A Quickbird's-eye view on marmots

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by

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Abstract

The population of *Marmota siberica* in Mongolia decreased by 75% in the 1990s . In respond, in 2006 the Mongolian government banned all marmot hunting, but the response of the population this ban is not known. Because demographic research is time-consuming, there is a need for alternative methods, such as remote sensing, to monitor the marmot population. The aim of this study was to determine the applicability of Quickbird imagery to map the mounds of marmot burrows in Hustai National Park, Mongolia, and to assess whether the density of mounds is related to the levels of conservation in the different management zones of the park: a core zone dedicated to conservation, a tourist zone for tourism, and a buffer zone where people live and herd animals.

In all bands of the Quickbird imagery, the radiance of active mounds differed from that of non-active mounds and vegetation. In addition mound size and vegetation cover, as recorded in the field, differs between active and non-active mounds. Based on these results, an object-oriented classification rule was built to detect active mounds in the Quickbird images. The resulting mound distribution map had a user accuracy of 69% and a producer accuracy of 87%. The density of active mounds was 279 per km^2 in the core zone, 212 per km^2 in the tourist and 62 per km^2 in the buffer zone, respectively. A logistic regression was used to find out if differences in mound density across the study area were only related to environmental variables (topographical elevation, slope, and southern exposure, and vegetation type) or whether, in addition, they were related to conservation practices. Although in general, the model performed poorly as evaluated by area under the ROC, it performed better after the management zones were added as an additional predictor.

This study shows for the first time the potential of object-oriented image analysis for marmot population monitoring, through the detection of active marmot mounds. However, it produces a high number of false positive in desertified areas, dry valleys and on unpaved old roads and tracks, because these objects have a reflectance similar to that of active mounds. The logistic regression model suggests that different management practices in the Hustai National Park affect the marmot population.

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1. Introduction

1.1. Background

The world is losing its mammal species diversity at an accelerating pace. A quarter of all mammal species are at risk of extinction due to climate change and other anthropogenic impacts, such as illegal hunting and habitat destruction (Ceballos, Ehrlich et al. 2005; Wingard and Zahler 2006). Establishment of protected areas is advised to conserve the remaining biodiversity. Present studies shows that 11% of earth land surface would need to be managed to protect 10% of the terrestrial mammals geographical range (Ceballos, Ehrlich et al. 2005)

Mongolia's diverse landscapes have traditionally been a refuge for a diversity of mammals. Today 128 mammal species, most of them endemic to northeast Asia, live in and outside Mongolia's 55 reserve areas. As many as 21 % of these species are red-listed as threatened (Clark and Munkhbat 2006). Equally striking is that for 38 % of these 128 species, data are deemed insufficient to assess their conservation status

The relatively slow development of Mongolia during most of the 20th century allowed preservation of pristine landscapes with their native fauna into the 21st century. However, over the last 20 years the social and economic changes in Mongolia have been significant, resulting in an increased intensity of mining and agricultural land use. The number of livestock for example has increased dramatically, growing from 10 million head at the beginning of the 20th century to 33.6 million during the late 1990s, with the results of overgrazing occurring in many areas (Wingard and Zahler 2006).

Hunting further threatens Mongolian mammals, such as Siberian marmot (*Marmota siberica*), argali (*Ovis ammon*), and red deer (*Cervus elaphus*), be it for substance or for trade in furs and other products. Hunting has always been a prominent aspect of Mongolian culture, and most of the wild mammal species serve as a source of protein, fur and medicine. The marmot, *Marmota sibirica* has been particularly strongly affected, because it provides meat, fur for clothing, medicinal oils high in natural cortisone, and other medicinal products (Wingard and Zahler 2006). Reading (1998), who assessed the commercial harvest of wildlife in Mongolia, reported marmot as the most popular game species in the country. Between 1906 and 1994, 104.2 million marmot skins were prepared in Mongolia (Batbold 1996) and in 2004 more than 117 000 illegally harvested marmot skins were confiscated (Clark and Munkhbat 2006). This greatly contributed to the dramatic collapse of the Siberian marmot population observed in the 1990s in Mongolia: from an estimated 20 million individuals in 1990 to only 5 million in 2002 (Wingard and Zahler 2006), or a 75% decrease in population in less than 13 years.

It was not until 2005, in the Mongolian Biodiversity Workshop, where the regional guidelines were applied, that the conservation status of marmot was assessed for the first time and a conservation action plan was formulated (Clark and Munkhbat 2006). The species was identified as endangered and this forced the Mongolian government to ban all marmot hunting in 2005 for at least two years (Townsend and Zahler 2006).

Little is known about the biology of Siberian marmots, their distribution, or the response of its populations to hunting or hunting bans. The little research that has been done on these topics is not readily available to the international research community because it is mostly published in Mongolian. The dramatic decrease in their population, and the recent measures to protect them, makes efforts to monitor the Mongolian marmot population, and assess the impact of conservation activities, extremely urgent, in order to ensure the survival of the species. The present research assesses the previously outlined problem through remote sensing and geographical information systems. More specifically, it attempts to map the distribution of active marmot mounds

1.2. Marmots in Mongolia

The Siberian marmot is a rodent widely spread in northern Asia. Being social animals, they live in clans where a clan consists of a group of marmots of various ages and sex that are not necessarily related. The members of the clan mark the borders of their territory and graze and defend it together (Adiya 2007). In addition, they jointly build burrows and share them.

The marmot burrows consist of a network of holes and tunnels. The animals dig the burrows using their front paws and push away earth, soil, and stones which form mounds next to the entrances of the burrows (Figure 2).(Adiya 2007). As a result, digging burrows causes profound and widespread changes to the landscape. Soil structure, water percolation, as well as vegetation change in and around the burrows and mounds (Todgerel 1999), greatly increasing the spatial heterogeneity of the environment (Yoshihara 2008). In addition, marmot burrow systems are also used as shelter by other animals such as foxes and porcupines. Because of the aforementioned reasons, and the fact that marmots provide forage to large carnivores (birds of prey, foxes, wolves), the Siberian marmot can be considered both a "landscape engineer" and a "keystone species" (Murdoch, Munkhzul et al. in press).

Figure 1 Inhabited marmot burrows with their active mount of bare soil.

1.3. Mapping wildlife using remote sensing and GIS

Because surveys of animal demography are very time consuming, alternative techniques like remote sensing and GIS, have been applied to assess the distribution, density, and demography of wildlife populations (Lillesand and Kiefer 2000; de Leeuw, Ottichilo et al. 2002).
A review of the use of remote sensing for estimating terrestrial animal distribution and diversity is provided by Leyequien et al. (2007).

Some of the research that has used remote sensing to identify the presence and distribution of mammals in a specific area include Loffler and Margules (1980), who mapped the distribution of hairy-nosed wombat (*Lasiorhinus latifrons*) from Landsat imagery based on the identification of burrows and mounds, and Thomson and Milner (1989) who related the population densities of sheep to Landsat Thematic Mapper radiance. In Russia the distribution of steppe marmot was mapped, based on aerial photography (Rumiantsev 1993), Hubbs (2000) assessed the distribution and population size of ground squirrel (*Spermophilus parryii*) based on infrared thermal imaging . Davis et al. (2008) combined archived records of plague-carrying great gerbils (*Rhombomys opimus*) in Kazakhstan with satellite imagery detected gerbil burrows, to investigate if the number of gerbils in the area were related to occurrence of the disease.

Other research has focused on conservation management, assessing the impact of hunting using remote sensing and geoinformation systems. This is the case of Smith (2008) who demonstrated the value of mapping the boundaries of hunting zones and game kill sites to assess the impact of hunting on game species in tropical areas. Foster et al (1997) identified factors influencing efficiency of the white tailed deer harvest in Illinois.
Most of those studies apply a combination of traditional visual image interpretation or pixel-based image classification methods. More recently, however, so-called object-oriented image classification methods have also been tested to detect potential habitats of Grasshopper Sparrow (Jobin, Labrecque et al. 2007) or changes in the homerange of bears (*Ursus Arctos*)(Linke, Pape et al. 2008).
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1.3.1. Objected-oriented image classification

Object-oriented image classification methods segment an image into relatively homogenous clusters of pixels, termed 'object primitives'. The level of homogeneity required is determined by a user-specified scale parameter, where lower values of the scale parameter imply greater homogeneity and generate smaller clusters. Different segmentation algorithms exist: The Quad-tree algorithm, for example, generates square segments of which the area always is a power of two. After segmentation, a set of rules is then devised to classify these objects primitives based on their reflectance and non-reflectance-related properties. Among the reflectance-related properties can be straightforward metrics such as the mean radiance of an object and more complex metrics such as the Max Difference metric, which quantifies the contrast of the radiance of an object in the band in which it is brightest and the band in which it is darkest. The non-reflectance-related properties can be related to the shape and size of the object, or the properties of neighbouring objects (Definiens AG 2007; Definiens AG 2008).

1.4. Research Objectives

1.4.1. General Objective

To determine the applicability of Quickbird imagery to map marmot burrows in Hustai National Park, Mongolia.

1.4.2. Specific Objectives

To assess whether marmot burrows, and particularly the associated mounds, can be successfully distinguished from their surroundings in Quickbird imagery

To compare pixel and object-oriented image classification methods for the detection of marmot mounds in Hustai National Park using Quickbird imagery.

To assess the accuracy that can be achieved by algorithms aimed at detecting active marmot mounds.

To estimate the density and number of active marmot mounds in the different zones of the Hustai National Park using Quickbird imagery.

To investigate potential reasons for the spatial variation in active burrow density, by modelling the distribution of active marmot mounds in and around Hustai National Park using environmental variables and the different management zones of the park as predictors.

1.5. Research questions

How accurate can the location and number of active marmot mound be mapped using Quickbird imagery and classification algorithms?

Does object-oriented image classification better classify marmot mounds in Quickbird imagery than pixel-based classification?

Are there differences between the density of burrows in the core zone, tourism zone and buffer zone of the Hustai National Park?
If so, are these differences only due to environmental variables or also related with conservation management practices?

1.6. Hypotheses

H0: There is no difference in radiance between active and non active mounds and surrounding vegetation.
H1: There is a different in radiance between active, non active and surrounding vegetation..

H0: Object-oriented image classification does not classify marmot mounds more accurately than pixel-oriented classification does.

H1: Object-oriented image classification classifies marmot mounds more accurately than pixel-oriented image classification.

H0: The density of active marmot burrows does not differ between the core, tourism and buffer zones of the Hustai National Park.

H1: The density of active marmot burrows does differ between the core, tourism and buffer zones of the Hustai National Park.

2. H0: Any difference in active marmot burrow density between the core, tourism and buffer zones of the Hustai National Park are due to environmental variables, without an effect of management practices.

   H1: Differences in active marmot burrow density between the core, tourism and buffer zones of the Hustai National Park are at least partly due to management practices.

1.7. Research approach

Given the pivotal role marmots play in the steppe ecosystem of Mongolia, and the decline in their population, there is a pressing need for monitoring of the marmot populations and assessing the efficacy of conservation measures aimed at protecting them.

In order to address the objectives formulated at the outset of this research, field data was collected in order to develop and validate active marmot mound detection algorithms for Quickbird imagery. The resulting maps were then validated and used to analyze active marmot burrow distribution in Hustai National Park (**Figure 2**).

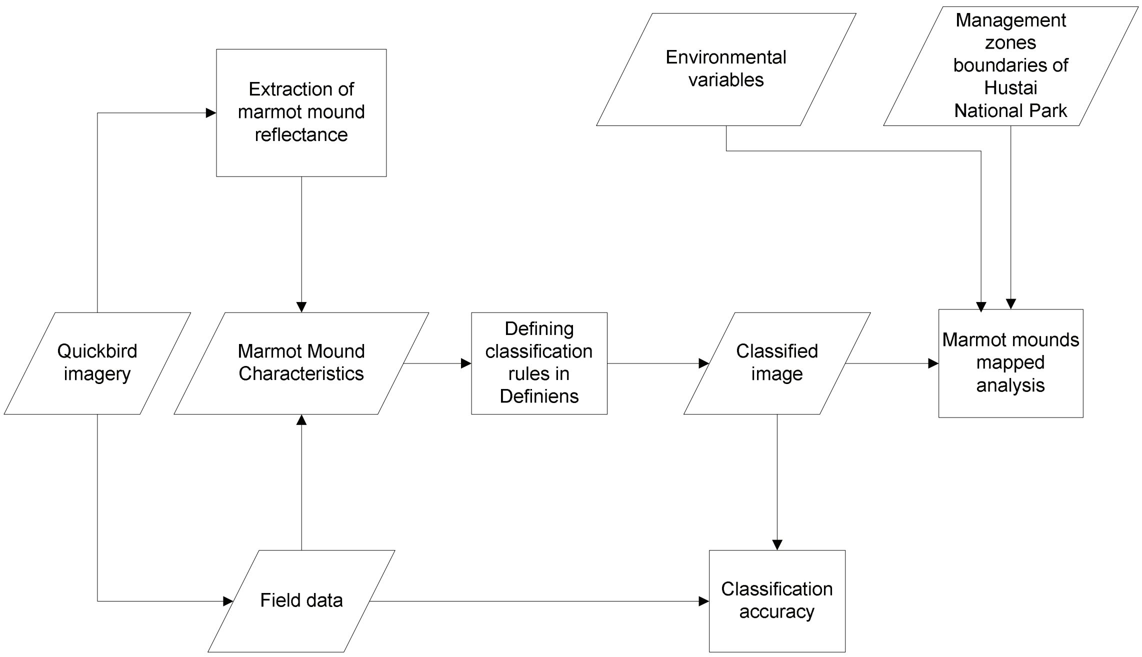

Figure 2. Outline of the main workflow of the presented research.

A detection algorithms to detect active marmot mounds was developed for Quickbird imagery, training and validating them using field observations. Resulting maps of active marmot mounds distribution were then used to analyze the distribution of marmot burrows, and their relationship to environmental variables and the borders of different managements zones of the Hustai National Park.

2. Material and Methods

2.1. Study Area

The study was made in and around Hustai National Park, a protected area about 100 km southwest of Ullan Bator, the capital city of Mongolia (Figure 3). The 50600 ha park was established as a reserve in 1993 and upgraded to national park status in 1998 (Tserendeleg 1999). It is situated at elevations ranging from 1100 to 1840 m.a.s.l. and has a landscape of gently undulating hills and a wide flood plain along the braiding Tuul river (Bouman 1998).

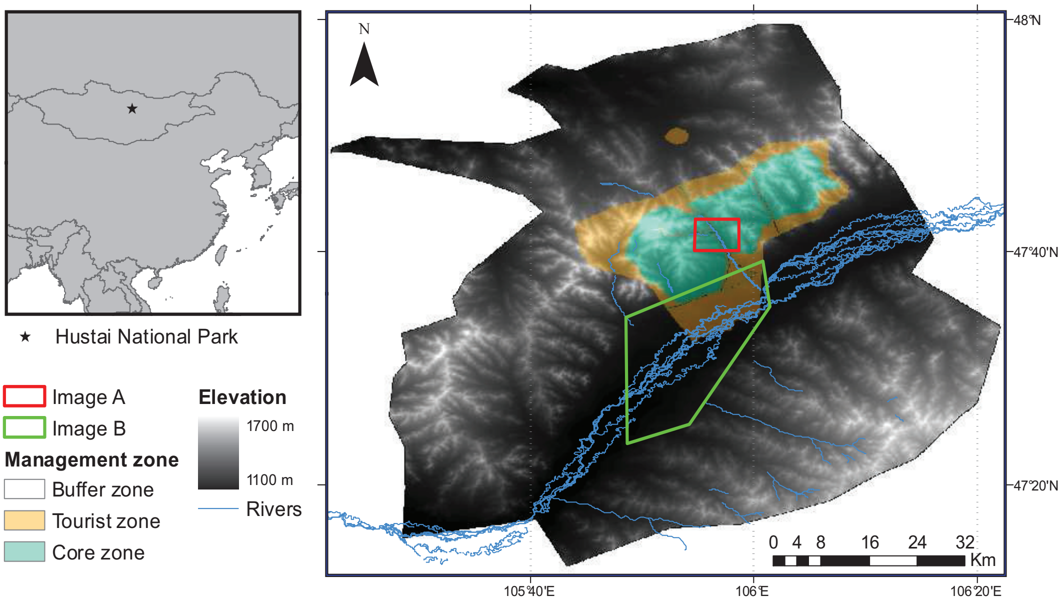

Figure 3 The location of Mongolia, location of management zones in Hustai National Park and position of the QuickBird images used for the research.

2.1.1. Climate and meteorological conditions

Hustai National Park has a continental climate, with strong contrast between summer and winter temperatures. The mean annual temperature is 0°C, with July the warmest month with mean temperature of 30°C and January the coldest when the minimum temperature can drop as low as -50°C (van Staalduinen 2005). The average annual precipitation is 270 mm with 80% of the rainfall between May and September. There is relatively great variation in precipitation with annual droughts of several weeks to several months. During springtime storms and strong winds are frequent (van Staalduinen 2005).

2.1.2. Fauna

The park hosts 46 mammal species, including takhi (*Equus przewalskii*), the last wild-living horse which was successfully reintroduced into the park in 1993 XX, red deer (*Cervus elaphus*), roe deer (*Capreolus capreolus*), Mongolian gazelle (*Procapra gutturosa*), wolves (*Canis lupus*) siberian lynx (*Lynx lynx*) and Siberian marmot (*Marmota siberica*) among others. 172 bird species have also been recorded in the park, including Golden eagle (*Aquila chrysaetos*), Black vulture (*Aegupius monochus*), and Saker Falcon *(Falco cherrug*) (van Staalduinen 2005; FPPPH 2009)

2.1.3. Vegetation

Hustai National Park is located in the mountain steppe region of Mongolia. Steppe vegetation dominates the park, while forest occupies only 5% of the park. The species that dominate the lowland steppe are, *Stipa krylovii*, *Artemisia adamsii* while in the upland steppe *Thermopsis lanceolata, Stipa krylovii* and *Caragana pygmaea C. microphylla*, *Artemisia frigida, Heteropappus altaicus, Chamaerhodos erecta, Cleistogenes squarrosa.* The predominated forest species are the trees *Betula platyphylla* and *Populus tremula* and the shrubs *Cotoneaster melanocarpa*, *Spiraea media* and *Rosa acicularis* (van Staalduinen 2005; van Staalduinen and Werger 2007).

2.1.4. Management zones

The area where now is Hustai National Park, was used as hunting grounds by Mongolia's leaders, from the last khan at the beginning of the 20^{th} century to political officials more recently. In 1993, however, the area was declared a reserve, because it had been chosen as the site for the reintroduction of takhi (*Przewalski horse*), of which no wild populations remained after the 1960s. The successful reintroduction also benefited the conservation and protection of other species in the area.

Based on the success of the conservation efforts, the reserve was promoted to a national park and expanded: while the 252 km^2 that had formed the initial reserve, became the 'core area' of the newly formed park, 225Km^2 was added around it as a 'tourist zone' and a 3500 km^2 'buffer zone'.

In the core zone, little tourism is allowed and the area is focus in research and conservation. In the tourist zone, the only economic activity allowed is tourism, meaning that hunting or grazing of livestock is banned and nomads are not allowed to set up gears there. The buffer zone was established around the park with the goal of reducing the effect of activities around the park on the park itself, Even though hunting and grazing is allowed and there is not law to protect the area. It aims at enhancing the participation of local people into the conservation effort in order to decrease poverty and promote the sustainable use of natural resources. More than 10,800 nomadic people and 175,000 animals (sheep, goat, horse and cattle) live in the Hustai National Park Buffer Zone and about 50-75% of these families are considered as poor (Bouman 1998)

2.2. Methods

2.2.1. Field data collection

Two methods were used for recording mound presence:, line-transect and photo-interpretation guided. Through the two sampling methods, 335 mounds of non active burrows and 361 mounds of active burrows were recorded in the field.

The line-transect sampling consisted of 15 transects, varying in length from 2 to 7 km, generally oriented from NE to SW based on Buckland (2001). Along each transect, all mounds were recorded in a strip with a width of approximately 20 meters. The orientation of the transects ensured that they covered the macro-topographical gradient, being perpendicular to the river in the tourism and buffer area, and crossed the major topographical aspects in the core area. The transects allow to record areas with and without mounds. In addition, the method provides systematic observations of not only mound presence, but also mound absence.
Because it had not tested before whether QuickBird data was useful to detect marmot mounds, as soon as the image was obtained, 23 sites with apparently high burrow density were selected through visual interpretation of the Quickbird-images and were visited in the field for verification. This photo-interpretation guided sampling maximized the number of marmot mounds that could be recorded in the field.
The location and characteristics of marmot mounds were registered in the field, and the following five characteristics recorded: 1) geographic location 2) the presence of marmot pellets, 2) the size of the mound around the burrow, 3) the number of entrances to the burrow, 4) the % cover of vegetation on the mound and 5) whether the mound was active or inactive (Appendix 7.1).

Active mounds were defined as the mound that had pellets or the mound belongs to burrows that had a clan hibernating at the time of field work. Burrows of hibernating marmots were easy to identify by their closed entrances consisting of stones and dry vegetation. Inactive mounds were defined as the mounds without pellets, based on the methodology of Townsend (2006).
Here, the term burrow denotes a group of entrances to a marmot den, as well as the mound that surrounds them and the tunnels. Mound is used to describe the heap of earth excavated and deposited next to the entrances. The mound is the most striking feature of the burrow visible on the satellite imagery.

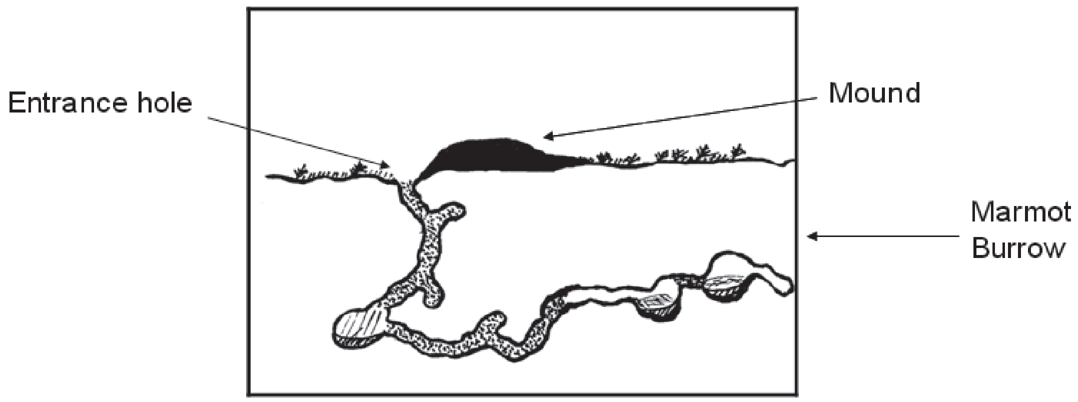

Figure 4.Marmot burrow with entrance hole, corridors and mound of excavated soil, Source Adiya (2007).

2.3. Remote sensing data: Quickbird images

Two Quickbird images of the Hustai National Park on 12 August 2007 were acquired: Image A covers a part of the core area ($25km^2$), and image B covers parts of the core, tourism, and buffer area ($274km^2$) (Figure 3). Quickbird is a commercial Earth-imaging spacecraft that was launched in October 2001 aboard a Delta 2 rocket. With pixel-sizes in Quickbird imagery as small as 61 cm, it provides some of the highest resolution data currently available to the public from space-born sensors and this in the visible and near-infrared spectra (Table 1). The data were purchased from DigitalGlobe (Longmong, Colorado USA) after georegistration to a UTM projection and with radiance represented on an 11 bit scale, i.e. with the value 2047 representing the maximum radiance measurable by the Quickbird sensor and all analyses were performed on the data in this format.

Table 1. Specifications of the bands of the Quickbird instrument

Band index	Wavelength (nm)	Spectrum	Resolution at NADIR (m)
1	450 – 520	Blue	2.44
2	520 - 600	Green	2.44
3	630 – 690	Red	2.44
4	760 - 900	Near-infrared	2.44
PAN	450 - 900	Panchromatic	0.61

2.4. Descriptive statistics

In order to guide the classification of the Quickbird imagery for the marmot mounds detection, the metrics recorded in the field were first analyzed and compared to the matching radiance values extracted from the Quickbird imagery. The two sample Student t-test, was used when comparing the means of two samples, and ANOVA when comparing the means of more than two samples. Games-Howell post-hoc tests were used with the ANOVAs in order to detect the source of statistically significant differences detected.

2.5. Burrow detection techniques

2.5.1. Pixel-based image classification

The Quickbird scenes were classified into active mounds-and non-active mounds, based on their reflectance in the three multispectral bands and the field data of burrow and non-burrow locations collected using the two field sampling methods. The minimum-distance algorithm considers the mean reflectance of the mound and non-mound training data, and classifies pixels in the image based on their distance to these means in the multi-dimensional space created by the Quickbird bands.

2.5.2. Object Oriented Image classification

The commercially available Definiens Developer Image Analysis Software was used for the object-oriented image analysis. Although the *Definiens eCognition Server* can process millions of images and perform detailed analyses in a single, fully-automated run, the software available at ITC that is Definiens Developer, does not have this option. Due to limitation of the Definiens Developer software, it was necessary to clip the Quickbird images in segments of 2000 m by 2000 m, for sequential processing. As a result image A was clipped in 9 segments and image B in 82 segments, after which the classification was performed for each segment separately and the result mosaicked back together.

The object-oriented image classification consisted of the following sequence of operations:

1.The image segmentation was performed, employing the Quad-tree segmentation algorithm, with the scale-parameter set to 30. This scale parameter represents the trade-off between processing time and low object heterogeneity. Then the resulting object primitives (OPs) were classified as burrows using the following sequence of rules:

2. The area of the OPs had to be smaller than 30 m^2. The Quad-tree algorithm generates OPs of sizes p^2, $4*p^2$, $16*p^2$,$64*p^2$,$256*p^2$, etc. where p is the pixel size. The pixel size of the panchromatic imagery is 61 cm. After the first segmentation it was noticed that mounds, roads and Objects with high brightness had a high heterogeneity, thus they were composed for many small objects. Mean while areas with low brightness with predominant vegetation had low heterogeneity generating objects bigger than 93.75 m^2 Thus, for the identification of mounds It was reasonable to take out the Ops bigger than 93 m^2.

3.The mean brightness of the OPs had to be higher than 540, This value was chosen because although the lowest radiance measured over an active mound was 510, visual interpretation of the panchromatic image, indicated that a threshold of 540 distinguished best between active and inactive mounds. This adjustment should reduce the number of false positives in the classification but might increase the number of false negatives, i.e.cases where active mounds are not detected.

4. The OPs with radiance higher than 540 were merged.
The brightness of the mounds around burrows is very similar to that of roads, footprints of gears, sites in dry valleys, and rocks, leading to a large number of false positives. Hence:

5.The area of the OPs had to be smaller than 29 m^2 and greater than 0.8 m^2.
Because the biggest mound observed was 29 m^2 and the smallest 0.8 m^2

6.The length of the OPs had to be lower than 6 m, which is the largest length of a burrow-site observed in the field.

7.The ellipse fit should be from 0.7 to 1
The ratio of the short axis to the long axis of the smallest ellipse that could be fit around the OP had to be greater than 0.7.

Some small segment of roads and dry valleys were classified as mounds. To avoid that the roads were digitized and parallel a classification for valleys and roads was performed. The results were extracted from the mound classification.

2.6. Burrow detection validation

11 zones were delimited in image A and 17 zones were delimited in image B for the validation of the automated marmot mounds detection algorithms. The zones cover the geographic extent and the topographical diversity of the two study areas. All marmot mounds in the validation zones were mapped in the field, either through the line-transect sampling or the photo-interpretation guided sampling. Therefore, the user's as well as the producer's accuracy could be calculated for each of the validation zones, and assessed with regard to the characteristics of the particular zone.

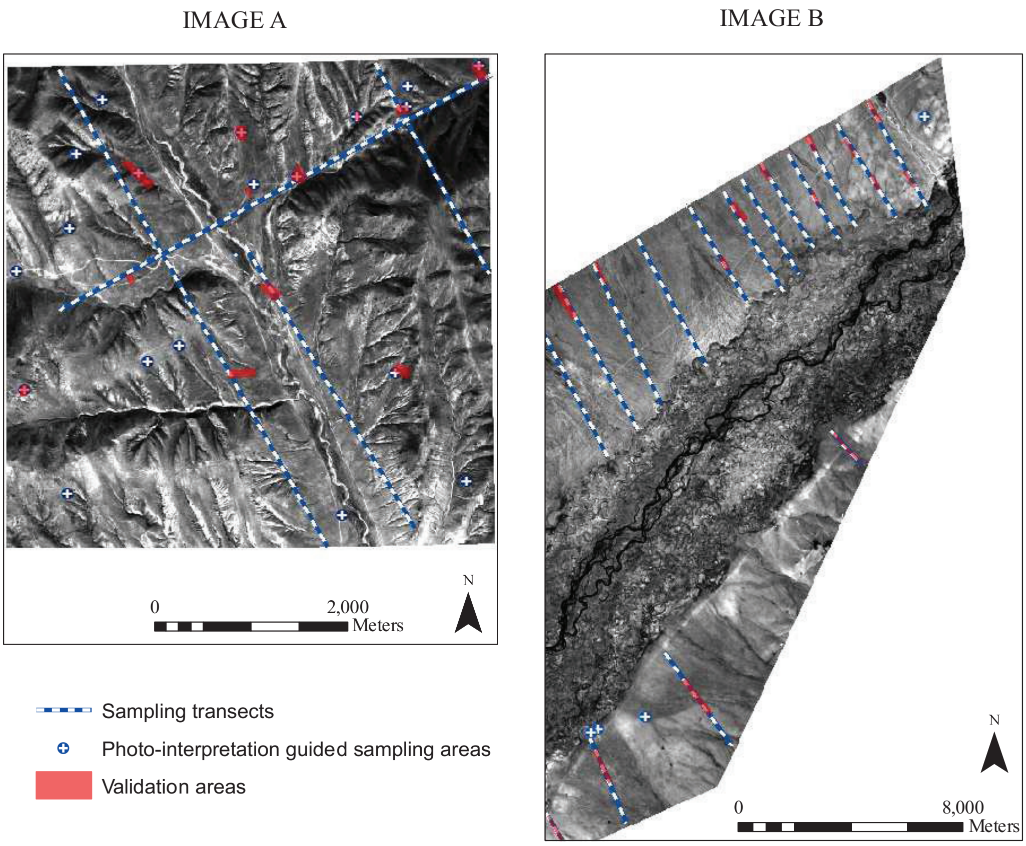

Figure 5.Areas in red were used to validate the maps produced by the automated burrow-mapping algorithms in Image A on the left (core zone) and in Image B on the right (core, tourism and buffer zones) of the Hustai National Park. The background images are Quickbird panchromatic data.

2.7. Estimating marmot burrow density

The density of active marmot mounds was estimated in the core, tourist and buffer zones of the Hustai National Park. The estimates were made using the maps generated by the object oriented automated marmot mound detection using the Quickbird imagery, overlaid with the maps depicting the outline of the different management areas of the park. The river bed was not taken into account because it was not possible to sample there and the characteristics of the area could be completely different.

2.8. Modelling the presence of marmot burrows using environmental data

The active marmot mound distribution maps were also used to analyze the relation with environmental factors. The effects of the distance from roads and rivers which had been hand-digitized using the Quickbird imagery as well as elevation, topographical slope, and topographical southern-exposure, all derived from a DEM with 90 m pixels, and vegetation type were examined. Topographical southern-exposure was calculated as -1*cos(topographical aspect) to represent a south-north gradient (Guisan, Theurillat et al. 1998).

The relationship between the environmental variables was analyzed using a multiple logistic regression approach, where the environmental variables served as predictor variables and the presence or absence of burrows as the response variable. Backward model selection based on the Akaike Information Criterion (Akaike 1973) was used to reduce the full model, i.e. including all the predictor variables to its more parsimonious form. An additional factor, describing whether a site falls into the core, tourism or buffer area of the national park was then added to this parsimonious model to test if the different park zones explain any of the variation in marmot burrow distribution unexplained by the environmental variables. Finally, the performance of the model was assessed using Cohen's κ (Cohen 1960), and the Area Under the receiver operating characteristics Curve (Zweig and Campbell 1993).

For the modelling, a dataset was created from 2663 sites of 100 by 100 meters, uniformly distributed across the study area and 150 m apart (Appendix 7.2). For each of the sites, marmot mound presence or absence was estimated from the mound distribution map and mean values of the environmental variables were calculated. The size of the sites should be large enough to generate a considerable variation in burrow density, yet small enough for the environmental variables to be relatively homogeneous. Because the sites were 150 m apart, the observations in the dataset can be considered independent, which is a critical assumption underlying logistic regression models. The sampling to create the dataset for the linear model was done using Hawth's analysis Tools for ArcGIS (Beyers 2004).

3. Results

3.1. Descriptive statistics

Analysis of variance revealed that the radiance differed significantly between the three categories, mounds near active marmot burrows, mounds near non active burrows and vegetation not associated with marmot burrows, for all Quickbird bands (ANOVA: $F_{band\ 1} = 354$, $F_{band\ 2} = 371$, $F_{band\ 3} = 341$, $F_{band\ 4} = 435$, $F_{PAN} = 412$, d.f = 695, $p < 0.000$ for all bands, Figure 6). Further post-hoc tests revealed that the three categories differed significantly among each other for all five bands (Games-Howell post-hoc test, $P < 0.001$ for all bands).

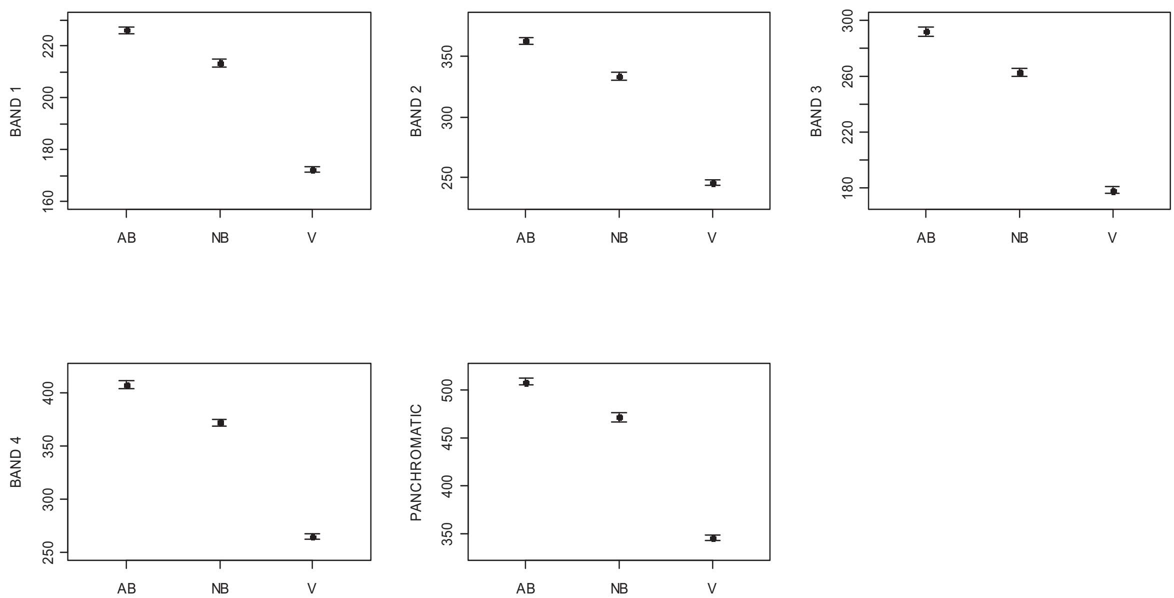

Figure 6. Mean and standard error (error bars) of the radiance of neighbouring vegetation (NV), and mounds near active(AB) and non active burrows (NB) in 4 multispectral and the panchromatic band of the Quickbird instrument

Mounds of active burrows were on average larger and had lower vegetation cover than those associated with non-active burrows (Figure 7, two sample T test, mound size: t = 4.743, df =438, p<0.000, vegetation cover: t= 5.5507, df =438, p<0.000).

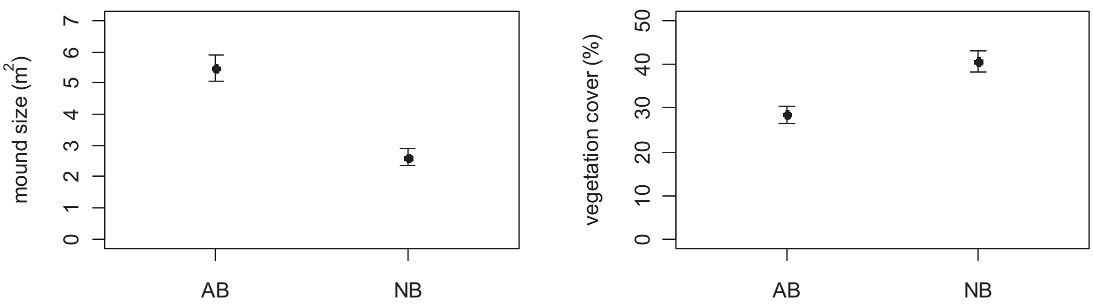

Figure 7. Mean and standard error of the size and vegetation cover of mounds associated with active (AB) and non active burrows (NB).

3.2. Quickbird image classification

In search for of the best algorithm to detect active marmot burrows in the Quickbird imagery, different classification methods were tested.

3.2.1. Pixel-based classification

Although most of the mounds were detected, the pixel-based classification using the Minimum-Distance criterion produced a very large number of false positives (Figure 8), resulting in a user's accuracy of only 15 % and a producer's accuracy of 91% (Table 2).

Table 2. Accuracy of the pixel-based classification

Zone	Area in 100 m^2	Marmot Mounds observed	Marmot Mounds detected	Marmot Mounds detected in non-mound areas	Marmot Mounds observed but not detected	Mounds correctly detected	Producer's Accuracy	User's Accuracy
Core1	35	5	9	4	0	5	100%	56%
Core2	168	11	50	39	0	11	100%	22%
Core3	97	6	46	40	0	6	100%	13%
Core4	207	17	64	47	0	17	100%	27%
Core5	141	10	10	0	0	10	100%	100%
Core6	48	5	29	24	0	5	100%	17%
Core7	92	3	40	37	0	3	100%	8%
Core8	287	20	93	73	0	20	100%	22%
Core9	221	15	72	57	0	15	100%	21%

Core10	191	4	25	21	0	4	100%	16%
IMAGE A TOTAL	1487	96	438	342	0	96	100%	22%
Tourist1	979	4	20	17	1	3	75%	15%
Core2	296	1	7	6	0	1	100%	14%
Tourist3	111	5	59	54	0	5	100%	8%
Tourist4	568	9	60	52	1	8	89%	13%
Tourist5	1003	7	99	93	1	6	86%	6%
Core6	880	31	155	124	0	31	100%	20%
Tourist7	1297	3	134	133	2	1	33%	1%
Core8	616	11	71	61	1	10	91%	14%
Tourist9	2798	14	98	96	12	2	14%	2%
Tourist10	785	12	86	76	2	10	83%	12%
Buffer11	1114	3	42	40	1	2	67%	5%
Buffer12	931	23	64	44	3	20	87%	31%
Buffer13	2059	5	118	113	0	5	100%	4%
Buffer14	1723	2	123	121	0	2	100%	2%
Buffer15	415	2	46	44	0	2	100%	4%
Buffer16	579	1	32	31	0	1	100%	3%
Buffer17	761	1	55	54	0	1	100%	2%
IMAGE B TOTAL	16915	134	1269	1159	24	110	82%	9%

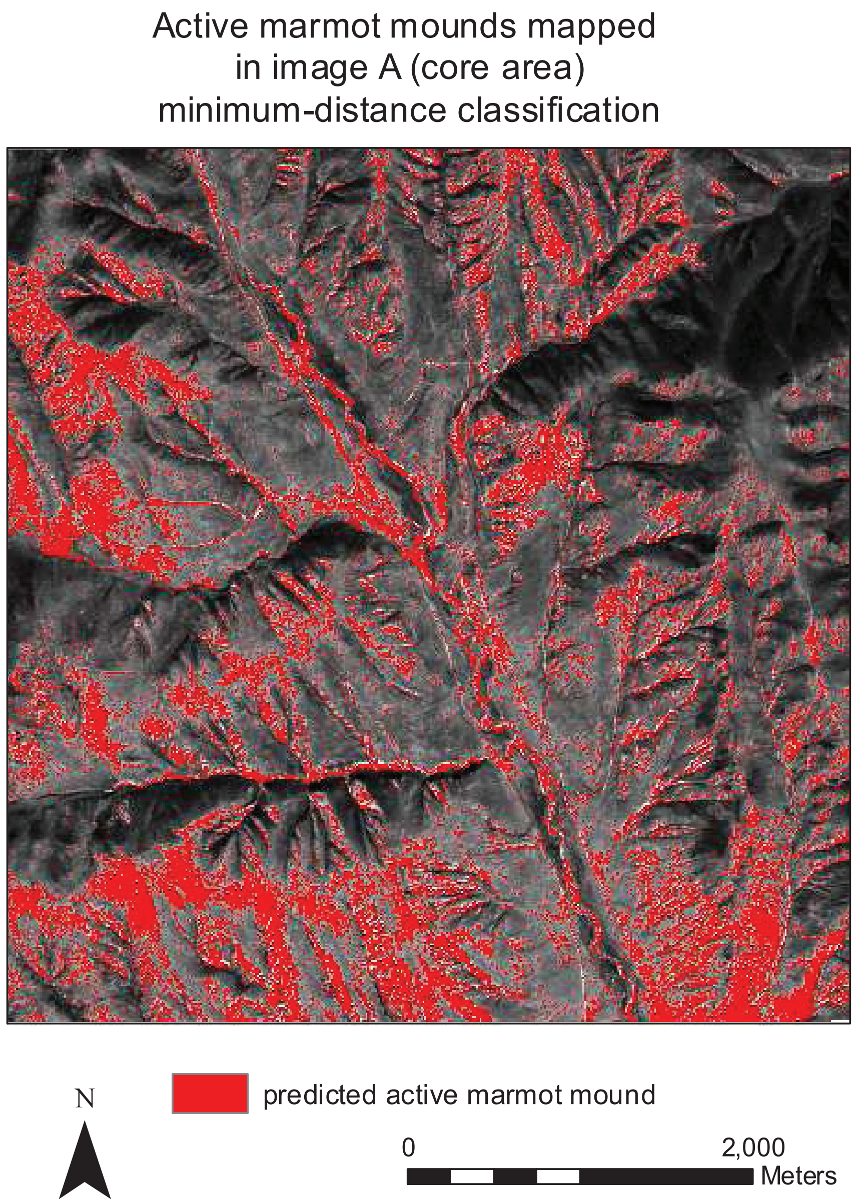

Figure 8. Result of pixel based classification, Image A, which covers part of the core area of Hustai National Park.

3.2.2. Object-oriented classification

The descriptive statistics showed that the radiance of active marmot mounds differed from that of non-active marmot mounds and the surrounding vegetation in all the bands of the Quickbird imagery Figures 9 and 10, show the results of the Object-oriented classification based on the rule developed. Because the panchromatic band has a higher resolution than the other bands (61 m vs 2.4 m), it was used for the object-oriented image classification. Figures 9 and 10 show the results of the object-oriented classification based on the sequence of classification rules developed.

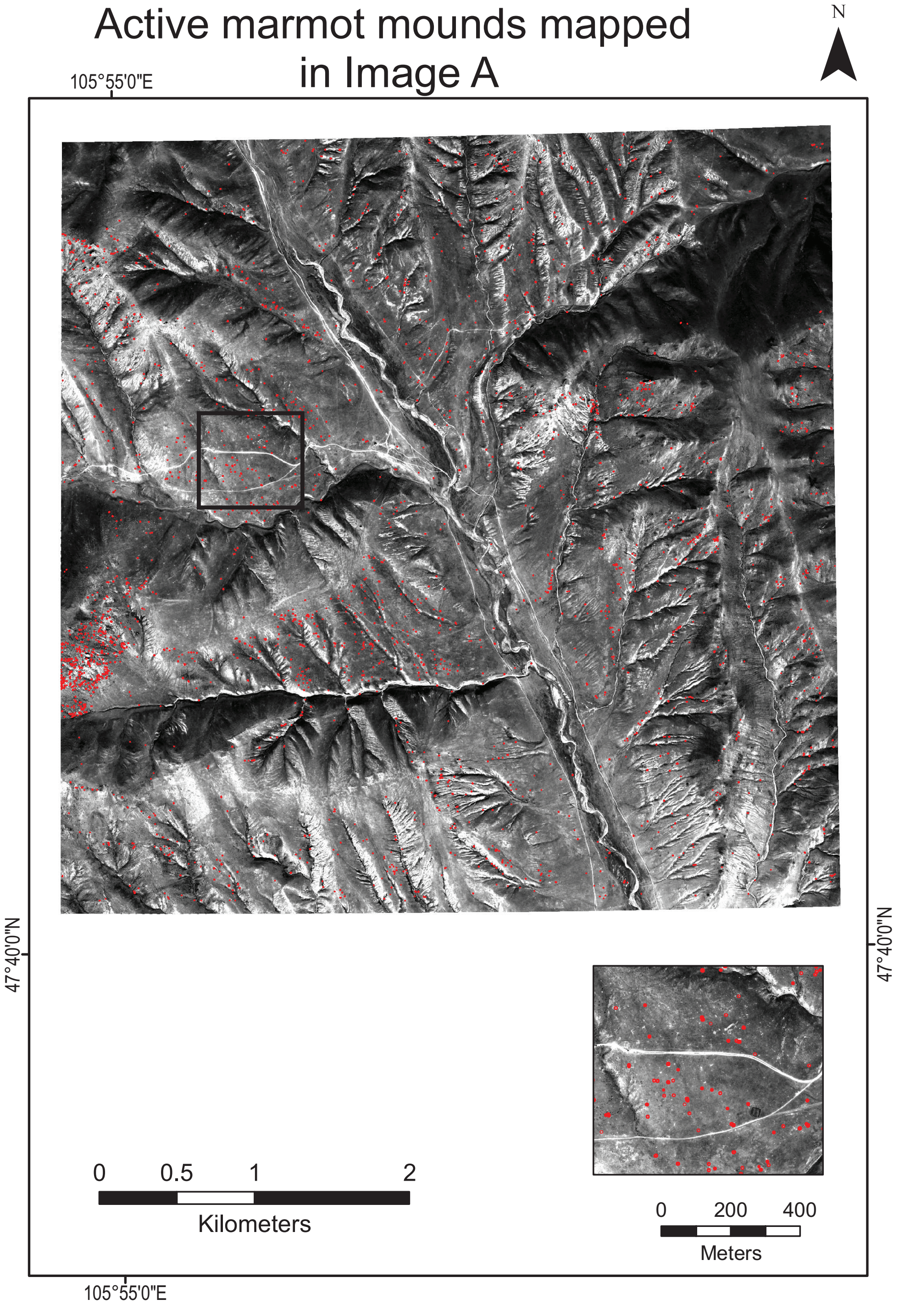

Figure 9. Active marmot mounds mapped in Image A using the object-oriented classification approach.

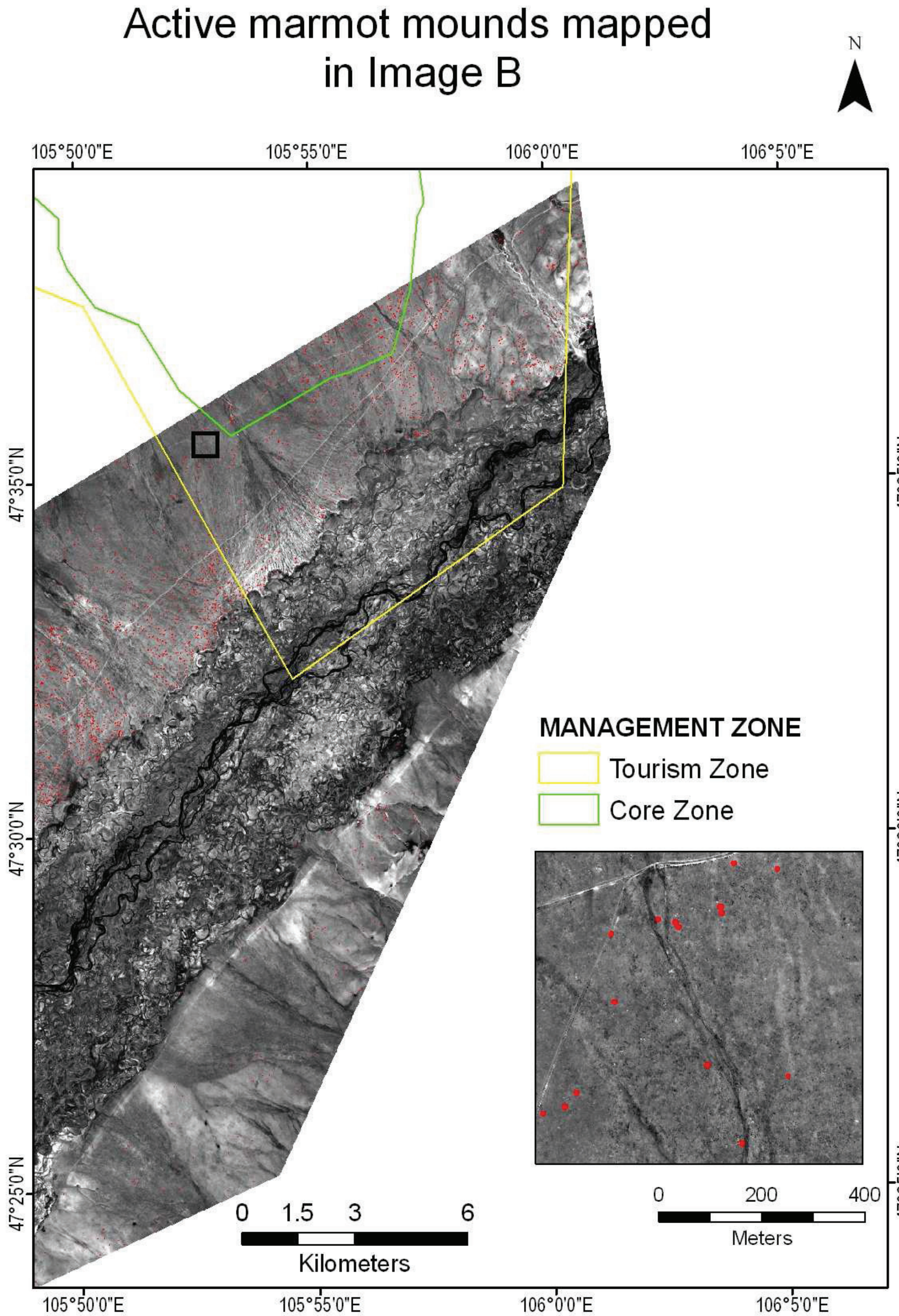

Figure 10. Active marmot mounds mapped in Image B using the object-oriented classification approach. Active marmot mounds are shown in red.

3.2.2.1. Validation of the object-oriented classification

The resulting map of the distribution of active marmot mounds achieved an average user's accuracy of 69.5 % and a producer's accuracy of 87%, when compared with the field data (Table 3).

Table 3. Accuracy of the object-oriented classification

Zone	Area in 100m^2	Marmot mounds observed	Marmot mounds detected	Marmot mounds detected in non-mound areas	Marmot mounds observed not detected	Correctly detected mound	PRODUCER'S ACCURACY	USER'S ACCURACY
Core 1	35	5	4	1	2	3	60%	75%
Core2	168	11	23	14	2	9	82%	39%
Core3	97	6	6	0	0	6	100%	100%
Core4	207	17	20	5	2	15	88%	75%
Core5	141	10	13	4	1	9	90%	69%
Core6	48	5	7	2	0	5	100%	71%
Core7	92	3	10	9	2	1	33%	10%
Core8	287	20	20	0	0	20	100%	100%
Core9	221	15	16	1	0	15	100%	94%
Core10	191	4	4	1	1	3	75%	75%
IMAGE A TOTAL	**1487**	**96**	**123**	**37**	**10**	**86**	**90%**	**70%**
Tourist1	979	4	1	0	3	1	25%	100%
Core2	296	2	5	3	0	2	100%	40%
Tourist3	111	5	4	0	1	4	80%	100%
Tourist4	568	9	10	3	2	7	78%	70%
Tourist5	1003	7	8	2	1	6	86%	75%
Core6	880	31	29	4	6	25	81%	86%
Tourist7	1297	3	2	1	2	1	33%	50%
Core8	616	11	13	2	0	11	100%	85%
Tourist9	2798	14	22	9	1	13	93%	59%
Tourist10	785	12	16	6	2	10	83%	63%
Buffer11	1114	3	4	1	0	3	100%	75%
Buffer12	931	22	22	3	3	19	86%	86%
Buffer13	2059	5	7	2	0	5	100%	71%
Buffer14	1723	2	12	10	0	2	100%	17%
Buffer15	415	2	6	4	0	2	100%	33%
Buffer16	579	1	1	0	0	1	100%	100%
Buffer17	761	1	1	0	0	1	100%	100%
IMAGE B TOTAL	**16915**	**134**	**163**	**50**	**21**	**113**	**84%**	**69%**

Inspection of the observed and predicted marmot mound locations, revealed that mounds around burrows that contrasted strongly with their surroundings were often correctly mapped (Figure 11).

Steep terrain reduced the contrast between mounds and their surroundings, sometimes resulting in unsuccessful detection of the mounds by the algorithm (Figure12). In areas with dry valleys, rather than vegetation, many areas of bare soil that were not marmot mounds were classified as active mounds (Figure 13, right side). In the image segmentation, long and large object primaries, typical of roads, were excluded from the burrow class. Nevertheless, when little-used dirt roads were segmented into small object primaries, these tended to be mistaken for active marmot mounds (Figure 13, left side).

Ghers, footprint of ghers and building were successfully not detected as active mounds (Figure14) During the photo-interpretation prior to the field work some marmot mounds were identified, that when visited in the field turned out to be dug by the rat *Lasiopodomys brandtii*, rather than by marmots. During the automated marmot mound detection, these were correctly classified as non-active mound, however, thanks to their relatively low radiance (Figure 15).

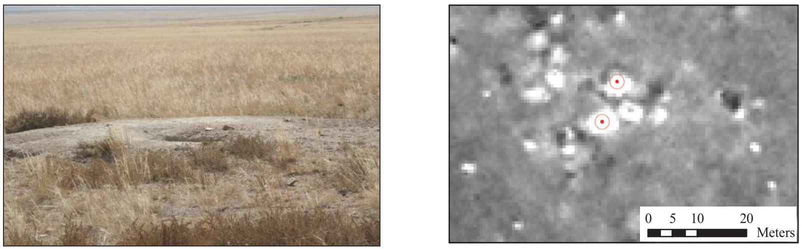

Figure 11. Picture of a mound that was successfully detected by the object-oriented algorithm, and its appearance in the Quickbird panchromatic image, and field-recorded location, indicated by a red dot.

Figure 12. Picture of a burrow that was not detected by the same algorithm, because the terrain steepness caused a decrease in radiance, as seen by the Quickbird sensor.

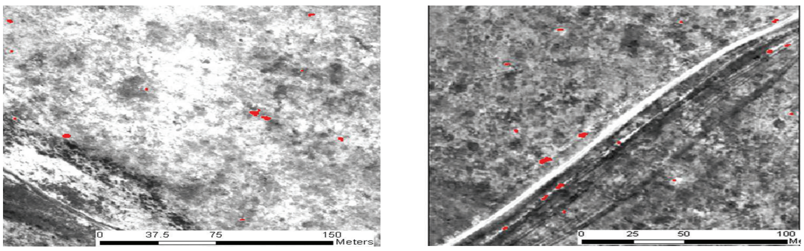

Figure 13. Misclassification of segment of dry valleys as active mounds (red dots, right side), and misclassification of segment of a little-used dirt roads as active burrows mounds (red dots, left side)

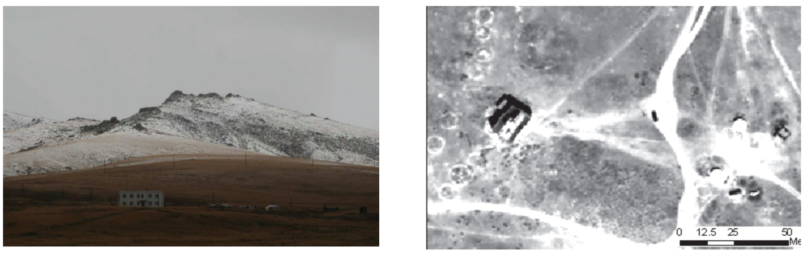

Figure 14. Subset of panchromatic Quickbird images A showing ghers, footspring of ghers, buildings that were successfully not identified as burrows.

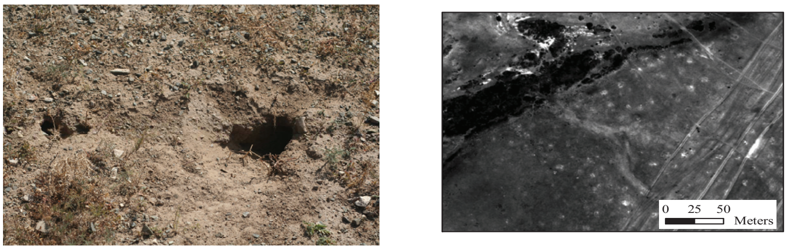

Figure 15 Panchromatic Quickbird image of an area with burrows (visible as grey spots right side) built by *Lasiopodomys brandtii*, a non-native rat which lives in desertified areas in and around Hustai National Park. The objected-oriented image classification successfully classified them as non-marmot mound,.

3.3. Burrow density in different management zones

The validation of the maps generated by the object-oriented automated marmot burrow detection using Quickbird imagery showed a systematic overestimation of the number of marmot burrows in areas where brightness values in the Quickbird image were very high and of low contrast, such as little used dirt roads, tracks and dry valleys. Prior to calculating the active marmot burrow density, these areas were excluded from the maps, to prevent a bias in the density estimates.
The density of active marmot mounds was estimated at 275 mound/km^2 in the core zone, 158 mound/km^2 in the tourist zone and 74 mound/km^2 in the buffer zone of the Hustai National Park.

3.4. Marmot burrow distribution related to environmental variables

The AIC selection criterion removed the distance to roads from the logistic regression model, generating a model with the distance from a river, elevation, topographical slope, southern exposure and vegetation as predictor variables. The model explained only a small amount of the variation in the marmot burrow presence-absence data, as represented by the relatively low AUC of 0.71, , and Cohen's κ of 0.32. Adding a variable representing the management zone, that is core, tourist, or buffer zone decreased the AIC from 2313 to 2275. This indicates that information on the management zone contributes to explaining the marmot burrow distribution. However, adding this variable to the model did not improve the model performance statistics significantly: AUC = 0.73, Cohen's κ = 0.34. The final model predicts the presence of marmot burrows to decrease with elevation, and to increase with topographical slope, southern exposure, vegetation and management zone (Table 4). In addition, it predicted increasing density of marmot burrows from the buffer zone, over the tourism zone, to the core zone of the Hustai National Park

Table 4. Influence of environmental variables on the presence of active marmot mounds as predicted by a logistic regression model, as well as the observed range of environmental variables.

variable	influence on active marmot burrow probability (parameter estimate ± standard error)	range
distance to river	-1.3 ± 0.77	10 m – 3210 m
elevation	-7.8 ± 1.7	10 m – 1202 m
topographical slope	+9.2 ± 2.9	0° – 25°
southern-exposure	+11 ± 0.99	-1 +1
management area:		
tourism zone compared to buffer zone	+4.7 ± 1.4	
core zone compared to buffer zone	+13.0 ± 2.7	
vegetation:		
class B compared to class A	+4.8 ± 3.6	
class C compared to class A	+4.9 ± 4.6	
class D compared to class A	-1.7 ± 3.1	

Description of vegetatioin classes: class A: Complex marsh: Lymegrass-sedge (70%), grass-herb (20%), achnatherum's grove with russianthistle-herb (10%) in combination with willow-poplar grove (10%), class B: Stony needlegrass-wormwood-thyme with participation of peashrub and almond, class C: Festuce-herb in combination with stony little soddygrass-herb (20%) and with shrubs, class D: Low soddygrass-needlegrass-wormwood with participation of peashrub

4. Discussion

4.1. The use of remote sensing to detect marmot burrows

This study revealed that Quickbird imagery can be used for detection of active marmot burrows based on the mounds associated with them and across large areas. More specifically, marmot mounds were detected with a producer's accuracy of 87% and a user's accuracy of 69% using object oriented analysis. In other words, about 87% of all burrows were successfully mapped and 69% of burrows mapped are actually active marmot burrows. Through this study it has become clear that high resolution remote sensing data can greatly facilitate the mapping and monitoring of active marmot burrow distribution. Nevertheless field work remains crucial to successful marmot burrow detection using remote sensing data, and areas where the algorithm could be improved were identified.

4.1.1. Pixel- based classification

The pixel-based classification which used the four spectral bands of the Quickbird sensor detected almost all burrows, but produced a great number of false positives, with most areas of bare soil classified as active marmot mounds. In fact, all the roads, dry valleys, rocks, ghers were classified as active mounds by the pixel-based classification. Only two classes were defined for the classification: 'active marmot mounds and 'other land cover classes'. Increasing the number of endmembers is likely to improve the classification, but would also increase the amount of field work. Nevertheless, the pixel-based classification makes it clear that based on spectral characteristics only, most active marmot mounds are indistinguishable from other areas of bare soil. This limits the success that can be achieved when detecting active marmot mounds solely based on their spectral characteristics, and indicates that including other characteristics of marmot mounds would be most effective for reducing the number of false positives when detecting active marmot mounds.

4.1.2. Object-oriented classification

The marmot burrows and the mounds associated with them in particular have characteristics that separate them from most other land cover types. The brightness of the mounds that surround them is one of their most striking characteristics in the remote sensing data. However, through the pixel-based classification it became apparent that this characteristic is insufficient for their successful detection, since the brightness of these mounds is similar to that of exposed rocks and other areas of bare soil, such as roads and dry areas. Hence, it was important to use other characteristics of the mound in the detection process, such as their size and shape. As a consequence, the object-oriented image classification algorithm outperformed the pixel-based classification algorithm.

Compared to a number of studies, using object oriented methods for image classification, the accuracy achieved here is relatively low. Kerle and de Leeuw (in press) used object-oriented classification to detect dot-like features in a digitized map, achieving an accuracy between 94 % and 98%. However, the potential for confusion of objects is much greater in a mosaic-like landscape of bare soil, vegetation and rocks, than when dealing with printed dots on a homogeneous background. Similarly, Kimani (2007), mapped savannah trees in the Kalahari, using imagery with a similar resolution to Quickbird data but from an airborne platform, and achieved an accuracy of 79 to 89 %. Based on the imagery provided in Kimani (2007), the dry savanna landscape shows a great contrast between trees and other vegetation. Therefore the potential for object confusion might have been lower than in the present study which focuses on a more heterogeneous landscape. Rutzinger (2006) detected buildings in high resolution Airborne Laser Scanning data using object-oriented classification methods and compared the result with a digital cadastral map, achieving a producer's accuracy of 91% and a user's accuracy of 90%. What sets the work presented here apart from the latter study, however, is the small size of the features to be detected, compared to the pixel size, complicating image segmentation.

The date of Quickbird image acquisition, as well as the mismatch in timing between image acquisition (August 2007) and field work (September 2008) might have negatively influenced the classification accuracy reported here. Climate data and multi-year remote sensing show that 2007 was an exceptionally dry year, as can be seen in a time series of summer NDVI, measured by the Moderate Imaging Spectroradiometer (MODIS, Figure 17)

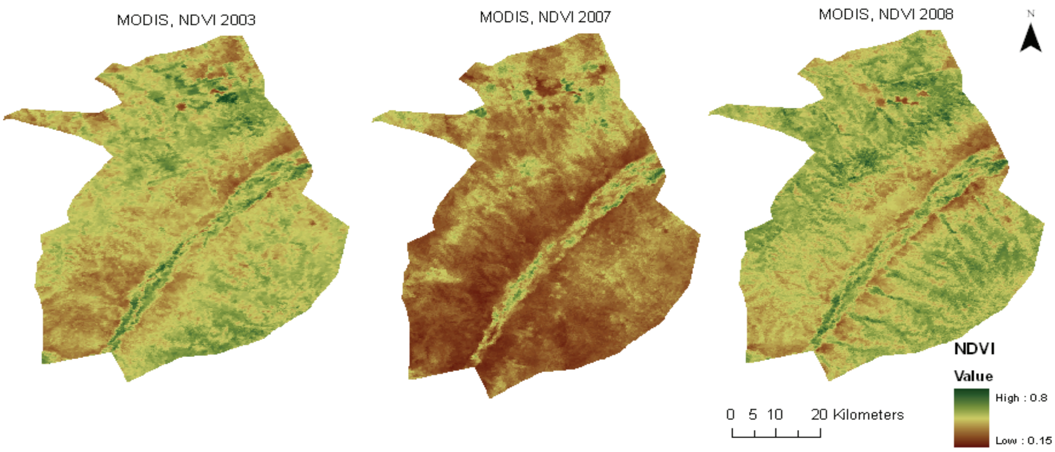

Figure 16. MODIS NDVI over Hustai National Park and the buffer zone summers of 2003, 2007, and 2008 indicating intense drought in the summer of 2007. (MODIS NDVI data is available from https://lpdaac.usgs.gov/lpdaac/products/modis_overview)

The drought of 2007 might have reduced the user's accuracy achieved in this study by increasing the number of false positives in the classification. The dry conditions probably created dry segments of bare soil around the roads, valleys and in the steppe that in 2008 were covered by vegetation. These areas might not be mistaken for marmot mounds in imagery where vegetation is more abundant or less drought-stressed.

At the same time, the draught in 2007 and the fact that field data were collected one year later might also have reduced the producer's accuracy by increasing the number of false negatives in the classification. Marmots might have abandoned burrows in dry areas during 2007, while re-occupying them in 2008, and new burrows might have been dug between the dates of image acquisition and field work, resulting in false negatives in the validation. However, the latter effect was probably small since it has been claimed that marmot in Hustai National Park rarely construct new burrows and continue to use the same burrows for many years (Todgerel 2000; Yoshihara 2008).

It is clear that the burrow-detection algorithm could be improved with more time: The algorithm performs poorly in the dry valleys and misclassifies small fragments of little-used roads as active mounds (Appendix 7.3). In the buffer area where the desertification is highest, the algorithm often identified small areas with hardly any vegetation as active mounds. This second type of error can result in a overestimate of mound densities in grazed and desertified areas, since the population density of another marmot species *(Marmot bobak*) is known to decrease with more intense cattle grazing and desertification in their habitats(Ronkin and Savchenko 2004).

Most roads were automatically masked in the image segmentation based on the area and length of object primitives. Nevertheless, the segmentation created some small object primitives that were part of little-used roads, which then were misclassified as active marmot mounds. This problem was identified during the validation of the burrow distribution maps. Because of the poor performance of the algorithms in the driest valleys and the occasional confusion of little-used roads and mounds, the driest valleys and roads remained were masked from the classification result when it was used for burrow density estimations.

Due to the mountainous topography of Hustai National park, some shadows are present in the QuickBird imagery, especially in the core area. Because the classification algorithm was partly based on the brightness of pixels, the presence of shadows could have affected the classification generating false negatives. Although this issue was identified, a topographic correction to resolve it was not applied to the imagery, because a digital elevation model with a spatial resolution comparable to that of the QuickBird imagery was not available.

Based on available literature, this is the first research that aims to identify marmot burrows using Quickbird imagery or object-oriented classification methods. Other classification techniques, such as visual image interpretation, is being explored by other research groups to detect marmot burrows. In 2008, Russian researchers started a project in Mongolia aiming to detect marmot burrows in aerial photographs and Google Earth images (Oleg, personal communication). Although that project is in the early stages, and the accuracy of the results have not yet been published, a main issue has been the confusion of other animals burrows such *Lasiopodomys brantii* with marmot burrows (Oleg, personal communication). In the present research *Lasiopodomys brantii* burrows were also identified as marmot burrows during the visual image interpretation of the remote sensing data. Validation of the results, however, showed that the algorithm built in the Definiens software, successfully distinguished active marmot mounds from *Lasiopodomys brantii* burrows, suggesting that the automated algorithm developed here can avoid potential pitfalls present in visual image interpretation. Another strong point of this method is that it is aimed at detecting active mounds, rather than all mounds or burrows, while during visual interpretation is difficult to distinguish both. This is essential if burrow distribution maps here are to be used to estimate the marmot population, since non active burrows remain or increase when marmot populations decline.

4.2. Marmot burrow density in the core and the tourism area

The density of active marmot burrow differed remarkably between the buffer zone, the tourist zone and the core zone of the Hustai National Park. This difference in marmot burrow density matches a gradient of increased conservation status of the different zones. The research presented here indicates that the density of active marmot burrows in the part of the core zone covered by the Quickbird images is four times higher than in the section of the buffer zone covered by the images. This result concurs with Thapaliya (2008) and Oleg (2008) who claimed, based on field data only that marmot burrows are more abundant in the core zone than in the buffer zone.

The density of marmot burrows differs clearly between the different management zones of Hustai National Park. Based on field observations, as well as the remote sensing data, it is clear that the cover changes abruptly at the boundary of the park. At the south of the Tuul river, several areas show a strong contrast in vegetation with signs of overgrazing and desertification, and local people confirm that this process has increased through the years. This abrupt change in the landscape was not only seen south of the Tuul river: At the western boundary of the park overgrazing is also apparent. This was confirmed by Hovens and Tungalaktuja (2005) who claim that a high number of horses died from starvation at the end of the winter of 2004 because the area around the park is overgrazed and Thapaliya (2008) who claim that the buffer zone is highly degraded as compared to the core zone (Figure 18).

Figure 17. Desertification in the buffer area of the Hustai national park (on the left), and healthy steppe vegetation in the core area of the park (on the right).

The difference in the vegetation cover between the noncore and the buffer area may affect the distribution of marmots directly. Marmots have a relatively small action radius and spend 87% of their lifetime in burrows underground or grazing near to a burrow (Bassano, Peracino et al. 1996; Lenti 1999; Adiya 2007). In addition, as they are hibernating animals, they need to maximize grazing to build fat reserves in anticipation of winter. As a consequence, they are restricted to habitats that are abundant in nutrient-rich vegetation.

Another factor affecting the difference in marmot burrow density, other than the differences in the landscape, could be the restrictions on hunting , which is the primary threat to the marmot in Mongolia (Wingard and Zahler 2006) .

A study in 1997, just 4 years after the areas was declared a natural reserve and hunting was banned, showed that the population of marmots in Hustai was relatively young (Todgerel and Tungalagtuya 1998). This indicates that it might have been recovering from years of intense hunting. Although a national ban on marmot hunting was put in to effect in 2006, three cases of hunting to the west of the core area were reported in 2008 (Hustai park authority, personal communication). During transect sampling for the present study a marmot trap placed in a burrow was encountered in the buffer area.

In the core area, and more specific in the river months of the Tariat, Bayan, Moilt and Jargalant were identified as the areas of highest density of marmots in the Hustai National park, based on the study of Todgerel and Tungalagtuya (1998). Those are also the areas where the Takhi was reintroduced and grazes, and hence they are intensely monitored, eliminating illegal hunting.

In contrast, some illegal hunting activity is ongoing in the buffer area of the Hustai national park, and a difference in hunting pressure, both now and in the past, might account at least partly for the observed difference in active marmot burrow density. It also indicates that the establishment of the Hustai National Park might have contributed to the protection of the Siberian marmots.

4.3. Model behaviour

Marmot burrow distribution was relatively poorly estimated by the database of environmental variables used by the model. Some of the variables taken into account were the same that explain the distribution of other mammals in the park.

Marmot burrow distribution was relatively poorly estimated by the database of environmental variables used by the model. Thapaliya (2008) modelled the distribution of red deer in and around Hustai National Park using environmental variables similar to the ones included here. In contrast to the active marmot burrow distribution, the distribution of red deer was well-explained by the environmental variables (AUC = 0.96 vs. AUC = 0.71). This might be due to the much smaller scale at which marmots act in the landscape, compared to red deer. As a consequence, micro topography is poorly represented by the DEM used here for the modelling, with a ground resolution of 90 m. So it is possible that marmots strongly prefer a specific elevations or slope but the 90 m resolution of the data make it difficult to detect this. At the same time, *Marmota siberica* lives in a wide range of elevations, from 680 to 3800 m.a.s.l. This study only took into account elevations from 1128 m.a.s.l. to 1629 m.a.s.l. , which limits the degree to which the effects of the elevation in the distribution can be seen.

Nevertheless, the southern topographical exposure was retained in the final model and this could be related with the marmot need of solar radiation (Barash 1989). Marmots must storage high proportion of energy for the hibernation time, thus they spend time sunning themselves close to their burrow entrance because they need to keep this energy for the winter season. Because of this, one would expect marmots to build their burrows on southerly exposed slopes, which was indeed observed in for *Marmota vancouverensis*(Bryant and Janz 1996).

Other environmental predictor variables might improve the model if they are quantified at a suitable scale. Soil type for example, may affect the distribution of marmot mounds because it affects the ease with which these can be dug. Unfortunately, soil data were not available for the entire area covered by the present study.

Normalized Difference Vegetation Index (NDVI) has been often reported as the principal explanatory variable in models of wild life species distribution (Herkt 2007). Here, the NDVI was not used as a predictor variable in the model because of the exceptionally low values recorded in 2007 due to drought. Nevertheless, in a year with normal amount of precipitation NDVI might be a useful variable in the model.

In the study area, the different management zones have different topography, with the core zone dominated by hilly slopes, and the tourism and buffer zones being dominated by river flats. Thus, there is the danger of confounding the effects of topography on the density of active mounds with that of the conservation measures associated with the different management zones. While, as stated before, the topography-related variables used for the modelling are at a coarse resolution, the model detected a significant effect of the management zone on marmot burrow density after the effect of course topography had been accounted for.

5. Conclusions and Recommendations

5.1. Conclusions

Radiance of active mounds, non-active active mounds and vegetation differed significantly in all bands of the Quickbird sensor. However, since mounds have a similar reflectance to other areas of bare soil, spectral information alone is insufficient to distinguish mounds in the landscape.

The object-oriented classification algorithm developed here proved itself valuable for the mapping of active marmot burrows, generating a user's accuracy of 69% and a producer's accuracy of 87 %, compared to the user's accuracy of 15% , and producer's accuracy of 91% generated by the pixel-based classification algorithm used here. Nevertheless, field work remains crucial to identify classification errors and their sources in both methods.

The algorithm behaves better in areas where the contrast between the marmot mound and the surrounding vegetation was high. As a result, mound density was overestimated in areas that suffer from desertification and overgrazing producing a high number of false positives.

In the study area, the density of marmot mounds increases from the buffer zone of Hustai National Park (74 mound/km2), where conservation is minimal, over the tourism area (158 mound/km2), to the core area (279 mound/km2), where conservation is the highest priority. A logistic regression model indicates that these differences cannot be explained by environmental variables alone, and that the management practices in Hustai National Park positively affect the marmot density in the park. However, it needs pointing out that the overall predictive power of the models was low, because potentially important environmental variables such as soil depth and texture and vegetation abundance were not included. In addition, the slope, elevation and topographical exposure variables, were derived from a 90 m DEM, which might be too coarse to describe marmot habitat preferences.

5.2. Recommendation

This study contributes to assessing and monitoring marmot populations in steppe areas. While it shows that active marmot mounds can be mapped using remote sensing data and object oriented image classification, further studies are needed to establish the link between active mounds or burrows densities and marmot densities. In other words, good estimates of the average number of marmots that occupy a single burrow are needed. Once such estimates are available, images acquired in different years could be compared to monitor the changes in marmot populations through the time.
Meanwhile, it is recommended to avoid gaps between the timing of field work and image acquisition, and avoid periods with exceptional climatic events.

The model used to identify the relationship between environmental variables and marmot burrow distribution, performed poorly. To further explore this relationship, predictor variables need to be measured at a scale that is more relevant to marmots, i.e. in greater detail than the data available for the present work. In addition, the inclusion of other environmental variables, such as soil structure, which might drive marmots in habitat selection, might be necessary to successfully model the distribution of marmot burrows.

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7. Appendices

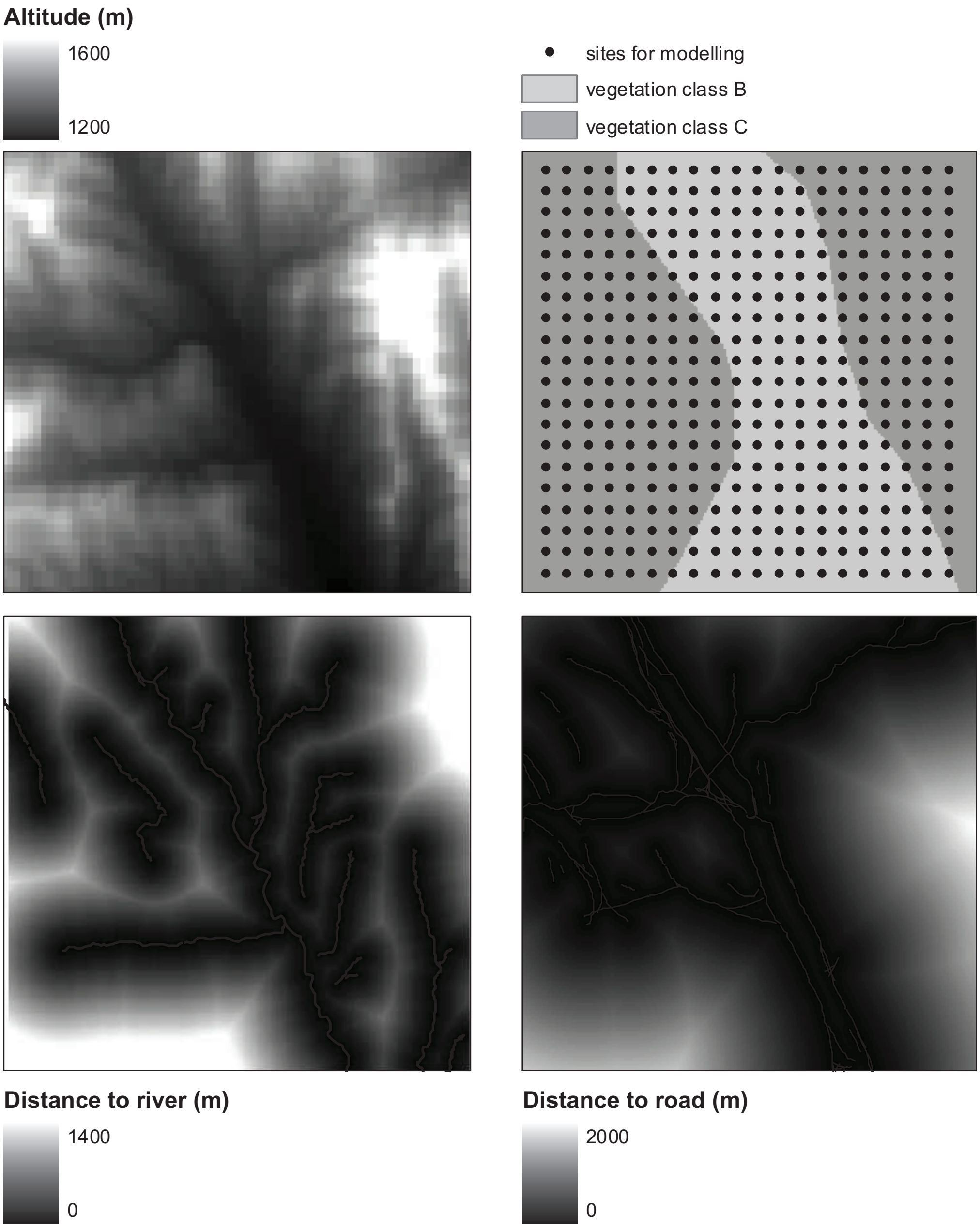
7.1. Field Format

DATE	COORDINATES	ZONE	MARMOT	DUNG	BORROW	MOUND	INHABITED	UNINHABITED

SIZE OF THE MOUND	VEGETATION COVER %	GENUS OF VEGETATION PRESENT	COMMENT	PICTURE NUMBER

7.2. GIS database for mound distribution modelling

Below are elements from the GIS database covering Quickbird image A and used for modelling the distribution of marmot mounds. Included are clockwise, starting top left: 1) the DEM, from which topographical slope and aspect were derived, 2) the vegetation map, overlaid with a grid of 100 by 100meter sites, for which marmot burrow density and mean values of the environmental variables were calculated to serve as data for the logistic regression model, 3) the distance to roads which were digitized from the Quickbird images, and 4) the distance to rivers which were digitized from the Quickbird images.



7.3. Areas where the object-oriented classification algorithm performs badly

Images on the left show the predicted marmot mounds in red. Images on the right show the original image.