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(DE)SCALING THE STRUCTURE OF DANISH AGRICULTURAL LANDSCAPES

Jesper Brandt, Geoff Groom and Esbern Holmes

What we want to present for you, is a very empirical approach to some basic scale-problems related to the study and monitoring of landscape heterogeneity, firstly

1) the problem of evaluating the representatively – in respect of heterogeneity – of detailed landscape monitoring surveys: Such surveys are in general – and especially when both detailed information on land cover and land use are included - very expensive. In area they will seldom take up more than one per thousand of the monitored landscapes, and heavy logistical problems seems to turn up before you reach the 1-200 square kilometres of surveyed area.
2) Secondly the problem of translating information on landscape heterogeneity from this detailed level to a broader landscape level, monitored by satellite remote sensing, in practise today mostly Landsat TM.
3) The problem of providing better empirical background for the understanding of the functioning and interpretation of different types of spatial indices for landscape heterogeneity

Certainly heterogeneity is fundamentally scale-dependant. But scale is a multifaceted concept, comprising both grain, categorical resolution, minimum mapping units and map extent. And basically it should be an important task to develop indices of landscape heterogeneity that can refer to the same or at least spatially correlated aspects of landscape heterogeneity, but observable in different map/grain/extent contexts. This is important to allow for a methodological link within landscape heterogeneity between the possibilities of a purposeful analysis and classification of satellite images on the one hand and detailed (and expensive!) landscape monitoring based on fieldwork on the other.

Further, this study is based on the assumption that it is meaningful to talk about landscape heterogeneity, not just as a multidimensional concept but also as a general concept permitting a scaling of landscapes from the most homogeneous to the most heterogeneous (Figure 1).

Although we recognise that many measures of landscape heterogeneity are not relating to each other, we nevertheless consider it possible to define complex heterogeneity measures that allow for a ranking of landscape heterogeneity within a given scale in a meaningful way. We do this in recognition of the importance of the connection to the vernacular concept of landscape heterogeneity developed around the growing public concern of the consequences of landscape homogenisation, although this concept is vague, open for discussion and easily will contradict rule-based interpretations. Accordingly we should respect that the concept of heterogeneity share properties with similar popular concepts concerning the environment like biodiversity and sustainability.

To sum up, the purpose of this study is – on an empirical basis – to propose a method for a ranking of landscapes according to a complex heterogeneity measure, so that the ranking can be kept invariable to the change of scale from detailed field-based surveys to Landsat TM based surveys - to establish a ranking based on the field data that correspond as good as possible with a ranking based on classified satellite data (Figure 2).

Our data is a combination of a detailed survey of 32 squares of 4 sq.km. large grids of Danish agricultural areas and a Landsat TM based land cover classification of Denmark.

The two datasets have been produced for different purposes (figure 3):
The detailed survey is a result of a stratified monitoring of Danish agricultural landscapes developed since 1981, with surveys every 5 years since then. It started with the explicit purpose to develop a system for a quantitative description of structure and dynamics of so-called small-biotopes, all the small uncultivated areas covering a considerable part of all nature areas in the densely cultivated Danish agricultural landscape. Due to the primarily (agri)cultural origin of these areas, a parallel survey of agricultural units and interviews with the farmers concerning farming system and the status and functions of the biotopes has been integrated in the survey. Thus the database describes the land cover as the culturally formed elements in the landscape as well as their functional linking, especially as expressed by the agricultural and related land use. A main purpose within a present interdisciplinary research project is to use the database as a supporting system for the development of scenarios for a multiple use of Danish agricultural landscapes.
All data had been geo-coded in a vectordatabase with a geometrical precision of app. 2 meters. A rough categorisation of the in-going land cover elements has been used for this presentation, with emphasis on agricultural crop types, and a few general categories for biotopes and other non-agricultural land cover types.

The Landsat TM-derived land cover map of Denmark has been produced as part of a programme for establishing a unitary spatial information system for the entire country. This 'Area Information System' (AIS). derives an area reference frame from a number of existing vector polygon data sets of topographic and environment and habitat related features. The land cover map is an additional information source to this system, providing independent information on the content of the reference frame polygon.
For production of the Land Cover Map the adopted methodology can be summarised as 'Iterative Supervised Maximum Likelihood Classification'. With a few refinements this follows the image classifications procedure previously used successfully for large area land cover mapping in Great Britain.
The classification uses six image data sets. *TM bands 3* (red), *4* (near-infrared) *5* (mid-infrared) at two seasonally contrasting dates. Through up to 10 iterations of subsequent identifications of training sites and maximum likelihood classifications an acceptable land cover map has been achieved.
In its national extent the Land Cover Map of Denmark actually represents a number of independent mappings related to individual satellite scenes; even for as small a country as Denmark (approx 200 by 200 miles), mappings from seven scenes (or part scenes) were required to make the full map
The Classified data consist of two levels: target class data, given in the legend (see Figure 3) and spectral subclass data, not so easy to interpret, but especially valuable in this context, since it contains important landscape structural information. So, both classifications have been used for this investigation.

Basically the analysis of the linkage between the detailed data and the TM-data has been organised around a statistical play with the FRAGSTAT-package, with the calculations derived from the field-based survey as a 'ground-truth'.

But to keep the expression of the combined aspects of heterogeneity as simple as possible we have as a departure chosen the following 3 measures that within our material has shown up to be almost uncorrelated, namely

1. The relative variance of landscape richness (R)
2. The relative variance of Dominance (D)
3. The relative variance of contrast, or contrast-weighted edge-density (C)

1. The relative variance of Landscape Richness (R). Richness is measured as the number of types of landscape elements (R_n) within each of the n landscapes. In our landscape model consisting of both linear and patchy elements, also landscape elements registered as linear elements will contribute to the richness.
2. The relative variance of Dominance (D). Dominance expresses how far a part of the types of landscape elements covers a dominating area of total landscape.
$D = \log_2(R) + \sum p_i * \log_2(p_i)$, where p_i = the relative area of the element type i within the landscape.
3. The relative variance of contrast or contrast-weighted edge-density (C). The edge-density expresses the landscape heterogeneity related to the influence of borders between the single landscape elements and eventual linear landscape elements associated with the borders. Edges in the landscape can however have very different character, and there landscape importance (e.g. for conductivity, barrier-effect, visual importance) vary correspondingly. Therefore, a contrast matrix is a part of the model. The following simple contrast matrix has been used in the example. (se fig. x)

For a pure topological analysis all cells can be set to 1, which means that the contrast will equal the edge-density.

A linear combination of these three aspects are gathered into what we for fun or personal reason provisionally have called a $JEFF_1$-index

$$JEFF_1 = |\alpha * \bar{R} + \beta * \bar{D} + \gamma * \bar{C}|, \text{ where } \alpha+\beta+\gamma=1$$

α, β and γ (as well as the cell values of the contrast matrix) is considered to be purpose-oriented, eventually a political matter, depending on the importance of the different aspects of heterogeneity relevant in the actual situation. Initially they have been equalised.

The $JEFF_1$-index is calculated at the detailed field-survey-based level for each of the four 1 square-kilometer-grids of the test-areas (figure 4). Beside the two areas at Bornholm also two other areas has to be preliminary excluded For verious reasons four of the 32 areas has been excluded, so that all in all 112 1-km-squares of 28 areas has been used up to now. These squares have subsequently been ranked according to the index, from the lowest to the highest heterogeneity.

By use of a standard SAS-procedure, regression models for a $JEFF_2$-index based on combinations of FRAGSTAT-indices derived from the Landsat-TM-material for the 1-square-kilometer-grids has been calculated, and the subsequent ranking of the squares have been compared with the $JEFF_1$-index-based ranking.
The regression-models have been derived from only two of the squares of each area, in all 56 squares considered as training areas, to allow for a better control by the comparison of the subsequent ranking of the remaining 56 squares with the field-based ranking of these squares, considered as test areas.

On Figure 5 you can see the two very first regression models. They look awful and very complicated, but are in fact very simple, and only 7 of the more than 50 formulas of Fragstat has been used, selected among those most correlated with the JEFF1-index. And it is interesting that these indexes are close related to those used for the JEFF1-index for the field-work based data: Patch Richness and Number of patches, Shannon evenness and Shannon diversity, and two variants of contrast-weighted edge-indices + a related contingency-type of index.
Both of these models explain only about 71 % of the total variance which is certainly not acceptable.

On the other hand, on Figure 6 you can see how the first model fits to the ranking of the JEFF1-index of the 56 training areas, and it is interesting that the same figure for the 56 test areas is in fact not that bad. These preliminary results have actually been produced in the days just before the congress started and we have to go much more in detail with the development of the model and the analysis of the results.

Certainly a lot of problems will show up in the interpretation of the results as well as in the further refinement of the model, and to some degree the usefulness of the procedure is very much related to the fact that it provokes a critical interpretation of quantitative data on landscape heterogeneity.
A few of the possibilities and problems should be mentioned here:
The most important factor influencing the result is the types and levels of the chosen land cover classifications. Due to the many iterations and the problems of fitting the several qualitatively different TM-scenes together, it is not realistically to make any major changes in the TM-derived land cover classification. The character of our field survey-based database is however very flexible, and here we have many possibilities of producing alternative land cover classifications to see what will be most useful in the search for TM-derived extrapolations of data on heterogeneity. All landscape elements has been described through a combination of physiographical, genetic and functional aspects that can be combined in land cover and land use classifications in many different ways and on many different levels (Figure 7).

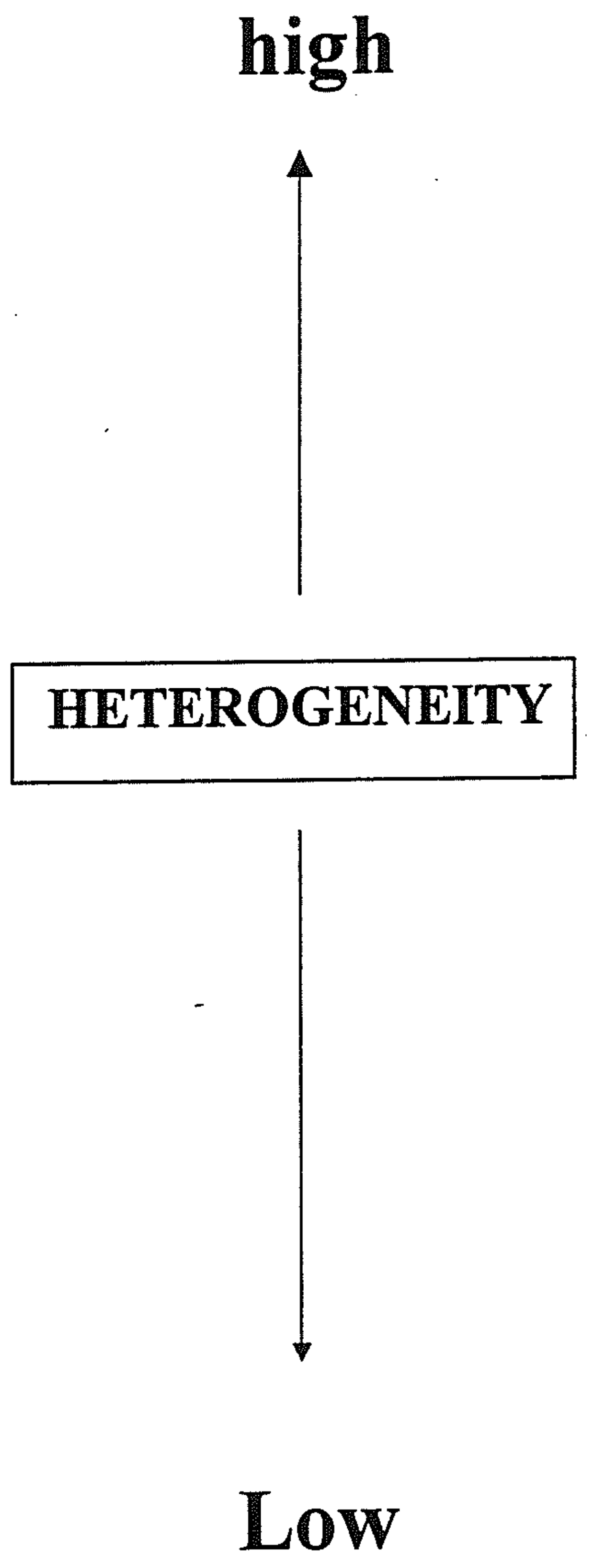
A fundamental problem in the model is the assumption that the field data can act as a ground truth. From a landscape point of view it is in fact not correct:

At least in our case it is clear that the field data in its spatial presentation is first of all based on a Forman'sk landscape perception, seeing the landscape as a cluster of distinct patches and corridors embedded in an dominating matrix, in our case agricultural fields where the underlying abiotic structure of the landscape is absent, since for historical reasons it is only to a minor degree reflected in the contemporary land cover structure of modern agricultural landscapes. This is to great extent also the aim of the TM-derived land cover classification. Here however the abiotic structure and its influence on the variations within the land necessarily will influence the derived spatial structure, including the heterogeneity. Some of the marked differences in the JEFF1 and JEFF2-index are certainly related to this effect.

In the handling of the data many transformations are made and it is not that easy to control what happens in detail:
As Fig. 8 shows, field data are stored in an Arc/info-coverage used as input to Arc view from where it has been rasterized and exported as binary files. The satellite data has been handled in Chips, stored in Arc/info-grid and also exported as binary files. These files have then been divided into quadrants by a visual basic script in excel and the data for each quadrant handled by FRAGSTAT. .Subsequently the regression model has been build in SAS lab and finally the graphs produced in Excel. One of the problems already observed is that SAS and Excell seems to round off in different ways, so that the model looks different depending on where you do your calculations. Another problem is the used rasterconversion of the field based data, deleting the linear features with spatial consequences especially in the cases where the land cover on both sides of the linear feature is the same. In such cases those patches will be merged together by FRAGSTAT.

In the further development we will not only have to go much more in detail with the relevance of the different indices and combination of these, but also have to experiment with changes in the composition of the indices that might be useful for the construction of a JEFF1-index.
The goal is however not only to find a method for an extrapolation of data on land cover heterogeneity by use of TM-data, but more to add to the understanding of different aspects of landscape heterogeneity and and its many quantitative expressions, by help of a reasonalbe amont of detailed and comparable sets of land cover data that we also can describe and visualise in many other different ways than by spatial statistics.
A fundamental problem is here how to overcome the problems of connecting the concept of landscape heterogeneity to the landscape reality as a lucid form, as discussed by the late Ernst Neef. But this important problem has not be treated in this presentation.

Figure 1



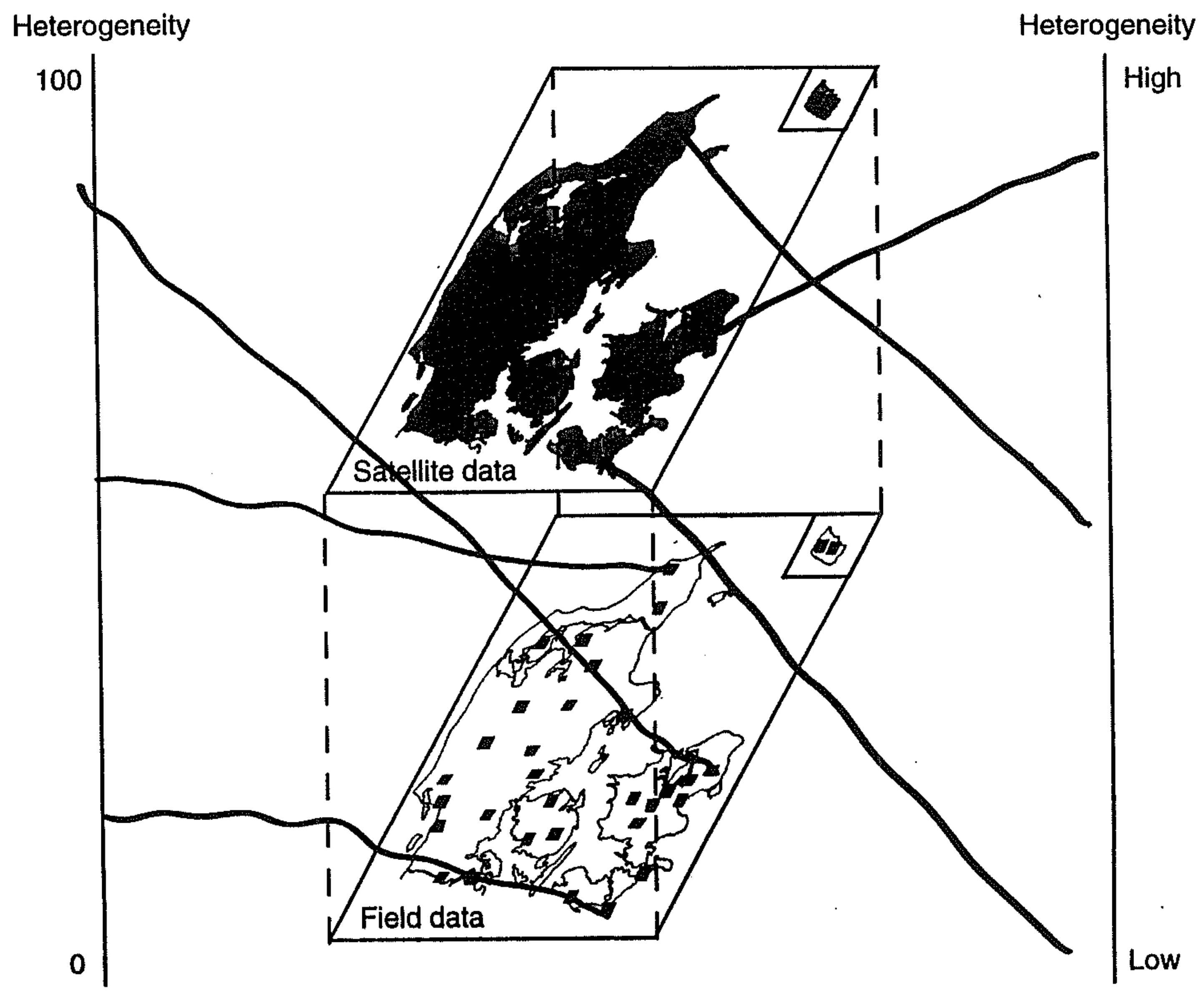
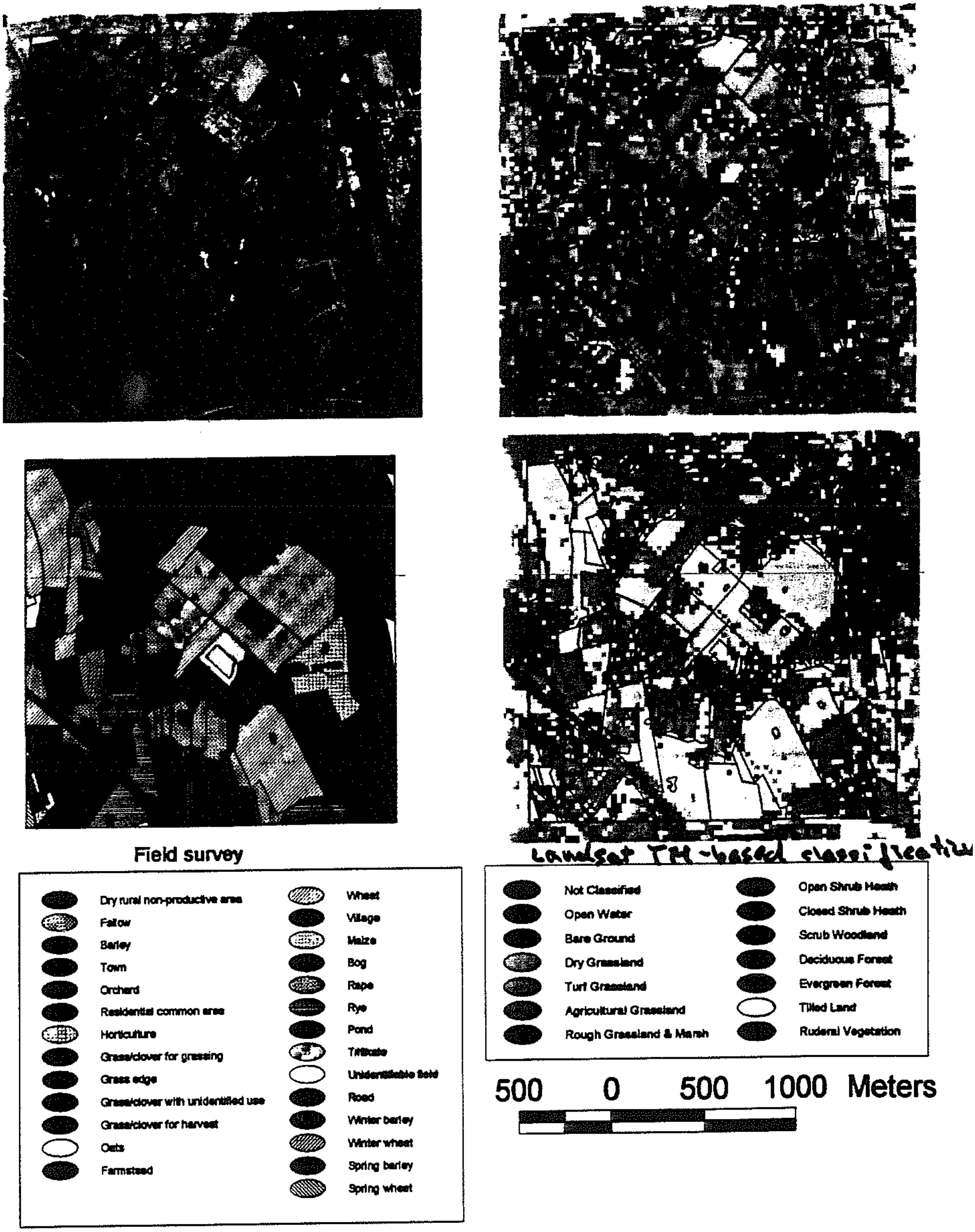

Heterogeneity
100
0
Heterogeneity
High
Low
Satellite data
Field data

Figure 2

Figure 3



Field survey
Dry rural non-productive area
Fallow
Barley
Town
Orchard
Residential common area
Horticulture
Grass/clover for grassing
Grass edge
Grass/clover with unidentified use
Grass/clover for harvest
Oats
Farmstead
Wheat
Village
Maize
Bog
Rape
Rye
Pond
Triticale
Unidentifiable field
Road
Winter barley
Winter wheat
Spring barley
Spring wheat
Landsat TM-based classification
Not Classified
Open Water
Bare Ground
Dry Grassland
Turf Grassland
Agricultural Grassland
Rough Grassland & Marsh
Open Shrub Heath
Closed Shrub Heath
Scrub Woodland
Deciduous Forest
Evergreen Forest
Tilled Land
Ruderal Vegetation
500 0 500 1000 Meters

Figur X

Complex heterogeneity-components

1. **The relative variance of landscape richness (R)**
2. **The relative variance of Dominance (D)**
3. **The relative variance of contrast, or contrast-weighted edge-density (C)**

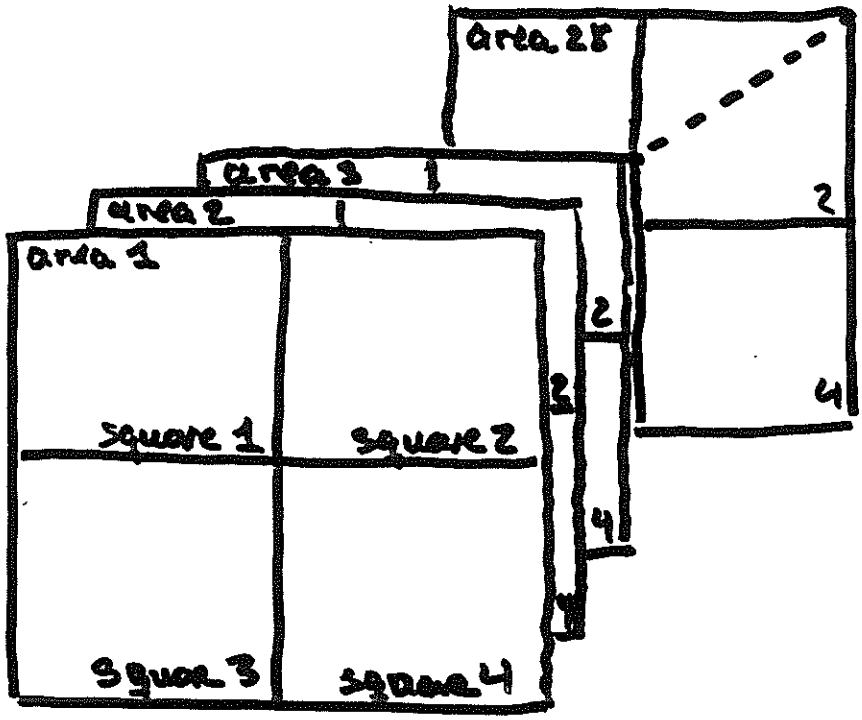
Contrast matrix:

	Urban classes	Crops classes	Semi-nature classes	Nature classes
Urban classes	0.25	0.50	0.75	1.00
Crop classes		0.25	0.50	0.75
Semi-nature classes			0.25	0.50
Nature classes				0.25

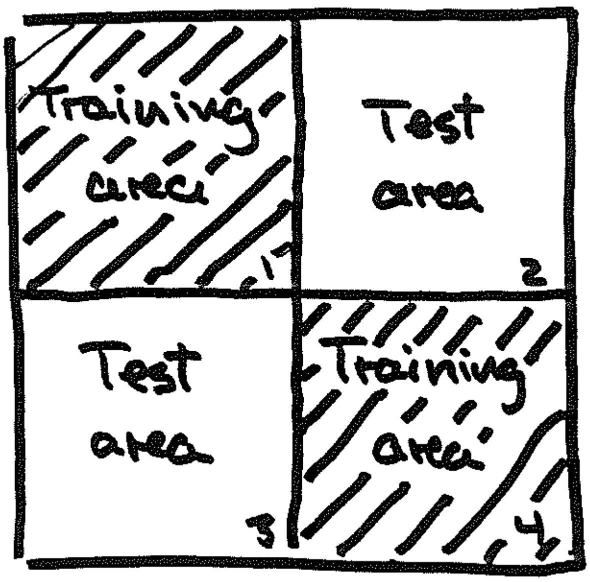
$$JEFF_1 = |\alpha * \bar{R} + \beta * \bar{D} + \gamma * \bar{C}|$$

where $\alpha+\beta+\gamma=1$
(Purpose-oriented weighting-factors)

Figure 4



area 28
2
4
area 3
1
area 2
1
2
4
area 1
square 1
square 2
2
4
square 3
square 4



Training area
1
Test area
2
Test area
3
Training area
4

Figure 5

Model 1

The predicted model is JEFF2_VEC = 0.426 -0.301*PR_TC -0.163*IJI_TC + 5.790*SHEI_FSS + 13.53*SHDI_TC -0.084*CWED_FSS -0.002*CWED_TC + 0.0137*PR_TC*IJI_TC + 0.0937*PR_TC*SHEI_FSS -0.679*PR_TC*SHDI_TC -0.002*PR_TC*CWED_FSS + 0.0052*PR_TC*CWED_TC + 0.0615*IJI_TC*SHEI_FSS -0.033*IJI_TC*SHDI_TC + 0.0017*IJI_TC*CWED_FSS -0.001*IJI_TC*CWED_TC -13.69*SHEI_FSS*SHDI_TC + 0.0278*SHEI_FSS*CWED_FSS + 0.0427*SHEI_FSS*CWED_TC + 0.03*SHDI_TC*CWED_FSS + 0.029*SHDI_TC*CWED_TC -48E-5*CWED_FSS*CWED_TC .

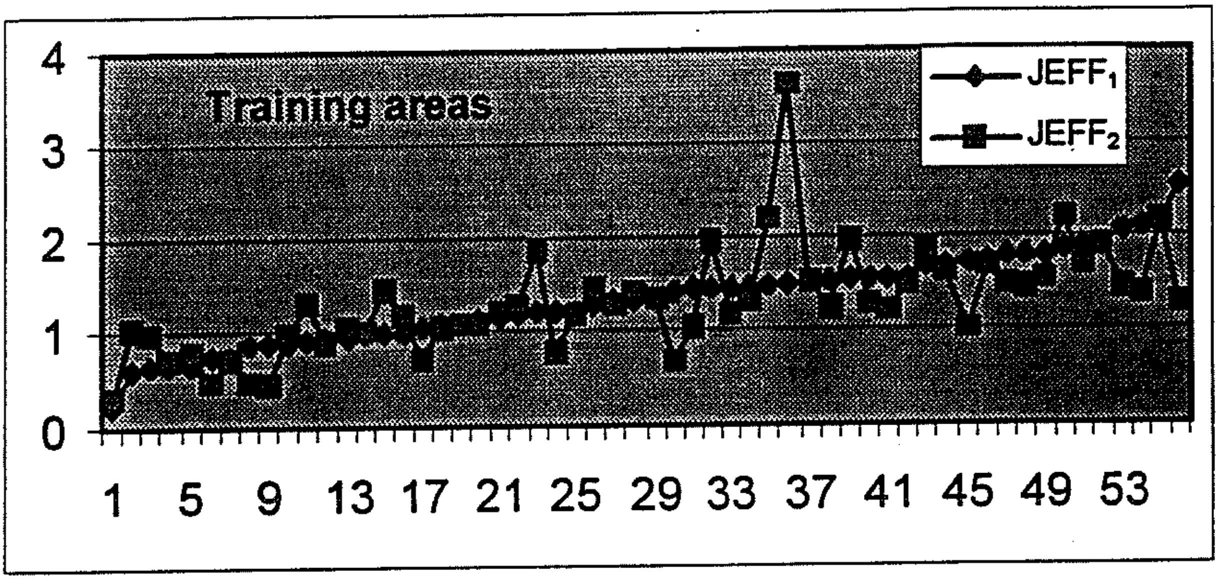
Model 2

The predicted model is JEFF2_VEC = -5.346 -0.392*PR_TC -0.051*IJI_TC -0.087*SHEI_FSS + 9.173*SHDI_TC -0.007*PR_FSSC + 0.366*AWMECI_T -0.03*NP_TC + 0.0204*PR_TC*IJI_TC + 0.126*PR_TC*SHEI_FSS -0.282*PR_TC*SHDI_TC -0.008*PR_TC*PR_FSSC -0.005*PR_TC*AWMECI_T + 0.0012*PR_TC*NP_TC -0.051*IJI_TC*SHEI_FSS -0.008*IJI_TC*SHDI_TC + 0.0006*IJI_TC*PR_FSSC -0.002*IJI_TC*AWMECI_T -0.001*IJI_TC*NP_TC + 5.822*SHEI_FSS*SHDI_TC + 0.251*SHEI_FSS*PR_FSSC -0.312*SHEI_FSS*AWMECI_T -0.041*SHEI_FSS*NP_TC -0.161*SHDI_TC*PR_FSSC -0.164*SHDI_TC*AWMECI_T + 0.0268*SHDI_TC*NP_TC + 0.0006*PR_FSSC*AWMECI_T + 0.0005*PR_FSSC*NP_TC + 0.0015*AWMECI_T*NP_TC

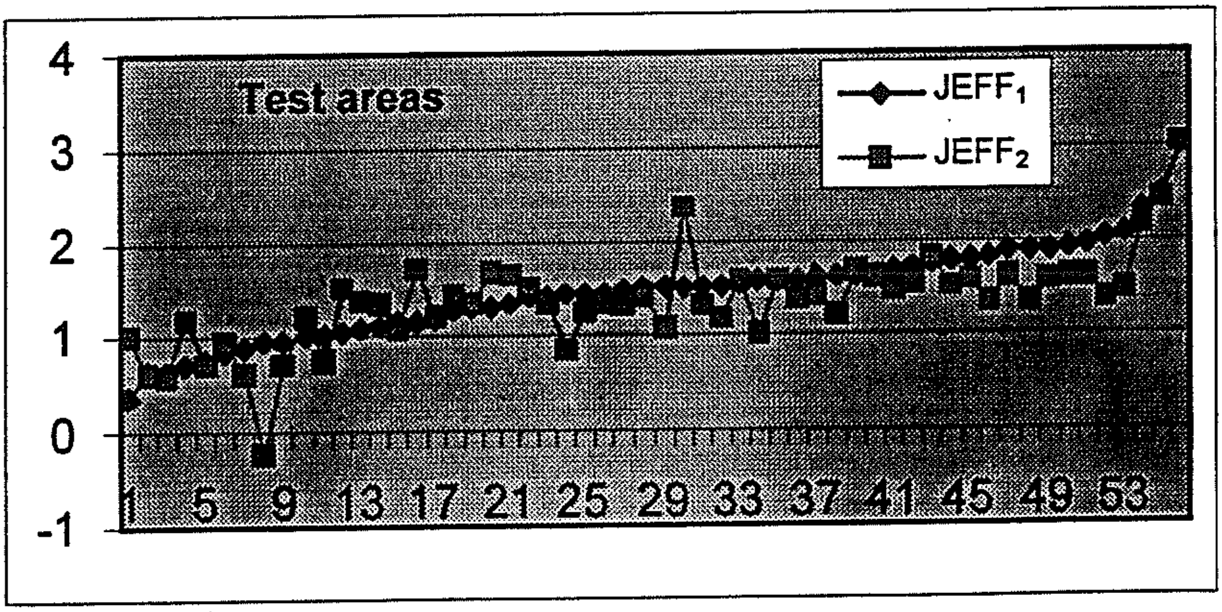
NP	Number of patches
PR	Patch richness
SHE I	Shannon evenness
SHDI	Shannon Diverswity
CW D	Contrast-weighted edge density
AWM CI	Area-weighted mean edge contrast index
IJI	Interspersion and Juxtaposition index

TC	Target classes
SSC	Spectral subclasses

Figure 6



4
3
2
1
0
Training areas
$JEFF_1$
$JEFF_2$
1 5 9 13 17 21 25 29 33 37 41 45 49 53



4
3
2
1
0
-1
Test areas
$JEFF_1$
$JEFF_2$
1 5 9 13 17 21 25 29 33 37 41 45 49 53

Figure 7

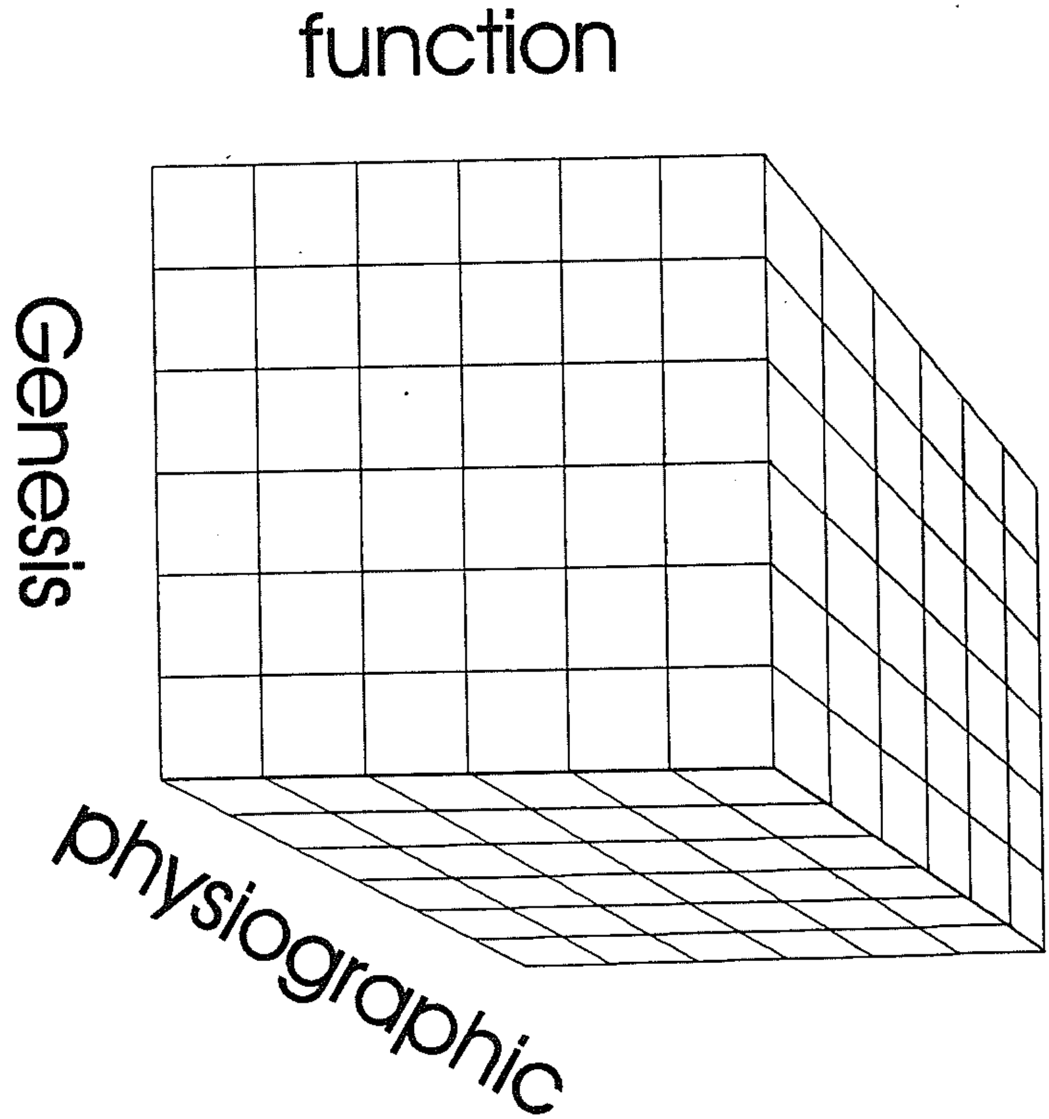
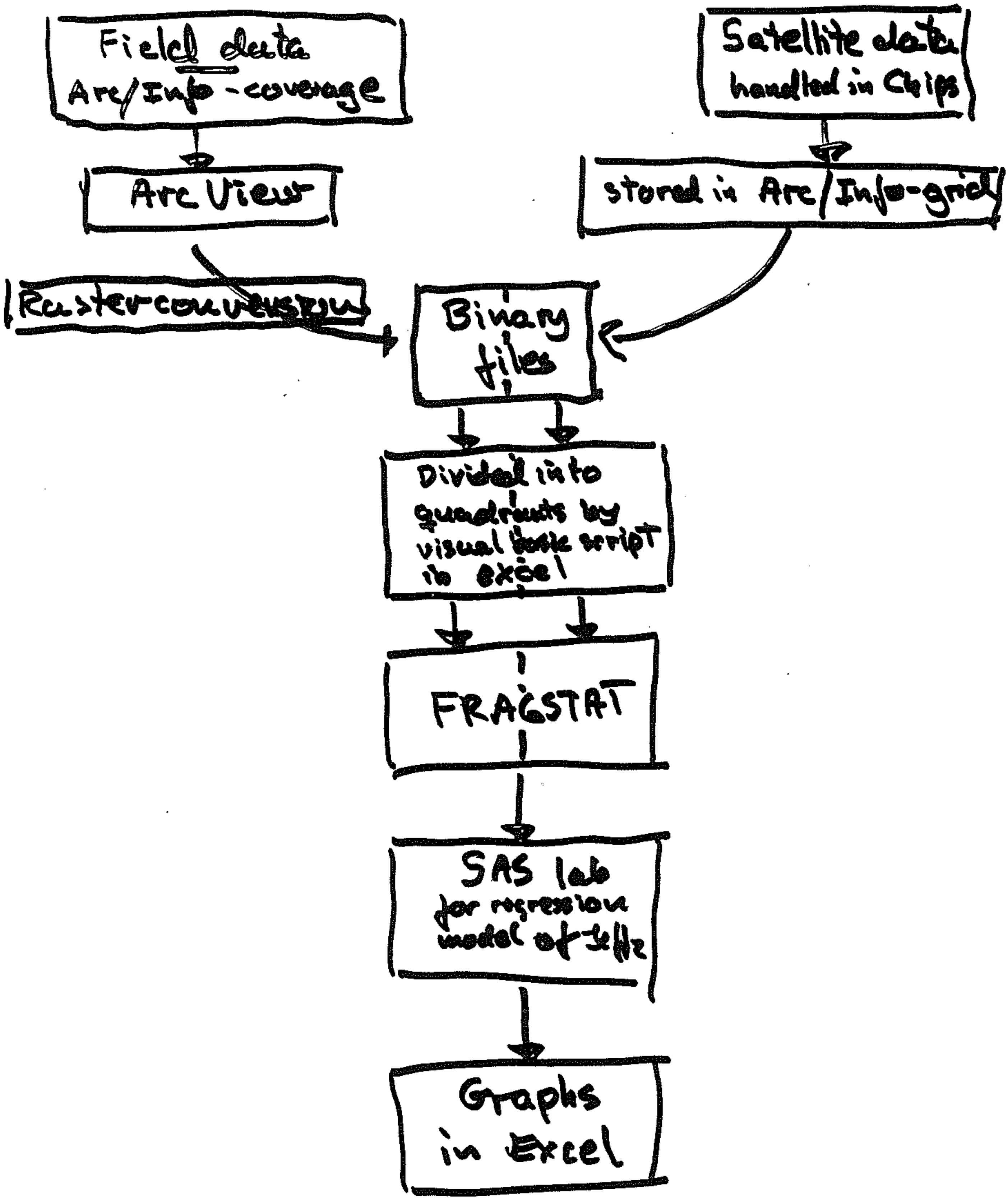


Figure 8


Field data
Arc/Info-coverage
Arc View
Raster conversion
Satellite data
handled in Chips
stored in Arc/Info-grid
Binary files
Divided into quadrants by visual basic script in excel
FRAGSTAT
SAS lab
for regression
Graphs in Excel