The validity of spatial data-based EIA screening decisions

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Abstract: Screening is an important step in the EIA process as it is here where the significance of possible impacts associated with a proposed development is first considered and the need for an assessment is determined. There is no one-size-fits-all approach to screening, but approaches can broadly be categorised into discretionary approaches and prescriptive approaches. In both types of approaches spatial information can be used to inform screening decisions and, in some cases, determine the screening outcome altogether. This paper explores the validity of spatially based screening decisions by evaluating the possible influence of spatial data on decisions – especially as it relates to data accuracy and scale. A sample of ten screening decisions for South African case studies are reviewed and spatial information analysed to illustrate the possible effects of data accuracy and scale on screening decision making. It was found that screening based on spatial data can lead to both unnecessary EIAs being conducted as well as potentially important EIAs being screened out. It is recommended that screening approaches should allow for more flexibility and allow for discretion where spatial data is concerned.

Keywords: EIA, screening, validity, spatial information, data quality, data scale

Highlights

- An evaluation of the validity of spatial data-based EIA screening decisions.
- Screening based on spatial information can result in invalid screening decisions.
- The accuracy and scale of spatial information might affect screening decisions.
- A more flexible and discretionary screening process is advocated.

1. Introduction

Screening is the first and arguably the most important step in the EIA process and has been evaluated in numerous publications (e.g. Pinho et al., 2010; Retief et al., 2011; Clarke & Menadue, 2016; Geneletti et al., 2017; Rocha & Fonseca, 2017). It is often contentious, as evidenced by the fact that screening decisions are typically the most frequent basis for court action: for example, Canter (1996) reports the most common basis for litigation under the National Environmental Policy Act in the US being the lack of EIS where one should have been prepared; and Wood and Becker (2005, p.353) cite screening as the most frequent source of "*actual infringements*" of the European EIA Directive. This is because it is the first point in the EIA process where the significance of impacts is considered and the subsequent need for an EIA is determined (IAIA, 1999; Ross et al., 2006; Weston, 2011).

Different EIA systems conduct screening in different ways that can be broadly described as either discretionary or prescriptive (Clarke & Menadue, 2016). In discretionary-based systems decision makers have to consider, usually on a case-by-case basis, the significance of possible impacts and make a decision on the need for an EIA (Macaulay & Richie, 2013). These decisions and the discretion involved are often influenced by subjective factors such as ideology, professional background and personal affinities as well as feasibility factors such as time-constraints and availability of resources (Christensen & Kørnøv, 2011). Prescriptive systems leave very limited room for discretion and are based on pre-determined activity lists, thresholds and other criteria such as capacity and size of developments to determine if a proposal should be subject to an EIA (Macaulay & Richie, 2013).

Many countries, however, employ a hybrid screening system combining discretionary and prescriptive approaches (Macaulay & Richie, 2013). There is therefore no one-size-fits-all approach to screening internationally, with many countries, and even jurisdictions within countries, implementing their own uniquely tailored systems, often with considerable variation in criteria and thresholds (Clarke & Menadue, 2016). This means that screening outcomes for the same proposed development will differ between countries, between different areas of jurisdiction within a country (Rocha and Fonseca, 2017), and between decision-makers within the same jurisdiction (Wood and Becker, 2005). That is, prescriptive requirements vary across jurisdictions, and the application of discretion varies both across, and within, jurisdictions.

In addition to activity lists and thresholds, some prescriptive screening systems also include the use of spatial data to determine screening decisions (Vanderhaegen & Muro, 2005; Geneletti, 2008; Retief et al., 2011). This is not to say that discretionary systems do not also consider spatial information, however, this will differ from prescriptive systems where there is limited interpretation or questioning of spatial information during the screening decision making process. An example of this is the South African EIA system that relies on a list-based screening mechanism (prescriptive) that is additionally informed by spatial data. According to the South African EIA Regulations (South Africa, 2017a), some activities will be subject to EIA if the proposed development footprint overlaps spatially with specified environmental attributes mapped in accordance with spatial datasets. In cases such as this, the screening decision on the need for and extent of an EIA will be significantly influenced by the availability and accuracy of spatial information (Haklay et al., 1998; Del Campo, 2012; Bahindwa, 2018; Underwood et al., 2018; Vanderhaegen & Muro, 2005; Geneletti, 2008; Retief et al., 2011).

The important role and contribution of spatial information in EIA has been widely discussed and demonstrated in the literature (e.g., João, 1998; Antunes et al., 2001; João, 2002; Patil et al., 2002; Satapathy et al., 2008; Campo, 2012; Gharehbaghi & Scott-Young, 2018). Moreover, these studies highlight the importance of spatial information accuracy in EIA processes, especially as it pertains to the issue of scale. João (2002) specifically evaluated the influence of scale on the outcomes of EIAs in the UK, concluding that it may influence results by affecting aspects such as the determination of impact significance and the measurement of environmental parameters. Expanding on this theme, this paper explores the validity of spatial data-based EIA screening decisions by addressing the following objectives:

- Objective 1: Evaluate the accuracy of spatial data in screening determinations through auditing.
- Objective 2: Analyse how data scale might influence screening decisions.

The paper uses South Africa as a case study area as it has an EIA system that employs a prescriptive list-based screening mechanism that is partially informed by spatial data (Alberts et al., 2020) and further has a well-established EIA system and a rich history and availability of spatial information. Nevertheless, the findings in relation to spatial accuracy and scale have relevance globally. Some important properties and characteristics of spatial information are discussed first followed by a description of the methodology. The results are next presented and discussed, followed by the conclusion and recommendations.

2. Spatial screening in South Africa

The South African EIA Regulations of 2017 (South Africa, 2017a) specifies a number of activities for which an environmental assessment will be required if the proposed development footprint overlaps with specified mapped environmental attributes. Listing Notice 3 of the EIA Regulations (South Africa, 2017b) makes specific reference to mapped environmental attributes such as areas of sensitive biodiversity, watercourses and wetlands. These environmental attributes are mapped at varying scales by a variety of government entities such as the Department of Forestry, Fisheries and the Environment (DFFE), the South African National Biodiversity Institute and the Chief Directorate: National Geo-spatial Information, who all act as data custodians for specific datasets. Datasets are made available to the DFFE for inclusion in the National Screening Tool, which is a web-based system through which development footprints are evaluated against all available spatial data. The system overlays the proposed development footprint with said spatial data and generates a report indicating which mapped environmental attributes are intersected by the proposed development footprint and might subsequently be affected. The report is submitted by a potential applicant to the relevant authorities for use in the screening decision. For example, if a developer proposes the construction of a water reservoir with a capacity exceeding 250 cubic meters and the report indicates that the development footprint intersects a mapped area of sensitive biodiversity (regardless of the spatial scale), the developer will be required to do an environmental assessment in terms of GNR 546 2(a)(i)(dd)[1]. The screening criteria and decision is reflected in the final EIA report.

3. Representing reality as spatial information

Mapping is the process of simplifying and displaying elements of the real world spatially (Bernhardsen, 2002). This process entails identifying real-world objects and processes and representing them as features, entities or continuous surfaces in spatial information which can be depicted on a map. When attempting this representation both the accuracy and the level of detail (scale of representation) at which it is done should be considered as this will ultimately determine the reliability and usability of the spatial data (Chang, 2009). The importance of data accuracy and data scale is subsequently discussed.

3.1. The importance of data accuracy

Maps have always been subject to inherent accuracy limitations (Thapa & Bossler, 1992) affecting the manner and extent to which they reflect reality (Foody, 2001). These limitations remain relevant in the digital era and often result in imperfections in spatial data that must be carefully considered (Devillers et al., 2010; Delavar & Devillers, 2010). The assertion by Thapa and Bossler (1992, p839) that the digital era has introduced a "*false sense of accuracy*" in spatial data, further highlights the importance of continued research into themes such as (Devillers & Jeansoulin, 2006; Bernhardsen, 2002; Thapa and Bossler, 1992):

- Positional accuracy: The accuracy of the position of features represented in spatial data in relation to reality, usually expressed in a measurement unit such

[1] GNR 546 refers to Government Notice Regulation 546, 2 refers to the specific activity and (a)(i)(dd) to the relevant spatial feature, which in this case is mapped areas of sensitive biodiversity.

as metres.

- **Attribute accuracy**: the accuracy of the quantitative and qualitative attributes describing spatial features.
- **Logical consistency**: the degree to which the logical rules of data structure, attribution and relationships are adhered to.
- **Dataset completeness**: the extent to which features, their attributes and relationships are present or absent in the dataset.
- **Temporal accuracy**: the temporal validity of a dataset (how current it is); the temporal consistency of a dataset (order in which events were captured); and rate of change the feature being mapped.

All of the above contributes to the overall accuracy of a spatial dataset, and many of these can be threatened by the introduction of errors during data capturing. Mainly three types of errors affect spatial data quality: human errors; instrumental errors; and environmental errors (Thapa and Bossler, 1992; Stine & Hunsaker, 2001; Züfle et al., 2020). Human error is introduced when those responsible for capturing the spatial data make mistakes – either accidentally or intentionally – such as inaccurately capturing variables, making typing errors or overlooking certain features. Instrumental errors concern faulty or incorrectly calibrated instrumentation; while environmental errors could result from environmental conditions at the time of measurement or measurements taken at the wrong time, e.g. not considering seasonality.

A final factor that can affect the accuracy of spatial data is the concept of error propagation. When a dataset is derived by combining several spatial datasets (e.g. identifying areas of high biodiversity based on data for individual species) the accuracy issues associated with each dataset are propagated due to the combination of variables (Delavar & Devilliers, 2010). Considering and acknowledging the limitations of spatial data in light of possible accuracy issues is of utmost importance to ensure responsible use and application.

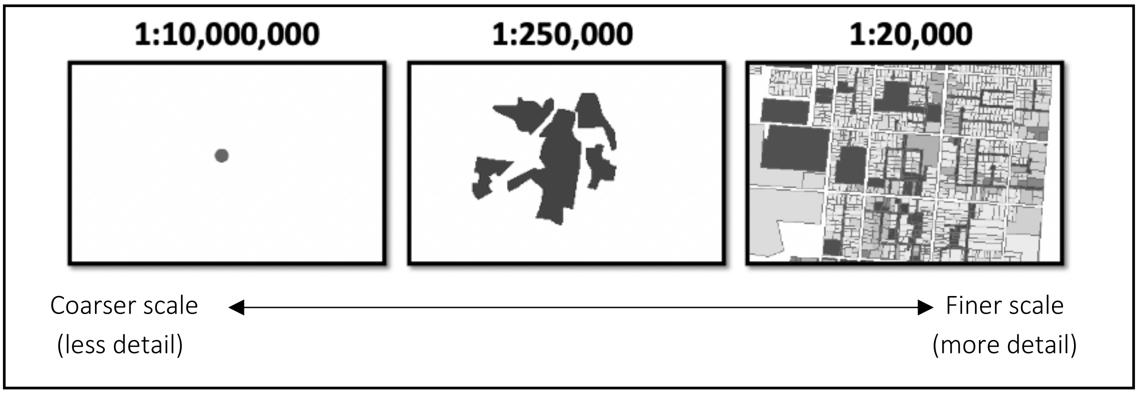
3.2. The importance of data scale

Depending on the level of detail at which real-world objects are translated to features on a map, the scale of the representation, i.e. scale of the spatial information, will differ (O'Sullivan & Unwin, 2003). Scale in this context can be understood as the degree of detail that is being reflected in the translation of real-world objects to features represented in spatial data (Zhang et al., 2004; Wong & Lee, 2005) and can be referred to as the data scale, i.e. the level of detail at which reality was translated into spatial information. Some detail will always be excluded when translating the complexities of the real world into maps and generalisation can subsequently be expected, i.e. cartographic generalisation.

Cartographic generalisation is the process of transforming real world features into forms suitable for representation on maps or in spatial data, and will increase with scale.

This concept can be illustrated when considering the representation of a city on a map. Our city can be represented as a dot on a map at a scale of 1:10 000 000, as an area at a scale of 1:250 000, or as a number of parcels, parks and streets clustered together to form a city, at a scale of 1:20 000 (Figure 1). The larger the scale of a dataset, the more detailed the representation will be. The use of 'large' and 'small' with the term 'scale' often leads to confusion and, for this reason, the terms 'coarse scale' and 'fine scale' will be used in this paper. A coarse scale dataset refers to a dataset that is at a small scale containing less detail, while a fine scale dataset refers to a dataset at a large scale containing more detail.

Figure 1. Implications of data scale



The translation of most real-world features into spatial information is scale dependant. One example is land cover which at a coarse scale only distinguishes between broad land cover types such as urban and natural areas, while at a finer scale, urban areas will consist of buildings and streets, while natural areas might be grasslands, shrubland and forests (Goodchild, 2011). According to Tobler (1987), when translating real-world features into spatial information, the size of the smallest detectable feature in a dataset will be twice that of the resolution of the dataset, i.e. if a building is 10m long it will be visible in a raster[2] dataset with a resolution of 5m or a vector dataset with a scale of approximately 1:10 000 if it is accepted that the smallest mark that can be displayed on a map is 0.5mm. The building will be visible at finer scales (larger than 1:10 000) or resolutions smaller than 5m, but not the other way around.

[2] Raster and vector data are two different formats used to store data in GIS. In raster data reality is represented as cells or pixels stored in rows and columns. A cell, therefore, represents the minimum mapping unit and can represent only one real-world observation, e.g. a lake or a tree. In vector data, reality is represented as either points, lines or polygons, e.g. a river as a line or a borehole as a point. Vector data generally allows for a more accurate representation of reality than raster data.

The data scale, therefore, has a direct influence on the scale at which data can be used for mapping and analysis purposes, often referred to as the working scale (Zhang et al., 2004). Working scale refers to the level at which the data can be assessed and is directly guided or determined by the scale of the available input data. Zhang et al. (2004) use the example of hydrological modelling to explain the concept. Hydrological modelling can be conducted for a sub-catchment or for a large region, either of which will affect the level of detail required, the questions that can be asked, and the answers that can be generated. Therefore, the two concepts are interdependent as the working scale will determine the data scale requirements while in the same way, the data scale will determine the working scale at which an analysis can be conducted. It is therefore important to understand what the spatial data represents at the given scale as most environmental processes are scale-dependent (Lam & Quattrochi, 1992; Zhang et al., 2004) and will be observed at certain scale intervals often referred to as process scale or characteristic scale (Wu & Li, 2006). If a certain process is required for analysis, the information must be collected and collated at that scale to ensure that the process is captured accurately (Zhang et al., 2004). For example, if individual plant species are to be mapped, a fine scale will be needed as opposed to mapping broad vegetation types which can be observed and mapped at a much coarser scale.

One challenge in practice is that the scale at which a phenomenon was measured and translated into spatial data, i.e. the data scale, and information on the accuracy of a dataset is not always declared or included in the metadata[3] (Johnston & Timlin, 2000; Foody, 2001; Cilliers, 2016). Without a clear understanding of data accuracy and scale, any decisions made based upon them, such as screening decisions informed by spatial data, might be questionable.

4. Methodology

A mixed-method approach was followed to address research Objectives 1 and 2 applying qualitative and quantitative methods, respectively. For Objective 1, the spatial information used during the screening phases of a selection of EIAs, i.e. the applicable spatial data in the National Screening Tool, were compared to the findings from specialist reports to determine the accuracy of the initial spatial information informing the screening decision. Only professionals registered with the South African Council for Natural Scientific Professions may compile specialist reports. They further have to follow the applicable protocols and guidelines for specialist studies (South Africa, 2020) to ensure that all studies adhere to set standards and produce high quality data. For Objective 2, spatial information on key environmental variables at different scales were compared and analysed to determine the extent to which scale might influence screening decisions.

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[3] Metadata can be understood as the information describing the spatial dataset. It will include information such as the age of dataset, the data format and the scale of the dataset.

4.1. Objective 1 –Evaluate the accuracy of spatial data in screening determinations through auditing

Selection of EIA studies and reports

EIA reports were obtained from an EIA database made accessible by the National Department of Environmental Forestry and Fisheries (DEFF). Reports were selected for review based on the following criteria:

- The EIA had to be triggered by an environmental feature indicated by a spatial dataset as being present in the EIA study area.
- The EIA report had to contain a specialist report dealing with the applicable environmental feature.
- The specialist report had to contain information or maps of the feature resulting from an on-site assessment for comparison with the spatial information used during screening.

A total of ten reports adhered to the criteria and were subsequently selected. The case study selection approach excludes screening decisions that EIA was not needed. Scale issues could have led to such decisions being made inappropriately, but the cases are difficult to identify as they are not available on a central database. The subsequent analysis is, therefore, limited by this exclusion.

Analysis

The spatial features used during the screening processes for the ten EIAs were first mapped from the EIA report. The findings from the applicable specialist reports, including maps generated by the specialists, were then compared to these maps to determine the extent to which the findings from the specialist study (on-site assessment more closely reflecting the real-world situation) aligned with the features used during screening. For each reviewed EIA screening decision, the screening dataset was rated as being either 'accurate', 'partially accurate' or 'inaccurate' through the site survey as documented in the specialist report. An 'accurate' rating was awarded if the site assessment confirmed all or most of the spatial data (features and their extent) used in the screening decision while a 'partially accurate' rating was awarded if at least some of the features in the screening dataset was confirmed to be present on site. Finally, an 'inaccurate' rating was awarded if little to none of the features in the screening dataset were confirmed.

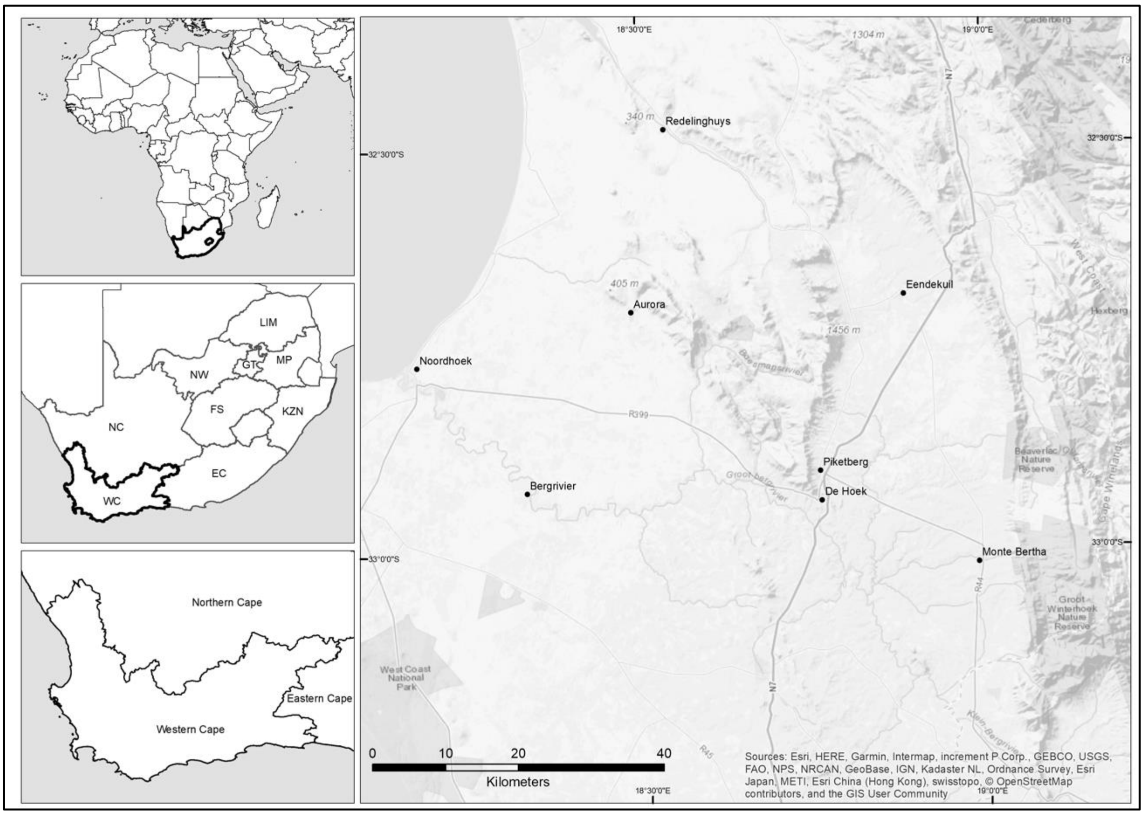
4.2. Objective 2 – Analyse how data scale might influence screening decisions

Study area

To analyse how data scale might influence EIA screening decisions based on spatial information, a study area had to be selected. The Bergrivier Local Municipality (Figure 2) located in the Western Cape Province was selected for the following reasons:

- The study area is characterised by a mixture of topographical features including relatively flat plains, valleys, as well as some mountainous areas which all result in a diverse and varying landscape.
- The area forms part of a Global Biodiversity Hotspot, and large sections are considered to be sensitive habitat.
- There are numerous water features, such as streams and rivers that flow through the study area.
- Data on environmental variables were readily available at different scales.

Figure 2. Bergrivier Local Municipality



Spatial datasets

Datasets on environmental variables were sourced from a variety of data custodians including the Department of Environmental Affairs, the South African National Biodiversity Institute (SANBI) and the Chief Directorate: National Geo-spatial Information

(CD:NGI). All datasets were reviewed for data scale, content and completeness. Although data on most environmental variables are generally available in South Africa, these datasets are often only available at one or two scale intervals and most often not at very fine scales, e.g. 1:5 000. This reality further supports the selection of South Africa as a case study as screening decisions are often made using spatial information at a relatively coarse scale. Only three environmental variables were found to have suitable and complete datasets available at two different scales of 1:50 000 (representing a relatively fine scale) and 1:250 000 (representing a relatively coarse scale) respectively, which were:

- Topography: Data on topography indicated hills and ridges in the study area and was derived from contour and spot height data obtained from a CD:NGI database used to compile national 1:50 000 and 1:250 000 map series. In South Africa, hills and ridges are regarded as important biodiversity corridors linking different habitats patches. This is especially relevant in heavily transformed areas such as the Gauteng Province which also has a 'Ridges guideline' dedicated to their protection (GDARD, 2019). Hills and ridges are, therefore, often reflected as sensitive areas in mechanisms such as environmental management frameworks (EMFs) which are used to inform screening decisions in terms of Listing Notice 3 of the EIA Regulations which calls for an EIA if a sensitive area as identified in an EMF is affected (South Africa, 2017b).
- Hydrology: The hydrology datasets, were also obtained from the CD:NGI database and indicated perennial and non-perennial rivers and streams, as well as wetlands for the area. Hydrological features such as rivers and wetlands are regarded as highly sensitive in South Africa. Listing Notice 3 (South Africa, 2017b) stipulates that certain activities will be subject to an EIA if they are within 100m of a watercourse or wetland.
- Sensitive biodiversity: Data on sensitive biodiversity was obtained from the SANBI and showed areas regarded as being either endangered or critically endangered. Most activities mentioned in Listing Notice 3 of the EIA Regulations (South Africa, 2017b) are subject to an EIA if the proposed footprint intersects with any mapped areas of sensitive biodiversity – often referred to as critical biodiversity in practice.

Although not crucial to the analysis, all three environmental variables are applicable to EIA screening in South Africa, either through direct reference in the EIA regulations or through use in related screening tools such as environmental management frameworks (EMFs).

Analysis

To analyse how data scale might influence screening decisions the selected datasets representing the three variables were first projected into the UTM 34S projection (WGS

1984 Datum) to allow for area calculation and distance measurement. Datasets were then analysed through two steps:

- Step 1: The three environmental variables were compared for the whole Bergrivier Local Municipality. Variables were mapped at the two different scales and clipped to the extent of the study area resulting in six datasets for use in further analysis. Features were either represented as polygons (topographical features and vegetation) or lines (rivers) for which geometrical properties were calculated using hectares (ha) and kilometres (km) respectively. The results were tabulated for further analysis and interpretation.
- Step 2: The three environmental variables were compared for a selection of simulated EIA footprints. A total of 100 sample points was randomly generated across the study area using the 'Create random point' tool in ArcMap 10.6.1. The 'Buffer' tool was then used to generate buffers of 200m around each of the 100 random sample points. The resulting polygons each covered an area of approximately 12.5ha (UTM 35S) and was used to simulate EIA project footprints. Data on the three environmental variables (topography, hydrology and sensitive biodiversity) were extracted for each site at the two different scales to determine whether environmental attributes were present on the simulation sites or not. The number of sites in which each dataset at each scale was present was tabulated and summarised for interpretation purposes.

The findings were analysed to determine the manner and extent to which data scale could further influence screening decisions in EIA.

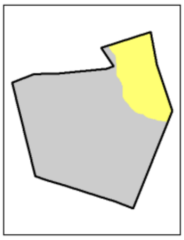
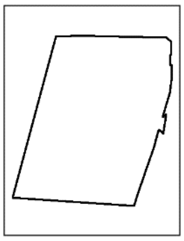
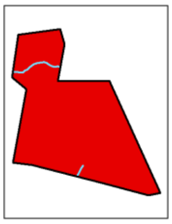
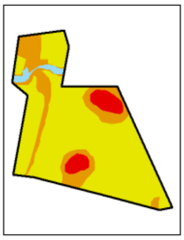
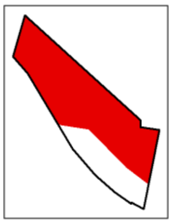
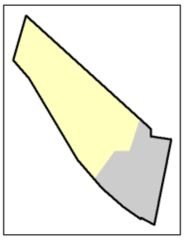
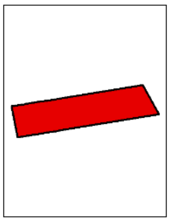
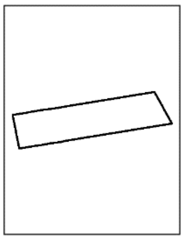
5. Results and discussion

The following sections present the findings for the two objectives. The accuracy of spatial data that informs screening decisions is discussed first followed by a discussion on the influence of scale on screening decisions.

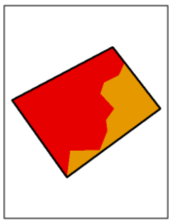
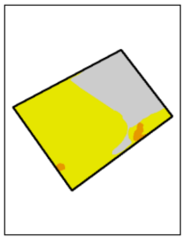
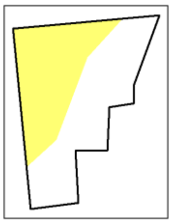
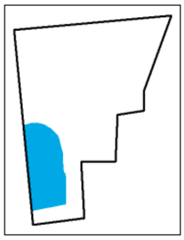
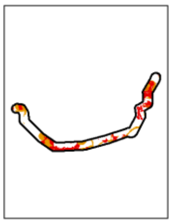
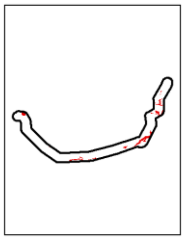
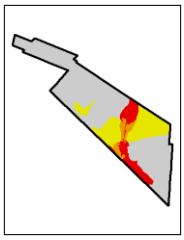
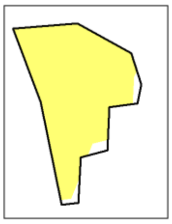
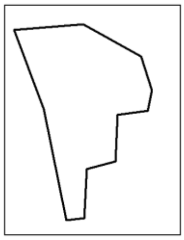
5.1. The role of spatial information accuracy in informing screening decisions (Objective 1)

Table 1 summarises the results from the review of ten EIA cases and shows the extent to which findings from the specialist reports confirmed the accuracy of the information contained in the applicable datasets used during screening.

Table 1. Results from evaluation process

	Screening			Notes on the accuracy of information	
EIA	Screening feature	Description of feature used during screening			
1	Terrestrial critical biodiversity areas (CBA) GNR 329 12(h)(iv)[4]	 The spatial dataset indicated that there were CBAs[5] (red on map) present on the site.	Inaccurate	Site assessment did not confirm any areas of critical biodiversity value to support justification as a CBA and rated the site as medium-low (yellow) to low sensitivity (Grey on map).	
2	Terrestrial critical biodiversity areas (CBA's) GNR 329 12(h)(iv)	 The spatial dataset indicated the total area as a CBA (red on map).	Inaccurate	Site assessment did not confirm any areas of critical biodiversity value to support justification as a CBA and rather reported erosion, alien invasive species and transformation. No features were mapped.	
3	Water course and terrestrial critical biodiversity areas (CBA's) GNR 983 12(xii)(a), GNR 985 2(e)(ii)(dd), GNR 985 12(a)(ii). GNR 985 14(xii)(a)(e)(i)(ff), GNR 985 16(d)(i)(ee)	 The spatial dataset indicated the total area as a CBA (red on map). It also indicated the presence of water courses (blue lines).	Accurate	Site assessment confirmed water course (blue) and areas of critical biodiversity (red and orange) which justified its status as a CBA.	
4	Terrestrial critical biodiversity areas (CBA's) GNR 324 6(h)(iv), GNR 324 6(h)(v), GNR 624 12(h)(iv)	 The dataset indicated that there was a large CBA (red) present on the site.	Inaccurate	Site assessment did not confirm any areas of critical biodiversity value to support justification as a CBA and rated the site as low (grey) and medium-low (yellow) sensitivity.	
5	Terrestrial critical biodiversity areas (CBA) GNR 327 12(h)(iv)	 The spatial dataset indicated the total area as a CBA (red on map).	Inaccurate	Site assessment did not confirm any areas of critical biodiversity value to support justification as a CBA. The report states that the presence of threatened animal and plant species is unlikely. No features of significance were mapped.	

[4] The GNR codes refer to the specific listed activity and environmental attribute applicable to the screening decision.
[5] Critical Biodiversity Areas (CBA's) are areas required to meet biodiversity targets for ecosystems, species and ecological processes, as identified in a systematic biodiversity plan.

	Screening			
EIA	Screening feature	Description of feature used during screening	Notes on the accuracy of information	
6	Terrestrial critical biodiversity areas (CBA's) GNR 324 12(e)(ii)	 The spatial dataset indicated a large portion of the site to be CBAs of different importance (red and orange on map).	Partially accurate	Although not regarded as a site of critical biodiversity value to support CBA status, some protected tree species did occur, resulting in a high (orange) and medium (yellow) sensitivity rating allocated to the site. 
7	Aquatic ecological support areas (ESA's) GNR 324 12(v)	 The spatial dataset indicated most of the area to be an ESA[6] (yellow on map).	Partially accurate	A wetland not indicated in the screening dataset was, however, present on the site (blue). Although the screening data indicated a 'support area' this was much more sensitive, i.e. wetland (CBA). 
8	Terrestrial critical biodiversity areas GNR 985 10(c)(iv), GNR 985 12 (c)(i)(ii)	 The spatial dataset indicated a number of CBAs (red and orange on map).	Partially accurate	Site assessment confirmed some of the sensitive features (red and orange) indicated in the screening dataset, but not all features. 
9	Terrestrial critical biodiversity areas GNR 324 12(a)(ii), GNR 324 14(h)(iv)	 The spatial dataset indicated a number of CBAs on the site (red on map).	Accurate	Site assessment confirmed many features indicated in the screening dataset. This included areas of very high (red), high (orange) and medium (yellow) sensitivity. 
10	Terrestrial ecological support area GNR 324 12(h)(iv)	 The spatial dataset indicated an ESA (yellow on map) covering part of the site.	Inaccurate	Site assessment reported high alien invasive richness as well as bush encroachment and did not confirm the area as an ESA serving a CBA. No features of significance were mapped. 

In five of the ten cases (cases 1, 2, 4, 5 & 10) reviewed the features represented in the spatial information used during screening was not confirmed through the site assessments and therefore regarded as inaccurate. The screening datasets indicated either critical biodiversity areas or ecological support areas to be present on the sites, but these were not confirmed through the site assessments which did not find any evidence that the species and species diversity that would constitute a critical biodiversity area were present on the site. Such inaccuracies are often a challenge with biodiversity

[6] Ecological Support Areas are not essential for meeting biodiversity targets but play an important role in supporting the ecological functioning of Critical Biodiversity Areas and/or in delivering ecosystem services.

mapping specifically which often combines data from various disciplines and databases (Bowker, 2000) that is not always objectively interpreted (Malavasi, 2020), affecting the manner in which biodiversity is mapped. Accuracy issues in individual datasets further often leads to error propagation (Delavar & Devilliers, 2010) affecting the accuracy of resultant biodiversity datasets. In addition to these, the mismatch between the screening dataset and the site assessment could also be ascribed to the temporal accuracy of the screening dataset. This is, however, unlikely as the biodiversity screening datasets, specifically, are regarded as living datasets that are regularly updated. The issue is much more likely the result of the spatial scale at which biodiversity features were mapped.

In three of the ten cases (cases 6, 7 & 8), the site assessments partially confirmed the features indicated in the screening datasets, while the screening datasets were regarded as fully accurate in only two of the ten cases (cases 3 & 9). These findings suggest that spatial data on its own – especially if used without the possibility of discretion – are in many cases inaccurate to inform screening decisions. This is both because features are sometimes overrepresented on some sites leading to unnecessary assessments and underrepresented on other sites resulting in assessments not being conducted erroneously.

This implies that screening processes should ideally not rely on lists and spatial data alone and should allow for discretion to be applied by the decision-makers. A case can also be made that information obtained through preliminary site surveys or site visits must be used to inform a screening decision where spatial information is concerned. In at least four of the ten cases (cases 2, 4, 5 & 10) the screening decisions would have been affected by an overrepresentation in spatial data as the screening dataset indicated large areas of sensitive biodiversity covering the entire EIA footprint (Table 1) while the site assessment could not confirm this. This issue of overrepresentation can most likely be attributed to the issue of data scale as is further explored in the next section.

5.2. Influence of data scale on screening decisions (Objective 2)

Tables 2 and 3 show the results for comparison of the datasets and the features contained in each dataset at different scales, ranging from coarser to finer scales. Table 2 shows the comparison across the entire study area, while Table 3 shows the comparison for the 100 simulated EIA footprints. The findings are presented per environmental variable. For each variable, the comparison across the entire study area is discussed first followed by a discussion of the findings for the 100 simulated EIA footprints.

Table 2: Comparison of datasets at different scales across the entire study area

Attribute	Coarse scale	Fine scale
Topography		
Hills and ridges	105 473ha	62 036ha

Hydrology		
Perennial rivers	480km	567km
Non-perennial rivers	126km	4 797km
Wetlands	17 wetlands	426 wetlands
Biodiversity		
Critically endangered	145 947ha	146 594ha
Endangered	187 936ha	147 027ha

Table 3: Comparison of datasets at different scales for 100 simulated EIA footprints

	Topography	Hydrology	Sensitive biodiversity threat status	
			Critically endangered	*Endangered*
Feature present in fine scale	56*	58	34	40
Feature present in coarse scale	45	10	31	46
Feature present in coarse scale only	10	0	3	15
Feature present in fine scale only	21	48	6	9
Feature present in fine scale and also reflected in coarse scale data	35	10	28	31
Accuracy of coarse scale#	63%	17%	82%	78%

* The figures represent the number of sample sites in which the relevant environmental feature was present.

Accuracy expressed as the percentage of the sample sites where fine scale features were present that was also reflected in the coarse scale dataset (e.g. 35/56)

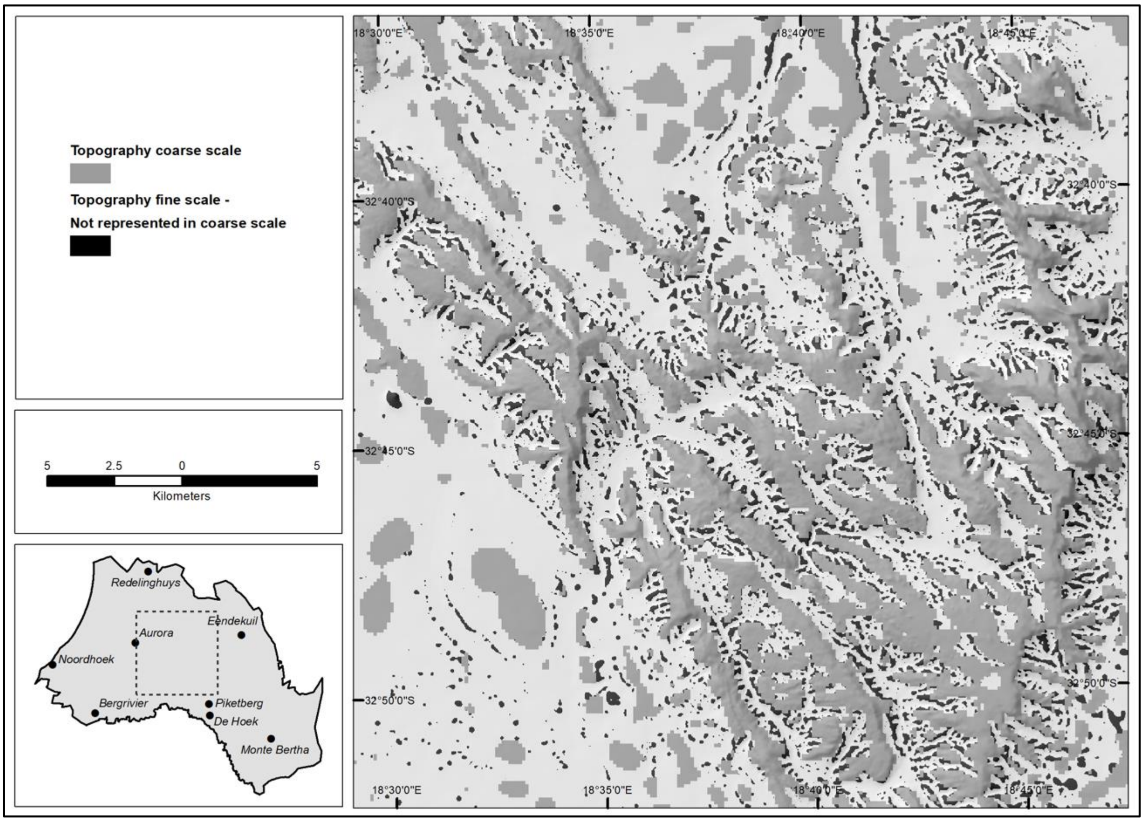
Topography

In terms of area size (Table 2), topographical features in the study area were overrepresented at a coarse scale when compared to the fine scale dataset (45 437ha larger than fine scale dataset). However, when comparing the spatial footprints of the two datasets (Figure 3), it was found that 43% of the fine scale dataset (26 410ha) was actually not represented in the coarse scale dataset at all. If it is accepted that the fine scale dataset is a more accurate and realistic representation of reality, this means that regardless of the difference in footprint size, many of the areas indicated as hills and ridges in the coarse scale dataset are in fact misrepresented in the data and many features not reflected at all.

In terms of the 100 simulation sites, topographical features were present in 56 sites at a fine scale and only 45 at the coarse scale (Table 3), suggesting that topographical features are underrepresented in the coarse scale dataset. This finding aligns with the finding above that, although the coarse scale dataset covers a larger footprint in hectares, the footprint does not include all the features indicated by the fine scale dataset. This is further illustrated by the fact that coarse scale topographical features were missing on 21 of the 56 sites where features were present in the fine scale dataset (37% of sites). The coarse scale dataset further indicated topographical features on ten sites for which features were not present in the fine scale dataset. However, 63% of the sites where coarse scale topographical features were present also contained fine scale topographical features.

This implies that although features might sometimes seem to be well represented in terms of area coverage at a coarse scale, the reality is that these features might often be misrepresentative of reality in terms of their positional accuracy and spatial form. In cases where coarse scale topography datasets are used to screen EIA applications, this might result in both unnecessary assessments being conducted and necessary EIAs being missed. This does not imply that these datasets cannot be used for screening purposes, but it should be noted that the idea that a coarse scale dataset, although producing false positives (possibly unnecessary EIAs), will cover all the issues reflected in a finer scale dataset does not necessarily hold true.

Figure 3. Topography across the study area



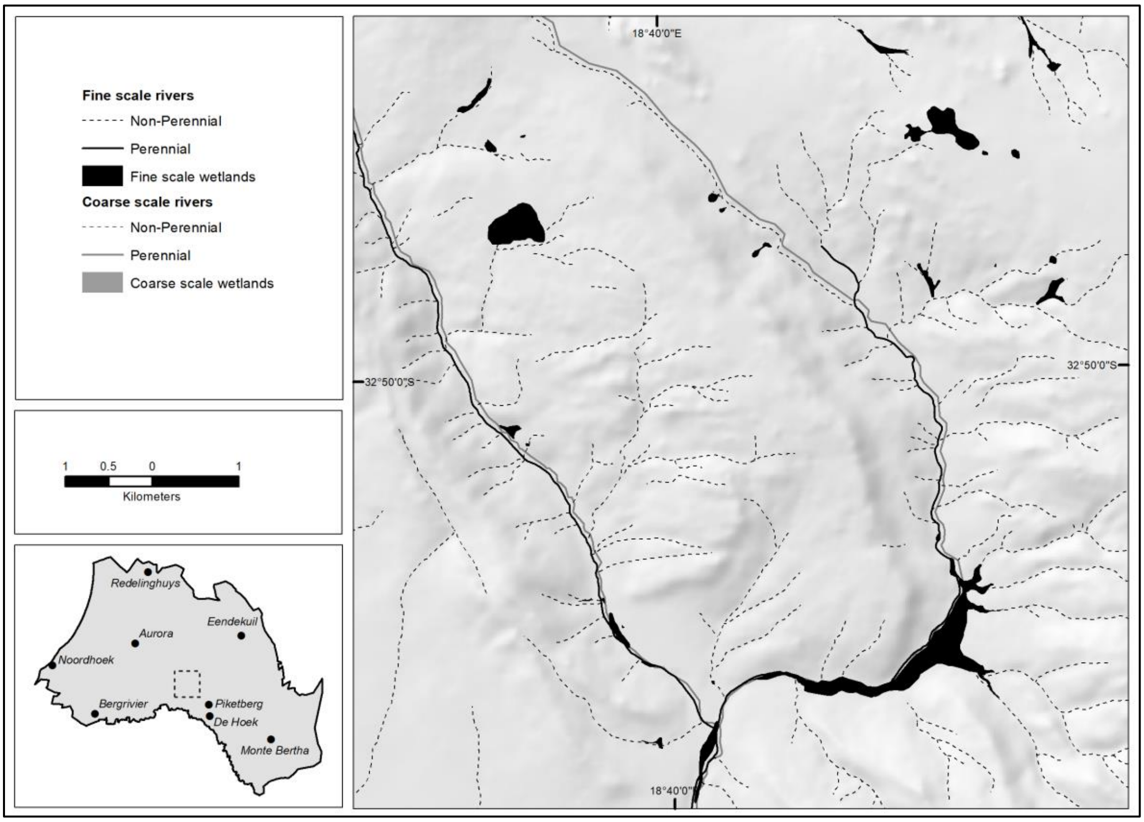
Hydrology

The total length for all perennial river features in the fine scale dataset was 567km compared to 480km for coarse scale rivers (Table 1). These differences were much more significant for non-perennial rivers which had a total length of 4 797km – in excess of 35 times more stream and river sections than the 126km indicated in the coarse scale dataset. The same trend was also present in the representation of wetlands where only 17 wetlands were indicated in the coarse scale dataset, while the fine scale dataset contained 426 (Table 2). In addition to the underrepresentation of rivers and wetlands in the coarse scale dataset, there was also a clear difference in the spatial accuracy of the representation (Figure 4). Shapes and locations of river features were not well retained in the coarse scale dataset, and positional accuracy issues ranging between 60m and 120m were measured across the study area.

The above was confirmed as hydrological features at the coarse scale was present in only ten simulation sites as opposed to fine scale features that were present on 58 sites (Table 3). Hydrological features were therefore severely underrepresented in the coarse scale dataset. From the 58 sites, a total of 48 (83%) sites reflected no coarse scale hydrological features. This is most likely as a result of the underrepresentation of non-perennial rivers in the coarse scale dataset.

The potential effect of these differences on the validity of EIA screening based on hydrological features can be illustrated through the consideration of a spatial screening criterion in South African legislation. According to Listing Notice 3 (South Africa, 2017), certain activities that are "within 100m of a watercourse or wetland" will be subject to an EIA. If this criterion is screened against a coarse scale dataset, this will mean that certain watercourses will be missed altogether or the distance between a development and a watercourse miscalculated. In both cases, this results in ineffective screening.

Figure 4. Hydrology across study area



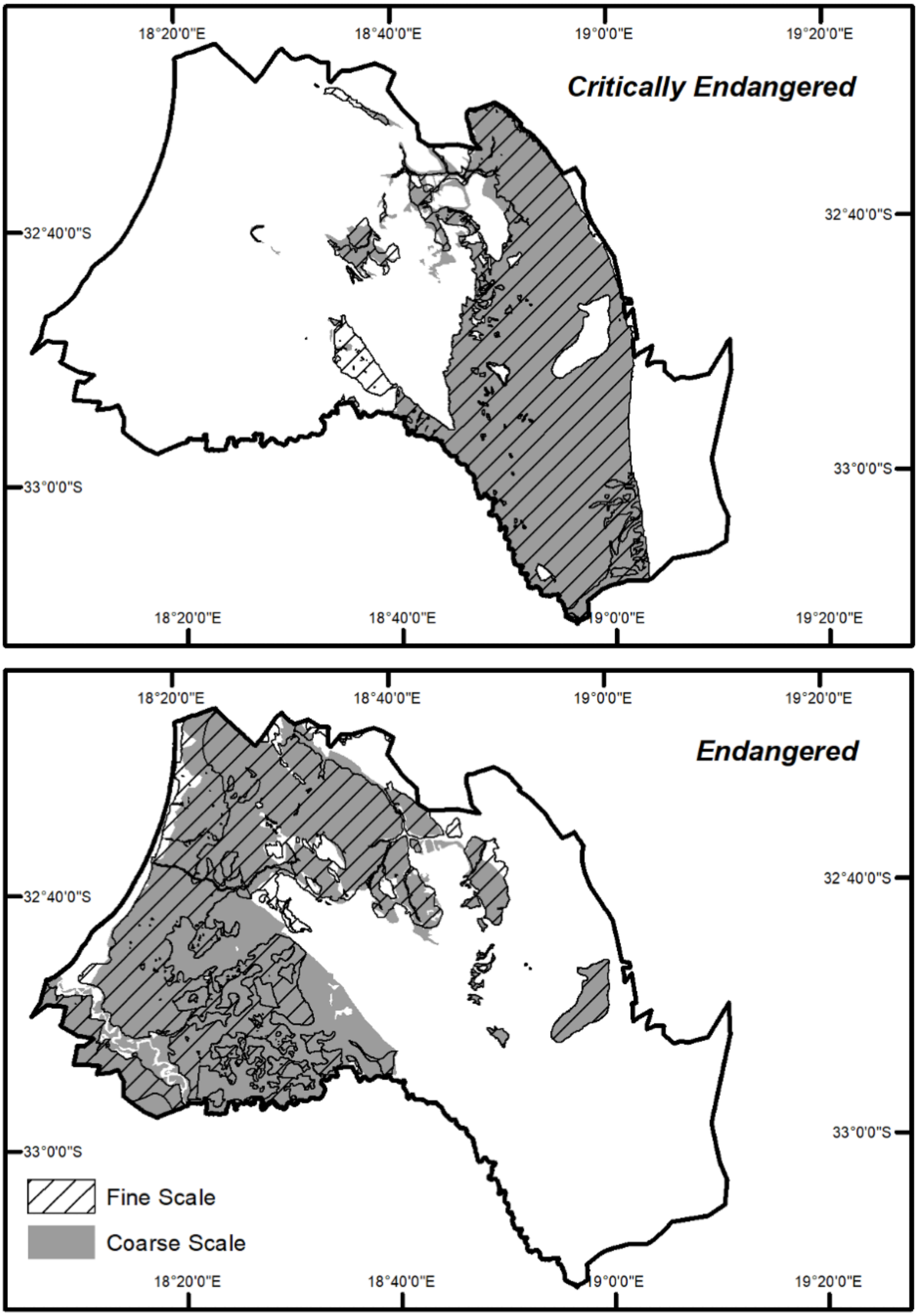
Biodiversity

The sensitive biodiversity datasets showed terrestrial areas in the study area that are regarded as being either endangered or critically endangered. The areas were derived from vegetation datasets at scales of 1:50 000 and 1:250 000 respectively. Although area sizes did not differ dramatically between the two datasets (Table 2), there were some clear differences in spatial extent and level of detail. The biggest differences were observable between the footprints of the fine and coarse scale datasets for endangered biodiversity (Figure 5) where the fine scale dataset was significantly more detailed.

In terms of the 100 simulation sites, the datasets at the two scales compared fairly well although the coarse scale dataset indicated critically endangered features on three sites where they were not indicated by the fine scale dataset, suggesting some overrepresentation. Endangered biodiversity again showed a larger variation between the coarse and fine scales with fine scale features registered for 40 sites while coarse scale features were present on 46. The number of sites on which only coarse scale features were present were much larger at 15, illustrating the effect of the lack of detail (lower spatial accuracy) of the coarse scale dataset.

The implication of data scale for biodiversity data is similar to that discussed for topographical features. This implies that assessments on areas regarded as being critically endangered might be missed as a result of misrepresentation in coarse scale datasets and also that unnecessary EIAs might be conducted due to overrepresentation which most likely explains the findings presented in Table 1.

Figure 5. Biodiversity across the study area



The findings suggest that data at a coarser scale can result in both unnecessary EIAs as well as important EIAs not being conducted. Although both of these scenarios could in some cases be at least partially avoided through site visits the non-discretionary list-based approach – as applied in South Africa – means that a decision will be made based on the information contained in the applicable spatial datasets. The absence of public participation in the screening phase of many systems, such as in the cases of South Africa, India (Dilay et al., 2020), Pakistan (Nadeem & Fischer, 2011), China (Brombal et al., 2007) and some European countries (Hasan et al., 2018), further means that inputs related to the presence of features not represented may be missed. In light of these issues, calls have been made for public participation to be included during the screening stage of EIA (Choudhury, 2014).

6. Conclusion and recommendations

This paper aimed to explore the validity of screening based on spatial information by evaluating the accuracy of spatial information in screening determinations through auditing and analysing how data scale might influence screening decisions. The research results suggest that – in the case of the South African prescriptive EIA screening system – decisions informed by spatial information might, in many cases, be informed by inaccurate data, exacerbated where the information used is at a relatively coarse scale. The paper illustrated how scale can influence EIA screening decision based on spatial data. An evaluation of EIA screening decisions further showed the effect that data accuracy, of which scale is a key component, can have on decisions, especially if data quality is not desirable.

Although it should be acknowledged that spatial data will never be completely accurate and that it will always be prone to a level of inaccuracy, the following recommendations are made to improve the validity of EIA screening:

- Consider and acknowledge the limitations of spatial information: It should be acknowledged that spatial data is at most only a simplified representation of reality (Bernhardsen, 2002) and therefore, only reflects a partial truth. This implies that some features might be missing or misrepresented; however, the scale of a dataset is a key aspect that determines the extent to which this happens.
- Consider the data scale: The scale of a dataset will have a direct impact on EIA screening. As the scale of datasets used in EIA screening decreases (becomes coarser) the likelihood increases for both unnecessary EIAs to be conducted and necessary EIAs to be overlooked. The former is as a result of false positives contained in the coarse scale data while the latter pertains to the incompleteness and positional accuracy associated with coarse scale data. The data scale associated with a particular dataset, therefore, gives an indication of the level of detail contained in the dataset (as a reflection of reality). The use of spatial information should, therefore, be confined to the limitations posed by the data scale.

- **Finer is better**: Although an ideal data scale for EIA cannot be proposed due to the various contextual complexities associated with capturing and maintaining spatial datasets, a general rule is that finer scale data is always better. Government agencies and data custodians should continually work towards developing improved and more detailed spatial datasets.

It is important that all EIA role-players apply critical spatial thinking when dealing with spatial information to ensure that the limitations of spatial information and its possible effects on screening decisions are well understood. Although there is generally a need for more flexibility in screening approaches (e.g. Geneletti et al., 2017) the following recommendations can be made pertaining to, specifically, prescriptive based screening processes relying on spatial information:

- **Allow for discretion:** Screening mechanisms relying on spatial information must allow for discretion to be applied when decisions are taken. This research has demonstrated that data are frequently inaccurately portrayed, and therefore there must be flexibility and discretion allowed to evaluate the relevance and applicability of spatial information.
- **Allow for the consideration of additional information:** The use of supporting evidence from site visits or site assessments could further be considered as a way to verify the accuracy of spatial information. Site visits by specialists as part of the screening phase might, despite being an additional cost, be a way to avoid unnecessary EIAs and thereby saving valuable time and resources. Advances in technology are already leading to low-cost approaches for additional site surveys using drones (e.g. Paneque-Gálvez et al., 2014) – and this may be a suitable means of ensuring more accurate data for screening purposes.
- **Allow for input into the screening process:** The inclusion of public participation during the screening stage already should also be considered. This will be especially valuable in cases where data is underrepresenting reality and the public might be aware of important environmental attributes that exist but are not indicated in the spatial information.
- **Determine metadata standards for spatial data used in screening:** Determining and publishing metadata standards for spatial datasets used in EIA screening processes should be considered. This will contribute to ensuring that data accuracy is acknowledged in the process and that spatial data is used within its limits.

Effective screening is a key requirement for any well-functioning EIA system. Spatial information is in many counties a critical input to decision making during the screening phase and therefore understanding and awareness of inaccuracies of spatial information as well as the effect of scale is important for regulators and consultants alike. Efforts should further be made by governments and their applicable data custodians to implement measures aimed at continually improving the accuracy of spatial datasets. An example of such an initiative is the establishment of the Infrastructure for Spatial Information in the European Community (INSPIRE) which contributes to improved quality and accessibility of spatial data across participating European countries (INSPIRE, 2021). Our hope is that this paper progressed our understanding of how spatial information and scale might influence the validity of screening decisions, and thereby the performance of EIA systems.

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