

ICT-Based Identification and Characterisation of Small Reservoirs in the Limpopo River Basin in Zimbabwe

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Abstract

Semi-arid conditions that prevail in the Limpopo basin in general and Zimbabwe in particular emphasise the importance of water storage. In this respect small reservoirs play a critical role in sustaining rural livelihoods. However, the management of small reservoirs in Zimbabwe is negatively affected by missing or poorly coordinated information relating to such key attributes as location, capacity, and environmental condition. A study was undertaken to identify and characterise small reservoirs in the Limpopo river basin in Zimbabwe. The objective of the study was to identify small reservoirs and characterise them in terms of capacity, and chlorophyll-a and turbidity indices, as proxies for measuring environmental degradation of catchments in which these are located. The study was carried out in Gwanda district that is located in South West Zimbabwe. Identification was done by processing Landsat TM 4-5 images of February-March and April-May 2009, using Geographical Information Systems. Time and cost considerations were the main factors in the selection of the technology and the images that were used. Field inspections were used to validate selected parameters from February to April 2011. A total of 256 small reservoirs, with an estimated total capacity of 17 million m³, were identified. The capacities of reservoirs were found to vary widely from around 4,000 m³ to over 650,000 m³. About half (46%) of the small reservoirs were found to be dry by May, just two months after the end of the wet season. Seven reservoirs, which represented 2% of the total number and 3% of the total capacity of reservoirs, were characterised as highly turbid. Twenty-three reservoirs, representing 9% of the total number and 3% of the total capacity of reservoirs, showed signs of environmental degradation in the catchments. The smallest reservoirs were found to be most vulnerable to environmental degradation. The study concluded that Information and Communication Technologies (ICTs) can successfully be used to identify and characterise small reservoirs in the data-poor Limpopo basin in Zimbabwe, and can be used by decentralised water institutions and River Basin Organisations (RBOs) to better manage available water resources for the benefit of rural communities found therein.

Keywords: small reservoirs, rural livelihoods, remote sensing, ICTs, environmental condition, Limpopo

1. Introduction

Small reservoirs are important sources of multiple water uses (such as domestic, livestock watering, smallholder irrigation, fishing, dip tanks, and brick making) for rural livelihoods in the Limpopo river basin in general and in Zimbabwe in particular (Manzungu et al., 2009; Senzanje et al., 2008), because of the semi-arid conditions that prevail in the area (Zimbabwe, 1983). In Zimbabwe small reservoirs refer to a storage capacity of less than one million cubic meters and less than eight meters of dam wall (Kabell, 1986). However, the contribution of small reservoirs to rural livelihoods in Zimbabwe is threatened by poor management. This is a consequence of missing or poorly coordinated information (Senzanje & Chimbari, 2002) on such key attributes as location, capacity, and environmental condition of the reservoirs. Such information is critical for allocating water between competing water uses as well as protection of water resources.

In Zimbabwe a number of institutions are directly or indirectly involved in the management of small reservoirs. The Zimbabwe National Water Authority (ZINWA), a quasi-government agency, has overall oversight of water management in the country including building and managing dams. For example, by law, ZINWA should be informed before any large dam is constructed (Zimbabwe, 1998). However, ZINWA's mandate does not extend to small dams. All the same ZINWA must be informed when a small reservoir is established. Significantly this is only after its completion (Zimbabwe, 1998). As a consequence ZINWA does not hold a comprehensive database on small reservoirs. Sometimes the management of small reservoirs is left to the discretion of funders of the reservoirs such as Non Governmental Organisations (NGOs), the state-owned District Development Fund (DDF), and local authorities known as rural district councils (RDCs). As the planning and development authorities, RDCs should ideally coordinate the establishment and management of small reservoirs. However, RDCs lack capacity to document small reservoirs, monitor water use, and ensure their environmental protection. More often than not, RDCs tend to leave management of small reservoirs to local people, who also lack capacity to effectively manage them (Mufute et al., 2008).

In order to improve the management of small reservoirs and, consequently, contribute to sustaining rural livelihoods that are dependent on them it is critical that adequate information about them is captured and stored. Information that is needed to effectively manage reservoirs includes, among other things, location of the reservoirs, estimation of their capacity (De Moustier, 1988; DEC, 1987), nutrient load characterisation and quantification (Koelmans & Lijklema, 1996; Muvundja et al., 2009), as well as assessing environmental impacts (DEC, 1987; Naiman & Dudgeon, 2009). This can be quite an expensive process if traditional methods are used. However, recent developments in Information and Communication Technologies (ICTs) provide an opportunity to undertake the same task at a fraction of the cost (Hayes & Rajao, 2011; Jansky & Uitto, 2005; Singh & Singh, 2004; Wainwright & Waring, 2004). ICT refers to the practical application of knowledge involving the development, maintenance, and use of computer systems and electronics in order to process and exchange messages through a common system of symbols (Encyclopaedia Britannica, 2010). Some examples of ICTs are mobile phone telecommunications, radio, television, internet, databases, remote sensing, and geographic information systems (CTA, 2011; Jansky & Uitto, 2005).

In water resource management ICT has been used to analyse rainfall (Kileshye & Taigbenu, 2009), locate and estimate capacity of reservoirs (Gupta & Banerji, 1985; Rakhamatullaev, 2010; Sawunyama et al., 2006) and assess groundwater potential (Moyce et al., 2006). Other applications included characterising water quality (Nas et al., 2010), assessing land use impacts on soil erosion (Shinde et al., 2010), producing geologic and soil maps, and conducting natural disaster and environmental assessments (Lillesand et al., 2004). In Zimbabwe ICTs have been used to collect and process information on small reservoirs in the Limpopo basin. Sawunyama et al. (2006) estimated the capacities of small reservoirs in Insiza district in South West Zimbabwe using remote sensing data and Geographic Information Systems (GIS). However, the study did not go as far as assessing critical management factors such as estimating the change of volume of a reservoir from a wet to a dry period, and assessing environmental conditions of the reservoirs such as assessing the quality of water.

In water quality assessment the first four of the seven bands that constitute Landsat TM 4-5 scenes have been effectively used because of their spectral resolutions that cover a large portion of wavelength between 400 and 850 nm (Hadjimitsis & Clayton, 2011; Usali & Ismail, 2010). In this paper, turbidity and chlorophyll-a were chosen for physico-chemical characterisation of small reservoirs. These two parameters have optical properties that make them measurable by remote sensing, and can accurately indicate the environmental status of the reservoirs (Moore, 1980). Turbidity is the measure of the light scattering in water due to suspended matter (Rasmussen et al., 2009). Chlorophyll-a is the substance responsible for the pigment of algal plants, which gives a good indication of algal biomass in water (Duan et al., 2007). High turbidity of a reservoir is generally caused by inflows that are heavily loaded by suspended matter (Valentin et al., 2008). Inflows that are heavily loaded by nutrients induce excessive algal growth and can cause proliferation of floating vegetation (Monaghan et al., 2009; Muvundja et al., 2009).

This study sought to use freely available Landsat TM 4-5 images in order to identify and characterise small reservoirs in terms of their capacity, turbidity and chlorophyll-a in Limpopo river basin in Zimbabwe. It used Gwanda district as a case study.

2. Study Area

The study was undertaken in Gwanda administrative district that is located in Matebeleland South province (Figure 1).

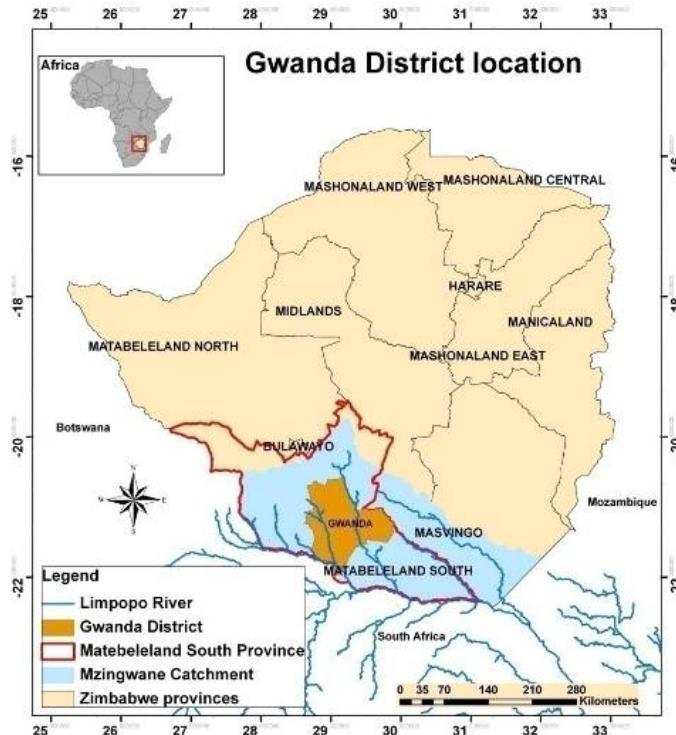


Figure 1. Location map of Gwanda district

The district covers approximately 11 000 km² and is drained by two main rivers, namely the Tuli in the West and Mzingwane in the East. Altitude ranges from around 560 m in the Southern part to greater than 1300 m in the Northern part. The district falls in three subcatchments (Shashe, Upper and Lower Mzingwane) in the hydrological zone B, which is one of the six hydrological zones into which Zimbabwe is divided. The zone is characterised by the lowest mean annual runoff (M.A.R.) of 19 mm, and has the highest coefficient of variation (130%) in the whole country (Mtisi & Nicol, 2003; Mupangwa et al., 2008; Zimbabwe, 1983). Lower Mzingwane has the lowest M.A.R. of 4 mm and the highest coefficient of Variation (C.V) of 160% (Zimbabwe, 1983). Consequently, the streams are generally ephemeral, which underlines the importance of water storage in the area. The rainy season ranges from November to March while the dry season starts from May to September. The soils in the district, which belong to the classes of leptosols, luvisols, lixisol, acrisols, and arenosols (FAO & UNESCO, 2006), are not suitable for agriculture unless fertilisers are applied (IUSS Working Group WRB, 2006).

Due to the erratic rainfall, rainfed crop production is difficult. Livestock farming is an important livelihood strategy. The main source of income is cattle and small stock production, although this is undertaken at subsistence level (PlanAfric, 2000). The human population in the district is estimated to be 133,167 in 2002 (CSO, 2002) and 150,000 in 2010 (UN, 2010). The general population in the communal areas is relatively poor (PlanAfric, 2000), and is characterised by an illiteracy level of around 18% and a Human Development Index (HDI) of 0.60 (FAO, 2011). This is worsened by a high rate of unemployment (UN, 2010).

3. Material and Methods

3.1 Overview of Methodological Approach

The methodological approach used in the study, as illustrated in Figure 2, consisted of four main steps:

- 1) Supervised classification of land cover using satellite images in order to extract areas of water bodies;
- 2) Identification and characterization of small reservoirs by determining turbidity and chlorophyll-a indices from satellite images;
- 3) Estimation of small reservoirs capacity from remotely sensed acquired information for wet and dry periods; and
- 4) Ground validation of obtained results.

These steps were carried out from January 2011 to April 2011. The Geographical Information Systems software ILWIS 3.31 was used. Mathematical and statistical computations were done using Excel and SPSS.

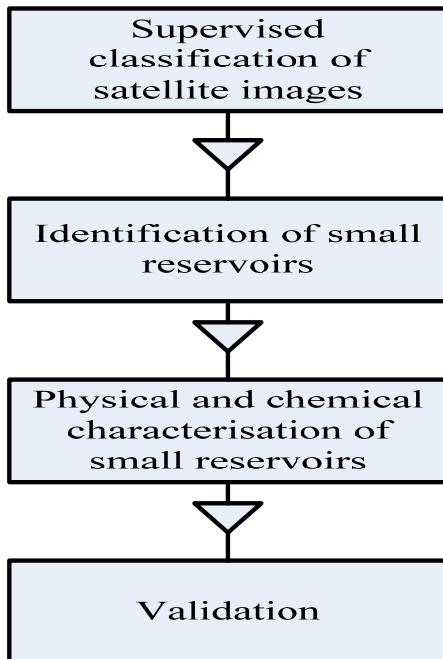


Figure 2. Methodological approach

3.2 Classification of Land Cover

To classify the land cover characteristics of the district, satellite images from Landsat TM 4-5 collection were chosen. The following reasons justified the choice of the particular images:

- The sensor has seven bands that cover a spectral resolution ranging from the visible to the infrared region (that is good for characterizing most of Earth surface materials and water in particular);
- The images are freely available and generally free of stripes;
- The spatial resolution of 30m that characterizes the bands 1, 2, 3, 4, 5 used in this study is good enough to identify small reservoirs; and
- The sensor records images at a radiometric resolution of 8 bits, which provides enough detail of information by discriminating 256 levels of reflectance intensity in a particular wavelength. This was important for both the classification of land cover in general and the physical and chemical characterization of small reservoirs in particular.

The satellite images were downloaded from the USGS website (<http://glovis.usgs.gov>) using the geographic coordinates of the boundaries of the district. Selecting appropriate images of the Landsat TM 4-5 collection was based on the following considerations:

- 1) Images that covered the geographic location of Gwanda district and were preferably cloud-free;
- 2) Latest images in order to identify all small reservoirs, including the most recently developed ; and
- 3) Two sets of images of the same year representing the wet and dry season so as to be able to estimate the capacity of the reservoirs in the two seasons.

Four scenes of Landsat TM 4-5 images were necessary to cover the whole district per season. Images of February-March 2009 were downloaded, which represented the end of the rainy season. There was, however, a challenge in finding recent images of around September that could be used to better estimate dry season capacity. The latest available images were around May 2009. All the images had low sun elevation angles, ranging from 36.7 to 55.1°. Low sun elevation is known to generate shadows in the presence of abrupt topography, which affects the classification of land cover types of low reflectance such as clear or deep water (Srestha & Zinck, 2001). These shadows were filtered from the classification using the first critical index of the identified small

reservoirs, as will be later explained.

Geometric and radiometric pre-processing of the images was done in order to fix satellite distortions, variation in solar illumination, and atmospheric effects on acquired images (Ouaidrari & Vermote, 1999; Verbyla & Boles, 2000). Geometric correction was carried out using an affine transformation on the basis of two topographic maps of 1:50,000 scale that cover the district. The nearest neighbour method was applied for resampling. Radiometric calibration was done based on standard procedure, as described by Chander and Markham (2003). Satellite images tiles were merged per spectral band and per period in order to obtain individual bands that cover the entirety of the district as per defined period.

A supervised classification was then run based on pseudo-natural colour composite (bands 5, 4, 3 for channels Red, Green, Blue) using the minimum distance to mean algorithm. A 2% histogram equalisation was applied for contrast enhancement. Six classes of land cover were sampled based on their specific spectral reflectances that could be distinctly separated on the pseudo-natural colour composite. These were clear or deep water and shadows, shallow or turbid water, forests and shrubs, healthy vegetation, white soil/sand, and brown soil/clay.

3.3 Identification and Characterisation of Small Reservoirs

3.3.1 Identification

From the six classes of the classified images, the two classes of water (clear or deep water and shallow or turbid water) were merged into one class of “water bodies”. The capacity-area relationship developed by Sawunyama *et al.* (2006), for which the R^2 was 95%, was used to determine the size limit in terms of surface area between small and larger reservoirs as defined (in volume terms) in Zimbabwe (Kabell, 1986; Zimbabwe, 1998). The reservoirs polygons were formed based on the contiguity of pixels using an automated 8-pixel connection method (that connects in horizontal, vertical, and diagonal pixels) and assigning such connected pixels a unique identifier. To that unique identifier was associated the location coordinates of the point at the center of the polygon. The surface areas were calculated based on the number of pixels that formed each polygon, taking into account that each pixel constitutes a square of 30 m wide. A threshold of 2 pixels was set to classify negligible water bodies. To remove larger residual water bodies in main rivers, namely Tuli and Mzingwane rivers, a masking map was created.

3.3.2 Characterisation of Turbidity and Chlorophyll-a

Reflectance data of Landsat TM 4-5 images have been used to develop algorithms that directly output the parameter under study from the input of reflectance in one or more satellite bands (Bustamante *et al.*, 2009; Raharimahefa & Kusky, 2010). However, the development of such models depends on the availability of *in situ* data to correlate with reflectance on the time of satellite overpass (Hadjimitsis *et al.*, 2006; Nas *et al.*, 2010). Again, the models are very diverse and specific to the reservoirs studied, which makes them not replicable elsewhere. It was concluded that this approach was not applicable in the case of small reservoirs in Gwanda district because of challenges highlighted above, which relate to data availability as well as time and costs considerations.

Although they differ in the quantification of the physico-chemical property studied, these divergent models have in common the reflectance bands, bands ratios, or bands combinations that strongly correlate with *in situ* measurements (Hadjimitsis & Clayton, 2011). Thus well selected bands can be used to effectively characterise the physico-chemical property in terms of a unitless index. Bands ratios are generally preferred because of the ability to discriminate atmospheric effects, and shadows due to variation of topography and sun elevation (Lawrence & Ripple, 1998; Nas *et al.*, 2010; Raharimahefa & Kusky, 2010). In this paper, bands ratios were therefore chosen as indices of turbidity and chlorophyll-a.

Best prediction of turbidity is performed with algorithms based on single bands 3 or 2 of Landsat TM 4-5 (Brezonik *et al.*, 2005; Bustamante *et al.*, 2009; Hadjimitsis *et al.*, 2006; Nas *et al.*, 2010), while band 1 also characterises turbidity by providing the best penetration in water (Raharimahefa & Kusky, 2010). Some studies have demonstrated that the ratios (band 3)/(band 1) and (band 2)/(band 1) best correlate with *in situ* measurements of turbidity (Nas *et al.*, 2010; Raharimahefa & Kusky, 2010). The turbidity index used in this study is thus the sum of the two ratios in a way that considers the spectral ranges where turbidity best correlates:

$$\text{Landsat TM 4-5 Turbidity Index} = (\text{Band 3} + \text{Band 2}) / (\text{Band 1}) \quad (1)$$

To characterise chlorophyll-a, Duan *et al.* (2007) showed that the reflectance of this substance positively correlates in bands 2 and 4 and has a remarkable pic of absorption in band 3 of Landsat TM 4-5 (Figure 3).

In this order, the simple ratio of vegetation index (Band 4)/(Band 3) and the ratio (Band 2)/(Band 3) are best indicators of chlorophyll-a reflectance (Duan *et al.*, 2007; Raharimahefa & Kusky, 2010).

The chlorophyll-a index used in this study is thus the sum of the two ratios in a way that considers the spectral ranges where chlorophyll-a concentration best correlates with spectral reflectance:

$$\text{Landsat TM chlorophyll-a index} = (\text{Band 2} + \text{Band 4}) / (\text{Band 3}) \quad (2)$$

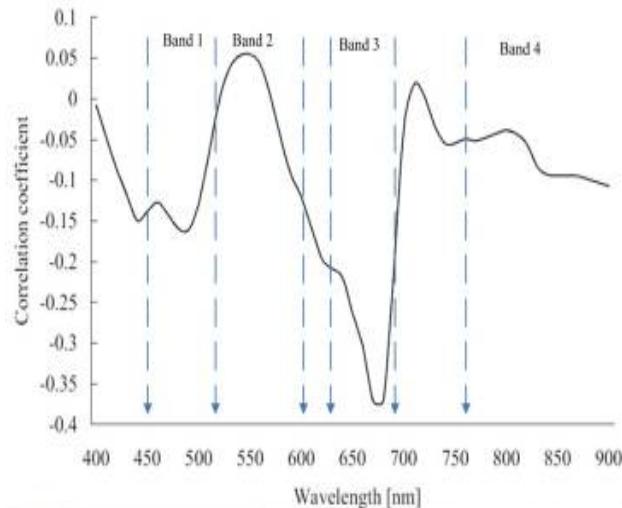


Figure 3. Correlation between chlorophyll-a concentration and reflectance in Landsat TM bands

To characterise the critical turbidity and chlorophyll-a of small reservoirs, it is important to consider the magnitude of these parameters compared to specified thresholds. To determine these thresholds (or critical indices) there are three aspects that need consideration. Firstly, remotely sensed turbidity from satellite is generally affected by the bottom soil reflectance of shallow reservoirs (Bustamante et al., 2009; Tolk et al., 2000). Secondly, ratio-based vegetation indices effectively discriminate shadows from clear water (Lawrence & Ripple, 1998). Thirdly, Irigoien and Castel (1997) found that excessive turbidity hinders chlorophyll-a concentration despite large inputs of nutrients. In the same vein, Scheffer et al. (2001) found that turbidity becomes critical when it continues increasing without increase in vegetation and, conversely, vegetation growth becomes critical when it continues increasing without turbidity increase.

Therefore, to characterise the environmental degradation of small reservoirs in the district, critical turbidity and chlorophyll-a indices were determined by the points of change of relationships between equations (1) and (2). As a prerequisite, the coefficients of determination (R^2) of these relationships were considered not to be affected by collinearity between the two equations. This is because the ratios $B3/B1$ and $B2/B1$, which were used for turbidity index (Equation 1), do not correlate (R^2 of less than 0.05) with chlorophyll-a concentration (Duan et al., 2007).

The highest and lowest values of the critical indices were determined on the basis of the absolute error that characterised the critical indices. These values represented the limits of the interval in which the change of relationship between turbidity and chlorophyll-a was occurring.

Considering that vegetation-based ratio indices discriminate shadows (Lawrence & Ripple, 1998), two critical indices of chlorophyll-a were determined. The first was used to eliminate shadows from the class of ‘clear or deep water’, using the criteria that they were characterised by an index greater than the lowest value of the first critical chlorophyll-a index. In this order, ‘true reservoirs’ remained. The second critical index was used to categorise ‘true reservoirs’ that are loaded with excessive vegetation and those that are not.

Four subclasses were determined considering the categorisation of small reservoirs based on the critical turbidity and chlorophyll-a indices, namely:

- 1) “Highly turbid” reservoirs were characterised by turbidity indices greater than the highest critical turbidity index;
- 2) “Moderately turbid” reservoirs were characterised by turbidity indices between the highest and lowest critical turbidity indices;
- 3) “Clear water and no floating vegetation” reservoirs were characterised by turbidity indices less than the lowest

critical turbidity index, and chlorophyll-a indices less than the lowest value of the second critical chlorophyll-a index; and

4) “Clear water but excessive floating vegetation” reservoirs were characterised by chlorophyll-a indices between the first and the lowest value of the second critical chlorophyll-a indices.

As far as decision-making is concerned, only the first and last types of reservoir require immediate attention as this impact on sustainability. Reservoirs of type (1) and (4) indicate poor erosion control and excessive nutrients loads, while type (2) reservoirs represent an ordinary status that includes the bottom soil reflectance of shallow ones. Type (3) reservoirs represent the best status of neither excessive turbidity nor excessive chlorophyll-a.

3.2.3 Capacity Estimation of Reservoirs

In order to use remote sensing for measuring a physical or chemical water parameter, it is important that the satellite images represent similar conditions of time and place of data collection or to use a model that was validated with field data (Bustamante et al., 2009; Hadjimitsis & Clayton, 2011). This consideration was confirmed by the diversity of models to estimate the capacity of small reservoirs, which were discussed to be sensitive to climatic conditions in the period of their development (Sawunyama et al., 2006).

In general, a small reservoir can be represented like a pyramid (Figure 4).

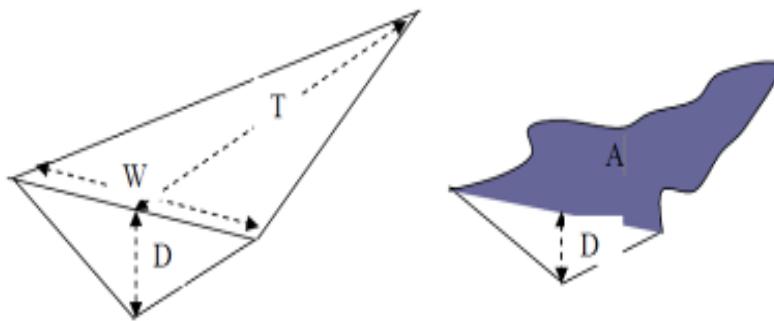


Figure 4. Pyramidal model for reservoir's capacity estimation (Sawunyama, 2005)

In this case, the capacity is estimated using the formula of the volume of a pyramid (3):

$$C_1 = (A * D)/3 \quad (3)$$

where D is the depth of water at the deepest point close to the dam wall, and A is the surface area. Although the surface area is easy to determine by remote sensing, field data is necessary to determine D for each small reservoir. This is time and resources intensive.

A relationship to directly estimate the capacity of a small reservoir from its surface area (4) was developed by Sawunyama et al. (2006) using field data in Insiza district, which also falls in the general study area:

$$C_2 = 0.023 * A^{1.33} (R^2 = 0.95) \quad (4)$$

This relationship was found very useful to estimate capacity because it only depends on the surface area of the reservoir that can be found by remote sensing. Indeed, the calculation of coefficients of variation (5) of the field data generated during the development of the relationship (Table 1) shows high variation of volume capacity (0.98, which is a good sign of a well diversified sample) and surface area (0.72), in opposition to low variation (0.22) for the pyramid model depth (6).

$$C.V = (\text{Standard deviation})/(\text{Average}) \quad (5)$$

$$D = 3*V_f/A_f \quad (6)$$

where V_f and A_f represent respectively the volume and the surface area determined from field measurements.

This explains why capacity could be expressed as a direct function of the area (4) while the variation of the depth D could be considered negligible. To put it differently, the depth D of small reservoirs can be considered as constant despite the significant variation in volume and surface area. In this regard, an average depth D of small reservoirs could be effectively used to estimate capacities. To validate this point, the application in (3) of the average depth of small reservoirs used by Sawunyama et al. (2006), which is 1.97, was used which gives a relative volume difference (7) of only 10% with the figures obtained with (4). This proves that the pyramidal

model is effectively applicable if the average depth of small reservoirs is known.

$$RVD = 100 * [\Sigma (C1 - C2) / \Sigma C2] \quad (7)$$

However, in order to apply the relationship (4) to other conditions of time and place, the authors pointed out that further research was necessary especially in heterogeneous conditions (Sawunyama et al., 2006). Such heterogeneous conditions exist in the Mzingwane catchment, the study area. The heterogeneity is illustrated by the catchment sub-zones that are characterised by significantly different mean annual runoff (M.A.R), ranging from 1 to 80, and coefficients of variation (C.V) of above 100 (Zimbabwe, 1983).

Consequently, this study used the average depth of a diversified sample of small reservoirs in Gwanda district. The validation process, which is further discussed below, enabled a choice between equations (3) and (4). The chosen equation was applied to both wet and dry season images in order to determine the capacity of all the small reservoirs in both seasons. A trend was deduced between wet and dry period capacities in order to establish the minimum size that could not go beyond the month of May, which marks the beginning of the dry season.

Table 1. Data used for establishing the capacity-area relationship in Insiza (Sawunyama et al., 2006)

Name of reservoir	Vf, volume field	Af, area field	D=3*Vf/Af	C ₁ (average D)	C ₂	C ₁ -C ₂
Sibasa	8114	15090	1.61	9926	10722	-796
Dehwa	17146	26516	1.94	17442	16037	1405
Avoca	41031	51171	2.41	33659	42155	-8496
Manzamhlope	15258	24284	1.88	15973	13588	2385
Vocola	11246	19297	1.75	12693	9132	3561
Mashoko	87504	90543	2.90	59557	85306	-25749
Tekwani	3244	7562	1.29	4974	2863	2111
Bova	14160	22955	1.85	15099	11478	3621
Sifinini	11582	19730	1.76	12978	11469	1509
Ndlegu	43405	53387	2.44	35117	45940	-10823
Masuto	12470	20859	1.79	13721	11741	1980
Mbondo	21775	31747	2.06	20882	20564	318
				total	280995	-28974
average	23911	31928	1.97			
Standard deviation	23466	22849	0.43		RVD	-10
C.V	0.98	0.72	0.22			

3.4 Validation

Field work was carried out from February to April 2011 to validate the land cover classification by using the coordinates of the water bodies. Features identified as shadows due to abrupt topography were validated using higher resolution images of Google Earth. They were then eliminated from the captured polygons of clear or deep waters. A random sampling of representative coordinates of 11 areas identified as shadows was used for the validation.

Turbidity measurements were carried out on 10 small reservoirs sampled in all the classes of turbidity. The measurements were correlated to the respective indices. Small reservoirs in the three categories based on chlorophyll-a index (excessive floating vegetation, sparse vegetation, and no vegetation) were visited. Correlations were carried out between the respective indices and the observed presence of floating vegetation on the ground. The presence and intensity of floating vegetation observed on the field was coded as follows: 1 (no vegetation), 2 (sparse floating vegetation) and 3 (excessive floating vegetation). This was performed for 25 small reservoirs.

To validate the applicability of the equations (3) or (4) to the small reservoirs in Gwanda district, the procedure illustrated in Figure 5 was used. Data presented by Sawunyama et al. (2006) was used for small reservoirs in

Insiza district (Table 1). Field work was carried out on 10 small reservoirs in Gwanda district to measure the pyramidal depth. The reservoirs were sampled on the basis of a high coefficient of variation of surface areas. To validate equation 4, a reliability analysis of scale was performed on surface areas and pyramidal depth of small reservoirs in Insiza and Gwanda districts. This step helped to determine if equation 4 could be applied on small reservoirs that are comparable for both districts in terms of surface areas and pyramidal depth. Equation 4 developed in Insiza district could be successfully used if those conditions were met. On the contrary, equation (3) could be used with an average pyramidal depth on the condition that the coefficient of variation (C.V) of the depth was less than the one for the surface area. This validated the point that the surface area is the most determinant parameter of the volume. If all these conditions are not met, none of the equations can be used to successfully estimate capacities of all small reservoirs.

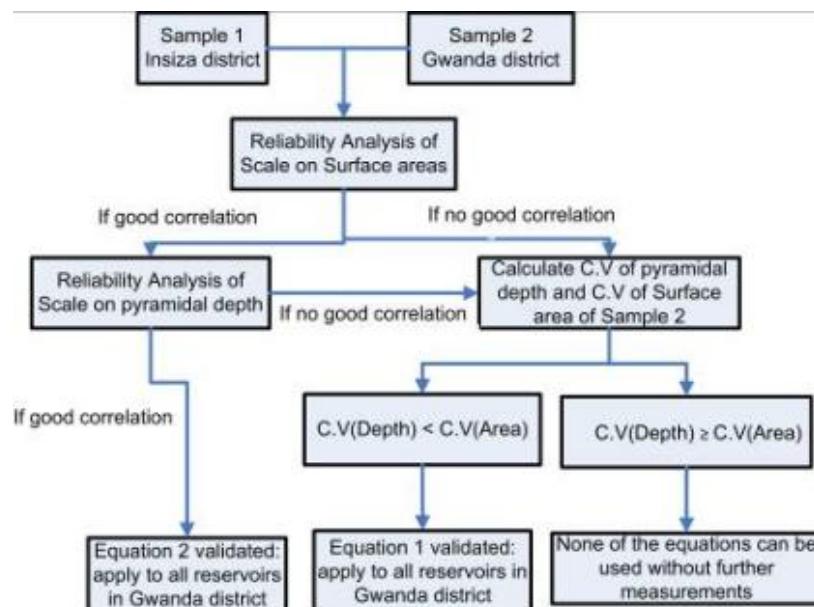


Figure 5. Validation and choice of capacity estimation

4. Results

4.1 Land Cover Classification

With an overall accuracy of 93.44 % for the first set of images, and an overall accuracy of 91.58 % for the second, the confusion matrices suggested a good confidence level in the obtained classification. The classification of satellite images of the six classes identified is presented in Table 2 for both wet and dry period.

Table 2. Classification of land cover for wet and dry periods

Feature Class	First set of images		Second set of images	
	Surface area percentage	Grouped percentage	Surface area percentage	grouped percentage
1 forests and shrubs	77.86	79.55	31.68	31.70
2 healthy vegetation	1.69	vegetation	0.02	vegetation
3 white soil/sand	18.77	19.94 bare soil	6.19	67.77 bare soil
4 brown soil/clay	1.17		61.58	
5 clear or deep water and shadows	0.31		0.45	
6 shallow or turbid water	0.12		0.06	
undefined areas	0.08	0.08 undefined	0.02	0.02 undefined
total	100	100	100	100

Table 2 shows that there was a change in major land cover types between the respective periods of the two sets of images. This was characterised by a reduction in vegetation from around 80% in February-March to around 32% in May 2009, and an increase in bare soil from around 20% in February-March to around 68% in May 2009. The class of ‘clear or deep water’ was affected by the bias caused by increased shadows size induced by lower sun elevations in dry season images (Figure 6) than in wet season images (Figure 7).

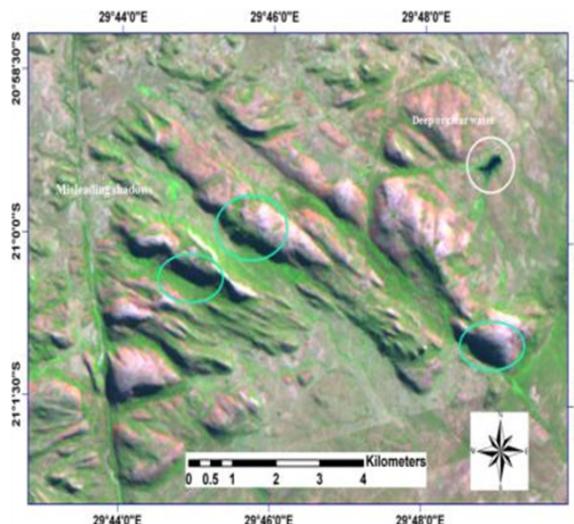


Figure 6. Dry season images in false colour composite (large shadows in green circles)

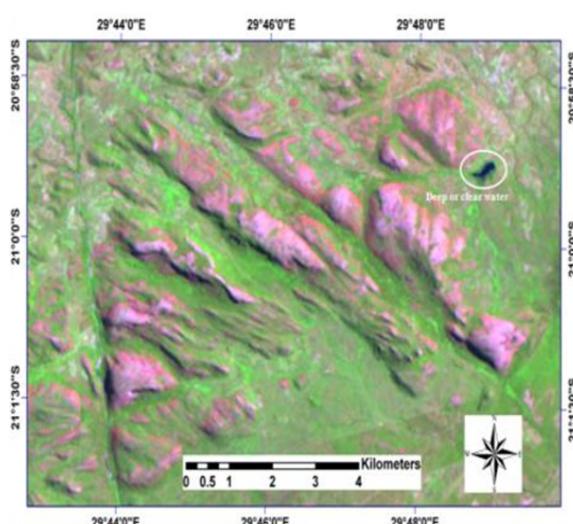


Figure 7. Rainy season images in false colour composite (shadows less observed)

4.2 Determination of Number of Small Reservoirs and Their Physico-chemical Status

4.2.1 Preliminary Number of Small Reservoirs

Using the classes specified above, the number of identified reservoirs in Gwanda district was obtained and their respective sizes (Table 3).

Table 3. Sizes categories of identified reservoirs in Gwanda district

Category of reservoir	Criteria	Number of reservoirs in category
Medium to large reservoirs	More than 614 pixels	7
Small reservoirs	More than 2 and at most 614 pixels	473
Negligible reservoirs	1 or 2 pixels	359
Total		839

The 473 identified small reservoirs in Table 3 still contain confusion of “clear or deep water” with shadows due to low sun elevation and topography variation.

4.2.2 Physico-chemical Status

Figure 8 shows the relationship between turbidity and chlorophyll-a indices for the 473 small reservoirs. This was used to find the critical turbidity.

The change in relationship between turbidity index and chlorophyll-a index in a second degree trendline equation is shown in Figure 8. Using this equation, the point of change in the trend was determined by calculating the value for which the following derivative was null. In this order:

$(dy/dx) = 0$,

Thus: $7.848*2*x - 20.63 = 0$

Consequently: $x = 1.31$ was the turbidity index from which the turbidity of the reservoir was considered as critical. Considering the confidence level of 83.6%, the critical turbidity index could be written with its absolute error as $1.31 (\pm 0.215)$. In other words, the lower and upper limits of the turbidity index were 1.095 and 1.525.

From this we can deduce the following:

- 1) Any small reservoir with a turbidity index greater than or equal to 1.525 is highly turbid. 7 small reservoirs corresponded to this criteria;
- 2) Any small reservoir with a turbidity index greater than or equal to 1.095 but less than 1.525 can be considered as moderately turbid and a total of 79 reservoirs fell under this criterion; and
- 3) Any small reservoir with a turbidity index of less than 1.095 can be considered as less turbid or clear water. However, the category of clear water includes shadows, as pointed out earlier, which will be discriminated using critical chlorophyll-a index.

Figure 9 was used to determine the critical chlorophyll-a index.

From the trendline's equation (confidence level of 86.7%), the point of change in chlorophyll-a index (more of vegetation than water) is calculated as the point of inflection of this second order equation, using derivatives:

$(dy/dx) = 0$,

Thus: $0.105*2*x - 0.777 = 0$

Consequently: $x = 3.70$ is the chlorophyll-a index from which the algal biomass concentration increases without increase in turbidity. This represents more biomass than water. Considering the confidence level of 86.7%, the critical chlorophyll-a index can be written with its absolute error as 3.70 ± 0.493 . In other words, its lower and upper limits are 3.207 and 4.193.

The following observations can be drawn:

- 1) Any "small reservoir" with a chlorophyll-a index greater than or equal to 3.207 can be considered to be more of vegetation than a water reservoir (a total of 217 polygons picked as "small reservoirs water" that are associated to shadows due to topography and low sun elevation corresponded to this criteria), and
- 2) Any small reservoir with a chlorophyll-a index lesser than 3.207 is a true water reservoir, and contains more water than vegetation (256 small reservoirs corresponded to this criteria).

Figure 10 shows the second critical chlorophyll-a index for the 256 small reservoirs.

The first derivative of the trendline equation of Figure 10 was used to determine the second critical chlorophyll-a index. This was found to be 2.846. This means that at 85.4% confidence level, any small reservoir characterized by a chlorophyll-a index greater or equal to 2.846 is susceptible to develop dense floating vegetation on its surface. Conversely, any small reservoir for which the chlorophyll-a index is less than this threshold, is categorized as a reservoir with no vegetation spreading (233 of the 256 small reservoirs were found in this category).

4.2.3 Final Number and Physico-chemical Characterisation of Small Reservoirs

The final identification and physico-chemical characterisation of small reservoirs from above is summarised in the Figure 11.

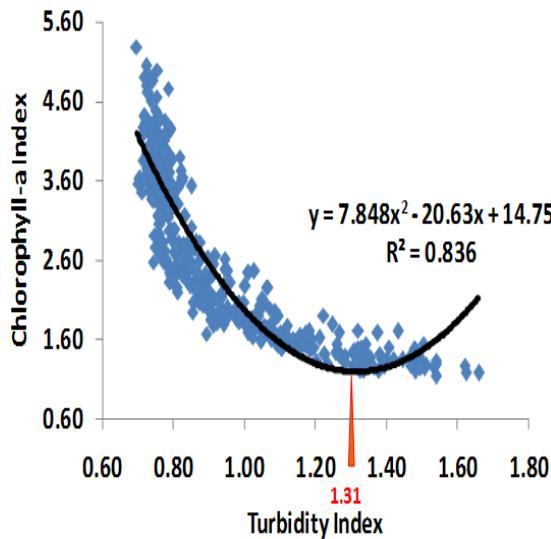


Figure 8. Determination of the critical turbidity index

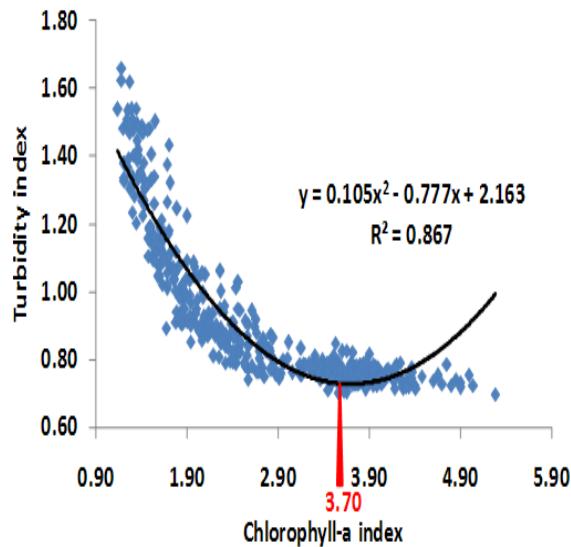


Figure 9. Determination of the first critical Chlorophyll-a index

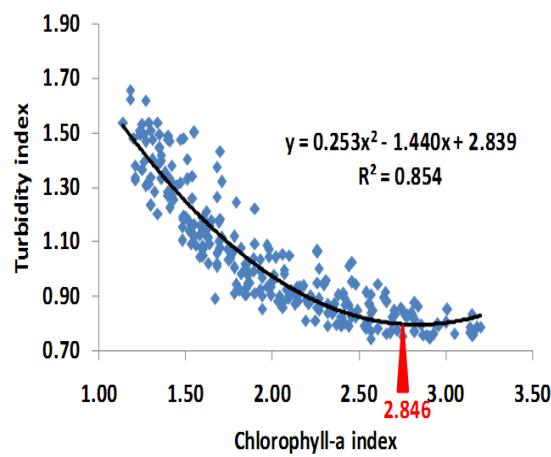


Figure 10. Determination of the second critical chlorophyll-a index

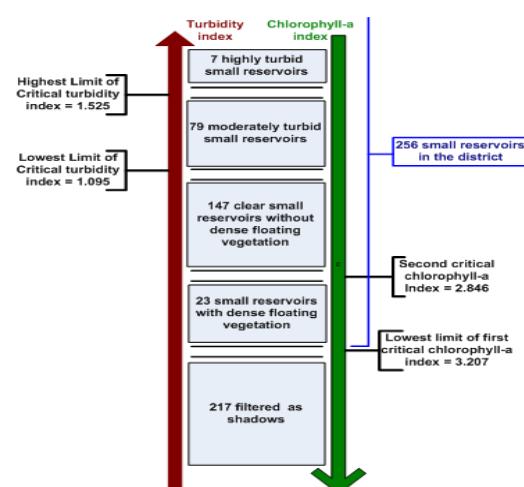


Figure 11. Summary of identification and physico-chemical characterisation

4.3 Estimation of Capacity

4.3.1 Choice and Validation of Model

The reliability analysis of scale was based on 10 cases between small reservoirs in Gwanda district and the ones used by Sawunyama et al. (2006). The unbiased estimate of reliability was 0.76 for surface areas and -1.22 for the pyramidal depth. In other words, the small reservoirs in the two samples were found comparable with respect to their surface areas only, but not for the pyramidal depth. Therefore, the conditions to apply the capacity-area relationship determined in Insiza district were not met for Gwanda district.

The C.V of the small reservoirs in Gwanda district was found to be 0.85 for surface area and 0.31 for their pyramidal depth (Table 4).

The conditions to use the pyramidal model based on an average depth of small reservoirs were therefore realised. The average depth was found to be 4.25 m.

Table 4. Depth and surface area of sampled reservoirs in Gwanda district

reservoir	depth (m)	area (m ²)
Sivume	2	10800
Sophaphu	3	25200
Langaphakathi 2	4	10800
Dondoriyo	4	17100
Ngonyama	4	37800
Matsenyanane	4	67500
Mgodi	4.5	5400
Matambo	5	5400
Langaphakathi 1	5	45000
Makhanka	7	13500
average	4.25	23850
Standard deviation	1.32	20339
C.V	0.31	0.85

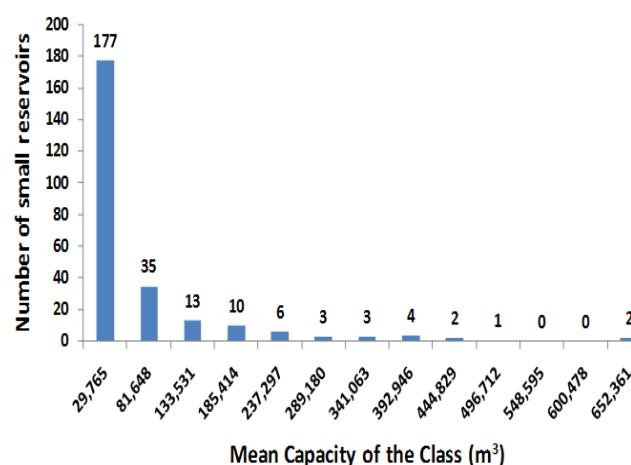


Figure 12. Distribution of mean capacities among small reservoirs

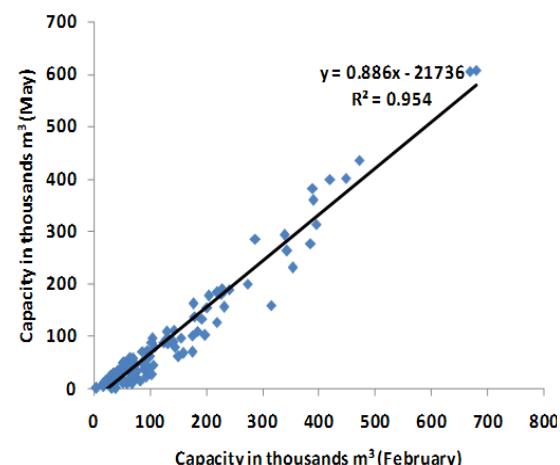


Figure 13. Drying relationship of small reservoirs

4.3.2 Application of Model

The total capacity of small reservoirs in the district was then estimated to 17 million m³. The volume capacity that is within the 7 highly turbid reservoirs (2% of the total number) corresponds to approximately 3% of the total capacity. The 23 small reservoirs, corresponding to 9% of the total number, are characterised by excessive floating vegetation amount for about 3% of the total capacity.

The largest estimated capacity value (678, 300 m³) is more than 150 times bigger than the smallest (3,824 m³), indicating a wide range of capacities for small reservoirs in the district (Figure 12). This wide range distribution of capacities is very much skewed to right (+ 2.97), in the same way the median (value which divides the distribution in two equal parts, which is 28,687 m³) is lower than the half of the average value (67,919 m³). Thus most of the small reservoirs (69% of the 256 small reservoirs) were found to have small capacities of around 30000 m³ (Figure 12).

Based on this trend, only small reservoirs of a size greater than 24533 m³ were found able to carry water beyond the month of May. Some 119 small reservoirs (46% of the total number of small reservoirs) were identified as likely to fail by May due to the dry season and their very small capacity.

4.4 Validation

The field visit to 27 small reservoirs served to validate the classification and identification of small reservoirs at 100%. All the 11 areas' coordinates used in Google Earth were also confirmed to be shadows behind abrupt topography.

Strong linear correlation of 0.79 was found between the turbidity index and the field measurement of turbidity. The measured turbidity varied from around 20 NTU for the clearest reservoirs to above 300 NTU for the highly turbid reservoirs (Figure 14).

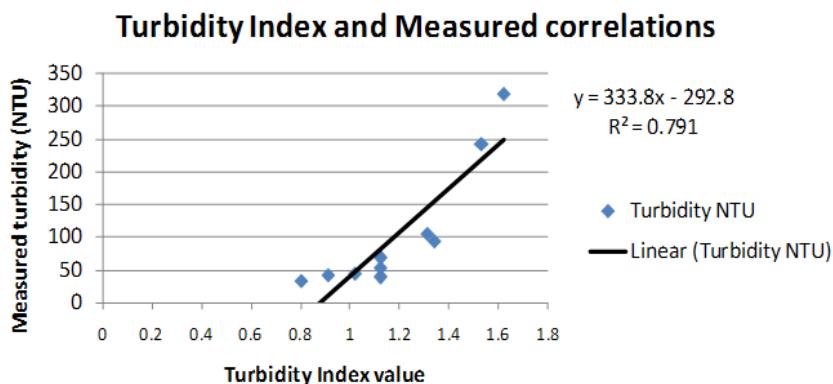


Figure 14. Correlation between measured turbidity and turbidity index

A good linear correlation of 0.68 was found between the encoded presence of vegetation and the respective chlorophyll-a index. This good correlation indicates the effectiveness of the indices used and their ability to be used over time to monitor small reservoirs in particular and water resources in general, using remote sensing data and GIS.

5. Discussion and Conclusions

The changes in land cover showed that the first and second sets of images can be considered to be representing a wetter and a drier period respectively. It was also observed that the sun elevation level went down to about 12° in the drier season images. This was the reason why wide shadowed areas in front of abrupt topography were either generated or increased (Figures 6 and 7). As a consequence, a bias in the class of 'clear or deep water' was induced -it was the class with the lowest reflectance in all bands. Similar issues have been pointed out in studies that dealt with the classification of land cover in mountainous area (Srestha & Zinck, 2001).

The influence of the sun angle and induced shadows in presence of abrupt topography could not be perceived in other areas, as it did not exceed 1% of the land cover. The change in surface area of shadows, which was induced by the presence of abrupt topography and low sun angle, was sensitive for the class of clear or deep water. Indeed, surface water occupied less than 1% of the land cover, just as much as the land area covered by shadows. Consequently, the change in the surface area of shadows induced significant change in the class of clear or deep water. Nonetheless, this bias was not critical to the study considering that this was later corrected using band ration indices. The use of bands ratios is well known to discriminate shadows due to topography (Lawrence & Ripple, 1998).

The size categorization of reservoirs in the district was validated by the number of medium to large dams. This was confirmed by the national water authority (ZINWA), which has management responsibility of medium to large dams. It could be argued that some very small reservoirs may have been eliminated together with residual waters by the 2 pixels threshold. However, the existence or reliability of such reservoirs may not be useful as any small reservoir of a capacity less than 24,533 m³ (that corresponds to 19 pixels of surface area) is likely to fail by May.

The number of 256 small reservoirs is higher than the 149 small reservoirs identified by DDF, or 154 small reservoirs in RDC records, or the 205 small reservoirs in ZINWA records for the whole area of Shashe, Upper

and Lower Mzingwane subcatchments that fall under the Mzingwane catchment area. The three subcatchments cover an area that is greater than the district. Further field research may be necessary to confirm whether such difference is due to unreliability and disparate data in various organisations' records or there were non-captured small reservoirs that were finally identified. Still, the findings of the identification exercise emphasise what was discussed by Sawunyama et al. (2006) - remote sensing and GIS can be used effectively to identify small reservoirs in data scarce areas, which saves time and cost.

The study did not develop an algorithm to provide values of turbidity and chlorophyll-a based on reflectance because of lack of ancillary data on the time of satellite overpass. However, the approach used proved effective in judging the quality of the water in the reservoirs as critical or acceptable. The approach was useful to indicate if there was environmental degradation in their specific catchments.

The study confirmed that the capacity of reservoirs is more dependent on the surface area than the depth. Therefore a formula based on the area itself could provide an estimate of the capacity, as reviewed and successfully applied in Insiza district by Sawunyama et al. (2006). However, different scales in terms of the average depth of the small reservoirs, proved to be a limitation to apply the formula determined in Insiza district to Gwanda district. A model based on the shape of a pyramid was successfully used to estimate capacity of small reservoirs using remotely sensed surface area and an average depth.

The study successfully illustrated that it is possible to apply ICTs in order to generate information for effective management of small reservoirs in the Limpopo basin in Zimbabwe, where data was found to be lacking or disparate. The critical information is the location, capacity, as well as turbidity and chlorophyll-a occurrence. The study also proved that relating indices of turbidity and chlorophyll-a based on the basis of remote sensing data can be used to establish classes of severity or acceptability of turbidity and chlorophyll-a levels of small reservoirs.

Overall, the study demonstrated that ICTs can successfully be used to identify and characterise small reservoirs in the Limpopo basin in Zimbabwe. This can be used to manage available water resources for the benefit of the rural communities in the Limpopo river basin in Zimbabwe and in the entire Limpopo river basin.

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