The impact of modifiable areal unit problem on estimation of lake extent

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The impact of modifiable areal unit problem on estimation of lake extent

by

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Thesis submitted to the University of Twente, faculty ITC, in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation for Environmental Modelling and Management

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ITC FACULTY OF GEO-INFORMATION SCIENCE AND EARTH OBSERVATION
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Abstract

Pixels are the basic modifiable units of remotely sensed data. Modification in the size of the pixels or shift in location of the grid relative to scene can lead to a numerous possible datasets, which can lead to different inferences of same object. This problem is recognized as modifiable areal unit problem (MAUP). The research explored the impact of the MAUP on remote sensing by investigating the aggregation and zonation components of the MAUP using crisp and vague lake boundaries. Comparison of the aggregated data with actual sensor resolution was also studied. The study was conducted on two lakes, one with a crisp (Lake IJsselmeer, Netherlands) and other with a vague boundary (Lake Naivasha, Kenya). Landsat TM (Thematic Mapper) data of both lakes were used to study the aggregation and zonation components. Seven aggregation levels were carried out of TM data of Lake IJsselmeer and 4 aggregation levels of TM data of Lake Naivasha. Images were classified into two classes ‘water and no water’. Lake parameters were estimated for all classifications and results were compared and analysed. MODIS (Moderate Resolution Imaging Spectroradiometer), TM and ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) data of Lake IJsselmeer were used to compare aggregations with actual sensor. The results revealed that with increasing levels of aggregation, both the lakes show almost contrasting trends. Despite having same level of aggregation, drastic differences were observed in the area and perimeter of lake at different zonations. On comparing MODIS, TM and ASTER, it was realized that the ASTER data provided highest value of area and perimeter. Differences in the area and perimeter were observed on comparing aggregated data with actual data. The study demonstrated the dependence of remotely sensed data on the arrangement and spatial resolution of the sampling grid. It was observed that at lower aggregation levels of a fine spatial resolution dataset (with respect to object size), the effects of MAUP are too small to be significant. Therefore, can be ignored but at coarser resolutions it becomes crucial. The study has highlighted MAUP as major spatial uncertainty in remote sensing.

Keywords: modifiable areal unit problem (MAUP), aggregation & zonation.
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1. Introduction

1.1. Motivation

Owing to the capability of synoptic coverage, Earth observation satellites have a potential to provide data on natural resources at different scales for better differentiation of landcover types and improved understanding of landscape pattern. The tremendous progress in the field of satellite remote sensing has provided enormous choices to the scientific users in terms of satellite data at various spectral, spatial and temporal resolutions. Diverse ranges of satellite data starting from very fine spatial resolution imagery like IKONOS (1m) to very coarse spatial resolution datasets like AVHRR (1km) are available. In order to use effectively the information from the remotely sensed data, it is crucial to understand the issues concerning their use. Since archives of satellite remotely sensed data are at different spatial resolution, it is difficult to extract the significant information on spatial extent accurately. The enormous information contained at each data source becomes serious issue of concern when there is a need to integrate the various datasets (Ludwig et al. 2007). The difference in spectral bands, acquisition time and spatial resolution affect the land cover classification and its interpretation (Kerr and Ostrovsky 2003; Lu and Weng 2007). The difference in spatial resolution makes different datasets incomparable. Therefore, seriously limits the potential usefulness of quantitative analysis of landscape patterns (Saura 2004). The issue of scale has been recognized many years ago by scientists in several fields, including ecology (Turner et al. 1989), hydrology (Stewart et al. 1996), environmental modelling and remote sensing (Raffy 1992). However, limited attention has been paid to the element of uncertainty attached to it.
1.2. Background and Significance

Natural processes occur at different spatial and temporal scales. For some processes like, monitoring the trends in lake extent, it is imperative to study images over several years or decades. During this period the availability of sensors change, hence data from different sensors is used to assess the change over time. Remote sensing provides the data on multiple scales to draw inferences about the processes. Different sensors provide data with different resolutions which poses the issues of scale, accuracy and has implications of uncertainty associated with the sensor resolutions (Fisher 1997; Stein et al. 2009).

There is difference between the scene and the image. Scene is real that exists on ground. However, the image is “collection of spatially arranged measurements drawn from scene” (Strahler et al. 1986). These spatially arranged measurements are the basic unit of remotely sensed datasets, often called pixels. These basic units can be of different sizes or resolutions. If the sizes of the pixels are changed or shift in location of the grid relative to real scene on ground, then it can lead to a numerous new datasets which will provide different results. One object might have different shape and size when inferred from different images at different resolutions. This problem is recognized as the modifiable areal unit problem (MAUP) (Openshaw 1984; Jelinski and Wu 1996).

The MAUP includes two distinctive though related components: scale or aggregation and zonation. In other words it can be said that MAUP involves both effect of altered pixel size and the way of its alteration in a spatial context. In order to understand certain spatial patterns at landscape level, aggregation of fine resolution spatial data to coarser resolution is often performed (Turner et al. 1989). Often this leads to a problem in spatial analysis where, areal units have been aggregated to different sizes. This is known as aggregation effect of MAUP. The process in which number of pixels remains unchanged or fixed but their arrangement changes is a zoning process which gives rise to various zonations or zoning system (Wong 2009). Despite fixed scale, there is multitude of ways in which basic areal
units of analysis can be aggregated into different spatial arrangements or zonations. The areal units combine in various zones of same size, but their boundaries differ (Stein et al. 2009). Different zonations of same region can provide different interpretations. This inconsistency due to different zonations creates zoning problems, which is another component of MAUP. Zoning problem occurs due to two different reasons. Firstly when aggregation is done based on different starting point (figure 1). Secondly, due to shift in location of the grid relative to the scene (figure2). These lead to a numerous new datasets with different interpretations.

Figure 1. Four possible different zoning systems resulting from 2x2 level aggregation of satellite data.
1.3. Problem Statement

Effects of the MAUP should be completely understood in order to avoid flaws in the result (Marceau and Hay 1999). However, limited attention has been paid to the complete understanding of the MAUP. Though there is no dearth of literature in GIS, little attention has been paid to zoning aspects of the MAUP in remote sensing. This is considered as a vital lacuna in understanding of MAUP issues. Moreover, no studies have so far determined the modifiable areal unit problem in addressing lake extent using multiscale datasets.
1.4. **Research Objectives**

The proposed study identifies the objectives mentioned and addresses questions on issue of MAUP.

1.4.1. **General Objective**

The general objective of the study is to investigate zonation and aggregation component of MAUP using crisp and vague lake boundaries.

1.4.2. **Specific Objectives and Questions**

The specific objectives and research questions addressed in the study are given in Table 1.1.

<table>
<thead>
<tr>
<th>Specific research objectives</th>
<th>Research questions</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. To evaluate the impact of aggregation on the inferences of spatial extent.</td>
<td>1. How do the estimates of lake parameters (area, perimeter and compactness) change on spatially aggregating the fine resolution data to coarser resolutions?</td>
</tr>
<tr>
<td>2. To investigate the impact of zonations on inferences of spatial extent.</td>
<td>3. How do the estimates of lake parameters change on using different zonations?</td>
</tr>
<tr>
<td>3. To compare the estimates (area and perimeter) inferred from aggregated data with the estimates inferred from data of similar native resolution (actual data).</td>
<td>4. Do the lake parameters estimated from of aggregated satellite data differ from estimates inferred from data of same native resolution of different sensor?</td>
</tr>
</tbody>
</table>
1.5. Organization of Thesis

The thesis is structured in 7 main chapters. Chapter 1 provides introduction to the MAUP and its components, research problem and objectives of the study. Chapter 2 deals with the literature reviewed pertaining to the research. Study areas are presented in chapter 3 followed by data used and its processing for study. Chapter 4 provides the methodology adopted to fulfil the research objectives. Results obtained from the study have been given in chapter 5. The results are studied and discussed in chapter 6. The study has been concluded with recommendations in chapter 7 followed by references and appendices.
2. Literature Review

2.1. Historical perspective

The modifiable areal unit problem (MAUP) was first observed by Gehlke and Biehl (1934) on exploring the effects of different groupings on the size of correlation coefficients. Later some studies also found similar patterns and experienced the issue of MAUP (Robinson 1956; Clark and Avery 1976). Perle (1977) linked the issue of MAUP to the concept of ecological fallacy. The ecological fallacy refers to the inconsistency in analytical results of statistical data collected for the group to draw inferences about individuals of group (in ecological context). Openshaw and Taylor (1979) first coined the term MAUP, they studied it in context of proportion of elderly voters by county. They aggregated the smaller areal units to larger areal units and concluded that at different levels of spatial aggregation, the correlation coefficients between two variables (elderly and republican voters) carry range of values. The reason of this inconsistency was modifiable boundaries of areal units. On changing the boundaries of areal units in a different way affected the results in a different manner. This discrepancy in results due to alteration of boundary was recognized as MAUP and hence this term was as coined, thereby drew attention of researchers on severity of MAUP. Scientists experienced MAUP in location-allocation modelling (Goodchild 1979; Fotheringham et al. 1995) and several overviews of MAUP have been illustrated (Openshaw1984; Wong 1995). Due to MAUP, the reliability of the results can be doubted as results likely to vary with different levels of aggregation and different spatial arrangements. Most statistical analyses are subjected to MAUP. Evidence has been provided on unreliability of multivariate statistical analysis with data from areal units (Fotheringham and Wong 1991). Although the mean statistics do not show any significant impact of aggregation effect, however other statistical measures i.e. variance and correlation coefficients show drastic effects. Amerhein (1995 & 1996) performed statistical
simulation to explore the MAUP impacts. Hunt and Boots (1996) studied the MAUP effects on principal component analysis. Despite several studies on the MAUP, no attention was paid to the issue of MAUP in remote sensing until 1994. It was first time by Marceau (1994) who recognized the MAUP in remote sensing. Later, effects of MAUP have also been reported in on accuracy of maximum likelihood classification of multispectral images from remotely sensed data (Arbia et al. 1996). Marceau and Hay (1999) presented insights of MAUP and described it as ‘the sensitivity of analytical results to the definition of data collection units’. Dark and Bram (2007) presented the comprehensive review on MAUP in physical geography both in remote sensing and GIS with its implications. Hay et al. (2001) suggested that the remotely sensed datasets are imperative for our understanding on landscape structure analysis although MAUP is one of its limitations. Therefore it is crucial to understand MAUP and its effect.

2.2. Modifiable Areal Unit Problem (MAUP) and its components

The MAUP comprises two components: scale and zonation. As described by Openshaw and Taylor (1979), the former one is “variation in results that may be obtained when the same areal data are combined into sets of increasingly larger areal units of analysis”. The zoning effect is described as “any variation in results due to alternative units of analysis where \( n \), the number of units is constant”. Figure 3 published in a study by Jelinski and Wu (1996), provides an illustration to show the effect of aggregation (a-c) and zonation (d-f) by calculating mean and variance. In figure 3 (a-c) states that on performing aggregation mean values does not change but variance declines. However, figure 3 (d-f) states that both mean and variance changes at different zonations despite having same aggregation level.
2.2.1. The scale/aggregation effect

The spatial scale of remotely sensed data is comprised of grain and extent. Grain refers to cell size and extent is overall study area (Turner et al. 1989). Aggregation effect deals with altering the grain without changing the extent. The terms fine and coarse resolutions are used in relative sense. Studies which studied the effects and process of aggregation are summarized in this section. Several studies need datasets on coarser resolution for specific purposes therefore, making aggregation a necessary component of studies. Studies have been conducted to explore the effects of aggregation of the raster spatial datasets. Turner et al. (1989) studied the effects of aggregation on landscape pattern analysis. Qi and Wu (1996) studied the effect of changing scale on landscape pattern analysis using three spatial autocorrelation indices, i.e., Moran’s I, Geary’s C and Cliff-Ord statistics. The study was more
concentrated on aggregation effects of the MAUP. It was observed as the aggregation increased the value of Moran’s I and Cliff-Ord statistics increases. Effect of aggregation on landscape metrics were also investigated and demonstrated that the values of the metrics changed with increasing cell size (Wu et al. 2002) and scaling relations were explored with respect to changing grain size (Wu et al. 2004). MAUP has also been studied in the context of landscape ecology and data aggregation effects on landscape structure were reported (Hay et al. 2001; Wu et al. 2002; Arnot et al. 2004; Dendoncker et al. 2008). Effects of aggregations on several landscape metrics like number of patches, mean patch size, edge density have also been reported to determine the impact of scale on forest fragmentation (Saura 2004; Wu 2004).

Studies have also been conducted on different methods of aggregation to understand MAUP from different perspective. Gardner et al. (2008) developed a method for rescaling of spatial data to take account of aggregation. Raj (2009) examined the effect of categorical and numerical aggregation approaches and understood its effects. Zimmerman and Bijker (2004) studied the aggregation methods and its effects on the classification results of fine spatial resolution and found that, the patterns change on aggregation.

Jelnski and Wu (1996) studied the aggregation effects by calculating NDVI (Normalized Difference Vegetation Index) from three Landsat TM scenes of 30 m cell size. The data was then aggregated to various aggregation levels from 1x1 to 15x15. Moran’s I statistics and Geary’s c statistics were used as measures of spatial autocorrelation. It was concluded by the study that the autocorrelation changes with scale hence presence of MAUP was evident. Marceau et al. (1994) studied the impact of scale by performing supervised classification on four aggregation levels of airborne MEIS-II remotely sensed data. On changing the aggregation level the values of measures of descriptive statistics changed. Several authors degraded Landsat MSS data to coarser resolutions and concluded that the land cover type proportion is a function of spatial resolution. (Townshend and Justice 1988; Moody...
and Woodcock 1994). Karl and Maurer (2010) performed multivariate correlations between imagery and field measurements by comparing pixel aggregation and image segmentation.

Some studies have been conducted to investigate the effect of MAUP in forest context. Alexandridis et al. (2010) explored MAUP by studying the effect of aggregation in monitoring vegetation condition using MODIS NDVI 16 day composites. Vegetation type map was prepared and zonal statistics (mean and std. deviation) were calculated for each composite period using three existing aggregation schemes (provinces of Greece, fire services units of Greece and forest services units of Greece). Statistics from three different aggregated schemes were compared. As a result all the aggregation schemes provided significantly different results thereby indicated the presence of MAUP effect in monitoring vegetation condition. Few more authors have studied effects of MAUP in the context of forests (Atkinson and Curran 1995; Hlavaka and Dungan 2002; Nelson et al. 2009) and concluded it as one of the major limitation in their studies.

2.2.2. The zonation/zoning systems effect

Zonation is another component of MAUP. Zonations might occur due to two reasons. Firstly due to different starting points of aggregation and secondly due to different grid alignment with the scene. It was first studied by Openshaw (1977), he studied the effects of zoning system on parameter values and provided implications for spatial model building. Different zoning methods also affect the outcomes of spatial data aggregation (Jelinski and Wu 1996; Stein 2009). Zonation component of MAUP has received very little attention in remote sensing as compared to aggregation component. Jelinski and Wu (1996) studied effects of zoning at two separate scales, fine and coarse, in three different landscapes and demonstrated that, the MAUP affects the result of landscape analysis. Stein et al. (2009) studied the uncertainties in handling studies pertaining to remote sensing, since MAUP is one of the uncertainty, it was also studied using lake as a study object. They found strong
influence of aggregation and zonations in their study. The present study attempts to emphasize both the aspects of MAUP in a detailed context.
3. **Study Area and Data Processing**

3.1. **Study area**

The MAUP was studied in the context of two lakes, one with a man-made crisp boundary, Lake IJsselmeer in Netherlands and other with vague natural boundary, Lake Naivasha in Kenya.

3.1.1. **Lake IJsselmeer**

IJsselmeer is the largest shallow freshwater lake in Western Europe (Figure 4) and is named after the IJssel River. The lake receives the Rhine water from IJssel river. It is an artificial lake situated in the central Netherlands. It was created in 1932 from the southern part of the former Zuiderzee by a dam, Afsluitdijk which separates it from Waddenzee and the North Sea. The lake borders the provinces of Utrecht, Gelderland, Overijssel and Friesland. The original IJsselmeer was then bisected by a dyke in 1975, which separated it from the southern part now called Markermeer. In this study IJsselmeer and Markermeer both are considered as one single unit. Large parts of the lake have been reclaimed by constructing encircling dikes. Therefore, it has crisp boundaries.

Lake IJsselmeer is a wetland habitat to many bird species. Therefore, designated as wetland of international importance and has been included in the list of Ramsar sites in 2000 (BirdLife International 2011)
3.1.2. Lake Naivasha

Naivasha is also shallow fresh water lake. It is situated in the West of Naivasha town in Kakkuru district within Rift Valley Province (figure 5). It is second largest lake in Kenya and since it is 1880 meters above mean sea level, it is highest lakes among all lakes of Rift valley. Unlike freshwater lakes Lake Naivasha does not have any visible outlet and the lake is fed by Gilgil and Melwa rivers in north.

The lake and its surroundings are home to biodiversity. It is rich in terrestrial and aquatic life forms. There are over 450 species of birds, bird watching is a popular recreation. Lake Naivasha was declared as Ramsar site in 1995, being a wetland of international importance. Lake Naivasha is fringed by thick papyrus, forests of yellow barked tree *Acacia xanthophlea*, swamps and submerged vegetation. The presence of this vegetation on fringes makes the lake boundary vague (not clearly defined). It has surface area fluctuating between 100-150 km² (Adams et al. 2002) due to seasonal variation.
3.2. Data used

MODIS (Moderate Resolution Imaging Spectroradiometer, 250 m), Landsat TM (Thematic Mapper, 30m) and ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer, 15m) data were used for studying MAUP in case of Lake IJsselmeer (Table 2). The ASTER data had the finest resolution among all the data used in study. The aggregations of ASTER were comparable to both TM and MODIS data. All these datasets were selected because of their wide use in scientific community and due to their free availability.

Table 2. Details of the satellite data used to study Lake IJsselmeer.

<table>
<thead>
<tr>
<th>Datasets</th>
<th>Scenes</th>
<th>Sensor</th>
<th>Platform</th>
<th>Path &amp; Row</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>MODIS</td>
<td>Terra</td>
<td>H-18 &amp; V-03*</td>
<td>02-Jun-10</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>TM</td>
<td>Landsat 5</td>
<td>198 &amp; 23</td>
<td>06-Sep-10</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>TM</td>
<td>Landsat 5</td>
<td>198 &amp; 24</td>
<td>04-Aug-10</td>
</tr>
<tr>
<td>3</td>
<td>4</td>
<td>ASTER</td>
<td>Terra</td>
<td>198 &amp; 23</td>
<td>16-Sep-09</td>
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<tr>
<td></td>
<td>5</td>
<td>ASTER</td>
<td>Terra</td>
<td>198 &amp; 23</td>
<td>13-Sep-10</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>ASTER</td>
<td>Terra</td>
<td>198 &amp; 23</td>
<td>14-Jul-10</td>
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<td></td>
<td>7</td>
<td>ASTER</td>
<td>Terra</td>
<td>198 &amp; 24</td>
<td>14-Jul-10</td>
</tr>
</tbody>
</table>

* ‘H’ refers to horizontal tile and ‘V’ to vertical tile
For Lake Naivasha only Landsat TM data was procured to study the aggregation and zonation effects of MAUP (Table 3).

Table 3. Details of satellite data used to study Lake Naivasha.

<table>
<thead>
<tr>
<th>Scenes</th>
<th>Sensor</th>
<th>Platform</th>
<th>Path</th>
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<tr>
<td>1</td>
<td>Landsat</td>
<td>TM</td>
<td>169</td>
<td>60</td>
<td>30-Jan-10</td>
</tr>
</tbody>
</table>

3.3. Satellite data processing

For Lake IJsselmeer, TM and MODIS data was downloaded from United States Geological Survey (USGS) website (www.glovis.usgs.gov) in GeoTIFF and HDF formats respectively. ASTER data was made available by ITC (Faculty of Geo-Observation Science and Earth Observation, University of Twente) and in EOS HDF format. For Lake Naivasha, TM data was downloaded. All the images were imported from their respective formats to IMG format and the original projections were retained. UTM WGS 84 projection was retained for ASTER and TM data. Sinusoidal WGS 84 was retained for MODIS data. All the bands of TM data (all bands except 7th band) were stacked together. Since four scenes of ASTER were required to complete Lake IJsselmeer, all four of them were mosaicked using overlay option. Two scenes of TM were mosaicked in the similar way. Area of interest (AOI) was extracted from all the datasets using a rectangular AOI file so as to have large buffer around the lake. Data import and its processing were performed using ERDAS Imagine (2010).

For Lake Naivasha, single TM scene was downloaded and imported into IMG format. Later all the bands (all bands except 7th band) were stacked together and AOI was extracted using rectangular AOI file. All processing operations were performed using ERDAS Imagine (2010).
4. Methodology

The clipped satellite datasets (AOI) were then used to evaluate aggregation and zonation aspects. Landsat TM data was used to understand aggregation and zonation component in the study. The other two datasets, ASTER and MODIS were used for comparison.

4.1. Methodology flow charts

The methodologies adopted in the present study for aggregation and zonation are shown in the form of flowcharts.

4.1.1. Methodology I: TM image aggregation

TM data of Lake IJsselmeer was used to study the aggregation component of MAUP. The data was aggregated to 7 different aggregation levels (table 4) using mean aggregation approach (figure 6). This approach estimates the mean of DN values over specified pixels of input grid and assigns the result in one output pixel (Moody & Woodcock 1996). A total of 7 images were classified using maximum likelihood classifier and lake parameters were estimated to study aggregation effect. Figure 7 shows the flowchart of methodology used to study aggregation.

<table>
<thead>
<tr>
<th>TM aggregation levels</th>
<th>2x2</th>
<th>6x6</th>
<th>8x8</th>
<th>10x10</th>
<th>16x16</th>
<th>32x32</th>
<th>64x64</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pixel size (m)</td>
<td>60</td>
<td>180</td>
<td>240</td>
<td>300</td>
<td>480</td>
<td>960</td>
<td>1920</td>
</tr>
</tbody>
</table>

Table 4 Aggregation levels of TM data of Lake IJsselmeer.
TM data of Lake Naivasha was also aggregated to 4 aggregation levels, 8×8, 16×16, 32×32, 64×64 in a similar way.
4.1.2. Methodology III: Zonations using TM data

TM data was used to study zonations both in the case of Lake IJsselmeer and Lake Naivasha.

4.1.2.1. Lake IJsselmeer

For Lake IJsselmeer, zonations were studied at 7 different aggregation levels. All possible zonations were made from each aggregation level and images resulted from all zonations were classified into water and no water using maximum likelihood classifier. For this purpose of zonation and classification, an eml (ERDAS Macro Language) script (Appendix I) in ERDAS Imagine 2010 was used. A total of 5580 images of Lake IJsselmeer were classified and lake parameters were estimated using python script in Arc GIS (Appendix II). Table 5 shows all possible zonations at 7 different aggregation levels of TM. Figure 8 describes the flowchart of the methodology used for zonation process of TM data of Lake IJsselmeer.

<table>
<thead>
<tr>
<th>TM aggregation levels</th>
<th>2×2</th>
<th>6×6</th>
<th>8×8</th>
<th>10×10</th>
<th>16×16</th>
<th>32×32</th>
<th>64×64</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pixel size (m)</td>
<td>30</td>
<td>180</td>
<td>240</td>
<td>300</td>
<td>480</td>
<td>960</td>
<td>1920</td>
</tr>
<tr>
<td>Possible zonations</td>
<td>4</td>
<td>36</td>
<td>64</td>
<td>100</td>
<td>256</td>
<td>1024</td>
<td>4096</td>
</tr>
</tbody>
</table>

Table 5. Table showing all possible zonations at 7 different aggregation levels of TM data of Lake IJsselmeer.
All possible zonations at 4 aggregation levels were studied for Lake Naivasha. A total of 5440 images were classified and lake parameters were estimated for Lake Naivasha (table 6). Figure 9 describes the flowchart of the methodology used for zonation process of TM data of Lake Naivasha.
Table 6. Table showing all possible zonations at 4 different aggregation levels of TM data of Lake Naivasha.

<table>
<thead>
<tr>
<th>TM aggregation levels</th>
<th>8x8</th>
<th>16x16</th>
<th>32x32</th>
<th>64x64</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pixel size (m)</td>
<td>240</td>
<td>480</td>
<td>960</td>
<td>1920</td>
</tr>
<tr>
<td>Possible zonations</td>
<td>64</td>
<td>256</td>
<td>1024</td>
<td>4096</td>
</tr>
</tbody>
</table>

Figure 9. Zonations using TM data of Lake Naivasha.
4.1.3. Methodology II: MODIS, TM & ASTER data comparison and aggregated data comparison with native resolution

The MODIS, TM and ASTER data of Lake IJsselmeer were classified using maximum likelihood classifier of supervised classification. Area and perimeter of lake were estimated and the estimates were compared (figure 10).

The area and perimeter estimated from ASTER aggregations, 2x2 (30m) were compared to TM. Lake parameters obtained from TM data at 8x8 aggregation level were also compared with parameters obtained from ASTER 17x17 aggregation level and actual MODIS data (figure 10).

Figure 10. Methodology II: MODIS, TM & ASTER data comparison and aggregated data comparison with native resolution.
4.2. **Image classification**

All the clipped remotely sensed datasets were subjected to supervised classification using maximum likelihood supervisor. Signatures of water and non water areas were collected from image using AOI and the image was classified into two classes viz. water and no water.

4.2.1. **Evaluation of signature separability**

Signature files were created by collecting spectral signatures of water and non-water areas by marking several AOIs in geographical space. Signatures were then evaluated using two measures feature space and transformed divergence statistics.

4.2.1.1. **Using feature space**

Feature spaces (the graphs of signature statistics of an image) were created. The graphs display as set of ellipses in a feature space image (two dimensional histograms). Each ellipse is based on mean and standard deviation of one signature. Feature space was used to compare signatures. Combinations of bands were used to investigate the class separability. Signatures with overlapping ellipses were merged since they belong to similar pixels.

4.2.1.2. **Transformed divergence statistics**

It was used as another measure of signature separability. Transformed divergence (TD) “gives an exponentially decreasing weight to increasing distances between the classes.” (Bourne and Graves 2001). Swain and Davis (1978) indicated that “the larger the transformed divergence, the greater the ‘statistical distance’ between training patterns and the higher probability of correct classification of classes.” The scale of the divergence values can range from 0 to 2 (though, ERDAS Imagine scales it from 0 to 2000). Interpreting results after applying transformed divergence requires analysis of the numerical divergence values. If the calculated divergence is equal to the upper limit then signatures are said to be totally separable. Between 1.7 and 2, the separation is fairly good. Below 1.5, it is poor separation (Bourne and Graves 2001). Merge and deletion of classes were decided on the basis of
transformed divergence results. Equation for transformed divergence is given below (Richards and Jia 2006).

$$TD_{ij} = 2 \left(1 - e^{-d_{ij}/8}\right)$$

After evaluation, signature files were corrected by deleting the redundant signatures and merging similar signatures. Different signature files were made for different aggregations and one common signature file was used for all zonations resulting from a common aggregation. For example, common signature file was used for all 36 zonations from 6x6 aggregation level.

4.3. Parameter estimation

Three parameters of lake estimated were, area, perimeter and compactness. Once the image was classified, python script was run in Arc GIS 10 to calculate the area and perimeter (Appendix II) of Lake IJsselmeer and Lake Naivasha at all zonations of various aggregations. Compactness was calculated from area and perimeter using ratio quoted in Selkirk (1982) as the "circularity ratio."

$$\text{Compactness} = 4\pi A/p^2$$

4.4. Data analysis

Data estimated from all the three methodologies were analysed differently. The following categories describe the data analysis under each of them.

4.4.1. Comparisons of TM aggregations

Area, perimeter and compactness were calculated from all 7 classified images of Lake IJsselmeer at different aggregation levels of TM (2x2; 6x6; 8x8; 10x10; 16x16; 32x32 and 64x64) and 4 classified images of Lake Naivasha at aggregation levels (8x8; 16x16; 32x32 and 64x64). All the parameters were compared and assessed.
4.4.2. **TM zonations**

To analyse the data for zonations, at each aggregation level of TM, descriptive statistics (mean, median, mode, standard deviation (SD), coefficient of variation (CV), range, minimum and maximum) for area and perimeter were calculated. Histograms of area and perimeter were plotted at each aggregation level studied to analyse the pattern of area and perimeter at each aggregation level.

4.4.3. **Comparison of ASTER, TM and MODIS datasets**

Parameters were estimated from 3 datasets of Lake IJsselmeer (ASTER, TM and MODIS) and compared among themselves.

4.4.4. **Aggregated vs. actual data**

Parameters estimated from ASTER 2×2 aggregation (30m) were compared to actual TM data of Lake IJsselmeer. Parameters estimated from ASTER 17×17 aggregation (255m) and TM 8×8 aggregation (240m) were compared to actual MODIS (250m) of Lake IJsselmeer.
5. Results

This chapter describes the main findings of the research. Impacts of aggregation and zonation were studied for both lakes. The results are presented under as three major sections
- Lake IJsselmeer, crisp boundaries,
- Lake Naivasha, vague boundaries
- Comparison of ASTER, TM and MODIS datasets of Lake IJsselmeer

5.1. Lake IJsselmeer, crisp boundary

This section deals with the results of aggregation and zonation of remotely sensed data of Lake IJsselmeer. The lake has crisp boundaries due to dike encircling its border.

5.1.1. Impact of aggregation

Landsat TM was aggregated to explore the impact of aggregation. TM data was aggregated to 7 levels of aggregation. All the images at 7 aggregation levels were classified using 7 different signature files. The transformed divergence statistics estimated for all signature files was above 1.8. Table 7 shows the lake parameters (area, perimeter and compactness) at all aggregation levels of TM data of Lake IJsselmeer. It was observed perimeter showed decreasing trend from lower to higher levels of aggregation.
Table 7. Lake parameters estimated at all aggregation levels of TM data of Lake IJsselmeer.

<table>
<thead>
<tr>
<th>Aggregation levels</th>
<th>Pixel size (m)</th>
<th>Area (km²)</th>
<th>Perimeter (km)</th>
<th>Compactness</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2x2</td>
<td>60</td>
<td>1814</td>
<td>633</td>
</tr>
<tr>
<td>2</td>
<td>6x6</td>
<td>180</td>
<td>1831</td>
<td>645</td>
</tr>
<tr>
<td>3</td>
<td>8x8</td>
<td>240</td>
<td>1819</td>
<td>600</td>
</tr>
<tr>
<td>4</td>
<td>10x10</td>
<td>300</td>
<td>1803</td>
<td>568</td>
</tr>
<tr>
<td>5</td>
<td>16x16</td>
<td>480</td>
<td>1760</td>
<td>477</td>
</tr>
<tr>
<td>6</td>
<td>32x32</td>
<td>960</td>
<td>1801</td>
<td>420</td>
</tr>
<tr>
<td>7</td>
<td>64x64</td>
<td>1920</td>
<td>1916</td>
<td>418</td>
</tr>
</tbody>
</table>

Figure 11 depicts that as the aggregation level increased, the perimeter of Lake IJsselmeer decreased and compactness increased. However, figure 12 depicts that the area of the lake first increased then decreased and later again increased.

Figure 11. Pattern followed by perimeter and compactness of Lake IJsselmeer with increasing spatial resolution.
5.1.2. Impact of zonation

The parameters Lake IJsselmeer were estimated from all possible zonations resulting from seven different aggregation levels of Landsat TM data.

Statistics of area of Lake IJsselmeer resulting from all aggregation levels

Descriptive statistics (minimum, 1st quartile, mean, median, 3rd quartile, maximum, standard deviation (SD) coefficient of variation (CV) and range) of area of Lake IJsselmeer was estimated at each aggregation level (table 8)
Table 8. Descriptive statistics of area of Lake IJsselmeer at different zonations at all
given aggregation levels of TM data.

<table>
<thead>
<tr>
<th>Aggregation level</th>
<th>2×2</th>
<th>6×6</th>
<th>8×8</th>
<th>10×10</th>
<th>16×16</th>
<th>32×32</th>
<th>64×64</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pixel size (m)</td>
<td>60</td>
<td>180</td>
<td>240</td>
<td>300</td>
<td>480</td>
<td>960</td>
<td>1920</td>
</tr>
<tr>
<td>Minimum</td>
<td>1814</td>
<td>1828</td>
<td>1785</td>
<td>1774</td>
<td>1757</td>
<td>1778</td>
<td>1817</td>
</tr>
<tr>
<td>1st Quartile</td>
<td>1814</td>
<td>1830</td>
<td>1810</td>
<td>1799</td>
<td>1762</td>
<td>1793</td>
<td>1854</td>
</tr>
<tr>
<td>Mean</td>
<td>1814</td>
<td>1835</td>
<td>1809</td>
<td>1799</td>
<td>1767</td>
<td>1799</td>
<td>1876</td>
</tr>
<tr>
<td>Median</td>
<td>1814</td>
<td>1831</td>
<td>1814</td>
<td>1805</td>
<td>1768</td>
<td>1799</td>
<td>1876</td>
</tr>
<tr>
<td>3rd Quartile</td>
<td>1814</td>
<td>1834</td>
<td>1819</td>
<td>1807</td>
<td>1770</td>
<td>1803</td>
<td>1898</td>
</tr>
<tr>
<td>Maximum</td>
<td>1814</td>
<td>1857</td>
<td>1822</td>
<td>1810</td>
<td>1776</td>
<td>1829</td>
<td>1939</td>
</tr>
<tr>
<td>SD</td>
<td>0.1</td>
<td>9.2</td>
<td>12.2</td>
<td>11.3</td>
<td>4.6</td>
<td>8.8</td>
<td>25.6</td>
</tr>
<tr>
<td>CV</td>
<td>0.0</td>
<td>0.5</td>
<td>0.7</td>
<td>0.6</td>
<td>0.3</td>
<td>0.5</td>
<td>1.4</td>
</tr>
<tr>
<td>Range</td>
<td>0.1</td>
<td>29.1</td>
<td>37.3</td>
<td>35.6</td>
<td>19.4</td>
<td>50.7</td>
<td>121.7</td>
</tr>
</tbody>
</table>

Figure 13 illustrates the pattern followed by maximum area, mean area and
minimum area, estimated from all zonations at all given aggregation level.

![Figure 13](image-url)

Figure 13. Graph showing area statistics of Lake IJsselmeer with respect to spatial
resolution.
The behaviour of standard deviation of area as the aggregation level increased is depicted by graph below (figure 14).

**Figure 14.** Graph showing standard deviation of an area of Lake IJsselmeer with increasing spatial resolution.

*Area distribution of Lake IJsselmeer at different zonations*

Histograms showing area distribution of all possible zonations at each aggregation level of TM data of Lake IJsselmeer is shown in figure 15. At 6×6 aggregation level, histogram showed skewed distribution of an area of Lake IJsselmeer (estimated from all 36 zonations). Area estimated from most of the zonations (>75% zonations) at 6×6 aggregation level, lies between range of 1826km² to 1835km². At 8×8 aggregation level also skewed distribution of area of lake was shown when estimated at its different zonations. Area estimated from most of the zonations (>75% zonations) at 8×8 aggregation level lie between 1806km² to 1825km². Distribution of area estimated from different zonations at 10×10 and 16×16 aggregation levels showed skewed distribution as well. Area estimated from most of the zonations (>75% zonations) at 10×10 aggregation level lie between 1806km² to 1815km². At 16×16 aggregation level, area estimated from maximum zonations (>75%) lie in the range of 1776km² to 1785km². However, area estimated from zonations resulting
from 32×32 and 64×64 aggregation level showed symmetric distribution. At 32×32 aggregation level, area estimated from most of the zonations (>75% zonations) lie between 1796km² to 1805km². Zonations resulting from 64×64 aggregation level show fairly large range of area of area distribution. Area estimated from most of the zonations (>75% zonations) lie between 1836km² to 1925km². The pattern depicts the increased range at coarser aggregation levels.

Figure 15. Area distribution of Lake IJsselmeer at different zonations at all 7 aggregations of TM data.
Statistics of perimeter of Lake IJsselmeer at different zonations resulting from all aggregation levels

Descriptive statistics (minimum, 1st quartile, mean, median, 3rd quartile, maximum, SD, CV and range) of perimeter were estimated at each aggregation level (table 9)

Table 9. Descriptive statistics of perimeter of Lake IJsselmeer at different zonations at all given aggregation levels of TM data.

<table>
<thead>
<tr>
<th>Aggregation level</th>
<th>2x2</th>
<th>6x6</th>
<th>8x8</th>
<th>10x10</th>
<th>16x16</th>
<th>32x32</th>
<th>64x64</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pixel size (m)</td>
<td>60</td>
<td>180</td>
<td>240</td>
<td>300</td>
<td>480</td>
<td>960</td>
<td>1920</td>
</tr>
<tr>
<td>Minimum</td>
<td>633</td>
<td>603</td>
<td>509</td>
<td>490</td>
<td>469</td>
<td>376</td>
<td>322</td>
</tr>
<tr>
<td>1st Quartile</td>
<td>634</td>
<td>625</td>
<td>574</td>
<td>548</td>
<td>484</td>
<td>397</td>
<td>364</td>
</tr>
<tr>
<td>Mean</td>
<td>636</td>
<td>642</td>
<td>578</td>
<td>555</td>
<td>496</td>
<td>407</td>
<td>377</td>
</tr>
<tr>
<td>Median</td>
<td>635</td>
<td>638</td>
<td>591</td>
<td>567</td>
<td>496</td>
<td>405</td>
<td>376</td>
</tr>
<tr>
<td>3rd Quartile</td>
<td>637</td>
<td>657</td>
<td>574</td>
<td>571</td>
<td>505</td>
<td>414</td>
<td>395</td>
</tr>
<tr>
<td>Maximum</td>
<td>639</td>
<td>699</td>
<td>614</td>
<td>592</td>
<td>525</td>
<td>460</td>
<td>433</td>
</tr>
<tr>
<td>SD</td>
<td>2.5</td>
<td>23.2</td>
<td>29.9</td>
<td>27.2</td>
<td>12.6</td>
<td>15.5</td>
<td>23.6</td>
</tr>
<tr>
<td>CV</td>
<td>0.4</td>
<td>3.6</td>
<td>5.2</td>
<td>4.9</td>
<td>2.5</td>
<td>3.8</td>
<td>6.2</td>
</tr>
<tr>
<td>Range</td>
<td>5.5</td>
<td>95.8</td>
<td>105.1</td>
<td>101.4</td>
<td>55.7</td>
<td>84.5</td>
<td>111.4</td>
</tr>
</tbody>
</table>

Figure 16 shows the trend followed by minimum, mean and maximum perimeter of Lake IJsselmeer at different zonations at all given aggregations. Trend followed by standard deviation of perimeter of Lake IJsselmeer estimated at different zonations at all given aggregation is shown in figure 17.
Figure 16. Graph showing perimeter statistics of Lake IJsselmeer with respect to spatial resolution.

Figure 17. Graph showing standard deviation of perimeter of Lake IJsselmeer with increasing spatial resolution.

**Perimeter distribution of Lake IJsselmeer at different zonations**

Figure 18 shows the histogram depicting perimeter distribution of all possible zonations at each aggregation level of TM data of Lake IJsselmeer. The perimeter estimated from all zonations of TM from all aggregations showed skewed distributions.
Figure 18. Perimeter distribution of Lake IJsselmeer at different zonations from all 7 aggregation levels of TM data.
At 6×6 aggregation level, most of the zonations (>75% zonations) have perimeter in the range of 601km to 680km. At 8×8 aggregation level of TM, most of the zonations (>75% zonations) have perimeter in the range between 561km to 62km. At aggregation level 10×10, most of the zonations (>75% zonations) have perimeter in the range between 561km to 580km. At 16×16 aggregation level most of the zonations (>75% zonations) have perimeter in the range between 501km to 520km. Zonations from aggregation level 32×32 most of the zonations (>75% zonations)) have perimeter in the range between 401km to 420km. At 64×64 aggregation level most of the zonations (>75% zonations) have perimeter in the range between 361km to 420km. In general perimeter ranges from 320m to 700m.

Visible changes in the shape of Lake IJsselmeer

At very small levels of aggregations (2×2 and 6×6) there were no significant changes in the overall shape of Lake IJsselmeer. Although, features on the Lake IJsselmeer boundary which were smaller in extent showed remarkable change in shape at different zonation of same aggregation level. Figure 19 illustrates the change in shape of a feature near the boundary of Lake IJsselmeer, on changing the zonations at same aggregation level. However, at higher levels of aggregation (64×64) the major changes in the shape of Lake IJsselmeer were observed. Figure 20 depicts the overall change in shape of Lake IJsselmeer at different selective zonations resulting from same aggregation level (64×64).
Figure 19. Changes observed in the shape of the feature of Lake IJsselmeer at different zonations from 2×2 aggregation of TM data.
Figure 20. Changes observed in the overall shape of Lake IJsselmeer at different zonations from 64×64 aggregation level of TM.

5.2. Lake Naivasha, vague boundary

This section deals with the results of aggregation as well as zonation of Landsat TM data of Lake Naivasha. The lake has vague boundary due to presence of submerged vegetation and swamps around it. Four signature files were generated. The transformed divergence statistics estimated for all signature files was above 1.8. After classification lake parameters were estimated from all possible zonations resulting from four different aggregation levels of Landsat TM. Descriptive statistics of area and perimeter were estimated at each aggregation level in a similar way as that of Lake IJsselmeer.
5.2.1. Impact of aggregation

The area and perimeter of Lake Naivasha were estimated from all 4 aggregation levels (8×8, 16×16, 32×32, 64×64) of TM data (table 10).

Table 10. Estimated Parameters of Lake Naivasha at different aggregation levels (1, 1 zonation) of TM data.

<table>
<thead>
<tr>
<th>Aggregation level</th>
<th>8×8</th>
<th>16×16</th>
<th>32×32</th>
<th>64×64</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pixel size (m)</td>
<td>240</td>
<td>480</td>
<td>860</td>
<td>1920</td>
</tr>
<tr>
<td>Area (km²)</td>
<td>97.2</td>
<td>100.9</td>
<td>101.4</td>
<td>73.7</td>
</tr>
<tr>
<td>Perimeter (km)</td>
<td>53.8</td>
<td>54.7</td>
<td>55.7</td>
<td>46.1</td>
</tr>
<tr>
<td>Compactness</td>
<td>0.422</td>
<td>0.424</td>
<td>0.411</td>
<td>0.436</td>
</tr>
</tbody>
</table>

As the aggregation level increased or spatial resolution became coarser, the perimeter of the lake first increased and later decreased at 64×64 aggregation level. However, the compactness showed the trend opposite to it (figure 21).

Figure 21. Pattern followed by perimeter and compactness of Lake Naivasha with increasing spatial resolution.

The area of Lake Naivasha increased but later decreased at 64×64 aggregation level (figure 22)
5.2.2. **Impact of zonation**

The parameters Lake Naivasha were estimated from all possible zonations resulting from seven different aggregation levels of Landsat TM data (8×8, 16×16, 32×32, 64×64).

*Statistics of area of Lake Naivasha at different zonations resulting from all aggregation levels:*

Descriptive statistics (minimum, 1st quartile, mean, median, 3rd quartile, maximum, SD, CV and range) of area of Lake Naivasha is shown in table 11. The table shows how the area of Lake Naivasha estimated from different zonations at a given aggregation level, varied.
Table 11. Descriptive statistics of area of Lake Naivasha at different zonations at all given aggregation levels of TM data.

<table>
<thead>
<tr>
<th>Aggregation level</th>
<th>8×8</th>
<th>16×16</th>
<th>32×32</th>
<th>64×64</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pixel size (m)</td>
<td>240</td>
<td>480</td>
<td>860</td>
<td>1920</td>
</tr>
<tr>
<td>Minimum</td>
<td>96.8</td>
<td>99.3</td>
<td>100.5</td>
<td>66.7</td>
</tr>
<tr>
<td>1st Quartile</td>
<td>97.0</td>
<td>100.2</td>
<td>103.3</td>
<td>73.7</td>
</tr>
<tr>
<td>Mean</td>
<td>97.2</td>
<td>100.5</td>
<td>104.5</td>
<td>75.2</td>
</tr>
<tr>
<td>Median</td>
<td>97.2</td>
<td>100.5</td>
<td>104.1</td>
<td>73.7</td>
</tr>
<tr>
<td>3rd Quartile</td>
<td>97.3</td>
<td>100.7</td>
<td>105.9</td>
<td>77.4</td>
</tr>
<tr>
<td>Maximum</td>
<td>97.7</td>
<td>101.4</td>
<td>109.7</td>
<td>84.8</td>
</tr>
<tr>
<td>SD</td>
<td>0.19</td>
<td>0.39</td>
<td>2.05</td>
<td>3.17</td>
</tr>
<tr>
<td>CV</td>
<td>0.2</td>
<td>0.4</td>
<td>2.0</td>
<td>4.2</td>
</tr>
<tr>
<td>Range</td>
<td>0.81</td>
<td>2.07</td>
<td>9.22</td>
<td>18.43</td>
</tr>
</tbody>
</table>

Figure 23 shows the trend of minimum, mean and maximum area of Lake Naivasha at different zonations at all given aggregations. Figure 24 shows the variation in standard deviation of an area at different zonations at all given aggregations.

Figure 23. Graph showing area statistics of Lake Naivasha with respect to spatial resolution
The histogram depicting area distribution at all possible zonations at each aggregation level of TM data of Lake Naivasha (figure 25). Aggregation levels (8×8 and 16×16) showed skewed distribution. At 8×8 level area estimated from most of the zonations (>75% zonations) lie between 97km² and 99km². At 16×16 level, area estimated from most of the zonations (>75% zonations) lie between 99km² and 101km². At 32×32 level, areas estimated from most of the zonations (>75% zonations) lie between 103km² and 107km². At 64×64 level, area estimated from different zonations was fairly large range of distribution as compared to other aggregation levels.

Figure 24. Graph showing standard deviation of area of Lake Naivasha with increasing spatial resolution
Figure 25. Histograms depicting area distribution of all possible zonations at each aggregation level of TM data of Lake Naivasha.

Statistics of perimeter of Lake Naivasha at different zonations resulting from all aggregation levels:

Descriptive statistics (minimum, 1st quartile, mean, median, 3rd quartile, maximum, SD, CV and range) for perimeter of Lake Naivasha were estimated (table 12).
Table 12. Descriptive statistics of perimeter of Lake Naivasha at different zonations at all given aggregation levels of TM data.

<table>
<thead>
<tr>
<th>Aggregation level</th>
<th>8×8</th>
<th>16×16</th>
<th>32×32</th>
<th>64×64</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pixel size (m)</td>
<td>240</td>
<td>480</td>
<td>860</td>
<td>1920</td>
</tr>
<tr>
<td>Minimum</td>
<td>53.8</td>
<td>51.8</td>
<td>49.9</td>
<td>38.4</td>
</tr>
<tr>
<td>1st Quartile</td>
<td>54.2</td>
<td>53.8</td>
<td>55.7</td>
<td>42.2</td>
</tr>
<tr>
<td>Mean</td>
<td>54.7</td>
<td>54.3</td>
<td>57.9</td>
<td>42.3</td>
</tr>
<tr>
<td>Median</td>
<td>54.7</td>
<td>54.7</td>
<td>57.6</td>
<td>42.2</td>
</tr>
<tr>
<td>3rd Quartile</td>
<td>54.8</td>
<td>54.7</td>
<td>61.4</td>
<td>42.2</td>
</tr>
<tr>
<td>Maximum</td>
<td>55.7</td>
<td>55.7</td>
<td>72.9</td>
<td>49.9</td>
</tr>
<tr>
<td>SD</td>
<td>0.55</td>
<td>0.93</td>
<td>3.8</td>
<td>2.34</td>
</tr>
<tr>
<td>CV</td>
<td>1.0</td>
<td>1.7</td>
<td>6.6</td>
<td>5.5</td>
</tr>
<tr>
<td>Range</td>
<td>1.92</td>
<td>3.84</td>
<td>23.04</td>
<td>11.52</td>
</tr>
</tbody>
</table>

Figure 26 shows the trend followed by minimum, mean and maximum perimeter of Lake IJsselmeer estimated from different zonations at all given aggregations.

Figure 26. Graph showing perimeter statistics of Lake Naivasha with respect to spatial resolution.
Trend of standard deviation of perimeter of Lake Naivasha estimated at different zonations at all given aggregation is shown in figure 27.

Figure 27. Graph showing standard deviation of perimeter of Lake Naivasha with increasing spatial resolution.

Figure 29 shows the histogram depicting perimeter distribution at all possible zonations at each aggregation level of TM data of Lake Naivasha. Aggregation levels (8×8 and 16×16) showed skewed distribution of perimeter. At 8×8 level, perimeter estimated from most of the zonations (>75% zonations) lie between 54km and 56km. At 16×16 level, perimeter estimated from most of the zonations (>75% zonations) lie between 54km and 56km. At 32×32 level, perimeter estimated showed fairly large range of distribution. The histogram showed symmetrical distribution. At 32×32 aggregation of TM, perimeter estimated from most of the zonations (>75% zonations) lie between 75km and 79km.
Figure 28. Histograms depicting perimeter distribution of all possible zonations at each aggregation level of TM data Naivasha.

At higher level of aggregation (64×64), Lake Naivasha showed the overall change in its shape at different zonation. Few selective zoning systems have been shown to illustrate the changes in overall shape of Lake Naivasha (figure29)
5.3. Comparison of ASTER, TM and MODIS datasets

Lake parameters were estimated from ASTER, TM and MODIS data of Lake IJsselmeer (table 13). The classified map from ASTER, TM and MODIS data of Lake IJsselmeer of are shown by figure 30, 31 and 32 respectively.

Table 13. Table showing Lake parameters estimated from ASTER, TM and MODIS data of Lake IJsselmeer.

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Resolution (m)</th>
<th>Area (km²)</th>
<th>Perimeter (km)</th>
<th>Compactness</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>MODIS</td>
<td>250</td>
<td>1764</td>
<td>492</td>
</tr>
<tr>
<td>2</td>
<td>TM</td>
<td>30</td>
<td>1817</td>
<td>687</td>
</tr>
<tr>
<td>3</td>
<td>ASTER</td>
<td>15</td>
<td>1830</td>
<td>799</td>
</tr>
</tbody>
</table>
Figure 30. Classified map of Lake IJsselmeer using ASTER data.

Figure 31. Classified of Lake IJsselmeer using TM data.
5.3.1. ASTER aggregations and its comparisons with native resolutions (TM and MODIS)

Lake parameters estimated from aggregations of ASTER and TM data of Lake IJsselmeer were compared to parameters estimated from actual MODIS data.

5.3.1.1. Comparison with TM

Table 14 shows the comparison of ASTER aggregations with TM data of Lake IJsselmeer.
Table 14. Table showing parameters of Lake IJsselmeer estimated from ASTER aggregation (2×2) and TM data.

<table>
<thead>
<tr>
<th>Data</th>
<th>Cell size (m)</th>
<th>Area (km²)</th>
<th>Perimeter (km)</th>
<th>Compactness</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 ASTER 2×2 aggregation</td>
<td>30</td>
<td>1831</td>
<td>700</td>
<td>0.047</td>
</tr>
<tr>
<td>2 TM</td>
<td>30</td>
<td>1817</td>
<td>687</td>
<td>0.048</td>
</tr>
</tbody>
</table>

5.3.1.2. ASTER aggregated data and its comparisons with actual data (TM and MODIS).

Table 15 shows the comparison of ASTER and TM data aggregations of Lake IJsselmeer with MODIS data of Lake IJsselmeer.

Table 15. Table showing parameters of Lake IJsselmeer estimated from ASTER (17×17), TM (8×8) aggregations and actual MODIS data

<table>
<thead>
<tr>
<th>Data</th>
<th>Cell size (m)</th>
<th>Area (km²)</th>
<th>Perimeter (km)</th>
<th>Compactness</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 ASTER 17×17 aggregation (1, 1 zonation)</td>
<td>255</td>
<td>1882</td>
<td>617</td>
<td>0.062</td>
</tr>
<tr>
<td>2 TM 8×8 aggregation (1, 1 zonation)</td>
<td>240</td>
<td>1819</td>
<td>600</td>
<td>0.063</td>
</tr>
<tr>
<td>3 MODIS</td>
<td>250</td>
<td>1764</td>
<td>492</td>
<td>0.091</td>
</tr>
</tbody>
</table>
6. Discussion

The research has demonstrated that the information on geographical objects captured by remotely sensed data are not independent of sampling systems (grids) hence, subjected to issues of scale or zoning. Consequently MAUP is among one of the major spatial uncertainties in remote sensing. The two components of MAUP, aggregation and zonation are discussed below in the light of the findings of the study.

6.1. Impact of aggregation

Landsat TM data of Lake IJsselmeer was aggregated to 7 levels of aggregation, i.e. 2×2, 6×6, 8×8, 10×10, 16×16, 32×32 and 64×64, thereby spatial resolution was coarsened from 30m to 60m, 180m, 240m, 300m, 480m, 960m and 1920m respectively. It was observed in section 5.1.1, that as the spatial resolution coarsened, the perimeter of the Lake IJsselmeer shows a decreasing trend while the compactness increased with increasing spatial resolution. It would be expected that, on coarsening spatial resolution the complexity of the shape of the lake decreases which leads to an increase in compactness and therefore the perimeter decreases. However, the area of Lake IJsselmeer first decreased and then increased on increasing spatial resolution to coarser scales. The reason for this may be that, as the aggregation increases or spatial resolution become coarser, the very small or narrow features of water near the lake boundary (part of lake), might lose their identity or might not capture on coarse resolutions thus area reduced. This finding is in consistent with Turner et al. (1989) that non-dominant cover types decrease with increasing pixel size. Benson and Mackenzie (1995) had similar results in their study, as they observed that at coarser spatial resolutions the number of lakes decreased. However, at much coarser levels of aggregation i.e. 32×32 (960m) and 64×64 (1920m), the area of the lake increased because on coarsening the spatial
On aggregating the TM data of Lake Naivasha to four levels of aggregation thereby coarsening spatial resolution to 240m, 480m, 960m and 1920m, it was observed that the area and perimeter of Lake Naivasha first increased and then decreased at very high aggregation level (64×64) (section 5.2.1). This was the contrasting trend between the two lakes. Two reasons might contribute to this contrasting trend, the size of the lakes with respect to the pixel size and nature of the lake boundaries. As the spatial scale becomes coarser, the boundaries of smaller objects do not persist clearly and the objects tend to be absorbed into adjoining objects or start disappearing soon as compared to relatively bigger objects (Benson and Mackenzie 1995; Karl and Maurer 2010). The area and perimeter of Lake Naivasha increased when pixel size was 240m to 960m, as at this level the small water bodies present near the lake, merged into Lake Naivasha. However, as the spatial scale becomes much coarser (1920m) subsequently, the water and land gets merged in a pixel (near lake boundary) therefore classifying it as land, thereby reducing the lake area and perimeter. The conventional technique of hard classification assigns a dominant class to a pixel (Fisher 1997). Karl and Maurer (2010) confirmed the fact that at higher aggregation levels, when observations are made near boundaries, pixels capture the information from both sides of boundary obscuring the relation between the real scene on ground and remotely sensed image. On moving from fine to coarse resolution, the chances of mixed pixels increase, therefore the probability of errors in classification also increases (Arbia et al. 1996). The nature of the lake boundary also affects the estimation of parameters. Lake Naivasha has a vague boundary as it is fringed by swamps and submerged vegetation which makes it difficult to distinguish between land and water and makes delineation a complex task. Due to more reflectance of NIR radiations from vegetation near boundary, sensor provides a signal depicting the area near boundary of the lake as land, despite it being water with submerged vegetation. At relatively finer resolution, the delineation is rather less complicated as compared to coarser resolution.
6.2. Impact of zonation

Lake IJsselmeer parameters from all possible zonations resulting from all the 7 aggregations conducted on TM data were estimated as part of research findings. Section 5.1.2 showed that the mean perimeter, averaged over all zonations at a given resolutions, decreases with increasing aggregation. The reason may be again decreasing complexity of lake. The significant difference in the mean statistics (of area and perimeter) confirms that the inconsistency in mean is attributed to the zoning effect. This finding was corroborated with the study of Wong (2009), he explored the similar effect of zonation on GIS. He studied the effect of zonation on spatial patterns of the African-American population and found that on changing the boundaries of congressional districts the patterns of population changed. Substantial change in the standard deviation of the area of Lake IJsselmeer with respect to aggregation levels was also observed although no systematic variations were observed. This result can be compared to the study done by Fotheringham and Wong (1991) in which they argued that the spatial patterns resulting from data aggregation may be highly unpredictable. Stein et al. (2009) also found similar pattern. They calculated minimum, maximum and median of area of a lake at different zonations resulting from each level of aggregation and confirmed that large variability in the area of the lake was estimated, though no clear or systematic patterns were found.

Estimates derived from all possible zonations from four aggregation levels of TM data of Lake Naivasha also showed that on coarsening the spatial resolution, significant difference was observed between the different zonations for the mean area and mean perimeter. Standard deviation of both (area and perimeter) too showed considerable change (section 5.2.2). Jelinski and Wu (1996) provided similar illustrations (figure 3) in their study. The variation in area and perimeter of both lakes at different zonations resulting from a given aggregation level might be possible, because at higher levels of aggregation, the number of zonations increase and each individual zonation has a different starting point for pixel aggregation. This leads to the change in probability of a pixel to be assigned as water or no water,
consequently give rise to different sizes and shapes of the lakes. Moreover, at different zonations, different water bodies adjoining the lake also merge into Lake Naivasha which makes the area variable within same aggregation level. Therefore, explains the variation in area and perimeter at different zonations resulting from a same aggregation level.

The results also illustrate that at very lower levels of aggregation (2×2) of TM data of Lake IJsselmeer, very minor changes were observed, that are also limited to very small features of the lake (figure 19). At this stage MAUP might not influence the results, therefore can be ignored. However, at coarser resolutions the aggregation as well as its different zonations has a strong influence by changing the overall shape of the lake. Figure 19 and 20 showed change in the overall shape of both lakes at 64×64 aggregation level (1920m). Therefore, at higher aggregation levels the MAUP becomes severe and influence the results of classification drastically.

6.3. Comparison of ASTER, TM and MODIS and actual vs. aggregated data

The results from original ASTER, TM and MODIS data of Lake IJsselmeer were also compared in section 5.3 and it was found that the highest value of area and perimeter of Lake IJsselmeer were estimated from ASTER data (finest spatial resolution data among all the data used in study). It suggests that at the finer scales the details of the object are more discernible thereby area, perimeter and complexity in the shape of lake increased from MODIS data (250m) to ASTER data (15m). This is supported by several studies (Woodcock and Strahler 1987; Townshend and Justice 1990; Marceau et al. 1994), these studies mentioned that measurements of real objects acquired from remotely sensed images are not their true representatives, rather it varies due to variation in spatial resolution.

On comparing ASTER aggregation (2×2) with actual TM data of Lake Ijsselmeer, it was found that the values of area and perimeter derived from both datasets were
different (section 5.3.1.1). Lake IJsselmeer datasets, ASTER aggregation (17×17), TM aggregation (8×8) and MODIS with spatial resolution of 255m, 240m and 250m respectively, were also compared in section 5.3.1.2. Although the spatial resolutions were not identical, these simulations of ASTER and TM provided approximate comparisons with native spatial resolution of MODIS. It was found that despite near similar spatial resolution, the parameters (area, perimeter and compactness of the lake) estimated, differed from each other. These differences may be due to difference in the time of scene acquisition, as MODIS scene of June was acquired, TM scenes of August and September were acquired and ASTER data of July and September were acquired. Secondly, the spectral resolutions for all three datasets were different. Thirdly, due to difference in point spread functions (PSF) of sensor systems, the objects located at the centre of instantaneous field of view (IFOV) have more contribution to output signal than the farther lying objects (Huang et al. 2002). In addition the signal attributed to any pixel is not only contribution of that particular area to the ground but also affected by area adjacent to it (Cracknell 1998).

6.4. Limitations of study

There are certain limitations to this study. Fist, hard classification method has been used in classifying the remotely sensed datasets. In hard classification pixel to forced to classify in one of the classes given despite being mixed pixel (Pontius and Cheuk 2006). This is an important artifact of hard classification. Second, due to the time constraint, TM data of Lake Naivasha was not aggregated to all those aggregation levels which TM data Lake IJsselmeer was aggregated (7 aggregation levels). Moreover for Lake IJsselmeer too, results of only 7 aggregation level were estimated. However to conclude the existence of any pattern, sample size of 7 is quite small, therefore results would have been much emphatic if more number of aggregations were done.

Despite these limitations, the results from the study provide insights into the issues of spatial aggregation and zonation, components of MAUP on remote sensing.
7. Conclusion and Recommendations

*Impact of aggregation and zonation*

Remotely sensed data is collected at predefined spatial scale irrespective of the natural processes occurring on ground. Though users, of remotely sensed data have numerous choices of sensors for their study. The natural processes or the objects are always captured by the grid superimposed on the Earth’s surface. Therefore, remotely sensing represents a typical case of MAUP. The study explored the possible impact of two components (aggregation and zonation) of MAUP on remote sensing. It had shed a light on the way in which MAUP affect the output of image classification. Pixels being the modifiable areal units in remotely sensed data, can be modified into numerous ways on aggregation. TM data of Lake IJsselmeer and Lake Naivasha was aggregated to different aggregation levels in the study. Significant changes were observed for both lakes, in their shape and size at different aggregation level as well as different zonation at a given aggregation. Inconsistency in mean statistics of area and perimeter as well as standard deviation of area and perimeter of both lakes were found, when estimated at different zonations of all aggregation levels confirms the presence of MAUP. Despite having same level of aggregation, variation in area and perimeter of lakes were found at different zonations. This too made MAUP evident. It has been observed that, at lower aggregation levels of a fine spatial resolution dataset, the effects of MAUP are too small to be significant therefore, can be ignored. Although, the size of the study object with respect to pixel size should be taken into account. However as the spatial resolution becomes coarser, the outputs of classification differ radically at different zonations at a given aggregation. Therefore it can be concluded that the severity of MAUP increased with increasing aggregation level.
Comparison of ASTER, TM & MODIS and actual vs. aggregated data

The study has also examined the effects of increasing spatial resolution from 15 m to 250m, using three remotely sensed datasets, ASTER, TM and MODIS and comparison of actual with aggregated spatial resolution. It concludes that that the finest resolution dataset does not necessarily represent the truth of the objects on ground. The study has demonstrated the dependence of remotely sensed data on the arrangement and spatial resolution of the sampling grids of the sensor used for the acquisition of the real scene on ground. Modifications in the sampling grid lead to the different interpretations of the same phenomenon.

On bringing ASTER and TM to similar spatial resolutions as that of MODIS by aggregating it to 17×17 and 8×8 aggregation level respectively, drastic differences in the values of area and perimeter of Lake IJsselmeer were observed. Therefore, it can be concluded that estimation of lake parameters is not only dependent on sensor’s spatial resolution but also a function of spectral resolution and PSF of sensor.

7.1. Recommendations

It is recommended that if the object is much larger with respect to pixel size then at lower levels of aggregation the effects of MAUP can be ignored. However, at coarser aggregation levels it becomes crucial to take the effects of MAUP into consideration, otherwise inconsistent results can be obtained. Secondly, on aggregation of datasets to higher aggregation levels, the zoning system should be taken into consideration to avoid the discrepancies in the results. Thirdly, the issues of scale should not be neglected when classifying remotely sensed datasets and comparing them, as spatial phenomena interpreted by different datasets is influenced by its arrangement of sampling grid. Finally, the spectral resolution of datasets should also be taken into consideration on comparison of datasets from different sensors. Understanding the severity of MAUP is of considerable importance. It is imperative to understand its effects in order to avoid erroneous results. The study attempts to provide better understanding of potential impacts of MAUP and highlighted it as the major spatial uncertainty in remote sensing.
References


Appendix I: ERDAS Macro Language (eml) script

# clipped TM image was first degraded to different zonations of 2x2 aggregation

degrade c:/clip_tm.img c:/zon/tm11.img 1 1 2954 3579 -meter -a 2 2

degrade c:/clip_tm.img c:/zon/tm12.img 1 2 2954 3579 -meter -a 2 2

degrade c:/clip_tm.img c:/zon/tm21.img 2 1 2954 3579 -meter -a 2 2

#Images were classified using signature file

classifysupervised c:/zon/tm11.img c:/clasify/tm11.img
c:/signatre_file/mrg_nw_tm2x2.sig -n Non -o Par -u Par -p Max
-prob 0 -a none 0 -best 1 -dsc 0 0 0 0 0 0 -dsco 0 -z 0
-m classify

classifysupervised c:/zon/tm12.img c:/clasify/tm12.img
c:/signatre_file/mrg_nw_tm2x2.sig -n Non -o Par -u Par -p Max
-prob 0 -a none 0 -best 1 -dsc 0 0 0 0 0 0 -dsco 0 -z 0
-m classify

classifysupervised c:/zon/tm21.img c:/clasify/tm21.img
c:/signatre_file/mrg_nw_tm2x2.sig -n Non -o Par -u Par -p Max
-prob 0 -a none 0 -best 1 -dsc 0 0 0 0 0 0 -dsco 0 -z 0
-m classify

classifysupervised c:/zon/tm22.img c:/clasify/tm22.img
c:/signatre_file/mrg_nw_tm2x2.sig -n Non -o Par -u Par -p Max
-prob 0 -a none 0 -best 1 -dsc 0 0 0 0 0 0 -dsco 0 -z 0
-m classify

#Images were clumped

modeler -nq $IMAGINE_HOME/etc/models/clump.pmdl -meter -state
"c:/clasify/tm11.img" 1 "c:/clmp/tm11.img" 614955 5895945
modeler -nq $IMAGINE_HOME/etc/models/clump.pmdl -meter -state
"c:/clasify/tm12.img" 1 "c:/clmp/tm12.img" 614955 5895945
modeler -nq $IMAGINE_HOME/etc/models/clump.pmdl -meter -state
"c:/clasify/tm21.img" 1 "c:/clmp/tm21.img" 614955 5895945
modeler -nq $IMAGINE_HOME/etc/models/clump.pmdl -meter -state
"c:/clasify/tm22.img" 1 "c:/clmp/tm22.img" 614955 5895945

# Images were subjected to ‘seive’ analysis to extract image objects

modeler -nq $IMAGINE_HOME/etc/models/sieve.pmdl -meter -state
"c:/clmp/tm11.img" 1 "c:/seive/tm11.img" 100 "pixels" 614955 5895945
modeler -nq $IMAGINE_HOME/etc/models/sieve.pmdl -meter -state
"c:/clmp/tm12.img" 1 "c:/seive/tm12.img" 100 "pixels" 614955 5895945
modeler -nq $IMAGINE_HOME/etc/models/sieve.pmdl -meter -state
"c:/clmp/tm21.img" 1 "c:/seive/tm21.img" 100 "pixels" 614955 5895945
modeler -nq $IMAGINE_HOME/etc/models/sieve.pmdl -meter -state
"c:/clmp/tm22.img" 1 "c:/seive/tm22.img" 100 "pixels" 614955 5895945
Appendix II: Python script in Arc GIS

```python
>>> import arcpy

# set the workspace
>>> arcpy.env.workspace = r'C:\tm2x2'

# zonal statistics for extracting area and perimeter
>>> arcpy.sa.ZonalGeometryAsTable("tm11.img","Value","tm11.dbf","60")
>>> arcpy.sa.ZonalGeometryAsTable("tm12.img","Value","tm12.dbf","60")
>>> arcpy.sa.ZonalGeometryAsTable("tm21.img","Value","tm21.dbf","60")
>>> arcpy.sa.ZonalGeometryAsTable("tm22.img","Value","tm22.dbf","60")
```