts (or bed compaction surveys), identify changes or anomalies around those locations, and then consider what might have caused them. I could also identify important or interesting things I had missed from the ground and see them in context: at the Waiohine River (Chapter 3) it was heavy vehicle tracks in the wetted channel, while in the Tukituki River (Chapter 2) it was a large school of trout.

Undoubtedly, it is this 'visual context' that is the most valuable part of using drones for habitat quality assessment. While it makes little difference whether you use a drone or tape measure to make measurements represented by a number in a table, there is no substitute for the incredible sense of context that can be communicated through a photo, orthophoto, or video taken with a drone. In this context, a picture—when taken with a drone—really is worth a thousand words.

Table 1: Benefits and limitations of, and opportunities for improving, the use of drones for physical habitat assessment in rivers and streams.

Benefits	Limitations	Opportunities
• Increases accuracy of measurements of variables such as sinuosity; the areas of riffles, runs, pools, and backwaters; and riparian cover • Potentially measure other variables like instream cover (where water clarity allows), undercut banks (using DSMs/DEMs), and shading • Validate on-the-ground estimates of variables, or train experts and 'test' bankside estimates • Creates a visual record of change in physical habitat that can be peer-reviewed or re-assessed in future • Produce DEMs/DSMs to measure variables like floodplain width or streambank height • Allows for the systematic identification of areas of the river affected by change • Provides high quality imagery down to low Ground Sampling Distances (GSDs) • Provides a visual context to understand the scale and impacts of an activity, and allows for the 'placement' of measurements within a survey site • Can be used to create high resolutions orthophotos, maps, and 3D models	• Increases the time required to survey a site (where ground and drone-based methods are being used) • Requires time to charge batteries, check equipment for technical issues, update firmware/software, etc. • Increases pack-up times and creates a longer data logging/storage process • Involves large files requiring storage space on computers/servers • Requires investment of time and money in up-front training, qualifications, equipment, and software • Difficult to measure some components of habitat quality, such as substrate composition and sediment cover (noting drone imagery can provide an indication of these, see Chapter 2), and bed compaction • Acquiring high resolution imagery requires lower flight elevations at lower speeds, with greater overlap in flight lines, which takes more time and battery, and produces larger files • Flights must be operated below 120m above ground level, within line-of-sight, and require various permissions (unless specific legal permissions are obtained)[7]	• Research to establish the best parameters for measuring in-stream habitat variables with drones, and the subsequent development of guidance and recommendations for the best methodologies to capture accurate imagery • Increasingly accessible/affordable LiDAR sensors, which this would make measuring characteristic of underwater substrate characteristics such as sediment cover much easier • Increasingly affordable drones, with higher quality components and sensors • Continued improvements in open-source and commercial photogrammetry software • Higher resolution cameras/sensors to reduce GSDs while providing for high flight elevations (thereby reducing flight times and battery consumption) • Higher capacity batteries for longer flight times, allowing flights to cover larger areas • Adjusted permissions frameworks for operating drones beyond line-of-sight across large areas, which would allow much bigger areas of river to be covered in single surveys

[7] In Aotearoa New Zealand

In this sense, drone imagery is of substantial value to applied ecologists. However, where it could have a profound effect on the consideration of physical habitat quality is with those non-ecologists involved in resource management decisions: environmental planners, landscape architects, lawyers, judges, elected officials, and other non-expert decision-makers. Convincing these people that the often-unregulated activities undertaken in riverbeds can have significant adverse effects on natural character and physical habitat is likely to be much easier where that impact can be visually communicated. Changes in the quality of habitat in a river no longer need to be represented only by numbers in a table or photos of discrete sections of a riverbed taken on the ground. Instead, changes can be communicated through detailed maps, photos, orthophotos, and 3D models created using drones, and supported by robust measurements and statistics. And where impacts might have been disputed before, drone imagery provides a detailed and objective visual record that can be assessed again and again by experts and interested parties.

However, integrating drones into physical habitat assessment is not without limitations. In my experience undertaking this thesis, using a drone increased the time it took to survey a site; required additional preparation time to ensure batteries for equipment were charged and there were no technical issues; increased pack-up times and created a longer data logging/storage process; necessitated more digital storage space; and required an investment of time and money in up-front training, qualifications, equipment, and software. That's not to mention the limitations of drones in acquiring some data, such as measurements of sediment cover and substrate composition (though, as indicated in Chapter 2, attaining indications of these variables is feasible).

Despite this, in my opinion the benefits of integrating drones with physical habitat assessment significantly outweigh the limitations. And while comprehensive surveys might not be necessary in all circumstances, an action as small as capturing a few drone-based photos during surveys to provide a site overview could have significant implications for resource management decisions and physical habitat protection. Limitations such as the time required for preparation, surveying, and data processing could easily be addressed through training, ongoing experience, automated flights, and an efficient workflow; and are not indifferent from the limitations inherent in the training and preparation already required for established ground-based survey methods.

Other limitations are increasingly being addressed through rapid developments in technology, ever-decreasing costs, and open-source solutions, which means improvements in the resolution of cameras, increased battery capacities, greater accessibility to LiDAR (and other) sensors, and improved software are ever-emerging and could soon make assessments of those 'more difficult' variables possible. Between the collection of data and the writing of this synopsis, WebODM announced improvements to their software to sharpen orthophotos, increase the accuracy of elevation models, and double processing speeds; DJI increased the flight time on one of its consumer-grade drones by 13 minutes; and Apple introduced a LiDAR camera to several of its consumer-grade products—developments that in all likelihood will only continue to be announced across the tech.

industry. Numerous authors cited throughout this thesis are pushing the boundaries of what can be achieved every time a new development such as these emerges.

Overall, drones are not only an extremely useful tool for river habitat assessment, but a vital tool for ecologists in communicating the natural character and physical condition of rivers and streams. With minor adjustments to my application of the HQI, the hybrid drone/ground-based method presented in this thesis forms a useful addition to the river management and HQI toolbox. It is ideal for the assessment of changes in river habitat quality in rivers and streams in response to activities such as engineering and river restoration, and continued improvements in technology are only going to improve its efficacy over time.

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