INITIATIVE ON
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TECHNICAL REPORT

Artificial Intelligence-based Biomonitoring of Water Quality

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Abstract The miniSASS was developed as a citizen science tool for monitoring the health of river systems and reflecting the water quality through assessing macroinvertebrates communities. The miniSASS samples the macroinvertebrate community in a river reach and compares the community present to the expected community under ideal natural conditions. The information garnered during a survey relies heavily on the accurate identification of macroinvertebrates by low-skilled citizen scientists. This leaves a potential for errors in identification which may impact the accuracy of results and, ultimately, of the river health assessment. In response, we initiated the development of a smartphone application with built-in machine-learning algorithms for the automatic, real-time identification of macroinvertebrates. This report presents our data, methodology, and preliminary results from the automated identification algorithms.

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Artificial Intelligence-based Biomonitoring of Water Quality

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Introduction

GroundTruth, in conjunction with CGIAR, has engaged in a project until December 2023 regarding the development of linkages with the operation of natural resources in the Limpopo and Inkomati River Basins in terms of citizen science initiatives and tools as per Work Package (WP) 3 of CGIAR Research Initiative on Digital Innovation (DI). The DI Initiative seeks to harness digital technologies for timely decision-making across food, land, and water systems. The theory of change within DI is designed to address three challenge areas identified as key bottlenecks in digital transformation: 1) the digital divide, 2) inadequate information, and 3) limited digital capabilities. This project directly addresses the inadequate information in WP3, aiming to "Support diverse stakeholders across food-water-land systems in accessing timely, reliable, and actionable information, and codevelop real-time monitoring, integrated modeling, and enhanced early warning systems for natural resource management (NRM) and research organizations to manage climate risks in agrifood systems."

The overall project covers several sets of objectives. This technical report provides progress on upgrading the Stream Assessment Scoring System (miniSASS) (Graham et al. 2004), a citizen science-based, simplified version of the South African Scoring

System (SASS) version 5 (Dickens and Graham 2002) that provides real-time, actionable biomonitoring information to manage water quality and river health. Specifically, this report covers the progress regarding the following activities:

- Macroinvertebrate photographic database creation. Achieved via physical sampling of rivers/streams, macro-photography to photograph multiple specimens from all 13 target macroinvertebrate groupings, and image processing.
- Design, train, refine, and finalize the development of a machine-learning identification program.

Background

The miniSASS protocol was developed as an accessible citizen science tool for monitoring the health of river systems and reflecting the water quality through assessing macroinvertebrates communities (Graham et al. 2004). The concept is similar to that of the more in-depth SASS5 (Dickens and Graham 2002); different macroinvertebrates have different tolerance levels for disturbance; hence, water quality and river health are reflected in the macroinvertebrate community composition (i.e., the presence or absence of sensitive taxa indicate disturbance levels). Essentially, miniSASS samples the macroinvertebrate community in a river reach and compares the community present (identified to Order level allowing for easy identification by citizen scientists) to the expected community under ideal natural conditions. This comparison then indicates the health of the river, whereby high disparity between sampled *versus* expected suggests a heavily impacted system and high similarity suggests a near-natural system (Graham et al. 2004). The relevance of miniSASS here is that it was identified as the most promising citizen science tool for broader use in water quality monitoring out of a suite of tools being used in Southern Africa (Graham and Taylor 2018). This is related to the fact that it is a relatively easy technique to use, especially low-cost, and that there is no requirement for laboratory analyses – the results are developed in-field, real-time (Taylor et al. 2022). In fact, following a request from the United Nations committee responsible for SDG 6 on Water, miniSASS is now being explored for countries to use for SDG 6.3.2. as well as for SDG 6B. These two SDG6 indicators aim to improve the quality of water in rivers, lakes, and groundwater by reducing pollution.

MiniSASS is featured in the current progress report for indicator 6.3.2 - Progress on Ambient Water Quality Global Indicator 6.3.2 Updates and Acceleration Needs - 2021[1]. This again emphasizes the alignment between WP3 and SDG6.

As miniSASS currently stands, the information garnered during a survey relies heavily on the accurate identification of macroinvertebrates to Order (or Order-level groupings) level by low-skilled citizen scientists. This leaves a potential for errors in identification which may impact the accuracy of miniSASS results and, ultimately, of the river health assessment. In response, we proposed the development of a smartphone application (app) with built-in machine learning for the identification of macroinvertebrates. The app will use machine learning to analyze smartphone images of macroinvertebrates sampled during a miniSASS survey and provide real-time, precise, and geolocated identifications. The first step towards the development of the app was to collect images of specimens from all the macroinvertebrate miniSASS groups, creating a database that could inform the

[1] Available at: https://www.unwater.org/publications/progress-on-ambient-water-quality-632-2021-update

artificial intelligence (AI) machine-learning application. Thereafter, the machine-learning algorithm could begin development and identification training. the

Methods

This deliverable was achieved via physical sampling of rivers/streams and in-field mobile smartphone macro-photography of all specimens caught from all 13 target macroinvertebrate groupings. Images were subsequently processed out-of-field. The 13 sites were sampled to obtain images for all 13 MiniSASS groups (Figures 1 & 2; Table 1). This included six sites in the North-West (NW) and seven sites in Kwa-Zulu Natal (KZN) Provinces. Not all sites provided all biotopes for sampling; some sites had only a subset of biotopes sampled (Table 1).

Figure 1 Map showing the six sample sites in the North West (NW) Province, with North-West University indicated by a black dot, sample sites indicated by white dots, and the Mooi River filled in blue

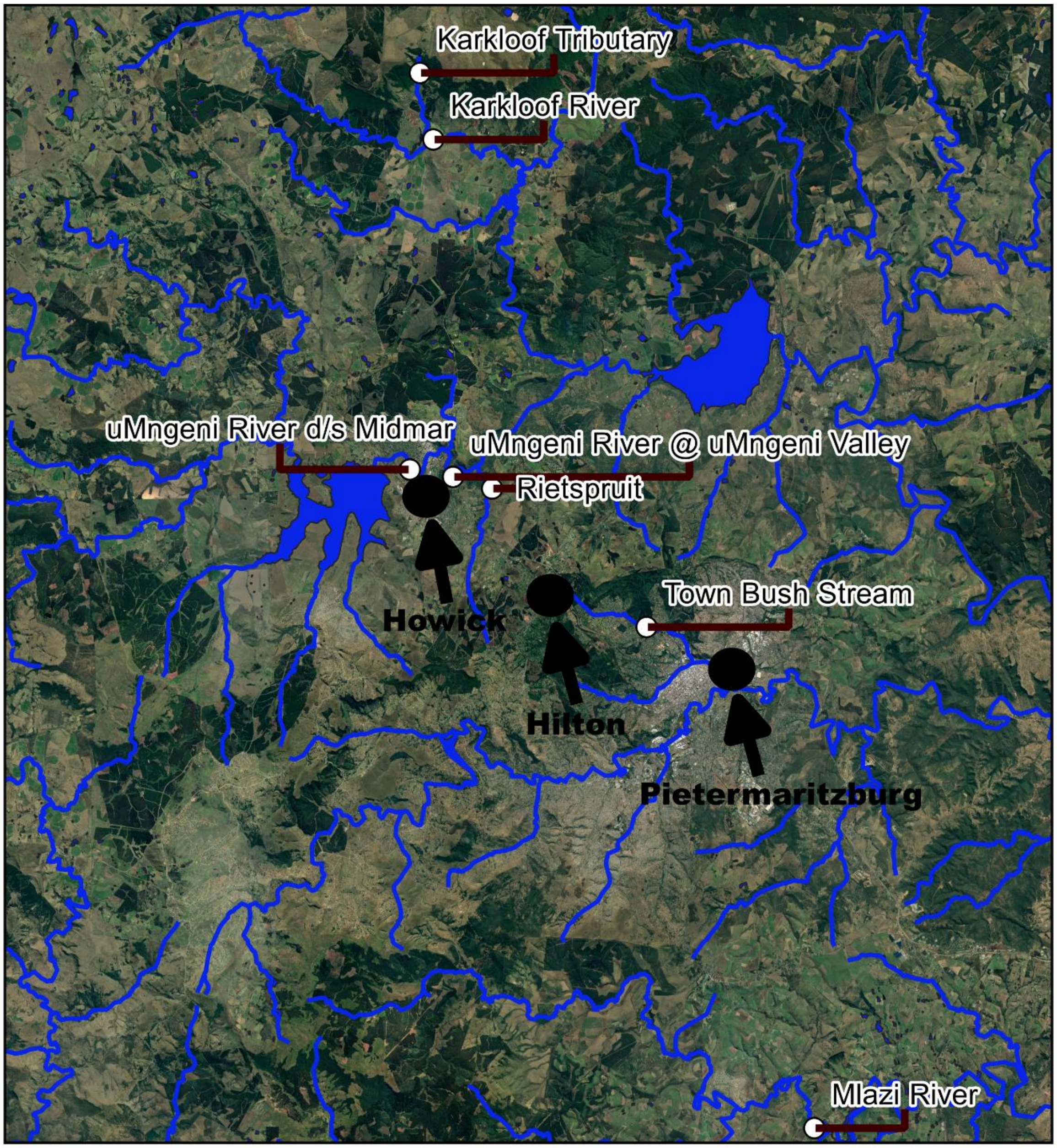

Figure 2 Map showing the seven sample sites in Kwa-Zulu Natal (KZN), with town centers indicated by black dots, sample sites indicated by white dots, and rivers and dams filled in blue.

Table 1 Sites sampled for macroinvertebrates within the Stream Scoring Assessment System (miniSASS) groupings. Site name, global positioning system (GPS) coordinates, a site description (including a subjective water quality measure), miniSASS groups sampled at the site, and the biotopes available for sampling (vegetation = VEG; gravel, sand, & mud = GSM; stone out of current = SOC; stones in current = SIC) are shown.

Site name	Location	Site description	Macroinvertebrate groups sampled	Biotopes sampled
S1 on the Mooi River	-26.68053, 27.0986	Medium depth, wide channel present with abundant riparian vegetation. Water quality is moderate.	All groups - No stoneflies; No clams	VEG, SOC, GSM
S2 on the Mooi River	-26.68119, 27.09838	Deep, wide channel with soft sediment. Many reeds were present. Water quality is moderate.	All groups - No stoneflies; No clams	VEG, GSM
S3 on the Mooi River	-26.68431, 27.09954	Small, deep channel, slow flowing. Abundant riparian vegetation. Water quality is moderate with some pollution evident.	All groups - Few dragonflies; No stoneflies	VEG, SOC, GSM
S4 on the Mooi River	-26.68558, 27.10148	Small, shallow stream with many boulders. High stream flow. Little to no riparian vegetation.	Mayflies; Bugs & Beetles; Some Dragonflies	SIC
S5 on the Mooi River	-26.68676, 27.10341	Heavily shaded stream, small channel width, and depth. Little riparian vegetation. Some pollution is present.	Most Groups - No Stoneflies; Many clams	GSM
S6 on the Mooi River	-26.6935, 27.10305	Site within NWU sports grounds. Many freshwater red algae. Strong current with many boulders. Some riparian vegetation.	All groups - No stoneflies; No clams	VEG, SIC, GSM
Karkloof Tributary	-29.30106, 30.22779	Pristine mountain stream, shading abundant. Shallow	All groups (mostly stoneflies)	VEG, SIC, GSM

		stream with scattered shallow pools. Some riparian vegetation.		
Karkloof River at Spitskop	-29.3336, 30.2353	Slightly impacted site is located under the bridge. Abundant riparian vegetation. Small stream with a sloped channel.	All groups	VEG, SIC, GSM
uMgeni River downstream of Midmar	-29.49484, 30.22218	Large, wide channel. Mostly large boulders are present. Little GSM. Some Riparian vegetation.	All groups - few stoneflies	VEG, SIC, SOC
Rietspruit	-29.50413, 30.26829	Small to medium stream, small waterfall present. High biotope diversity. Slightly impacted the site. Rocky habitat.	All groups - no stoneflies	VEG, SIC, SOC, GSM
uMgeni River at uMgeni Valley Nature Reserve	-29.49844, 30.24635	Large wide channel, deep with strong flow. Many large boulders with abundant algae. GSM is abundant with many aquatic worms.	All groups - no stoneflies	VEG, SIC, SOC, GSM
Town Bush Stream	-29.5717, 30.35493	Many large boulders with abundant algae. Little vegetation, abundant GSM.	All groups - Many crabs; No stoneflies	VEG, SIC, GSM
Mlazi River	-29.81584, 30.44901	Site near agriculture practice, small to medium stream. Biotopes abundant, little boulders. Good, fair condition.	All groups - Many stoneflies & Shrimp	VEG, SIC, SOC, GSM

Sites were sampled using standard miniSASS techniques (for details, see Graham et al. 2004; see Figures 3-6). However, each site was sampled exhaustively over several hours (as opposed to miniSASS sampling, where a site is only sampled for 15 minutes) since the objective was to collect as many specimens as possible from different taxa rather than to complete a miniSASS survey. At each site, all groups found were identified to miniSASS group level and photographed (digitally using a smartphone, and in some instances, a macro lensed DLSR camera), with a minimum of 5 photos per specimen taken (see Figure 3 7).

Figure 3 Sampling using the standard Stream Scoring Assessment System (miniSASS) net in the different biotopes along the Rietspruit, Hilton, Kwa-Zulu Natal.

Figure 4 Sampling in the stones biotope in the Umngeni River, Howick, Kwa-Zulu Natal (KZN).

Figure 5 Sampling in the stones biotope in the Umngeni River, Howick, Kwa-Zulu Natal (KZN).

Figure 6 Sampling along the Umngeni River, Howick, Kwa-Zulu Natal (KZN), where all biotopes were available for sampling.

Figure 7 Sample processing, including in-field identification and photographing using mobile smartphones and macro lenses in a DSLR camera alongside the Rietspruit, Hilton, Kwa-Zulu Natal (KZN).

Over 950 raw images of specimens within each miniSASS group were taken, labeled, and stored before pre-processing (Table 2). Pre-processing was done to modify images for AI training purposes and eliminate those unsuitable ones. Pre-processing entailed brightness adjustments, contrast changes, cropping, and any other fine-scale adjustments as required. From the pre-processed images, a thousand photos per group were selected to train the model (with the exception of the Dragonflies, where all 959 images were used; for examples within each group, see Figures in Appendix).

Table 2 Number of raw images taken of specimens within each Stream Scoring Assessment System (miniSASS) grouping (between 5 – 10 images taken of each individual specimen) and the number of pre-processed images eligible for use in the artificial intelligence (AI) identification program training.

miniSASS group	Raw images	Post pre-processing
Bugs & beetles	1570	1333
Caddisflies	1885	1636
Damselflies	1494	1398
Dragonflies	959	959
Flatworms	1228	1178
Crabs & Shrimps	1751	1587
Leeches	1015	1015
Minnow mayflies	1257	1155
Other mayflies	1784	1587
Snails/Clams/Mussels	1995	1935
Stoneflies	1930	1703
True flies	2247	2054
Worms	1596	1540

With the database of processed images for all miniSASS groupings created, a machine-learning algorithm was designed. The algorithm automatically identifies unique features of an image and, over repeated iterations, learns the common unique traits typical of each group. The algorithm was given 1,000 images within each group and trained over 19 epochs or iterations.

Results

Over each iteration, the model outcome was measured in terms of accuracy (as a percentage), or how well the model predicts group classification, by comparing those predictions made (training) with the true labels (validation; Figure 8). After 19 epochs, the training accuracy reached 95.5%.

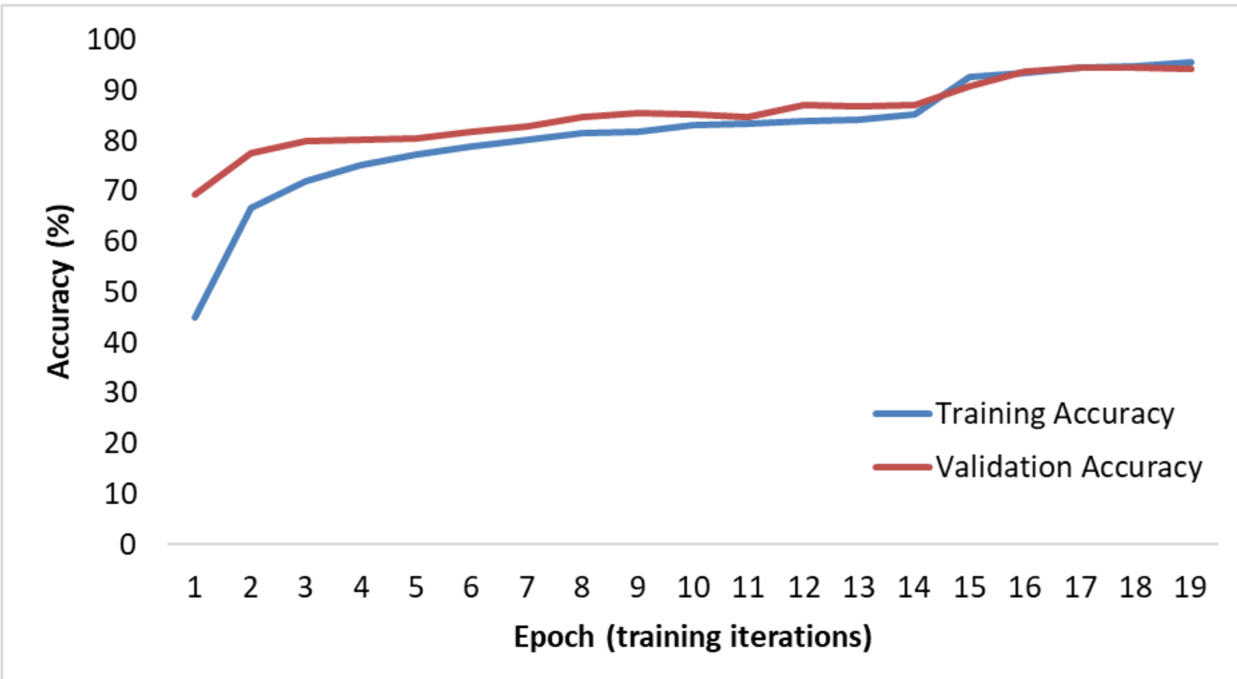

Figure 8 Model training performance shown as identification accuracy across 19 epochs (training iterations) assessing 1000 images within each Stream Scoring Assessment System (miniSASS) group. Training accuracy represents the model predictions, compared to the true labels or validation accuracy.

The loss of information during identification was also measured. Loss is a scalar value that needs to be minimized during model training. The lower the loss, the closer the predictions are to the true labels. As the training iterations increased, training and validation loss decreased (down to 0.13% training loss after 19 epochs), implying the model moved closer to the true labels of the images with epoch progression (Figure 9).

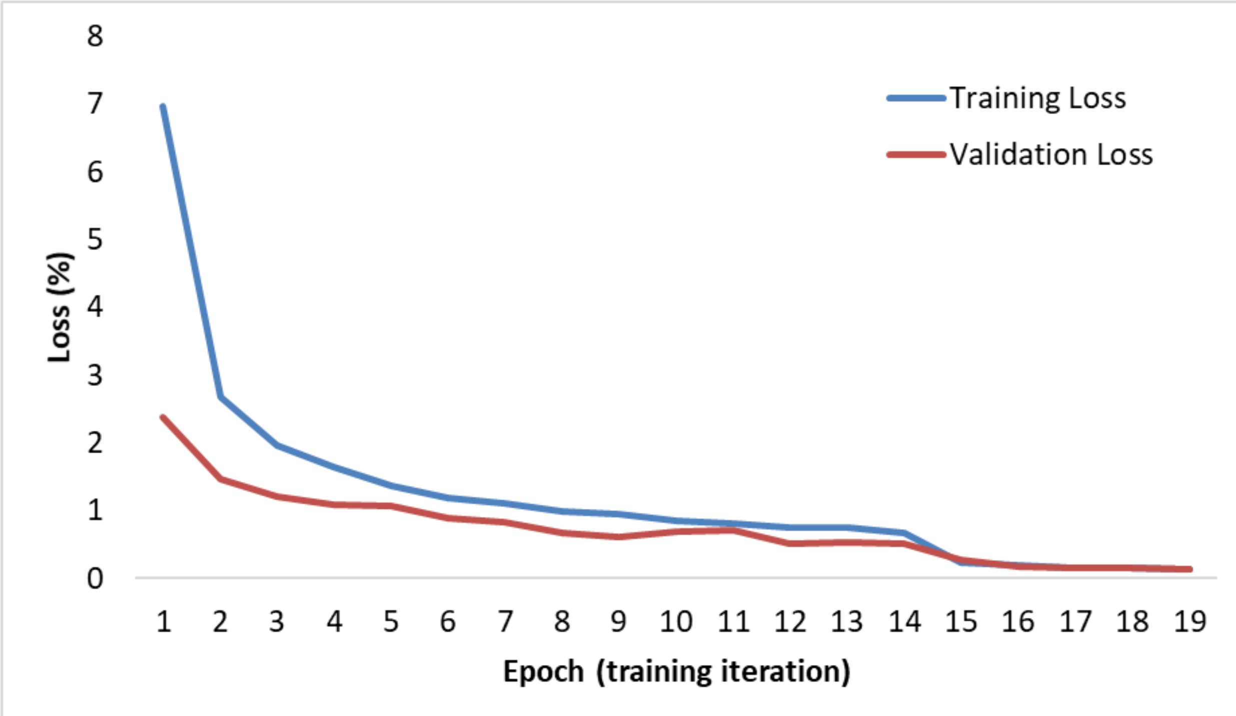

Figure 9 Model information loss across 19 epochs (training iterations) assessing 1000 images within each Stream Scoring Assessment System (miniSASS) group. Training loss represents the information lost in model predictions, compared to the validation loss, which shows the information lost in the true labels.

Summary

This technical report covers the progress made by CGIAR Digital Innovation Initiative Work Package 3 team's towards the implementation of artificial intelligence-based biomonitoring of water quality and river health by developing a machine learning algorithm to accurately identify the order of macroinvertebrate community sampled by citizen scientists in South Africa. More than 20,000 raw images of specimens were acquired across all 13 indicative macroinvertebrate groups during two field trips covering the North West and Kwa-Zulu Natal Provinces. From these raw images, a miniSASS photographic database was created by manually reviewing all the images and excluding unsuitable ones. The resulting database contained 19,080 pre-processed labeled images for use in the machine-learning algorithm training. About 1,000 images were used in each miniSASS group for training the identification model.

After 19 iterations, model training reached 96% identification accuracy to the miniSASS group level with 0.13% information loss, showing the desired identification accuracy based on the photographs submitted to the program.

Based on these promising results, the team initiated the next phase of the project activities, including:

1. Development of miniSASS mobile application embedded with the machine learning algorithm for the *in situ* real-time identifications.
2. In-field testing of the application and upscaling specimen photographic collection to increase the miniSASS photographic database for greater geographical coverage.

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Appendix

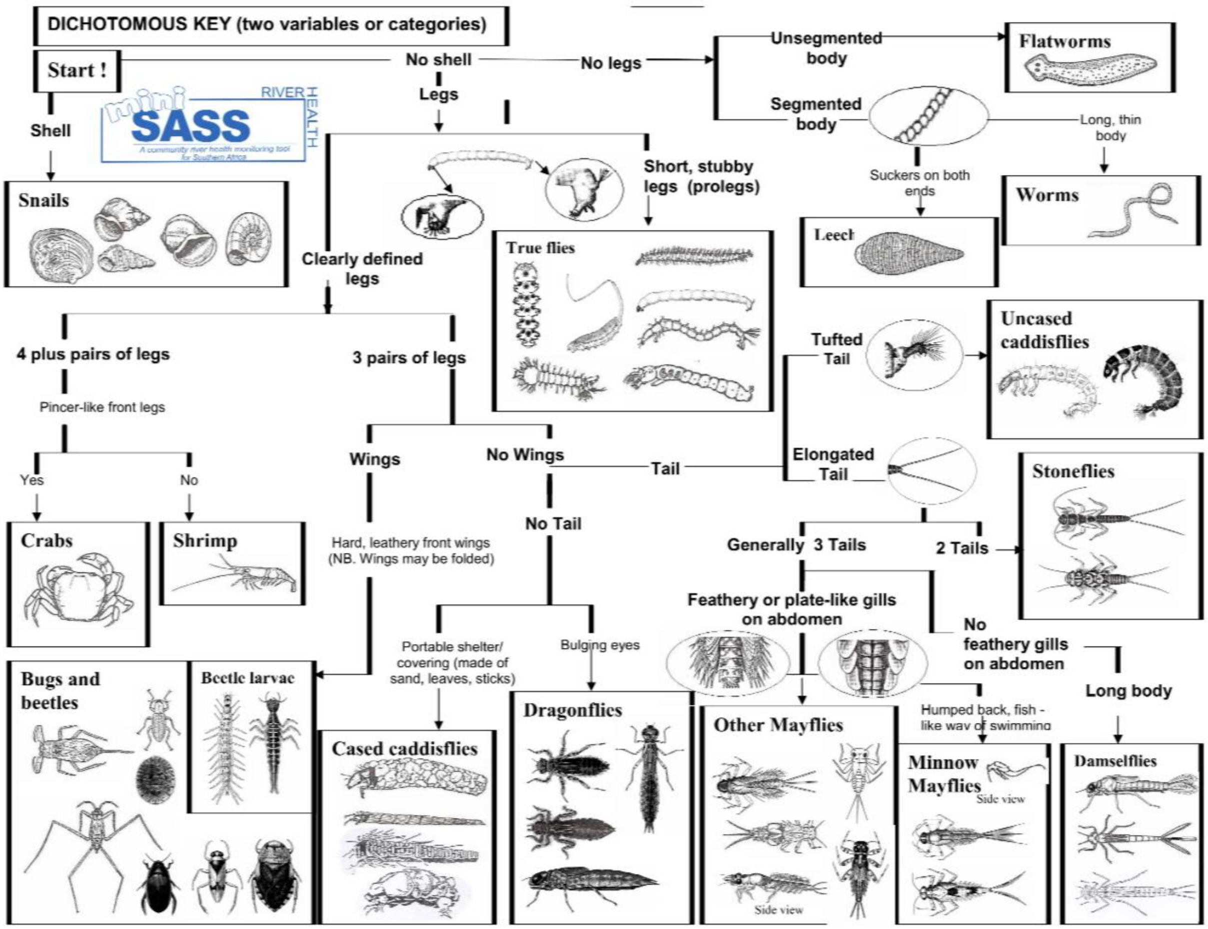

Figure A 1 The miniSASS dichotomous key diagram

Figure A 2 Photographs of four specimens from the "Bugs and Beetles" Stream Scoring Assessment System (miniSASS) group.

Figure A 3 Photographs of four specimens from the "Caddisflies" Stream Scoring Assessment System (miniSASS) group.

Figure A 4 Photographs of four specimens from the "Crabs and Shrimps" Stream Scoring Assessment System (miniSASS) group.

Figure A 5 Photographs of four specimens from the "Damselflies" Stream Scoring Assessment System (miniSASS) group.

Figure A 6 Photographs of four specimens from the "Dragonflies" Stream Scoring Assessment System (miniSASS) group.

Figure A 7 Photographs of four specimens from the "Flat Worms" Stream Scoring Assessment System (miniSASS) group.

Figure A 8 Photographs of four specimens from the "Leeches" Stream Scoring Assessment System (miniSASS) group.

Figure A 9 Photographs of four specimens from the “Mayflies” Stream Scoring Assessment System (miniSASS) group.

Figure A 10 Photographs of four specimens from the "Minnow Mayflies" Stream Scoring Assessment System (miniSASS) group.

Figure A 11 Photographs of four specimens from the "Snails, Clams, & Mussels" Stream Scoring Assessment System (miniSASS) group.

Figure A 12 Photographs of four specimens from the "Stoneflies" Stream Scoring Assessment System (miniSASS) group.

Figure A 13 Photographs of four specimens from the "True Flies" Stream Scoring Assessment System (miniSASS) group.

Figure A 14 Photographs of four specimens from the "Worms" Stream Scoring Assessment System (miniSASS) group.