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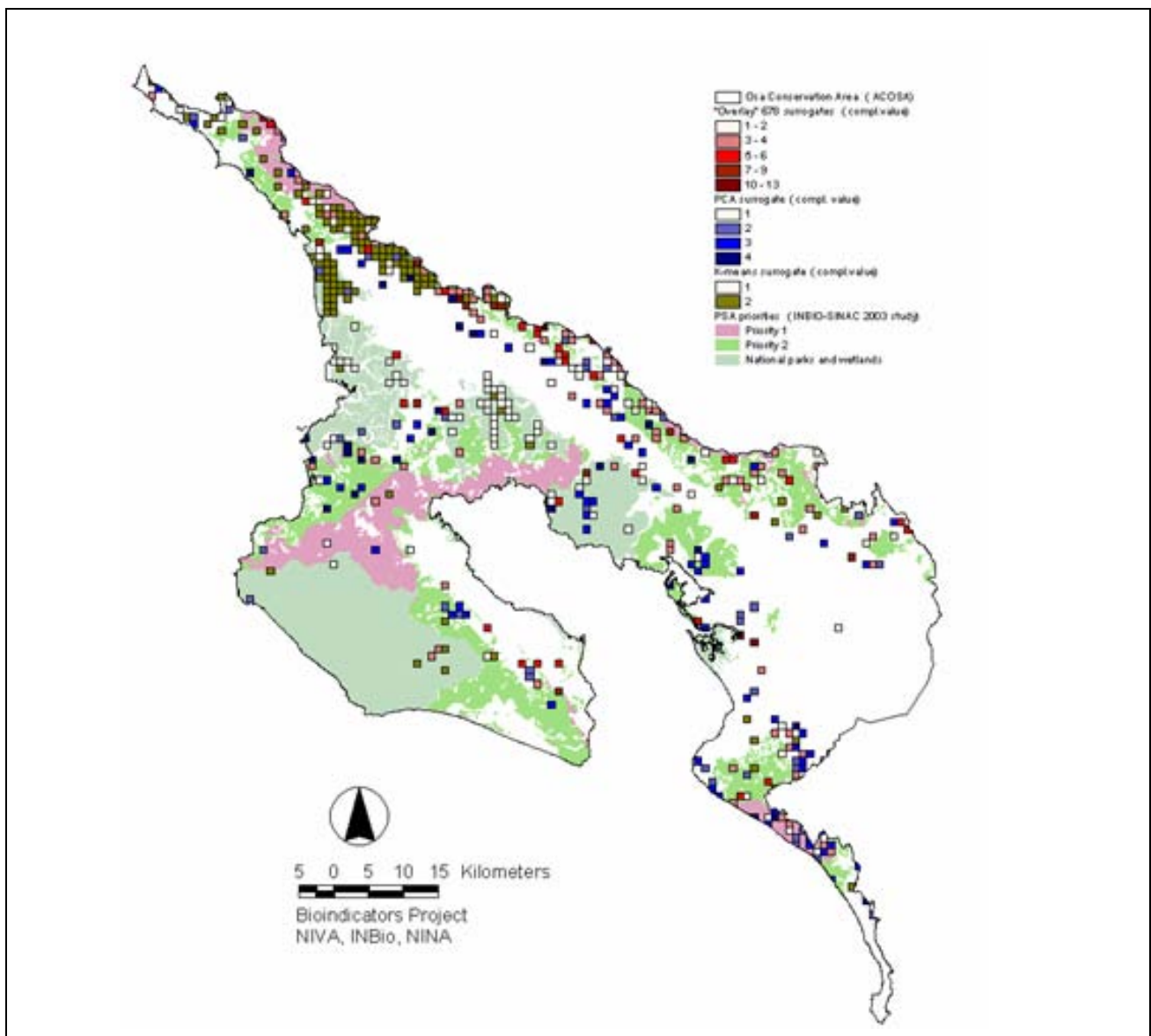Norwegian Institute for Nature Research

INBio
Instituto Nacional
de Biodiversidad

in collaboration with
Australian Museum

⊤**ARGET** as a tool for prioritising biodiversity conservation payments on private land - a sensitivity analysis

Bioindicators Project

Bioindicators Project
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REPORT

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Summary

The report is a companion to Barton, Faith et al. (2003) which motivates the use of the software TARGET for the prioritisation of biodiversity conservation payments on private land, or so-called "environmental service payments" in the Costa Rican context. The present report conducts an extensive sensitivity analysis for a number of variables that were deemed critical by managers reviewing initial TARGET results. Three different approaches to constructing the biodiversity indicators (attribute-based, PCA, and k-means) are followed, showing that the cost-efficient set of locations is most sensitive to this variable. The importance of the geographical scale and resolution of the environmental data for prioritisation of areas to receive payments is evaluated as these assumptions also implicitly define the comprehensiveness of the surrogate biodiversity indicator. Similarly, the generation of information on the opportunity cost of land-use for the whole study area is shown to be very sensitive to the GIS techniques used. Nevertheless, given an agreed set of assumptions on how to evaluate the existing georeferenced environmental and economic data – the TARGET algorithm provides quite robust and reliable sets of priority locations.

Fire norske emneord	Four English keywords
1. TARGET kostnadseffektivitetsanalyse	1. TARGET cost-effectiveness analysis
2. Biomangfolds indikatorer	2. biodiversity complementarity indicators
3. Betaling for miljøtjenester	3. environmental service payments
4. Costa Rica	4. Costa Rica

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TARGET as a tool for prioritising biodiversity conservation payments on private land - a sensitivity analysis

Preface

The Project "Decision-making models for evaluating cost-effectiveness of conservation priorities using alternative biodiversity indicators" (Short title: Bioindicators Project) has since its conception been motivated by applying the theoretical strengths of TARGET software to biodiversity conservation planning in practice. This report is in response to issues discussed in a series of training workshops on the TARGET software held at the National Biodiversity Institute of Costa Rica (INBio) in 2002-2004. Participants from Panamá, Costa Rica, Honduras, Guatemala, El Salvador and Belice raised a number of questions regarding the reliability of TARGET when applied to prioritising payments for biodiversity conservation. In an effort to test the robustness of TARGET under different data assumptions, and to answer the questions of protected area managers in Central America we have written this report.

David N. Barton (NIVA) has conducted TARGET analyses, produced GIS maps and written the main body of the report. Graciela Rusch and Jan Ove Gjershaug (NINA) have conducted the PCA and Cluster analyses and written sections on constructing biodiversity surrogates and the use of biodiversity data in Costa Rica. Dan P. Faith (Australian Museum) made the TARGET software available to the project and provided valuable comments to the report. L. Paniagua (INBio) has provided supplementary GIS data. Tuomo Saloranta (NIVA) wrote an algorithm for running correspondence analysis of TARGET output. We would like to thank Per Stalnacke (NIVA) for quality assuring the report.

The data used in this report builds on GIS data compiled by Marco Castro in INBio's *ECOMAPAS* project and species data compiled by Alvaro Herrera (INBio) from INBio's biodiversity inventory *Atta*. Mauricio and Edwin Vega (Instituto de Politicas para la Sostenibilidad, IPS) conducted the original studies of agricultural and forestry opportunity costs in ACOSA; Bodil Wilman (NINA) provided assistance in formatting GIS data to Access and TARGET input files.

The Bioindicators Project has been supported by a grant from the Norwegian Research Council. We are very grateful for their support. We would also like to thank NORAD for supporting the participation of conservation area managers from Central American countries in the workshops and to thank INBio for organisation and hosting of the events.

Oslo, June 2004

David N. Barton
Project Manager

Contents

Summary

Cost-efficient conservation priorities should be of high management relevance in countries with limited conservation budgets. However, in Costa Rica the fact that land use conversion from forestry to agriculture is illegal has been used as a general critique of conducting any kind of trade-offs analysis by some researchers and managers. In practice, gradual forest encroachment and fragmentation may lead to long term deforestation, calling for prioritisation of conservation efforts with limited resources available to authorities in charge of public protected areas and economic incentives for conservation on private lands. Another argument against trade-offs analysis has been that recent forest statistics have shown net reforestation in Costa Rica as a whole. However, trade-offs analysis may still be useful as TARGETs use of environmental biodiversity surrogates provides a guide to which areas have highest complementary value for reforestation/restoration.

These general arguments, along with a number of specific technical questions, have been posed by managers and researchers who have had a chance to review results of the Bioindicators Project on trade-offs analysis using TARGET software. The objectives of this report have been to answer the more technical questions regarding
- how biodiversity indicators have been constructed,
- how opportunity cost of protection have been calculated, and
- how varying assumptions will affect the set of cost-efficient locations selected by the TARGET algorithm.

Furthermore, the report is a companion to Barton, Faith et al. (2003) which motivates the use of TARGET for the prioritisation of biodiversity conservation payments on private land, or so-called "environmental service payments" in the Costa Rican context. This report is primarily written for readers who wish to learn more of the technical possibilities and limitations of the TARGET software, and the demands the model places on the underlying environmental and species data.

The report illustrates the impact of three different approaches to constructing the biodiversity indicator, showing that the cost-efficient set of locations is (naturally) most sensitive to this variable. Furthermore, we illustrate the importance of the geographical scale and resolution of the environmental data as these assumptions also implicitly define the comprehensiveness of the surrogate biodiversity indicator (as a substitute for pure species-based indicators). Similarly, the generation of opportunity cost information for the whole study area is very sensitive to the GIS techniques used. However, given an agreed set of assumptions on how to evaluate the existing georeferenced environmental and economic data – the TARGET algorithm provides quite robust and reliable sets of locations. The report shows that any use of such priority setting tools in allocating resources for conservation on private land in Costa Rica has a dual challenge:
- transparency and user-friendliness of the priority-setting model
- politically acceptable priority-setting 'rules' that may be established by conservation authorities (what we will call sets of assumptions, or 'model scenarios'

In the course of sensitivity analyses the report therefore discusses a number of potential improvements that could be made to the TARGET software, both for research and presentational purposes.

Other Reports in the Bioindicators Project:

Barton, D. N., D. P. Faith, et al., Eds. (2003). Spatial prioritisation of environmental service payments for biodiversity conservation. NIVA Report SNR 4746/2003.

Barrantes, G., E.Vega, et al. (2002). Determinación de los costos de manejo y protección en ACOSA (Bioindicators Project: NOTAT N-03/014). San Jose, Instituto para Políticas de Sostenibilidad**:** 26.

Vega, E. and M. Vega (2002). Determinación del costo de oportunidad y clasificación por clases de capacidad de uso (Bioindicators Project: NOTAT N-03/012), Instituto de Políticas para la Sostenibilidad**:** 34.

Vega, M. (2002). Determinación del rendimiento forestal en el Area de Conservación Osa (Bioindicators project: NOTAT N-03/013), Instituto de Políticas para la Sostenibilidad (IPS)**:** 24.

Reports can be downloaded from:

http://www.inbio.ac.cr/ecomapas/bioindicadores/paginas_eng/bioindic_05.html

Resumen

A pesar de que la priorización costo-efectiva de esfuerzos de conservación debería ser de relevancia general, el hecho de que la conversión del uso de la tierra es illegal en Costa Rica se ha usado como un cuestionamiento general contra los análisis de priorización entre bosque y otros usos de la tierra. Otro argumento en contra de análisis de priorización ha sido que el país experimenta la reforestación neta en los últimos años, lo que hace reduntante esfuerzos de análisis la deforestación. En la práctica, la conversion gradual de bosque en otros usos a través de procesos de cercenamiento y fragmentación puede a mediano y largo plazo conllevar la deforestación - por ende la necesidad de priorizar recursos para protección en tierras públicas y privadas de forma consistente. Además, indicadores ambientales de la biodiversidad empleados por TARGET presentan una guía a cuáles areas ofrecen la mayor biodiversidad complementaria potencial con la recuperación del bosque.

Estas preguntas y respuestas sobre políticas, junto con una serie de preguntas específicas y técnicas, se han hechos por funcionarios e investigadores que han revisado los resultados del Proyecto Bioindicadores y su uso del software TARGET. Los objetivos de este informe han sido de contestar a las preguntas más técnicas sobre:
- cómo los indicadores de biodiversidad han sido construidos,
- cómo costos de oportunidad han sido cálculados, y
- cómo diferentes supuestos han afectado el conjunto de areas prioritarias seleccionadas por el algoritmo de TARGET.

Además, este informe acompaña Barton, Faith et al. (2003), cuyo fin era justificar el uso de TARGET para la priorización de pagos por servicios ambientales (PSA) en tierras privadas en Costa Rica y contextos similares. Este informe ha sido escrito principalmente para los lectores que desean aprender más sobre las posibilidades y los limitantes técnicos-metodológicos del software TARGET, y lo que puede exigir de los datos ambientales y de especies que lo fundamentan.

El informe demuestra cómo el uso de diferentes tipos de bioindicadores afecta el conjunto costo-efectivo de localidades seleccionadas, siendo la priorización de las áreas sensible al tipo de indicador usado. Además, se ilustra cómo el cálculo de costos de oportunidad de la conservación son muy sensibles a las técnicas de sistemas geográficas que se utilisan. Sin embargo, dado un conjunto de supuestos de común acuerdo entre los usuarios de esta metodología, el algoritmo de TARGET provee conclusiones robustas y consistentes en el tiempo sobre cuáles áreas priorizar para PSA. El informe demuestra que el uso de cualquier herramienta de priorización de recursos de conservación en Costa Rica y el istmo tiene un reto doble:
- transparencia y amigabilidad al usuario
- "reglas del juego" sobre priorización de áreas y PSA que son de acuerdo político en el tiempo

Por tanto, en el transcurso del informe y sus análisis de sensibilidad se discuten una serie de mejoras posibles que se podrían hacer al software TARGET, tanto para propósitos de investigación como de presentación y capacitación.

1. Introduction

TARGET is one module of the DIVERSITY software package (Faith and Walker 1995) and is also a software module described in the BioRap toolbox (Faith and Walker 1996).   Extensive applications of TARGET are reported in the set of publications following the World Bank funded "BioRap" study in Papua New Guinea (Faith, Margules et al. 2001; Faith, Nix et al. 2001; Faith and Walker et al. 2001). Barton, Faith et al. (2003) apply TARGET to the study of priority-setting for environmental service payments to private land owners within the Osa Conservation Area (ACOSA) of southwestern Costa Rica.

Barton, Faith et al. (2003) demonstrated that TARGET could be used to achieve more cost-effective identification of areas for biodiversity protection in than the actual allocation of environmental service payments in the ACOSA study area for the years 1999-2001. Effectiveness was measured in terms of biodiversity complementarity – i.e. the degree of achievement of a target to represent – with a pre-defined probability - environmental attributes as a complement to those attributes already represented within existing protected areas.   The study also demonstrated an operational approach to using TARGET to prioritise payments to land-owners in "real time" , i.e. as applications for funding are sent in to the National Forestry Financing Fund (FONAFIFO) charged with allocating a limited budget.

Scepticism from managers in Costa Rica to using the TARGET model as a tool to actually prioritise payments to land owners in practice have centered on:

- reliability – is the selection of locations consistent over many model runs?

- robust – is the selection of locations consistent under varying conditions of access to and use of environmental, species and economic data ?

The purpose of this report is to evaluate these questions so that conservation area managers and funding agencies can better determine whether TARGET is sufficiently reliable and robust in order to be used as a day-to-day management tool.

Reliability and robustness will both be measured according to the criteria of whether the selection of priority locations is consistent in repeated trials, and for different assumptions of:

- geographical scale of analysis /extent of study area

- geographical resolution of environmental and economic data

- alternative definitions of biodiversity surrogates

More specifically the hypotheses tested in this paper are given in Table 1.

Table 1. Research questions for TARGET sensitivity analyses

Hypothesis	The selection of cost-effective set of locations…
1	is stable in repeated trials with a fixed starting point (preselect on a single location)
2	is stable in repeated trials with random starts
3	is not sensitive to the definition of the study area
4	is not sensitive to resolution of data

5	is not sensitive to the definition of the biodiversity surrogate when based on the same underlying data set.
6	is sensitive to including unique representations of biodiversity attributes such as endemic species

In addition to these hypotheses the report discusses some other limitations raised by managers, including:

- static definition of opportunity costs to agriculture and forestry of conservation. Alternative GIS approaches to extrapolating opportunity costs have been set forth by other studies (Ortiz et al. 2003; Wielaard 2003). Data on historical deforestation rates and projections of future deforestation are available for parts of the study area. We discuss the implications of using this data for our calculation of opportunity costs.

- comparing cost-effectiveness across property polygons of varying shape and size. The TARGET analysis is conducted on a grid of locations of equal size while the underlying data is in polygon format. We discuss the implications for the accuracy of the analysis.

Section 2 provides a brief description of the study area; an introduction to TARGET analysis methodology; a discussion of the availability of biodiversity data; the definition of alternative biodiversity surrogates based on this data; and a description of correspondence analysis for evaluating the sensitivity of TARGET to differing assumptions. Section 3 reviews the results regarding TARGET sensitivity to different sets of assumptions on biodiversity surrogates – henceforth called scenarios in this paper. In this section we test the different hypotheses laid out in Table 1. Section 4 evaluates alternative assumptions regarding calculation of opportunity costs. Section 5 presents conclusions and recommendations for for other avenues of research on biodiversity priority-setting.

For ease of presentation details regarding data, computational issues and additional maps have been placed in appendix. Appendix 1 contains further technical issues relating to computation of alternative biodiversity surrogates we have called "overlay", PCA and k-means. Appendix 2 contains a detailed overview of the TARGET model scenarios that were tested, including all key parameter settings and data assumptions. Appendix 3 contains further details on the reciprocal averaging technique used to compare TARGETresults for each scenario. Appendix 4 provides some background to the discussion of alternative definition of opportunity costs, including analysis of the correlation between deforestation probability and estimated opportunity costs of biodiversity protection. Finally, Appendix 5 provides some further examples of uncertainty inherent in converting polygon to grid data in the TARGET analysis.

2. Data and methodology

2.1 Study area

Figure 1 gives and overview of Area de Conservación Osa (ACOSA) and the study area for the Bioindicators Project. ACOSAs approximately 4 241 km^2 area is located on the southern Pacific coast of Costa Rica , bordering on Panamá. It comprises one of 11 conservation areas within the National System of Conservation Areas (SINAC) which covers the whole of Costa Rican territory. Land cover data from 2000 shows five broad categories of forest ecosystems, as well as mangrove and Yolillo palm wetland, dominating the natural vegetation. The area includes a number of national parks, forest reserves, wildlife reserves and wetland protected areas. National parks, of which Corcovado and Piedras Blancas are the biggest in ACOSA, represent the strictest land use regulations excluding forestry and agricultural activities. Through the report we will refer to the Osa Peninsula where Corcovado is located as the 'peninsula', and to the 'corridor' which comprises the section of Golfo Dulce Forest Reserve between Corcovado and Piedras Blancas national parks designated by SINAC authorities as a biological corridor.

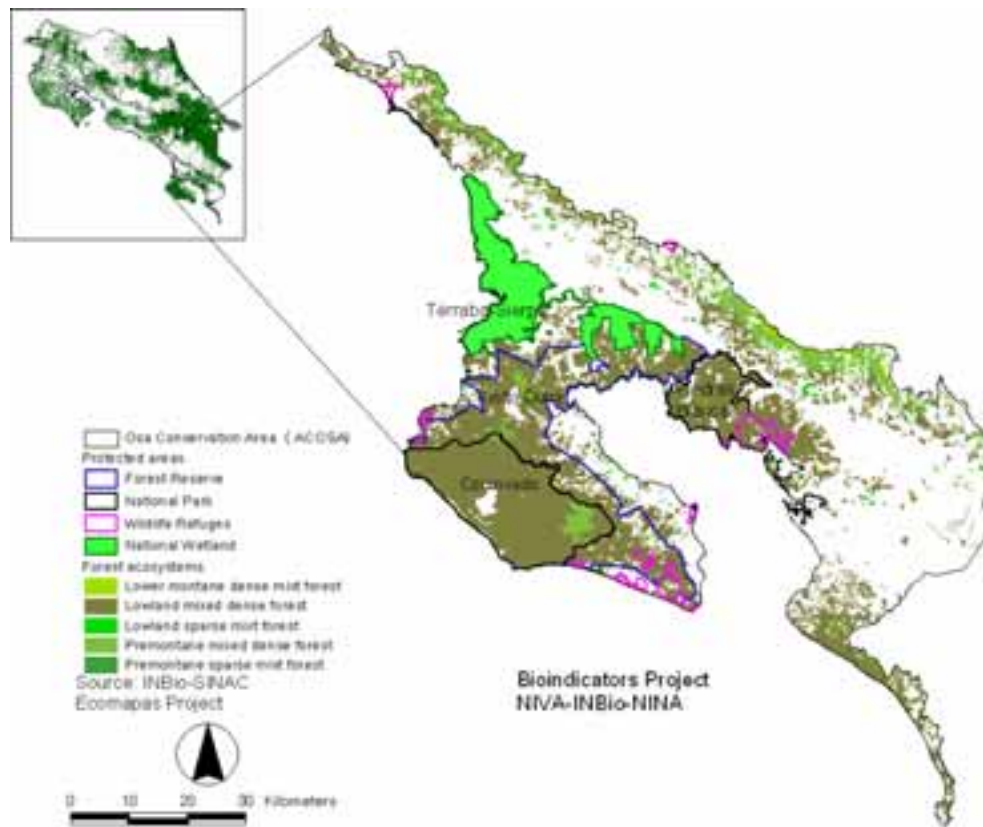**Figure 1.** ACOSA study area, including protected areas and forest cover[1].

The environmental and species data used in this study are the same as for the TARGET analyses conducted in Barton, Faith et al. (2003), unless stated otherwise. See Appendix 1 for a further

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[1] Costa Rica 1:50 000 maps of 2000 forest cover are also available at
http://www.eosl.eas.ualberta.ca/website/cr1/viewer.htm

description of available biodiversity data in Costa Rica. That study was to a large extent based on GIS data on land cover and environmental attributes available from the ECOMAPAS project coordinated by the Costa Rican National Biodiversity Institute (INBio) (Kappelle et al., 2003). ACOSA was the first conservation area covered by the ECOMAPAS project and was therefore the basis for the Bioindicators project. By 2006 the ECOMAPAS project will have mapped and ground truthed ecosystems for the whole of southern Costa Rica, making TARGET type analysis possible for several conservation areas at once. Combined with other comparable GIS datasets developed independently by other institutions for the northern and central parts of the country[2], TARGET type analysis based on biodiversity surrogates is now technically possible for most of the country. Before such analysis is undertaken however, questions regarding the sensitivity of priority-setting to the scale of the study area and the resolution of biodiversity and opportunity cost data need to be evaluated.

2.2 TARGET methodology

TARGET is one module of the DIVERSITY software package (Faith and Walker 1995) and is also a software module described in the BioRap toolbox (Faith and Walker 1996). Extensive applications of TARGET are reported in the set of publications following the World Bank funded "BioRap" study in Papua New Guinea (Faith, Margules et al. 2001; Faith, Nix et al. 2001; Faith and Walker et al. 2001). Barton, Faith et al. (2003) apply TARGET to the study of priority-setting for environmental service payments to private land owners within ACOSA.

TARGET assumes that locations in a region under study are described as containing one or more different biodiversity "attributes". Attributes that are assigned to locations (i.e. grids) may be environmental characteristics such as biotopes, habitat types, vegetation types etc. or the presence of known species. The available biophysical data constitutes the basis for the biodiversity surrogate indicator – all unique attributes have the same weight within the indicator, independent of whether they represent species of environmental data. Fundamental to all TARGET analysis are estimates of complementarity - the marginal contribution in biodiversity representation provided by a location in addition to that already represented in set of protected areas. Because complementarity always depends on the set of protected areas, TARGET algorithms operate by iteratively re-calculating complementarity as new locations are added to the protected set.

For priority-setting TARGET weighs biodiversity complementarity of a location j with the value of that location for other uses - in this case the returns to agriculture and forestry foregone from protecting existing vegetation – also called opportunity cost (OC_j). Comparison of complementarity and opportunity cost are made possible by a trade-off weight (β). The weight can be adjusted by the user of the model to conduct sensitivity analysis and generate trade-off curves representing the cost-efficient set of locations according to different assumptions about the relative importance of opportunity costs and biodiversity complementarity. The weight has the same economic interpretation as an isoquant (price ratio) in a production possibility frontier between biodiversity protection and agricultural-forestry production. A schematic overview of the input data, target algorithm, and output data is given in Figure 2. TARGET produces both maps showing locations selected for protection, as well as curves showing the optimal trade-off between target achievement and opportunity cost.

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[2] Amongst others Area de Conservación Cordillera Volcánica Central (ACCVC), Area de Conservación Guanacaste (ACG).
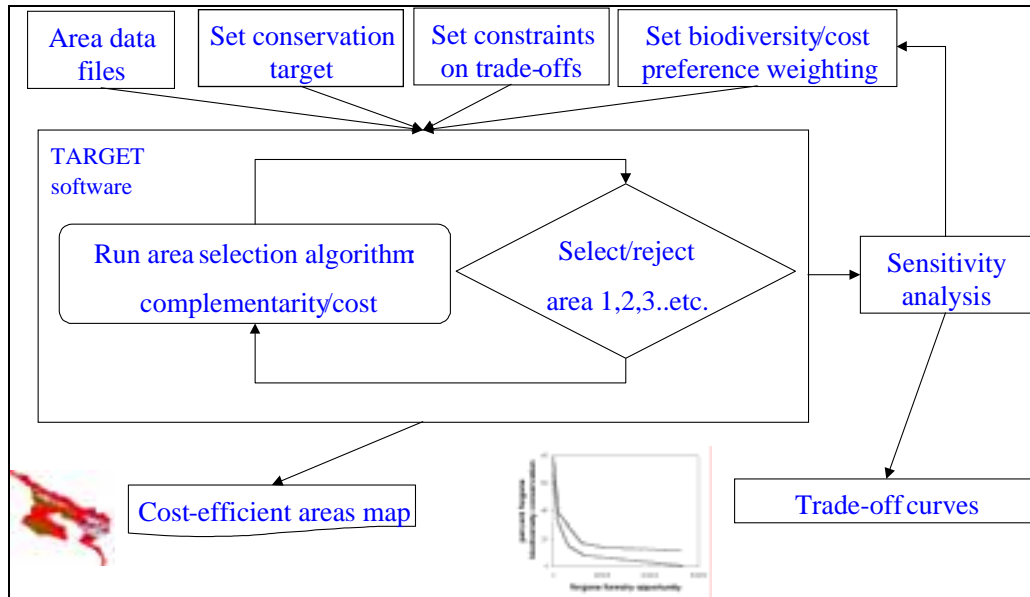
Figure 2. Schematic representation of TARGET algorithm

The first step in TARGET involves setting a target level for representation of biodiversity attributes. In this paper we will use the probability-based target-setting mode[3]. The user typically (in the simple case) nominates a target for the overall regional probability of persistence, R, of each attribute. This overall probability is to be achieved by one minus the products of the probabilities of extinction of the attribute over the different locations in the region. The user nominates a base probability of persistence, B – equivalent to a default or "do-nothing" value. Lastly the user nominates the probability of persistence, P, for an attribute in a protected location (equivalent to one minus the probability of extinction of the same attribute in any location that is not selected for protection).

Probabilities of persistence are equal to one minus probability of extinction of an attribute in a location that is not selected. Extinction is used in the sense that lack of protection increases the likelihood that the attributes in any specific location - be they environmental or species characteristics - will be lost due to land use conversion. Probability of extinction also applies to selected locations if the protection regime is less than 100% effective.

The study area for ACOSA is divided into a grid of J=4752 locations 1 km^2. The datafile describing locations will contain a total T_i occurrence of each attribute, N_i occurrences within existing protected areas, and T_i -N_i occurrences outside. In the simplest case where no location in the study area is protected initially, the total "do nothing" probability of persistence, B, for attribute i across the whole study area, is defined as;

$$(1) \quad B_i = e^{\sum_{}^{T} \ln Bij}$$

summing over the T occurrences in locations j =[1..4752] of attribute i.

The TARGET algorithm works directly on the number of attributes required to meet the probability of exctinction implied by the probability of persistence target. In other words, the overall regional probability of "extinction" is taken to be the product of the probabilities of extinction in the individual, independent, places. The formula above uses *ln* transform because it is convenient to express

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[3] The other mode involves setting a target for the % of locations with any given attribute to be represented within the selected set.

contributions of places additively. The algorithm initially calculates the number of occurrences of attributes N_i required of the selected set, given user defined probability values R, B, and P, as follows;

(2) $1 - R = (T - N) * (1 - B) * N * (1 - P)$

This is the simplest case where the same probabilities are applied to all attributes i; $R=R_i$, $B=B_i$, $P=P_i$.

The TARGET algorithm searches the study area maximising the difference between complementarity value of a location (CP_j) - the number of attributes it provides towards the target regional probability of persistence - and its β-weighted opportunity cost. Iterations continue until there are no locations in which the weighted opportunity cost ($\beta*OC_j$) is less than the complementarity value, or until the total probability of persistence for all attributes, protected and unprotected, is equal to the target (R).

(3) $\quad$ Max $\quad CP_j - \beta*OC_j$

subject to $\qquad N_j - \beta*OC_j > 0$ for all j locations
and $\qquad 1 - R \quad (T - N) * (1 - B) * N * (1 - P)$ for all i attributes.

The iterative optimisation algorithm searches the study area based on initial conditions which may for example be the existing set of protected areas. Imposing existing protected areas on the solution modifies the amount of additional attributes needed,N, to reach the established target R.
The algorithm does not guarantee a global optimum, and hence the user is required to vary initial conditions in order to test for local optima in a heuristic approach. This is an issue to which we will return in the sensitivity analysis below. The strategy in TARGET of searching for optimal solutions by varying the weights on costs has been shown to be more effective than the standard approach for such problems of selecting places based on a simple benefit/cost ratio (Faith 2001).

As indicated in Figure 2 and equation (3) the TARGET user must set a weight on the ratio of trade-off between cost and units of biodiversity complementarity (β). By varying the importance of costs versus complementarity cost-efficient trade-off curves are generated in a what is basically a sensitivity analysis. We have seen that the user must also define the regional target (R), baseline (B) and protection (P) probabilities of persistence. These are variables for which there very seldom exist studies that would provide empirical values, encouraging users to do further sensitivity analysis.

Figure 3 illustrates the sensitivity of the cost-efficient set of locations to β and P. Increasing the effectiveness of protection reduces the cost of achieving any given target, because fewer locations are required to provide the same representation of biodiversity. Increasing P has incidentally the same effect as increasing B, because more biodiversity persists outside protected areas. **Figure 3** also illustrates the standard feature of the optimisation algorithm that the lower the importance of costs, the higher the cost of the optimal set for a given distance to the target.

Behind the particular analysis illustrated in **Figure 3** are two further features determined by the user:
  (i) $\quad$ *Pre-selected areas*: national parks are pre-selected and imposed on the solution, the biodiversity they contain being counted towards achievement of the target R.
  (ii) $\quad$ *Deteriorated areas*: non-forest areas are defined as not available for selection.

These are practical features for applied policy analysis. However, unless stated otherwise all sensitivity analyses in this report are conducted without imposing locations on the optimal solution and without excluding any locations from the analysis.
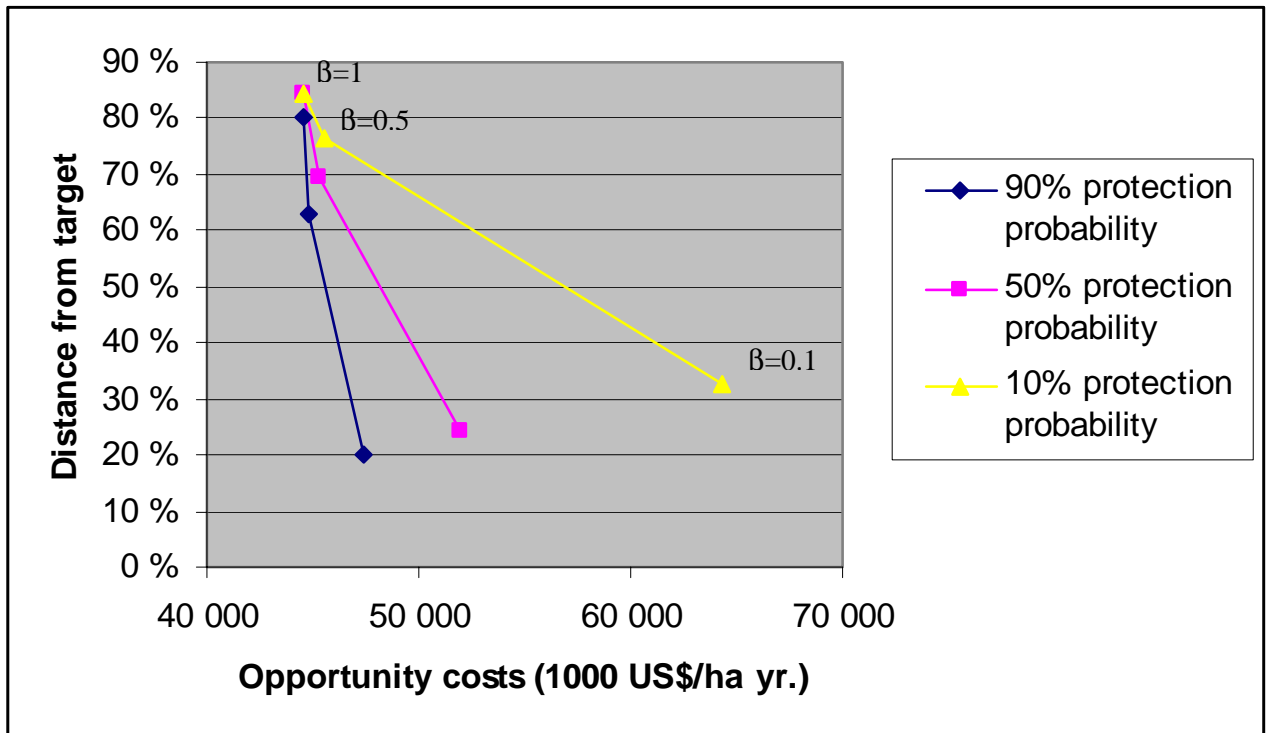
Figure 3. Sensitivity of biodiversity-cost trade-off to the effectiveness of protection and weight on costs. Note: Sensitivity analysis on P=90%, 50% and 10%. For all analyses B=0% and R=99%.

2.3 Alternative surrogate biodiversity indicators

2.3.1 Biodiversity indicators in site selection

This study has explored a methodological approach to incorporate biodiversity conservation goals into an existing program of environmental service payments implemented in Costa Rica. Since the protection of regional biodiversity requires that conservation priorities on individual areas are based on the contribution of the area to represent overall biodiversity, our aim was to improve overall biodiversity representation by selecting, among environmental service payment (ESP) candidates, areas with highest biodiversity *complementarity* value (sensu Faith & Walker 1996), i. e. those which would make the highest contribution to increase the representation of the existing biodiversity in the protected areas system.

Priority-setting in conservation planning must be based on some knowledge about the biodiversity of the areas. Since maps of the distribution of the biota are not available, the first step of the analyses was to identify the variables that would characterize the areas in terms of their biodiversity properties, or in other words, to identify surrogate variables that would represent the areas biodiversity complementarity value. One standard approach is to identify biodiversity surrogates based on indicator groups of taxa (Juutinen & Mönkkönen 2004). There are numerous studies in the literature that have explored the adequacy of a series of biodiversity surrogates (Noss, 1990, McGeogh 1998, Panzer & Schwartz 1998, Pharo et al. 2000, Polasky et al. 2001) but the support for the use of indicator taxa in reserve selection is often varied and conflicting (Reyers & van Jaarsveld 2000). The use of subsets of taxa for biodiversity representation requires testing the adequacy of the indicators and require both

thorough inventories of the selected taxa (Juutinen & Mönkkönen 2004) and rigorous validation in order to be interpreted with confidence (Reyers & van Jaarsveld 2000). These comprehensive data on species distributions are possible to obtain when the number of areas to be prioritized is small but are costly and not feasible when the analysis deals with large numbers of land units.

Our focus was therefore to use the natural environments or habitats of ACOSA as surrogates for more definite biodiversity data. We used maps of natural resources since they provide an important basis for nature conservation (Austin 1991, Pressey and Bedward 1991, Faith et al. 2001a), and have been amply used (García, 1996 (vegetation macrotypes), Powel et al. 2000 (life-zones), Austin 1991) due to the difficulty of obtaining comprehensive data on species relative to that of producing resource maps (Pressey & Bedward 1991). Our assumption was that since topography, climate and substrate are fundamental determinants of biological activity, the spatial distributions of these factors will reflect to a large extent the distribution of plant and animal species (Faith et al. 2001a).

Our approach relied largely on biophysical spatial data retrieved from cartography and aimed at developing a database with all existing significant data that gave complete coverage of ACOSA at the highest possible spatial resolution. Based on previous work in ACOSA (Madrigal and Rojas 1980; Herrera 1986; Gómez and Herrera 1993; Tournon and Alvarado 1997; Ardón and García 1998; Kappele, M.Castro et al. 2003) the major environmental variables influencing the distribution of forest types were assumed to be climate, soil, lithology, topography (elevation) and landform.

The use of a data set based on the natural environments was additionally supported by two features related to the nature of the ESP contract allocation and to the purpose of the study that preclude the feasibility of conducting biodiversity inventories of selected organisms. First, the number of ESP candidates is large and it would be administratively and financially unrealistic to conduct inventories on candidate farms prior to the selection process. Second, one of the aims of the ESP system is to provide incentives for conversion of land to forest. The potential biodiversity complementarity value of abandoned agricultural or pastoral land and of forest under natural regeneration will not be reflected in biodiversity inventories at early stages of land conversion but can be adequately predicted from a the natural environments or habitat features.

2.3.2 Testing the sensitivity of the priorization procedure to different biodiversity surrogates

The applicability of biodiversity indicators to identify areas with relatively higher conservation value will depend on the sensitivity of the priority setting procedure to the type of biodiversity surrogate used. One purpose of the study was then to assess the sensitivity of the outcome of the TARGET priority setting analysis to the type of biodiversity surrogate. Based on the same data set on biophysical features, we generated four biodiversity surrogate sets using three three different approaches: hereon i) "overlay", ii) "endemics" iii) "PCA" and iv) "k-means".

The comparison between the 'overlay' and 'endemics' data sets aimed at assessing the sensitivity of the prioritization analysis to including data on endemic species as attributes. Endemic species have a high conservation priority at the same time that the attributes have a narrow geographical distribution in the data set (i. e. occur in a limited number of grid-cells) and often the knowledge about the factors underlying their distributions in the area is poor.

The comparison between 'overlay', 'PCA' and ''k-means' biodiversity surrogates aimed at assessing the sensitivity of the TARGET analysis to the method used to generate the biodiversity surrogates. The four types of biodiversity surrogates (including the 'endemics' data set) were generated using the same database of environmental data and since the TARGET analysis is sensitive to the number of

attributes, the four biodiversity surrogate sets were generated with a comparable number of biodiversity attributes.

2.3.3 The 'overlay' and 'endemics' indicators

The first set was created by overlaying each class of climate, soil, landform, geology and altitude. These resulted into 678 actual combinations. Seven additional attributes were generated for combinations when any of the environmental layers was missing. Three additional attributes resulted from the combinations of open water, altitude and climate classes, and 4 attributes resulted from the combination of climate, soil, land form and elevation band with mosaics of geological classes that could not be distinguished at the grid-cell level. In total this rendered 685 surrogate biodiversity attributes. In order to make a more refined use of available data we additionally included major vegetation formations (vegetation macro-types). Appendix I gives a detailed account of the data sources and the criteria used to construct the biodiversity attributes. The retrieval of cartographic data was conducted by the Institute of Biodiversity in Costa Rica (INBio).

Each mapping unit was allocated the area of the attributes that was derived from the polygons on the biophysical maps (climate, soil, geology and landform). The ACOSA boundaries of the different digitised maps were compared and searches were conducted to detect boundary errors (area mismatches) that result from digitising. When the polygon areas of the overlain variable classes differed within a grid cell, the area allocated to the environmental attribute (product of crossing variable classes) was that of the variable class with lowest coverage. A biodiversity attribute was consider to be represented in a land unit when the cover in a grid cell was larger than 5 % (5 ha).

The second data set, 'endemics', included 685 biodiversity attributes and the endemic species as described in appendix 1. Including these endemics raised the total number of attributes to 744.

Cartographic data was associated with land-use capacity polygons in the whole study area and converted to 25 ha grid cells (raster), and then 1x1 km mapping units for purposes of analysis in TARGET. Although biodiversity attribute data are available at 25 ha resolution, while using a 1 km^2 resolution in the trade-off analysis was a restriction set by the processing capacity of TARGET.

Finally, the biodiversity attributes were coded for each land unit and the files were prepared in TARGET-readable format.

2.3.4 The principal component analysis and "PCA" indicator

In the 'overlay data set' all environmental features (e.g. different classes of climate, altitude ranges) had the same weight in defining the biodiversity surrogate attributes. Therefore, each combination of environmental classes and vegetation macro-types were used as biodiversity surrogate ("habitat type"). However, it was expected some underlying structure in the biophysical variables data set, i. e. some variables to be more important than others to characterize the variation between grid cells. It was also expected that some variables would covariate or be correlated with each other, e.g. hypothetically climate and altitudinal classes could show such correlation.

The main advantages of using a multivariate analysis technique as a base to generate the biodiversity surrogates is first that, by allowing the analysis of a large number of variables simultaneously, it makes possible to combine all data available for the entire set of land units and therefore allows a finer definition of biodiversity surrogates than if only one criteria had been used, as for example, vegetation macro-types. Secondly, the ordination permits to structure the data set and reduce redundancy, by

establishing the relative contribution of the variables to the total variation of the data set and by identifying correlations among variables. Methodological details are provided in Appendix 1.

To identify and reduce redundancy of correlated variables in the environmental data set, we used principal component analysis (PCA) a multivariate analysis technique to summarize the data and extract a few 'important' components of variation (Palmer 2004), by using the software package CANOCO for Windows 4.5 (ter Braak & Smilauer 2002). The PCA was conducted on the matrix of the biophysical classes used to generate the 'overlay' biodiversity surrogates in the 18 062 grid cells (25 ha).

The three first axis of the PCA ordination accounted to 72 % of the variation (table 2). The two main variation sources in the data set appeared to be a gradient related to humidity and the length of the dry season (axis 1), and the second one was related to differences in substrate, soils and elevation ranges (axis II) (Fig. 4). The climate classes related to high humid climate, i.e. very high humidity index, short dry season, low aridity index and hydric deficit were negatively related to PCA axis 1 and as expected, strongly related to each other. Positively related to PCA axis 1 were climate classes related to dryer climate, with moderate hydric and aridity indices and dry season. PCA axis 2 was positively related to elevation bands between 200 and 800 meters, inceptisol and ultisol soils on basalt formations. PCA axis 2 was negatively related to elevations up to 200 masl, and mollisol soils on sedimentary formations and alluvial deposits. The correlation between soil types, geology and elevation revealed by the ordination shows that these variables are spatially correlated in the data set.

Table 2. Eigenvalues and cumulative % variance of 4 Principal Component axes derived from the biophysical data set (environmental variables and vegetation macro-types).

	PCA axis 1	PCA axis 2	PCA axis 3	PCA axis 4
Eigenvalue	0.523	0.138	0.063	0.042
Cummulative % variance	52,3	66,1	72,4	76.6

Note: Cummulative % variance indicates the accumulated fraction of the variance accounted for by the PCA axes.

The PCA also produced an ordination diagram where the 18 062 grid cells (25 ha) were plotted and where their relative positions were related to the number of biophysical classes shared with other grid cells (Fig. 5). Grid cells close to each other shared more biophysical classes than grid cells far apart.

The 3-dimensional PCA ordination space (ordination along PCA axes 1-3) was divided in 1000 cube volumes by splitting each of the first three ordination axis at 10-units intervals. Each of these 1000 cubes represented a 3-dimensional range within the major environmental gradients and corresponded to a particular combination of environmental characteristics. Each 3-dimensional portion of the PCA space was considered as a "habitat type" and used as a biodiversity surrogate. The number of biodiversity surrogates was determined by the number of cubes in the environmental space where grid cells occurred, in total 573.
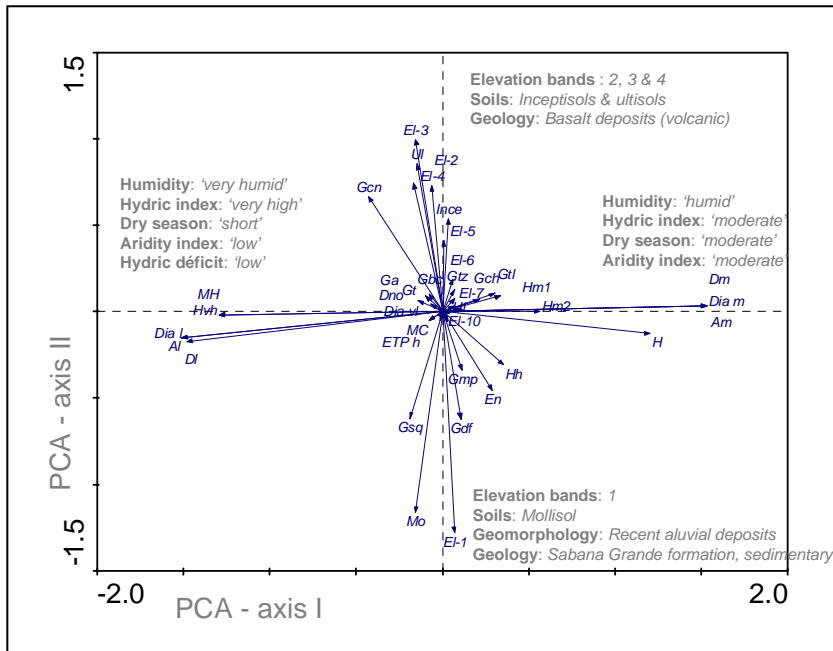
Figure 4. Two dimensional PCA diagram indicating the relationships among the environmental variables in the   ordination space.
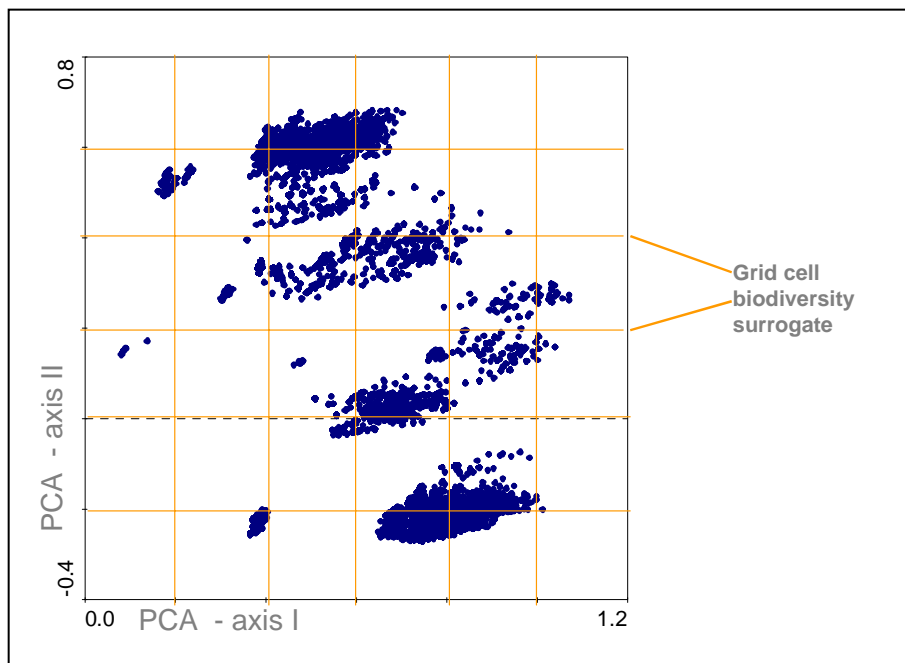

Figure 5. Two dimensional PCA diagram indicating the distribution of the 500 x 500 m grid cells in the environmental space.

2.3.5 The k-means analysis and indicator

In order to obtain a third set of biodiversity surrogates of comparable size and of the same type as those of the 'overlay' and the 'PCA' biodiversity surrogates, we applied a classification technique using the same data set of environmental variables used previously.

Comparable to ordinations, classifications of multivariate data sets are also aimed to reduce redundancy in the data set by identifying relatively homogeneous groups of cases based on selected characteristics (in our case, classes of the environmental variables). We applied k-means, a non-hierarchical classification method, in the software package SPSS version 11.5 for Windows to the same set of 18 062, 25 ha grid-cells and environmental variables. The methods was appropriate to our data set as it uses an algorithm that can handle large numbers of cases, being efficient primarily because it does not compute the distances between all pairs of cases, as do many clustering algorithms (SPSS version 12.1 manual).

By applying the k-means algorithm we could *a priori* specify the number of clusters the grid cells should be grouped into, and was therefore appropriate for the purpose of our study where we aimed to contrast the outcome of TARGET priority setting using sets of biodiversity surrogates of comparable size, generated in different ways.

The environmental variables classes were represented as dummy variables as in the PCA data set (see section 2.3.4). The grid cells were grouped into 684 clusters according to their similarity regarding the environmental variables classes used in the PCA analysis. The resulting clusters were regarded as the biodiversity surrogates, which was allocated to each 500 x 500 m grid cell.

Table 3 summarises the theoretical and appliced advantages of the three types of indicators evaluated in the study.

Table 3. Theoretical and applied advantages of surrogate biodiversity indicators evaluated

Surrogate indicator	Theoretical advantages	Applied advantages
"Overlay"	Relationship between original data and attributes intuitively evident.	Represents the number of attributes per location, and requires only simple GIS techniques to specify
PCA (or other ordination techniques)	Identify the most important factors that underlay the variation in the data set. Reduce redundancy in the data set by reducing the importance of correlated variables.	The number of biodiversity surrogates can be easily changed according to the purpose of the analysis.
k-means (or other classification technique)	[4]Identify biodiversity surrogates by grouping land management areas according to their similarity with respect to a set of descriptive variables. It provides a formal grouping into classes (as compared to the proposed division of ordination space used in this study).	It can be performed with commercial statistical packages. The generation of biodiversity surrogates by identifying relatively homogenous groups of cases.

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[4] K-means classification was used in this study because of the extension of the data set (K-means is a technique suitable for large data sets as it uses an algorithm that can handle large number of cases). With a smaller data set a hierarchical classification technique would be preferable and comparable to an ordination in the sense of allowing to generate a continuous number of biodiversity surrogates.

2.4 Evaluating scenarios and sensitivity analysis

Following a counterfactual approach we have tried to identify assumptions we *a priori* think will have a significant impact on the locations and attributes selected by TARGET. Decision-makers should be interested in both the robustness of the cost-effcicient set of locations, as well as which biodiversity surrogate attributes are protected. TARGETs results include (i) a list of selected locations, (ii) the occurrence of attributes per selected location, and (iii) the complementarity value of selected locations, and these are analysed as if they are species occurrences.

Correspondance analysis (CA), or reciprocal averaging, (Palmer 1993) was used as a method for comparing the results of TARGET model scenarios. Whereas Pearsons R computes correlation between two vectors, correspondance analysis allows for multiple vector comparisons. Model scenarios refer to the set of assumptions or parameter settings that are applied in running TARGET. Appendix 2 gives a summary of the scenarios used in running the TARGET model. A further description of the CA method used to compare scenario results is given in appendix 3.

The use of CA is based on the following analogy with the more traditional use of correspondence analysis of site species lists (**Table 4**). In the traditional correspondence analysis the data consist of species occurrences by sampling location. Each scenario is analogous to a "site".

Table 4. Analogy between comparing site species lists and TARGET output

Data matrix:	Comparing species lists by site:	Comparing TARGET output by scenarios:
Rows	Observed occurences of species	Complementarity value of locations Occurences of surrogate attributes
Columns	Sampling location	Model scenarios (sets of assumptions)

A minimum of three different scenarios need to be compared for correspondence to have meaning given that correspondence scores are relative (they sum to 0). The assumptions of each scenario are presented in Appendix 2. The essential differences between the scenarios are summarised in Table 5.

Table 5. Assumptions of each scenario subject to sensitivity analysis

Key assumption tested	Scenario name
1. Initial location(s) within set of protected areas	"Impose random location"; "Select nat.parks"; "Select PSA"
2. Definition of study area	"ACOSA"; "Peninsula", "Corridor"
3. Definition of surrogate biodiversity indicator	"ACOSA"(overlay); "Endemics"; "K-means"; "PCA"

In the first set of assumptions (1) in **Table 5** we vary the starting point for the optimisation algorithm used by TARGET to select the cost-efficient set. In an analysis with no pre-selected locations TARGET searches the whole study area sequentially, starting with location #1 (north-west corner of study area) and then searches for a more cost-efficient location[5]. TARGET can be started with a single randomly selected location (we tested locations #1, #500, #1000), or with a set of locations such as the set of locations within national parks, or within environmental service payment contract areas (PSA).

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[5] In case two adjacent locations have the same complementarity and cost, the first sequential location is chosen by default.

In the second set of assumptions (2) we vary the definition of the study area, well aware of the fact that complementarity value of any location depends on the universe of attributes under consideration. Had we had data for the whole of Costa Rica - or the whole of Central America for that matter – would the same set of locations as in ACOSA be selected as cost-efficient?   Similarly, and with data only available for ACOSA, we ran TARGET for the whole of "ACOSA", and smaller study areas we have called the Osa "Peninsula" and the "Corridor" between Corcovado and Piedras Blancas National Park (see **Figure 1**).

In the third set of assumptions (3) we vary the definition of the biodiversity surrogate indicator. We look at the simple "overlay" indicator, the "k-means" indicator based on clustering techniques, and the "PCA" indicator base on principle component analysis.

3. Sensitivity to alternate biodiversity surrogates and model scenarios

3.1 Overall correspondence analysis of scenarios

The correspondance analysis gives an initial scan of the similarity of results from different TARGET scenarios. These results are discussed first before we illustrate the difference between scenarios in terms of selected locations in the study area.

3.1.1 Correspondance of location selection

Figure 6 shows the correspondance between the locations selected across all analyses. The three graphs are organised with correspondence across all scenarios first. In the two following panels the most dissimilar scenarios are removed to evaluate smaller differences that are not visible across all scenarios.

Relatively speaking the biodiversity surrogates "k-means" and "pca" are dissimilar to all the analyses using the "overlay" indicator . Eliminating these two surrogates from the comparison, panel 2 (Figure 3) shows that the starting point for the analysis (whether national parks and psa areas are "select" i.e. pre-selected) has a large impact on the selection of the cost-efficient solution, indicating that there are several local cost-efficient optima in the ACOSA study area. Given that random pre-selection of several separate locations did not produce significant dissimilarities it would seem that there are relatively few local cost-efficient optima. Removing the most dissimilar "national park" and "psa" scenarios we see in panel 3 (**Figure 6**), that the definition of the study area has the expected effect – the smaller the study area - peninsula or corridor - the more dissimilar the selection of locations.
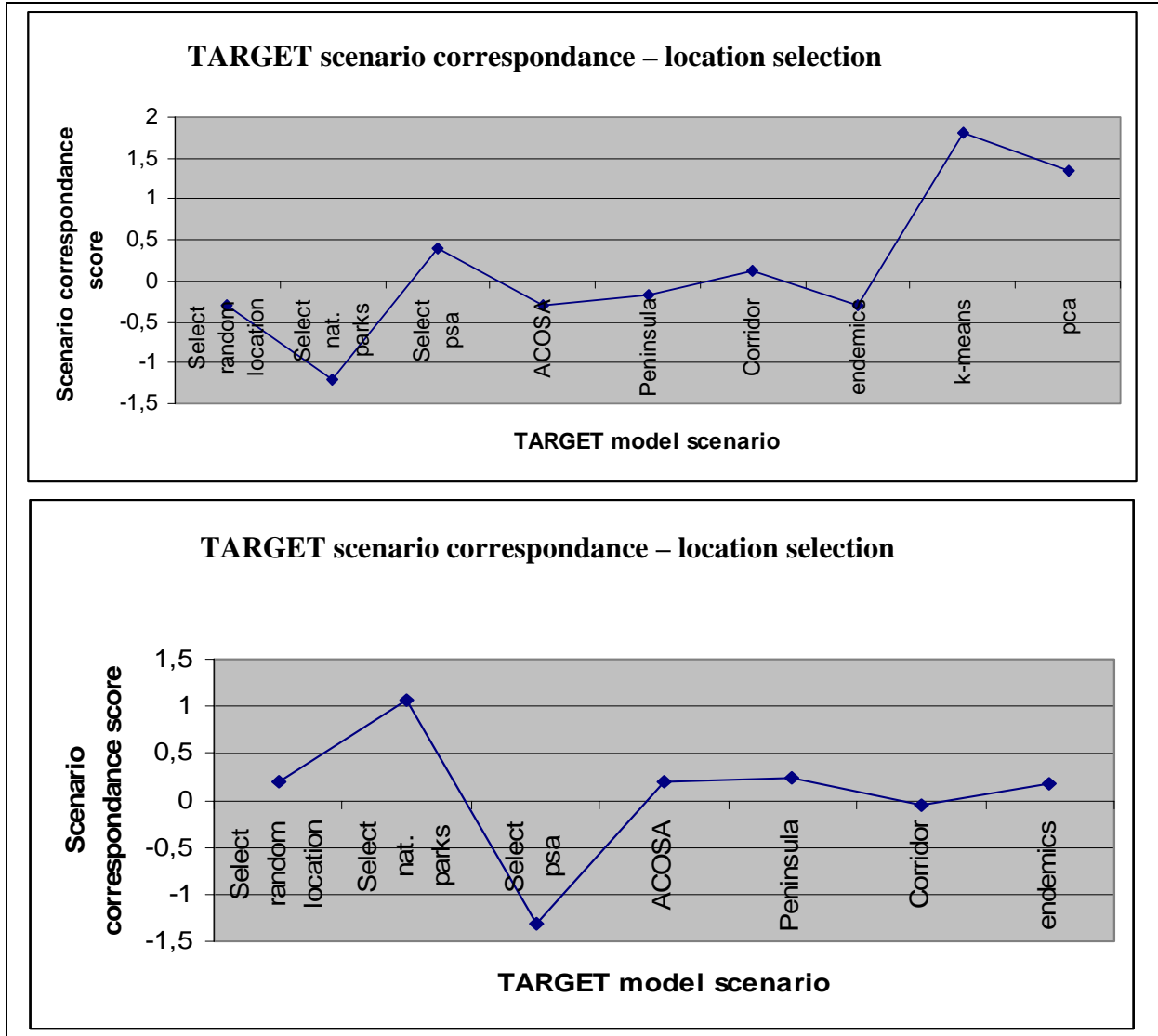
The addition of endemic species to the "overlay" indicator had very little impact on the selection of optimal sites, contrary to expectations implicit in the calculation of biodiversity complementarity.

In summary, the cost-efficient selection is most sensitive to the methodology used to define of the biodiversity surrogate, followed by the definition of pre-selected locations (e.g. in existing national parks), the definition of the study area, and finally is not sensitive to the addition of endemic species.

3.1.2 Correspondance of location complementarity

Figure 7 compares the complementarity value of selected locations in the set, i.e. what contribution each location selected makes to attaining the biodiversity protection target. The locations selected are the same as those discussed under each scenario in **Figure 6**, except that locations are compared for numerical similarity of complementarity value, rather than simply selected/not selected (1/0).   At the broad level the same pattern emerges with biodiversity surrogates "k-means" and "pca" producing both selected locations and complementarity values that are most different from other scenarios. However, after eliminating these scenarios from the comparison it is the scope of study area that has the greatest effect on the solution (second panel, **Figure 7**) . Removing "corridor" and "peninsula", the scenario that most stands out among those remaining is "select psa" and to a lesser extent "nat.parks" as before (third panel, **Figure 7**).

These results were as expected because both changing the surrogate indicator, as well as the study area, changes the number of attributes, which has a very direct bearing on complementarity values of locations.
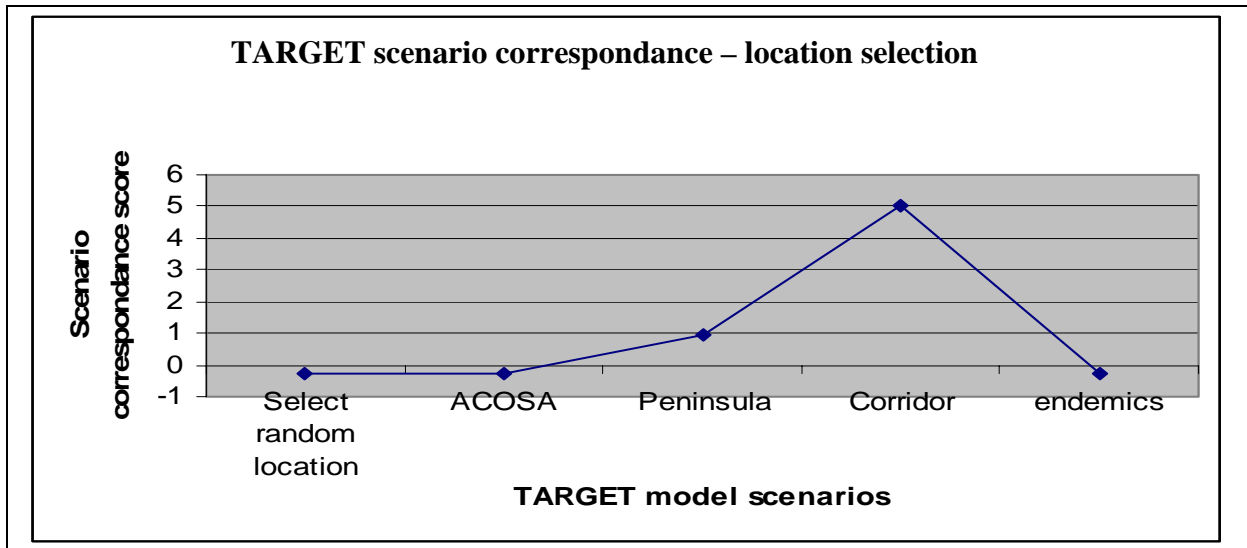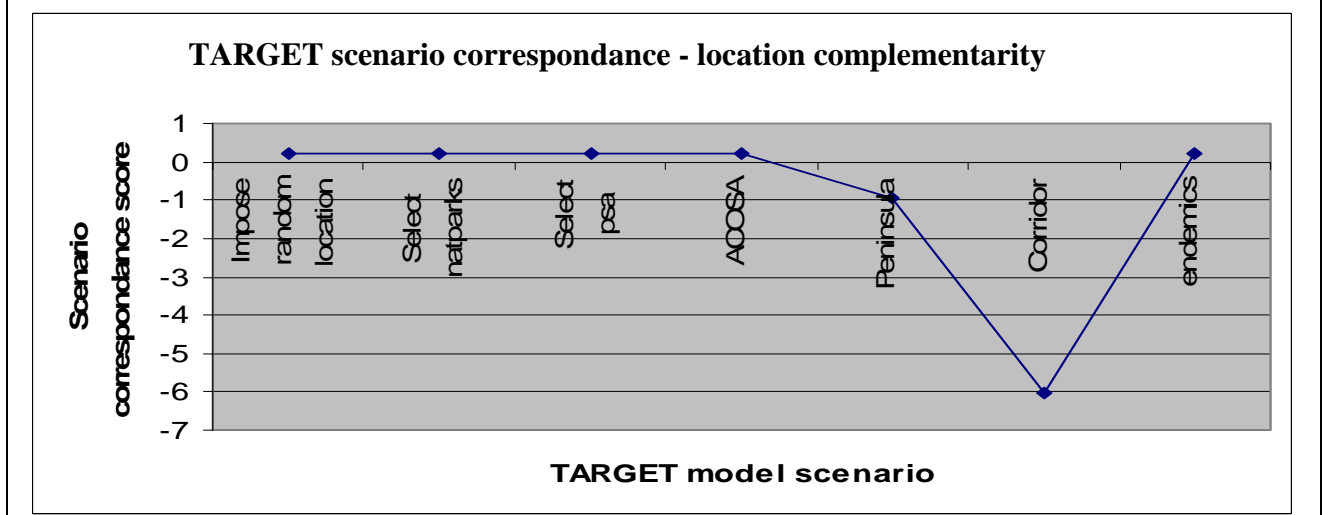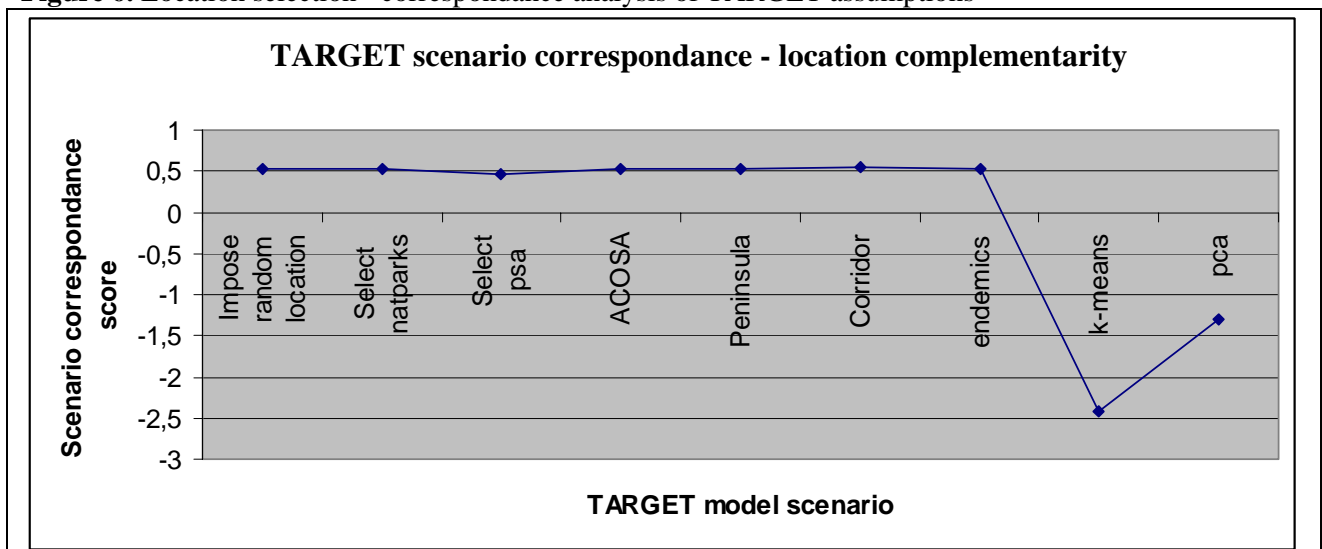

TARGET scenario correspondance – location selection

TARGET scenario correspondance – location selection

Figure 6. Location selection - correspondance analysis of TARGET assumptions
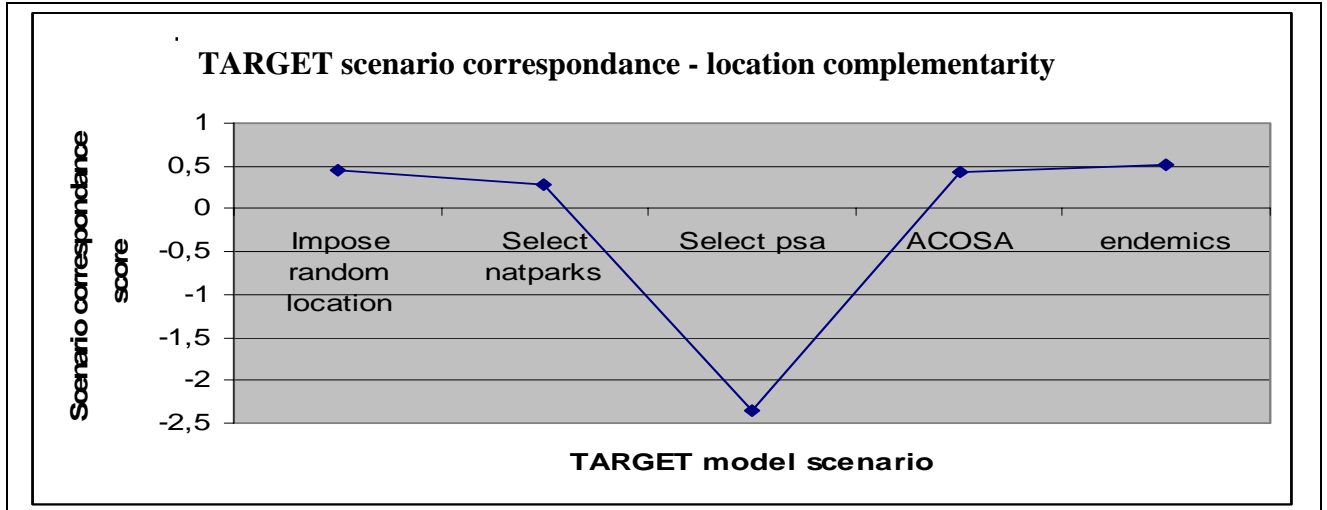
Figure 7. Location complementarity - correspondance analysis of TARGET assumptions

3.1.3 Correspondance of attribute occurrence

Finally, we compared the extent to which similar attributes are protected under the different scenarios by looking at the occurrence, or representation, of attributes in the cost-efficient set of locations. We can imagine this type of robustness mattering to managers in a global sense – independently of which specific locations are chosen, and what their complementarity values may be, they will want to know whether the final solution under the different scenarios selects the same biodiversity attributes for protection.

Figure 8 shows that scenarios offer very different attribute selection, which can roughly be grouped in two clusters (i) "select random location", "select psa" and "ACOSA" are more similar in terms of attributes than (ii) " select national parks" , "peninsula" and " "corridor".   This is as expected. Pre-selecting a single random starting location or no location at all within ACOSA both reach very similar local optima, while pre-selecting a large number of locations as under the 1999-2001 PSA programme forces TARGET to sample over the whole study area, thereby increasing the chances that highly complementary attributes will be selected. On the other hand, "select national parks" pre-selects a large number of locations in the Corcovado and Piedras Blancas national parks largely within the same geographical area as the scenario confined to "peninsula" (**Figure 1**). The scenario defined as "corridor" overlaps less with national parks, but lies in an area with similar environmental conditions thereby leading to similar selection of attributes. This was confirmed by a review of forest ecosystem types mapped by the ECOMAPAS Project (**Figure 1**).
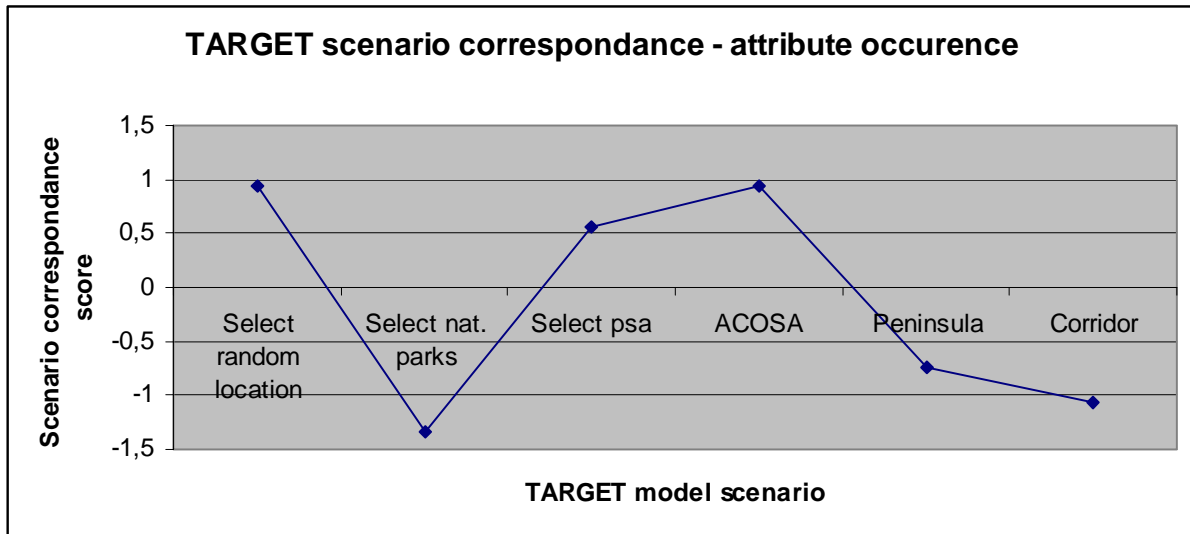
Figure 8. Attribute occurence - correspondance analysis of TARGET assumptions

3.1.4 Conclusion – overall correspondence of scenarios

The sensitivity analyses show that a number of local cost-efficient optima exist within the study area. This has several implications:

- prior to applying TARGET to the priority-setting for environmental service payment locations, authorities such as FONAFIFO have to clarify which assumptions or which 'scenario' the selection criteria for payments is to be based on.

- once the Conservation Areas that are to be included in the biodiversity-cost trade-off analysis has been defined (study area definition), and a biodiversity surrogate has been chosen, TARGET provides relatively robust solutions, sa far as we can see from this correspondance analysis.

- a drawback to this observed robustness is that adding endemic species data to the mainly environmentally determined surrogate did not have the expected large impact on the locations selected or even the attributes selected. This implies that preferences for protecting endemic species should be dealt with differently. Two approaches are possible in TARGET:

  o by pre-selecting and imposing all locations with endemics on the solution found by TARGET.
  o alternately, the locations with endemics or restricted range threatened species can be evaluated using a "look here first" strategy within TARGET (an initial mask restricts the search to these locations). In a study from Papua New Guinea (Faith et al 2001) this strategy showed how representativeness and sampling of the key species were efficiently accommodated.

Overlay surrogate

PCA surrogate

K-means surrogate

Figure 9. Biodiversity surrogates – site selection
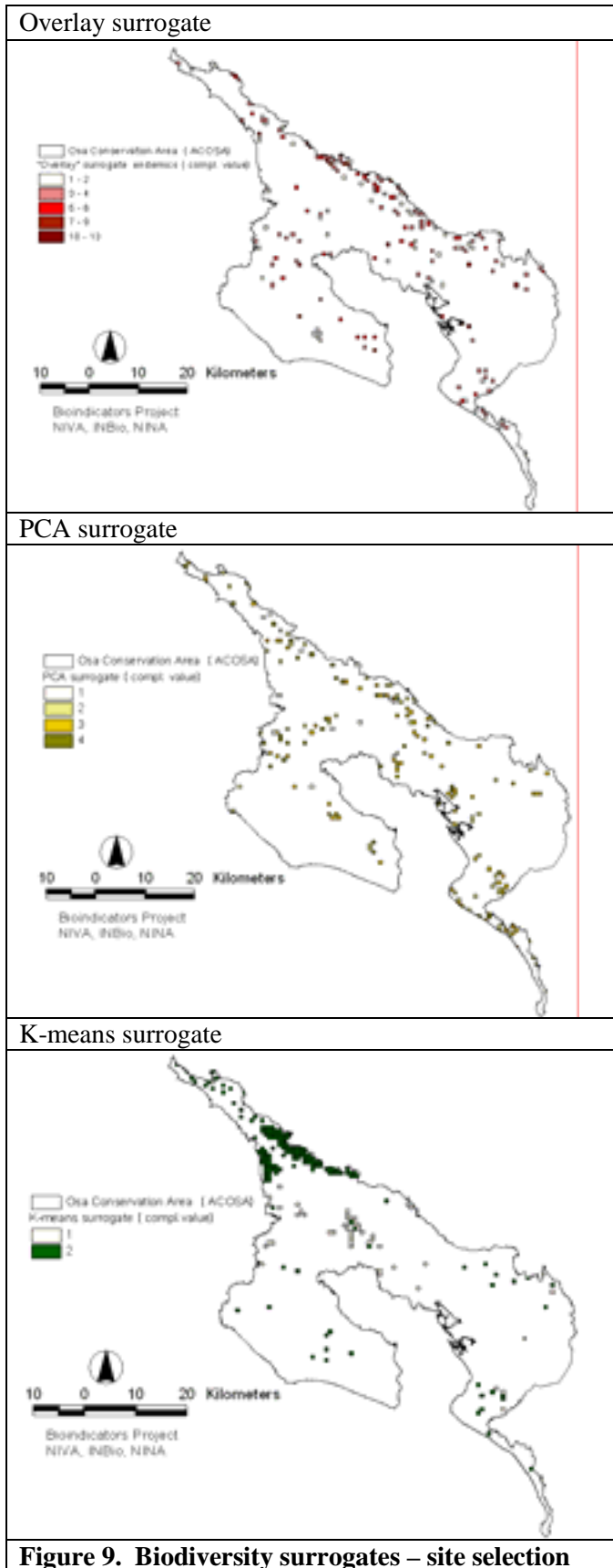
3.2 Sensitivity to the definition of the biodiversity surrogate

To provide a visual appreciation of the degree of correspondance between the different scenarios this section looks at the spatial distribution of the selected locations under each set of TARGET assumptions. We are interested in observing whether any broad patterns emerge which correspond to official prioritisation strategies for environmental service payments in the area.

3.2.1 Selected set with different surrogate indicators

Figure 9 confirms the pattern in the correspondance analysis. K-means results in a set of locations that differs more from the "overlay" indicator than PCA. Locations to the north east are favoured in all scenarios, although "clustering" effects are more pronounced with the k-means approach (which after all a cluster analysis approach). Areas within the Golfo Dulce corridor and buffer zone around around Corcovado National Park are also selected (refer to **Figure 1** for a definition of the park boundaries). Areas to the south east are favoured using the "overlay" and PCA indicator.

An INBio-SINAC study (Acevedo et al.; 2002) compiled a number of prioritisation criteria for environmental service payments (PSA). The most important conclusions from that study are reflected in the category "PSA priorities" in **Figure 10**. These priority areas also coincide with those chosen by the National Forestry Financing Fund (FONAFIFO) for their prioritisation of PSAs. Broadly speaking the locations selected by TARGET using different biodiversity surrogates cluster in two of the three "priority 1" areas. The exception is the biological corridor straddling the Peninsula between the two national parks. This is not prioritised by TARGET because complementarity focuses on biodiversity representation – the attributes within the corridor are already well represented within the adjacent national parks. If the area designated a corridor by authorities is indeed important for

species viability, this illustrates quite clearly that functional criteria are best dealt with outside the TARGET framework.
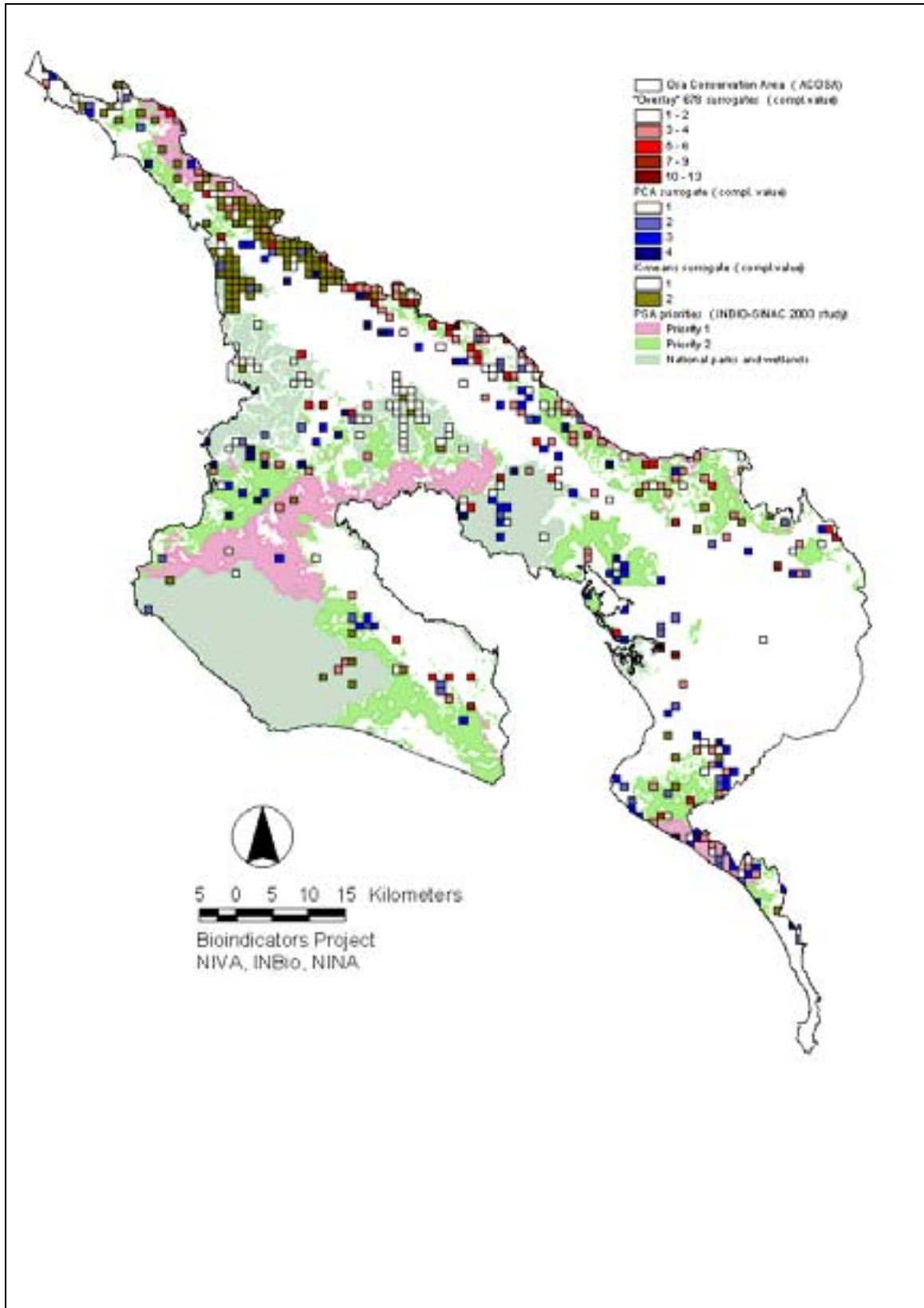

Figure 10. Priority areas based on three distinct biodiversity surrogates

The observed clustering effect and the coincidence with the priority areas is also driven by opportunity costs. One of the Costa Rican authorities criteria for defining priorities in the INBio-SINAC study was minimising land use conflict by prioritising areas of low agricultural value. Given that opportunity costs play a part in the trade-off in TARGET, priority locations tend towards land of low value for agriculture and forestry, producing some of the clustering observed. Over all, given the disparity in selected locations, the sensitivity analysis shows the importance of authorities such as FONAFIFO establishing a consistent set of criteria - what we have called a scenario – under which to run all priority-setting analyses.

3.2.2 Surrogate indicators including endemic species

We hypothesised that TARGET solutions would be highly sensitive to the inclusion of ACOSA's endemic vascular plant species[6] in the surrogate indicator. As can be seen in **Figure 11**, the TARGET algorithm selects only a few of the locations with endemics for any particular study area.

A couple of reasons for why all locations with endemics were not selected are:

1.   single locations have multiple observations of endemics so sites not selected may have observations of an endemic, but "redundant" species (i.e.already included in the selected set). The clustering of observations of endemics in **Figure 11** point towards the possibility of repeated observations of the same species across locations. It also suggests that species sampling has not been conducted with TARGET type analysis in mind[7] – where area-proportional sampling is preferred across the whole study area if species data are to be included in a consistent manner in the biodiversity surrogate.

2.   if the biodiversity conservations target is set relatively low; probability of persistence is relatively high outside protected areas; while weight on costs is set high; and the attribute is found in an area with a high opportunity cost, a location with an endemic may not be selected by TARGET despite a relatively high complementarity value. However, in this case regional biodiversity target was R= 99%, meaning only a 0.01% chance of non-representation. Probability of persistence outside protected areas B=0%, while within protected areas we set P=90%. So this particular reason doesn't then seem to explain the fact that alle endemics were not selected.

Another lesson emerges for application of TARGET in practice. Given the TARGET algorithm's focus on complementarity, rather than simply species richness, locations with endemic species should be imposed on the solution in the same way as e.g. national parks if they are consistently to be prioritised for conservation. It is worth noting that the objective in TARGET is not to have *every* location with one or more endemics. If this is the goal then these locations are simply imposed on the seleted set.

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[6] endemics recorded in Atta and Ecomapas databases at INBio as of May 2003.
[7] For example, anecdotal evidence from the area shows that observations of endemics clusters in protected areas at risk of deforestation, and is correlated to accessibility around research stations.

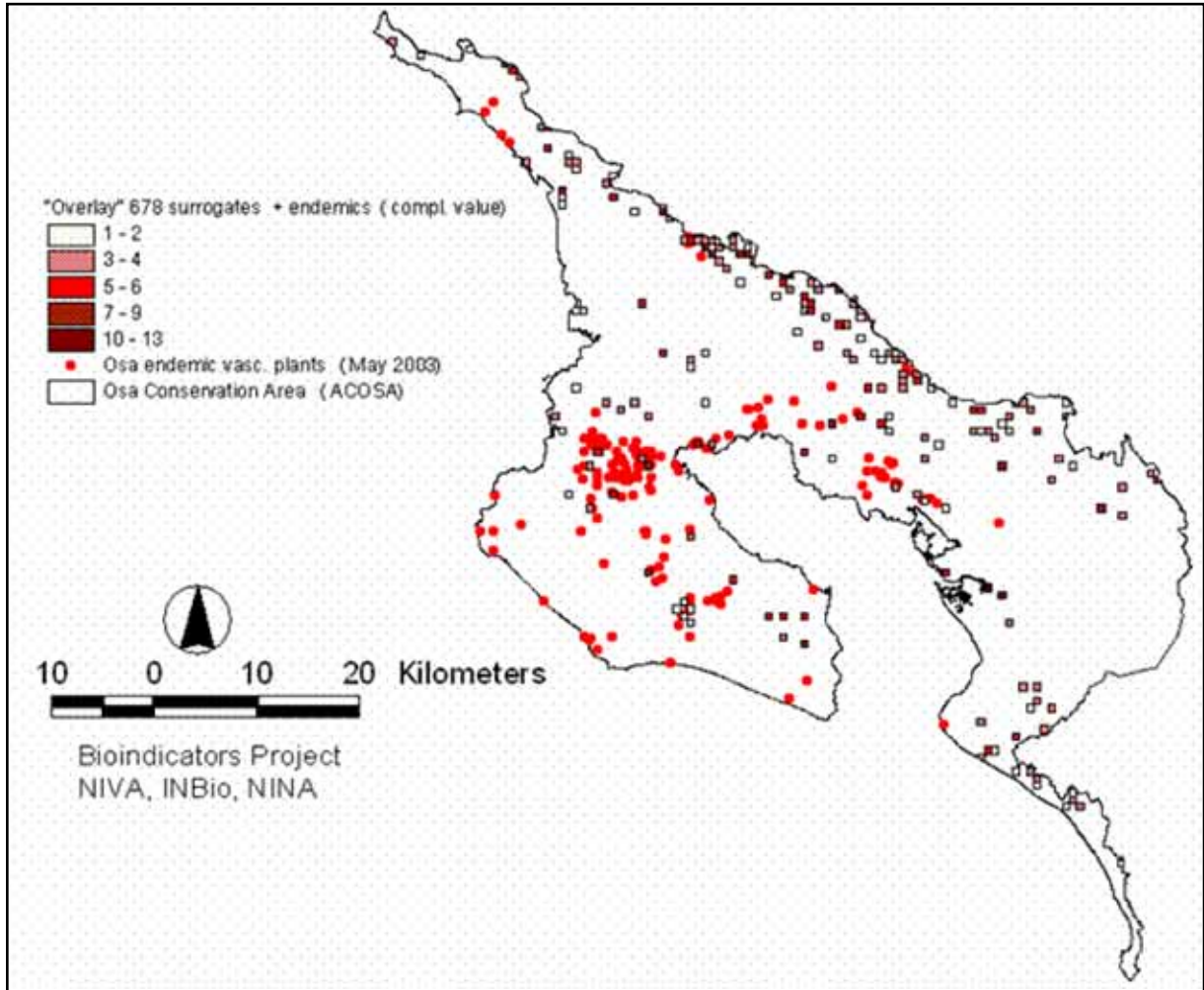**Figure 11.** Correspondance between selected locations and observations of endemic vascular plant species as of May 2003.

3.3 Sensitivity to the extent of the study area

Figure 12 shows TARGET scenarios selecting from either the Corcovado-Piedras Blancas Biological Corridor, the Osa Peninsula or the whole of the ACOSA region.
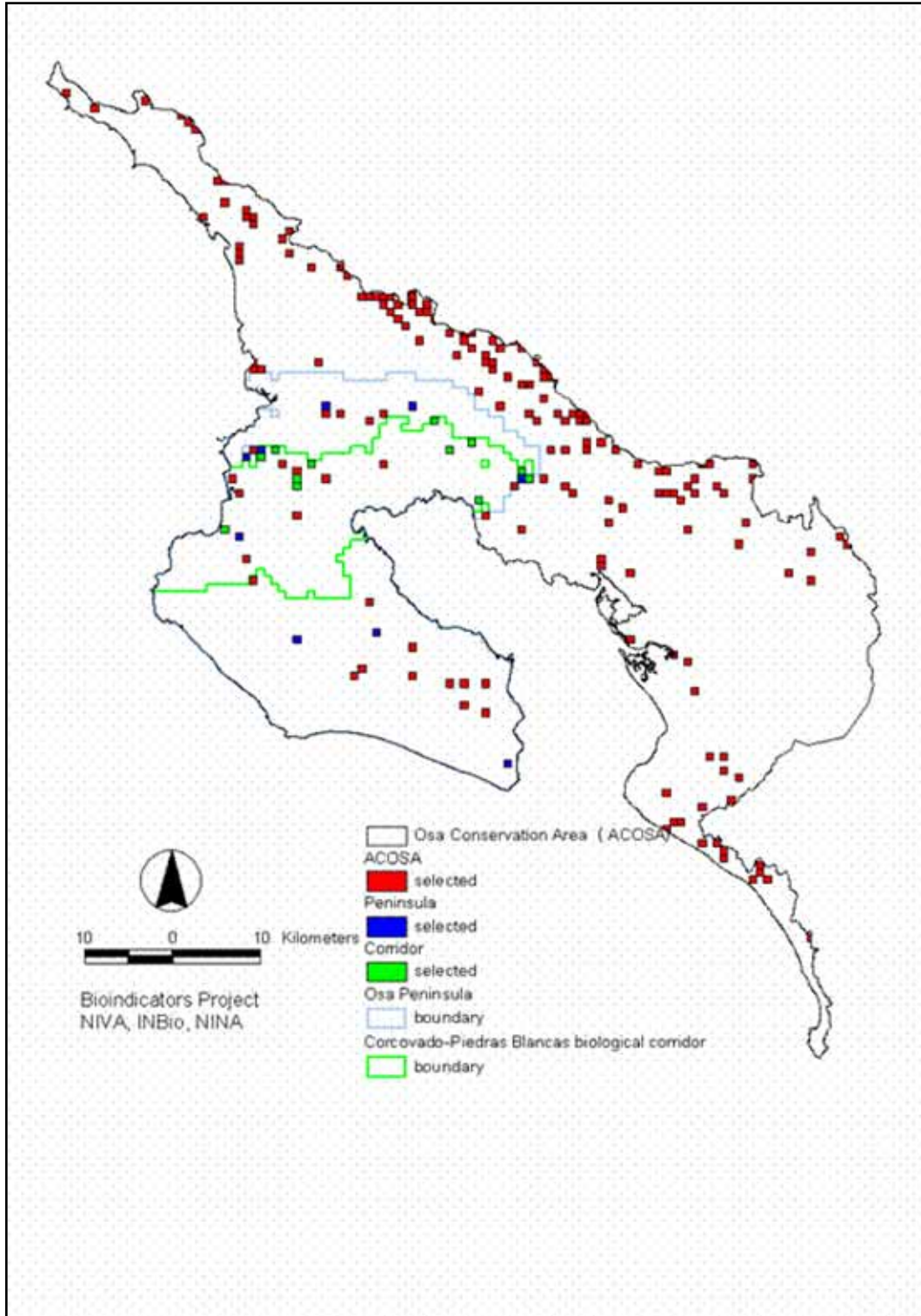

Figure 12. Extent of study area and effect on site selection

The GIS themes in **Figure 12** are ordered as follows: the map theme containing locations selected within ACOSA (black outline) is overlaid the theme containing locations selected within the peninsula (blue line), which in turn is overlaid the theme containing locations selected within the corridor (green line).

Organising the modelling results in GIS in this way showed that within the *corridor*, locations selected under the 'ACOSA' scenario (red dots) or 'peninsula' scenario (blue dots) coincided with locations selected under the 'corridor' scenario (green dots). Within the *peninsula*, locations selected under the 'ACOSA' scenario (red dots) coincided with locations selected under the peninsula scenario (blue dots) (see map legend **Figure 12**). In other words, any green and blue dots/locations seen on the map are unique to the corridor and peninsula scenarios, respectively. These locations are "in excess" compared to cost-efficient sets of locations selected in the scenarios for consecutively larger study areas.

The tendency for TARGET to select "clusters" of locations along the edge of the study area to the northeast and southeast may be due to a large altitudinal gradient and a larger number of correlated attributes per area than on e.g. the peninsula. None of the scenarios had pre-selected national parks, so clustering must be explained by relatively higher attribute density with high altitude gradients, as well as lower opportunity costs than in lowland areas. We have no observations for the reverse slope gradient towards the east and outside the ACOSA study area. If the study area were extended to cover both sides of the mountain range to the northeast we would expect the density of selected locations in this area to decrease.

So as a general conclusion, the smaller the study area the greater tendency there is to "over-select" locations. This is because the attributes selected within progressively smaller study areas may be found elsewhere within the initial study area (in this case ACOSA). By analogy, some of the locations selected in the 'ACOSA' scenario will be redundant if the study area is increased to include the adjacent conservation area, southern Costa Rica, or indeed the whole country. This in turn raises a question regarding the definition of a "valid" study area in prioritisation exercises.

3.4 Sensitivity to local optima – robustness of the selected set

Repeated random starts with a single pre-selected location produced the same final set of locations[8], showing that TARGET solution is robust to small changes in the initial conditions of the optimisation. However, more "radical" starting points for the TARGET optimisation showed that there are several local optima. Pre-selection of areas within Corcovado and Piedras Blancas national parks and pre-selection of the areas under contract for PSAs between 1999-2001 produced very different (local) cost-efficient solutions (**Figure 13**). The approach to pre-selection used here was to designate either national parks or PSA areas as part of the selected set, but allow TARGET to search the whole study area for better alternative locations. In other words, the locations in the initial set are not imposed on the solution, but are ' radical' enough to illustrate the presence of several optima. Random starts with sets of locations is feature of TARGET allows for extensive sensitivity analysis.

A particular point to note was how both pre-selection strategies led to "lumpiness" in the final solution adjacent to or within the locations that were pre-selected. Particularly curious was the fact that none of the locations within the Corcovado Nation Park were rejected from the solution under the scenario where national parks were pre-selected (middle panel, **Figure 13**)[9].

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[8] We tried three different random starts set by the user. A potential improvement of the software would allow for automatically generated multiple random starts, possibly with Monte Carlo simulation functionality.
[9] This result was counter-intuitive - we ran the analysis twice to double check obtaining the same result as for the first run. See footnore in Figure 11 (next page).

| Random pre-selection of single location | Pre-selection of national parks[10] | Pre-selection of 1999-2001 PSA areas |
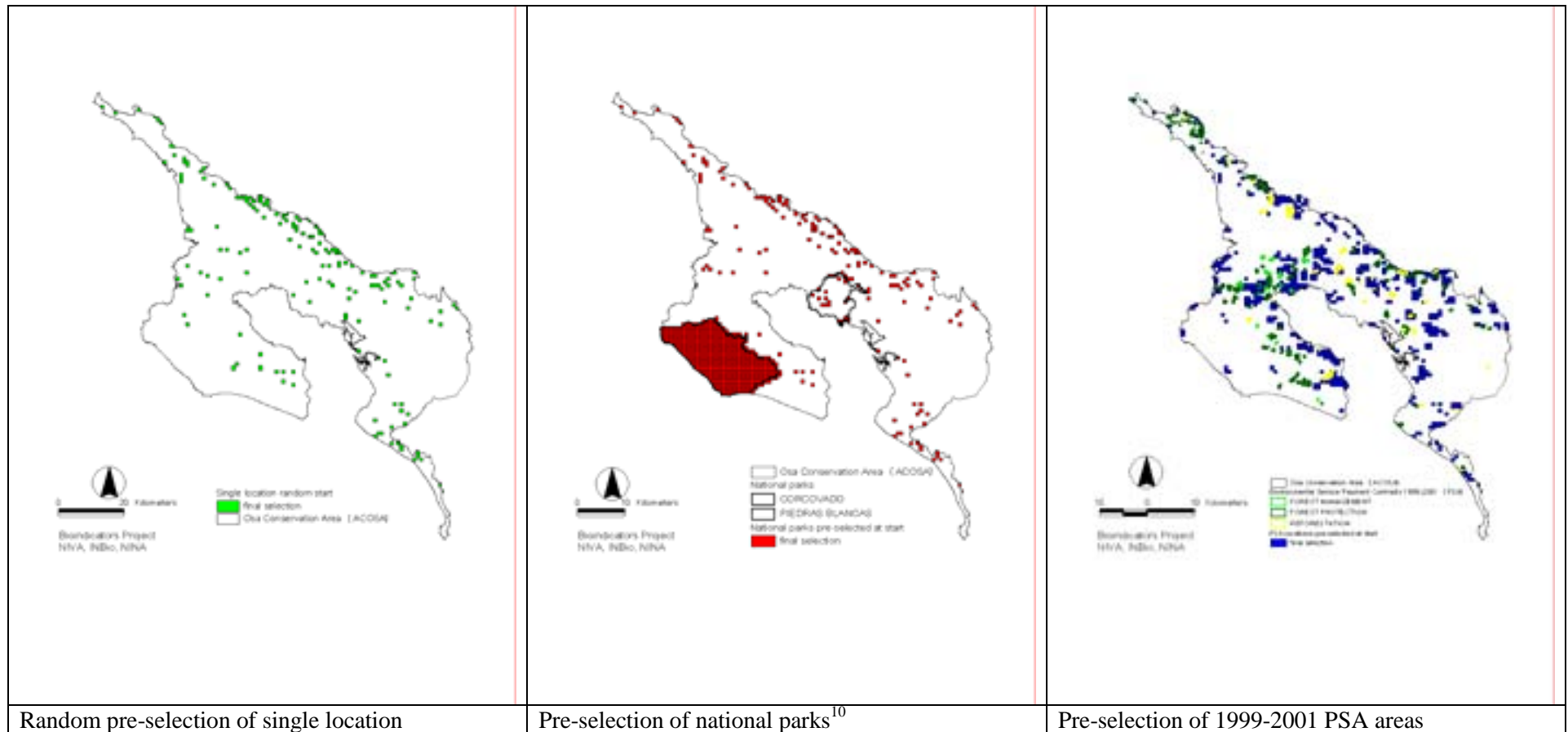
Figure 13. Sensitivity to different assumptions of an initial selected set

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[10] Note that both Piedras Blancas an Corcovado were in the pre-selected set of areas. Whereas TARGET readily traded off pre-selected locations in Piedras Blancas, this did not happen for Corcovado where all locations remained in the final set. Given that Piedras Blancas lies to the north of Corcovado its location sequence # are lower. One explanation is that the sequential search algorithm reaches a solution before having to search in areas to the south of Piedras Blancas. Further evaluation is merited of this explanation. If true it could be mitigated by using a random rather than sequential optimisation algorithm.

Part of the explanation for local optima lies in TARGETs optimisation routine which searches the study area sequentially from first location applying a "tie-break" rule of selecting the first of two equal locations. This means that locations in the north-western sector of the study area have a higher probability of being in the selected set than to the south-east, while pre-selected areas have a higher probability of being in the set, *ceteris paribus*. Currently this problem can be addressed in TARGET by shuffling the order of the locations in the input files and re-running the analysis - for most data sets, there should not be an extensive tie-breaking problem. A random rather than sequential optimisation routine would also resolve this problem.

Sensitivity analysis can also be used to test the strategic importance of particular locations. If there is an argument about the "necessity" of having a particular location in the set - then an approach to this is to carry out runs with versus without that location excluded from the analysis ("masked out") - if it is not possible to obtain the same optimality when it is masked out then there is some argument for its necessity.

As a final note, whether priority-setting is based on weighing complementarity with costs should also affect the extent of local optima. Costless choice is expected to result in the highest number of local optima, because cost acts as a "tie-break" rule when two locations have otherwise similar biodiversity complementarity. The higher the weight on costs the stronger this effect and the fewer local solutions expected.

3.5 Accuracy issues – resolution of data

Current processing capacity of TARGET[11] sets an upper limit on the number of locations that can be analysed at 5000. Underlying GIS data on e.g. forest cover has an accuracy of 100-400 meters[12] (4-16 hectares) which led us to convert polygon themes to a grid of 500m x 500m (25 hectares). This produced a total of 18156 gridcells, i.e. far above the current processing limit of TARGET[13]. In order to deal with the whole of the ACOSA study area we used 4753 1000m x1000m (100 hectare) gridcells as the unit of analysis for all the model runs discussed above. An obvious question during initial analyses was whether the selection of locations would vary if the resolution was changed while holding study area constant. In order to evaluate this question we ran TARGET only for the corridor area; first on 623 1000m x1000m gridcells and then the same analysis on 2235 500m x 500m gridcells. The corridor area contains only 12,9% (85/685) of the attribute richness of the ACOSA area[14] .

The results are presented in **Figure 14** showing both the selected locations and their complementarity value. Only about 1/3 of the selected locations coincided between the two analyses. It is immediately obvious that location selection is highly sensitive to the aggregation approach we used in GIS. The two main sources of error are:

- *Opportunity costs:* values in 25 hectare gridcells were based on an area-weighted average of the underlying polygon values for that cell. 100 hectare gridcells were the simple average of four 25 hectare gridcells.

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[11] Windows 2000 (beta version)

[12] Personal communication Marco Castro, ECOMAPAS project, INBio

[13] The processing limit is likely a feature left over from the DOS version first used in 1995 when processing power for personal computers was more limited. In future versions of TARGET it should be possible to increase the processing limits manifold.

[14] The corridor represents approximately 12,2% of ACOSAs area, i.e. attribute richness by area is about "average".

- *Attribute values*: 25 hectare gridcells were given an attribute value if more than 5% of the cell area had that specific attribute. The 100 hectare gridcell represents all the attributes in underlying gridcells, as well as counting the number of times the attribute occurs (i.e. a maximum of four times per 100 hectare gridcell). The complementarity value of gridcells could also vary substantially across resolutions.

The approaches we used tried to represent as much of the underlying information as possible, but it is inescapable that decreasing resolution changes the characteristics of the units of analysis. The only viable solution to this issue is to use the most detailed information available within the available research budget. In our case the increased costs of using 25 hectare gridcells would be minimal considering the available GIS data, while increasing resolution to e.g. 16 hectares would require more GIS work on accommodating a new grid, but would also feasible with little additional funding. Beyond that costs increase sharply because better satellite imagery or aerial photos become necessary, including digitisation costs. On the other hand, the benefits to increasing resolution in the context of allocating PSAs are equally obvious; sub-optimal allocations of payments in as much as 65% of the cases would probably justify quite substantial investments in increasing the accuracy of the underlying GIS data.
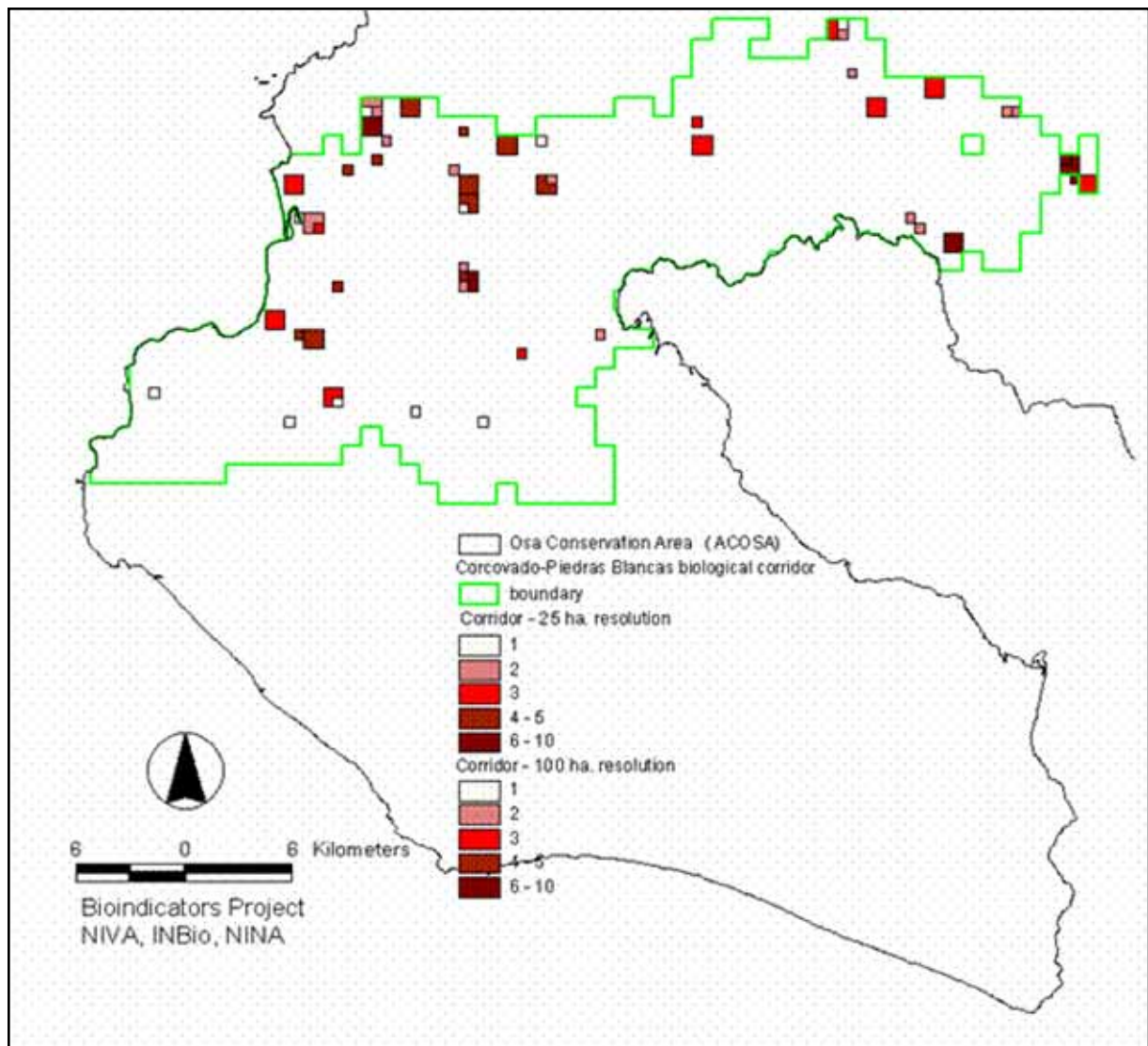

Figure 14. Sensitivity to spatial resolution of data

4. Sensitivity to opportunity costs

Chapter 3 evaluated the sensitivity of priority-setting to assumptions concerning the surrogate biodiversity indicator. In this chapter we look at some other sensitivity issues raised by managers, particularly the definition of opportunity costs.

Opportunity costs used in this study have been estimated based on land-use suitability data and average regional returns to typical crops for suitability classes. The advantage of this approach is that it uses nationally available datasets and is relatively easy to apply. Critique of the approach has focused on:
1. opportunity costs are deterministic and static; do not account for access costs, economies of scale, and the likelihood of deforestation within existing protected areas.
2. per hectare returns to agriculture on marginal land do not sufficiently account for poor suitability in the lowland humid areas of ACOSA, resulting in inflated opportunity costs for these areas
3. alternative approaches to calculating area-weighted average returns give lower opportunity cost estimates

In the following, we address some of these questions.

4.1 Deforestation probabilities and expected opportunity costs

ACOSA is a relatively well studied part of Costa Rica from a conservation point of view. Amongst others, Rosero-Bixby et al. (2002) conducted a regression analysis of the causes of deforestation on the Osa Peninsula which has been used to predict future probabilities of deforestation until 2010. Obvious questions arise as to whether historical deforestation rates can be used as :
•   an empirical measure of predicted probability of persistence.
•   a determinant of expected opportunity costs.

To answer these questions we first rapidly review the results from Rosero-Bixby et al. (2002).   The reduced model regressors employed to predict deforestation on the Osa Peninsula in 2010 are listed in **Table 6**, along with their sign and significance. The dependent variable is change in forest cover per 12.5 hectare gridcell between 1980 and 1995/96(17 806 observations). In table 5 we have added a column regarding the expected correlation with returns to agriculture and forestry and hence opportunity costs.

Predicted probability of persistence

TARGET calculates aggregate probabilities of persistence for individual attributes by assuming independence of probabilities of extinction between locations. In GIS jargon there is no spatial autocorrelation between locations for extinction. While this is a strong simplifying assumption which excludes ecological functions, it is generally more valid the smaller the range requirements of a species – more valid for plants and insects than vertebrate animals and birds. However, probabilities of deforestation were also calculated based on an assumption of independence - or no spatial autocorrelation – making the Rosero-Bixby et al. approach a relevant starting point for empirically setting the baseline probability of persistence value B (equation 2).

One current limitation in TARGET is that the software allows probabilities to be defined for attributes rather than locations.   A possible approach is to weight attribute values of locations by probabilities

of deforestation directly in GIS as part of generating the location input data files for TARGET. [15] The other approach explored below is in calculating expected opportunity costs.

Table 6. Predictors of deforestation in Osa Peninsula

Regressor	Significance	Probable determinants of forest and agricultural return
Number of households per gridcell in 1984	+++	
Km from edge of forest	---	(accessibility)
Km from road	---	accessibility
Km from coastline	---	(accessibility)
Corcovado National Park (dummy)	---	
Golfo Dulce Forest Reserve (dummy)	---	
Agricultural institute (IDA) settlement (dummy)	+++	
Precipitation > 4000 pmc (dummy)	0	suitability
Slope>3% (dummy)	0	suitability accessibility
Life zones (forest types):		
Bosque Muy humedo tropical (dummy)	---	
Bosque muy húmedo-premontano trans. Basal (dummy)	0	
Bosque muy húmedo Tropical	Ref.	
Bosque muy húmedo-tropical transición premontano (dummy)	---	
Bosque pluvial-premontano transición basal (dummy)	++	
R2=0.247		

Source: adapted from Rosero-Bixby et al. (2002). Note: +++ coefficient positive and significant at 1%, ++ at 5% and + at 10% levels, and similarly for negative coefficient signs. Variables in grey are expected to be correlated with opportunity costs. The model was not run for spatial autocorrelation and is therefore, according to the authors, more relevant for prediction than hypothesis testing.

Expected opportunity costs

We expect returns to forestry and agriculture to be correlated to measures of accessibility, both in terms of distance to roads, forest edge and coastline (in that order of importance), as well to criteria for land suitability for agriculture. In the Rosero-Bixby et al. study all distance related variables were strongly correlated to deforestation rates, while precipitation and slope, also used in evaluation of land use suitability, were not significant[16]. There is a weak positive but significant relationship between total deforestation probabilities calculated by Rosero-Bixby et al. and our estimates of total opportunity cost based on land use suitability and standing forest (Figure A1, Appendix 4). We expect that agricultural land use suitability explains some of the probability of deforestation, but this cannot be concluded from the regression analysis of Rosero-Bixby et al.. Their study does suggest that the opportunity cost estimates should be adjusted by access or transportation costs. Standing forest is used to calculate the opportunity cost of forestry of protection. Because deforestation probability is higher for fragmented forest these are significantly negatively correlated and offer little in the way of additional explanation (Figure A2, Appendix 4).

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[15] This would be the subject of future research as similar studies on deforestation probabilities exist for the whole of Costa Rica (see Barton, Faith et al. 2003 for an overview).

[16] A number of other criteria are used to calculate land use suitability indices in Costa Rica including i.a. soil type, drainage (Barton, Faith et al. 2003).

If probability of deforestation is not correlated to opportunity costs, but rather to population pressure or other exogenous variables[17], probability of deforestation could be used to generate expected opportunity costs. Probability of deforestation can then be interpreted as a baseline probability of opportunity costs being incurred if the location in question is protected. The regression results in **Table 6** also show that the probability of deforestation is significantly lower within national parks and forest reserves than otherwise.

In **Figure 15** we illustrate the principle of adjusting opportunity cost estimates by probabilities of deforestation to generate expected opportunity costs. Moving clockwise, the original probability of deforestation data in Rosero-Bixby et al. (2002) (step 1) is converted to a 100 hectare gridcell format (step 2). This is then multiplied for each location with the original opportunity costs(step 3) to generate expected opportunity costs (step 4). Comparing step 3 and 4 we see that the main impact on TARGET analyses is to make the high opportunity cost areas within Corcovado National Park less costly and therefore more likely to be selected for protection.
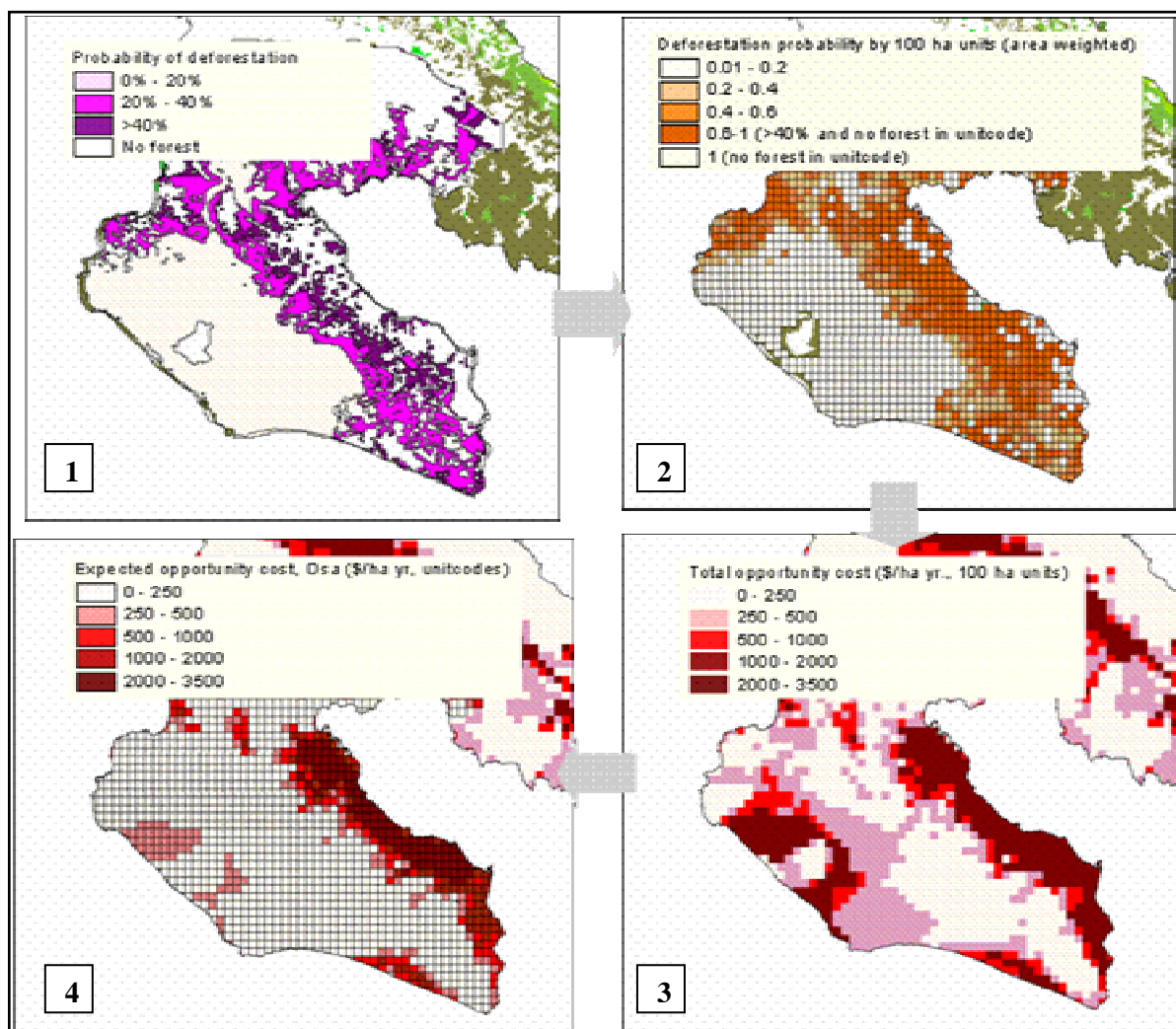
Figure 15. Incorporating probability of deforestation - expected opportunity costs

Although this has an intuitive and theoretical appeal, it is unlikely that locations within national parks would be subject to TARGET-type trade-offs analysis by Costa Rican authorities (they would be pre-

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[17] There is some evidence to support this in Rosero, Bixby et al. (2002), but that begs the question whether population growth is causally related to returns to land use.

selected and imposed on the selected set). For large inaccessible forest areas outside national parks, adjustments to opportunity costs are probably better dealt with by explicitely by calculating distance dependent accessibility costs.

4.2 Calculation method for opportunity costs

Opportunity costs used in this study were calculated based on land use suitability maps for ACOSA and average returns for crop types present in each suitability class within the Brunca region, of which ACOSA is a part (Barton, Faith et al. 2003; Vega and Vega, 2002). Average returns for each crop type were weighted by the relative crop area to generate average returns by suitability class. One critique of this approach is that the Brunca region includes higher altitudes than are found in ACOSA with amongst other high value dairy pasture[18]. This has tended to inflate the opportunity costs of low suitability land use classes (with steep slopes, poor drainage and fertility soils). This will lead to relatively fewer locations in marginal areas being selected for protection by TARGET if costs are given a relatively high weight in the trade-off (Barton, Faith et al. 2003).

Wielaard (2003), using opportunity cost data generated by the Biodincators Project (Vega and Vega, 2002), employed a similar area-weighted averaging approach, where weights were based on the fraction of area cultivated in ACOSA. Whereas the approach used in Vega and Vega (2002) reflects average potential returns, Wielaards approach is more conservative by reflecting the fact that most land is underutilised despite its potential. Using this approach 82% of land area in ACOSA within the lowest suitability class VIII has no agricultural use and is assigned zero returns, while e.g rice has net returns of 1909 $/ha yr. (1996$), but is cultivated on 0,85 % of the area in class VIII. If TARGET is to be used for exercises implicitly valuing biodiversity using opportunity costs of protection (natural resource accounting) Wielaard's conservative valuation approach is more appropriate. With hindsight basing weights on crop areas within ACOSA seems more appropriate than weighting by areas in the larger Brunca region[19].

Opportunity costs used in this report are inappropriate for evaluating the incentive effects of payment levels for any particular location. The current data[20] is too coarse grained for predicting the regional demand for PSAs at any given particular payment levels – we would conduct ground truthing studies of actual returns to different crops and suitability classes before making such a recommendation. However, if the purpose is prioritising PSAs between locations, as was the case in Barton, Faith et al. (2003). the relative value of opportunity costs is sufficient to improve decision-making.

By way of conclusion, GIS techniques for extrapolating agricultural and forest returns to the whole study area have been used to illustrate the potential that TARGET offers for better priority-setting with existing data. Given the large sensitivity to different weighting assumptions, we recommend a conservative approach in future applications, combined with ground truthing of opportunity cost estimates.

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[18] Personal communication Edgar Ortiz, FONAFIFO and Ortiz et al. (2003).

[19] Brunca crop areas were originally used because statistics on crop returns were averages for the whole Brunca region (Vega and Vega, 2002).

[20] The Bioindicators Project used only available published data with no additional field work.

5. Conclusions

The purpose of this study has been to conduct sensitivity analysis of priority-setting in biodiversity protection using the TARGET software given a range of assumptions on input data. The study is in part a response to a number of questions raised by protected area managers and other stakeholders at workshops held by the Biodincators Project in Costa Rica in 2003-2004. Questions raised by stakeholders were 'distilled' to 6 main research questions or hypotheses. These questions and our concluding evaluation of them are summarised in **Table 7**.

Table 7. Concluding evaluation of research questions

Research questions	The selection of cost-effective set of locations…	Evaluation
1	is stable in repeated trials with a fixed starting point	TARGET solutions are identical for repeated trials using the same starting point, because of the sequential sampling optimisation routine (as opposed to a random sampling routine).
2	is stable in repeated trials with random starts (preselect a single location)	TARGET solutions were identical for three different random starts using single locations. However, using different sets of pre-selected locations as initial conditions for the optimisation routine produced different local optima.
3	is not sensitive to the definition of the study area	TARGET solutions are sensitive to the definition of the extent of study area, mainly due changing the absolute number of and relative importance of biodiversity attributes present within the study area, and thereby their complementarity values.
4	is not sensitive to resolution of data	TARGET is sensitive to resolution of the the units of analysis (gridcell) used. This is due mainly to the averaging effects of aggregating data to larger units of analysis.
5	is not sensitive to the definition of the biodiversity surrogate when based on the same underlying data set.	TARGET is (highly) sensitive to the choice of surrogate biodiversity indicator, in this case the so-called 'overlay', 'PCA' and 'k-means' approaches. There are practical and pedagogical reasons for choosing the 'overlay' indicator, while PCA and k-means may be preferable for theoretical reasons.
6	is sensitive to including unique representations of biodiversity attributes such as endemic species	TARGET analysis was not (highly) sensitive to inclusion of endemic vascular plant species in the biodiversity surrogate indicator. Although this is contrary to expectations this may be an artefact of the particular scenario defined by the user and should be evaluated further.

Further conclusions derived from this report regard biodiversity surrogates, opportunity costs, the TARGET algorithm and the management implications of the sensitivity analyses conducted here.

Biodiversity surrogates

Definition of the biodiversity surrogate has the greatest impact on the cost-efficient selection of locations, followed by the definition of pre-selected locations (e.g. in existing national parks), the definition of the study area, and finally is not sensitive to the addition of endemic species.

Can the data underlying the biodiversity surrogates be improved, particularly in including species information? The surveys of the Inventory program at INBio have posed restrictions on a formal statistical analysis of species distributions since the sampling design does not conform to an objective representation of areas and of ecological (environmental explanatory) factors. To be more valuable for priority setting, future sampling design may take some guidance from the TARGET analyses shown here, improving area representativity.

In addition to improving sampling and ground truthing, remote sensing images with better resolution can be employed. We think the additional costs will be justified by benefits to increasing resolution in the context of allocating PSAs; sub-optimal allocations of payments in as much as 65% of the cases in ACOSA would probably justify quite substantial investments in increasing the accuracy of the underlying GIS data.

Opportunity costs

The opportunity costs used in this study are overestimates for more marginal lands were forests are most common. They are also overestimates in the sense that transport and other access costs have not been factored in. For ACOSA this has the greatest impact on the relatively large and relatively inaccessible forested areas of the Corcovado National Park. For large inaccessible forest areas outside national parks, adjustments to opportunity costs should be explicitely by calculating distance dependent accessibility costs.

GIS techniques for extrapolating agricultural and forest returns to the whole study area have been used to illustrate the potential that TARGET offers for better priority-setting with existing data. Given the large sensitivity to different weighting assumptions, we recommend a conservative approach in future applications, combined with ground truthing of opportunity cost estimates.

TARGET algorithm

The procedure followed by TARGET is a formalisation of a selection procedure with the advantage of allowing documentation, repeated evaluation of the results and analyses of sensitivity. The algorithm does not guarantee a global optimum, and hence the user is required to vary initial conditions in order to test for local optima in a heuristic approach. However, the strategy in TARGET of searching for optimal solutions by varying the weights on costs has been shown to be more effective than the standard approach for such problems of selecting places based on a simple benefit/cost ratio (Faith 2001).

Management implications

The possibility of a number of local cost-efficient optima exist within the study area has several implications. Prior to applying TARGET to the priority-setting for environmental service payment locations, authorities such as FONAFIFO have to clarify which assumptions or which 'scenario' the selection criteria for payments is to be based on. Given a set of assumptions TARGET provides a robust selection of the cost-effective set of locations for protection.

Given the TARGET algorithm's focus on complementarity, rather than simply species richness, locations with endemic species should be imposed on the solution in the same way as e.g. national

parks if they are consistently to be prioritised for conservation. If the objective is simply to represent all endemics (but not all locations with endemics) within the system of protected areas, TARGET provides a sufficient solution.

Although trade-offs analysis in general has high management relevance, it is unlikely that locations within national parks would be subject to TARGET-type trade-offs analysis by Costa Rican authorities. In fact, land use conversion from forestry to agriculture is illegal and has been used as a general critique of conducting any kind of trade-offs analysis in Costa Rica. In practice, gradual forest encroachment and fragmentation may lead to long term deforestation, calling for prioritisation of conservation efforts with limited resources available to SINAC and FONAFIFO.   Another argument against trade-offs analysis has been that recent forest statistics have shown net reforestation in Costa Rica as a whole. TARGETs use of environmental biodiversity surrogates provides a guide to which areas have highest complementary value for restoration.

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7. Appendices

7.1 Appendix 1: Species data availability and use for ACOSA biodiversity and indicators for planning

Biodiversity surrogates were considered as 'environmental classes' or 'habitat types' generated from available cartography in digitized format from the ECOMAPAS project at the Costa Rican National Biodiversity Institute (INBio) (Kappelle et al., 2003). A set of biophysical attributes characterised the land units in terms of their natural environments in ACOSA. The basis for the environmental classes were topography, climate and substrate as these factors are fundamental determinants of biological activity and therefore, it was assumed that their spatial distribution correlated well with that of animal and plant species. The use of natural environments to generate surrogates for biodiversity, is an approach that has often been used in lack of more definitive biodiversity data (Austin 1991) due to the difficulty of obtaining comprehensive data on species relative to that of producing resource maps (Pressey and Bedward 1991).

Our approach aimed at developing a database with all existing significant data that gave complete coverage of ACOSA at the highest possible spatial resolution. Based on previous work in ACOSA (Madrigal and Rojas 1980; Herrera 1986; Gómez and Herrera 1993; Tournon and Alvarado 1997; Ardón and García 1998; Kappele, M.Castro et al. 2003), the major environmental variables influencing the distribution of the vegetation types were assumed to be climate, soil, lithology, topography (elevation) and landform.

7.1.1 Land units and biodiversity surrogates database

The first step was to identify the planning units to provide the basis of the database and the subsequent priority setting analysis. Since a land property map is not available for the whole ACOSA, we used a regular grid with 1x1 km^2 cells as the basic unit of analysis. The grid consisted of 4762 cells and it was overlaid on the ACOSA ecosystems map (Kappelle et al., 2003), using the ArcView GIS tool. The physical data consisted of 20 climate classes, 16 geological formations, 4 soil orders, 6 land-form classes, 9 elevation bands, and the presence or absence of open water. An additional data set consisting of vegetation macro-types was also generated from digitised cartography.

Each mapping unit (1 km^2 grid-cell) was allocated the class of the attributes that was derived from the polygons on the physical maps (climate, soil, geology and landform). The ACOSA boundaries of the different digitised maps were compared and searches were conducted to detect boundary errors (area mismatches) that result from digitising. The area (in ha) of the environmental variable classes in each of the 1x1 km cell was computed using the package ArcView 3.2 by overlying the grid with the digitised maps.When the polygon areas of the overlain variable classes differed within a grid cell, the area allocated to the environmental attribute (product of crossing variable classes) was that of the variable class with lowest area coverage. A biodiversity attribute was consider to be represented in a land unit when the cover in a grid cell was larger than 5 % (5 ha). The vegetation macro-type classes were considered additional biodiversity surrogates or 'grid cell attributes'.

Finally, the biodiversity attributes were coded for each land unit and the files were prepared in TARGET-readable format.

Climate

The climate database was created by digitising and combining climate maps from four different sources (Kappelle et al 2003). We used twenty climate types (Table A2.1 in Barton et al. 2003) derived by Kapelle et al. (2003) by overlying the variables and corresponding classes that define the Climate Types according to Herrera (1986, map scale 1:250.000) and the 3 Thermal and 3 Humidity Provinces, and the length of the dry season from Herrera & Gómez 1993 (map scale 1:685000, 'Biotic Units map'). The 9 variables that define the Climate Types in Herrera (1986) characterise the climate

in terms of 3 major gradients, humidity (mean annual rainfall, annual potential evapotranspiration (PET), hydric and aridity indices), seasonality (occurrence and length of the dry period) and temperature (mean annual temperature). Hydric index reflects the relationship between PET and mean annual precipitation $((P/PET)-1)*100$. Humidity provinces by Herrera 1986, are geographic areas with ranges defined by precipitation and PET (Kappelle et al. 2003). In ACOSA; there are three humidity provinces: sub-humid, humid, and very humid. The ranges of the Thermal Provinces (Herrera 1986) are defined by altitudinal belts (Kappelle et al. 2003). In ACOSA the three provinces are: tropical (0 – 500 m), subtropical (500 – 1200 m) and Temperate (1200 – 2100 m) (Kappelle et al. 2003). The length of the dry season based on days with soil water deficit was digitised from the maps by Herrera 1986 based on geographical areas with ranges delimited. A dry month is defined in their map as "a month in which precipitation is less than 50% of ETP".

Geology, landforms and soils

The geological data were obtained by digitising the map by Tournon & Alvarado 1997. There are 6 geological classes in ACOSA that characterise 16 formations (table A2.2 in Barton et al. 2003). Five classes correspond to rocks of sedimentary and intrusive origin, including recent swamps and fluvial, colluvial and coastal deposits (Kappelle et al. 2003). Two classes have volcanic origin and are characterised by basaltic rocks from the Cretaceous and Eocene, i.e. Complejo Nicoya and Grupo Golfito, respectively. Landform data were digitised from the geomorphology map by Madrigal & Rojas 1980 (Kappelle et al. 2003) where six land form classes are distinguished for ACOSA (Table A2.3 in Barton et al. 2003). Soil type classes were obtained by digitising the map of soil orders by Pérez et al. (1978 SEPSA, in Kappelle et al. 2003, table A2.4 in Barton et al. 2003).

Other environmental data

Additional environmental data were 9, 200 meters elevation bands derived from digitised 1:200.000 topographic maps (Instituto Geográfico Nacional (IGN), 1988. Talamanca & Golfito Topographic sheets. Scale map 1:200.000 scale. San José, Costa Rica.).

Areas with water

Based on colour photography (INBio) at 1:40 000 taken 1995 and 1996. Photos were interpreted and georeferenced at INBio.

Vegetation macro-types

Vegetation macro-types (Gómez 1986) were additionally used to characterise biodiversity. The macro-types geographical data base was obtained by digitising the map of by Gómez (1986b, scale 1: 200 000). Twelve types are found in ACOSA of a total of 55 for the entire country (Table A2.5 in Barton et al. 2003). The vegetation macro-types have been derived by the knowledge of experts about forest types, dominant species, elevation, soil type and geomorphology. The unit limits in the map have been drawn based on the field experience.

Endemic species

Endemic species are usually of high priority for biodiversity conservation world wide and in Costa Rica, and were therefore included as individual biodiversity attributes of the grid cells where they occurred. At present, four plant species have been published as endemics for ACOSA (Ardón & García 1998). However, the inventory database (Atta) at the Institute of Biodiversity Atta included, in March 2003, 178 endemic vascular plant species for the Conservation Area. Geo-referenced data of species endemic to ACOSA were obtained from the *Atta* database at the INBio. Of these, 59 were considered to be 'true' endemics of ACOSA and included in the 'endemic species' TARGET runs (Barton et al. 2003, Table A4).

However, the complete distribution of endemic species is poorly known, and therefore priority setting of areas where endemics are known to occur should be considered with caution. For example, anecdotal evidence from the area shows that observations of endemics clusters in protected areas at risk of deforestation, and is correlated to accessibility around research stations.

7.1.2 PCA surrogate data

Principal component analysis

Principal component analysis (PCA) is an ordination technique that constructs theoretical variables that minimize the total residual sum of squares after fitting straight lines to the data. The score of a variable in PCA is the slope of the line fitted for the variable against the PCA axis. A positive score means that the value of the variable increases along the axis, a negative score means that the value decreases and a score near 0 that the value is poorly related to the axis. The first axes of PCA is a theoretical variable minimizing the total residual sum of squares among all possible choices of one explanatory variable. The first PCA axis is the variable that explains the data best, and second and later axes also explain the data best but subject to the constraint of being uncorrelated with previous PCA axes. PCA axes that explain only a small proportion of variance in the data are in practice ignored (Jongman, ter Braak & van Tongeren 1987).

Multiple regression can also be used to study nominal (classes) variables or both quantitative and nominal variables. In the ACOSA data set each class of the environmental variables and vegetation macro-types were nominal variables and therefore defined as "dummy variables". For example, the dummy variable for the geological formation 'Sabana Azul' took value 1 if the grid cell was on that formation and 0 if the grid cell occurred on other formations.

PCA on 'overlay data set'

The complete 'overlay data set' included the data set on the physical environment and vegetation macro-type classes as attributes.

The aim of the PCA analysis was to generate biodiversity attributes ("habitat types") using all available information and at the same time to reduce redundancy in the 'overlay' data set. The first PCA analysis was conducted with the entire 'overlay' data set (derived from physical environmental variables) and vegetation macro types. The results of this analysis are presented in the section below. They indicate that climate, geology and soils were related with the main PCA axes and that only few vegetation macro types classes showed strong relationships with the PCA axes. Vegetation classes were also strongly related to the physical environmental variables.

Therefore a PCA analysis was conducted on the physical variables only. This analysis resulted a more robust model (explained higher portion of the variance, particularly that by the two first axis) while displaying very similar grid cells ordination (**Figure 5** in section 2 of this report and **Figure A1** of this appendix). The results of this PCA analysis were the ones used to generate the biodiversity surrogates as described in section 2.2.3.

Results of PCA with 'overlay' physical environmental and vegetation macro types data[21]

The three first axis of the PCA ordination on this data set accounted to 69.9 % of the variation (Table A1). The variables with strongest relationship with PCA axis-1 (scores > 0.65) were related to very humid and warm climate, low elevation (0-200 m), ultisols and molisols soils, and vegetation macro-types, "bosque tropical lluvioso de bajura sobre formaciones de origen tectónico" (lowland tropical rainforest on formations of tectonic origin) and "pantanos herbáceos" (wetlands with herbaceous vegetation). PCA axis 2 was strongest related to moderate hydric deficit, moderate aridity index, intermediate dry season. PCA Axis-3 was positively related to medium elevations (200 – 400 m), ultisol soils and negatively related to low elevations and molisol soils (Table A2 and Fig. A1).

Table A1 Eigenvalues and cumulative % variance of 4 Principal Component axes derived from the biophysical data set (environmental variables and vegetation macro-types). Cummulative % variance indicates the accumulated fraction of the variance accounted for by the PCA axes.

	PCA axis 1	PCA axis 2	PCA axis 3	PCA axis 4
Eigenvalue	0.499	0.127	0.074	0.047
Cummulative % variance	49.9	62.5	69.9	74.6

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[21] The software CANOCO provides a series of options at different steps of the analysis. For the analysis reported in section 2.2.3, the options were:
Principal component analysis with symmetric scaling of species and samples and species (in our analysis the physical environment variables) scores divided by standard deviation.

Table A2: PCA ordination on physical environmental data and vegetation macro-types. Variables with scores > 0.65

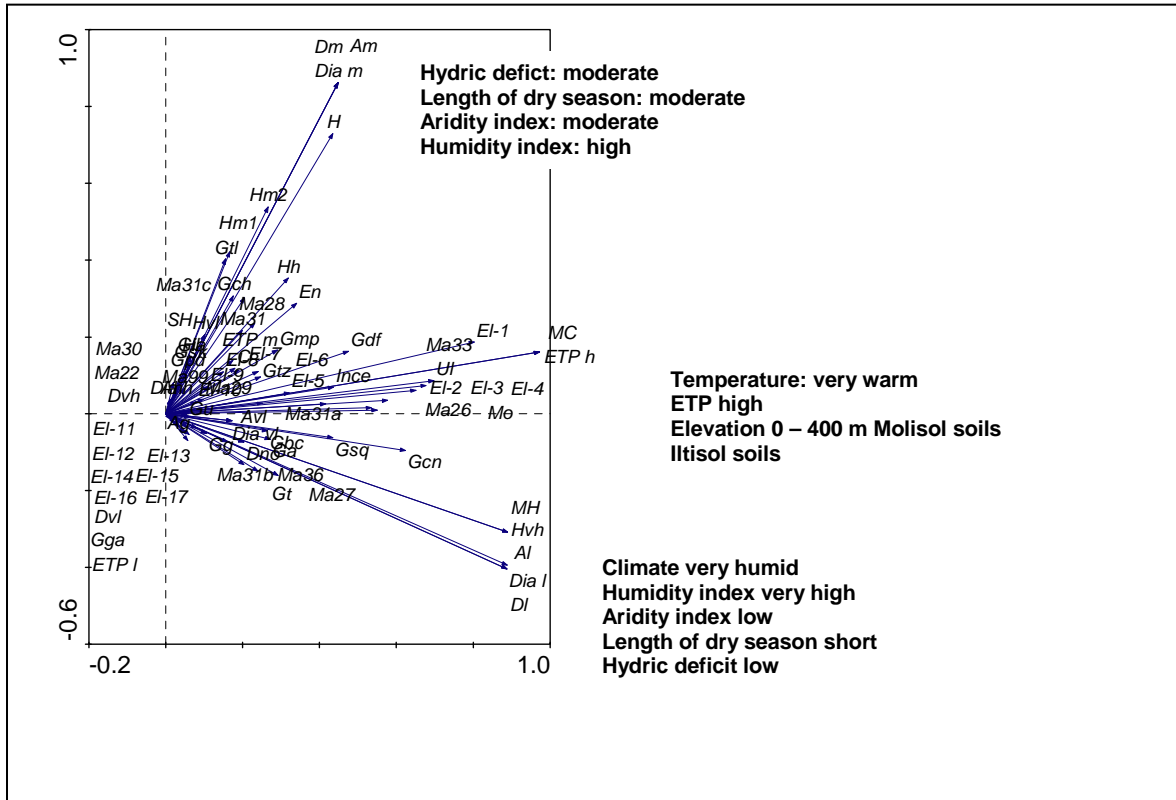| Variable code	Variable	Scores on PCA – w/veg Axis 1	Scores on PCA – w/veg Axis 2	Scores on PCA – w/veg Axis 3
MC	Temperature Very warm	1.1565		
ETP h	ETP high	1.1565		
MH	Humidity Very humid	1.0589		
Hvh	Hidric index very high	1.0589		
DI	Hidric deficit low	1.0569		
AI	Aridity index low	1.0564		
Dia l	Length of dry season low	1.0564		
El-1	Elevation 0-100	0.9554		
Ul	Ultisol soils	0.8300		
Ma33	Lowland ropical rainforest on alluvial formations, undulating topography	0.8061		
El-2	Elevation 100-200 m	0.7744		
Gcn	Complejo Nicoya (basalt)	0.7422		
Ma26	Lowland ropical rainforest on alluvial formations, flat topography	0.6866		
Mo	Molisol soils	0.6541		
Dm	Hydric deficit moderate		1.4458	
Am	Aridity index moderate		1.4458	
Dia m	Length dry season moderate		1.4458	
H	Humidy High		1.2222	
Hm2	Humidity index moderate-1		0.9024	
Hm1	Humidity index moderate-2		0.7075	
Gtl	Terraba formation		0.6756	
Al	Aridity index low		-0.6766	
Dia l	Length dry season low		-0.6766	
El-3	Elevation 200-300 m			1.0773
Ma33	Bosque tropical lluvioso de bajura sobre formación alluvial, undulating topography			1.0134
Ul	Ultisol soils			0.9154
El-4	Elevation 300-400 m			0.8974
El-2	Elevation 100-200 m			0.7964
Gcn	Formation Nicoya complex			0.7283
Mo	Molisol soils			-1.2670
Ma26	Bosque tropical lluvioso de bajura sobre formación alluvial, flat topography			-1.1453
El-1	Elvation 0-100			-0.8077
Gsq	Formation sabana grande			-0.8045
Gdf	Fluvial deposits			-0.6599

Figure A1. PCA ordination diagram (Axis I and II) on 'overlay physical data' and vegetation macro – types
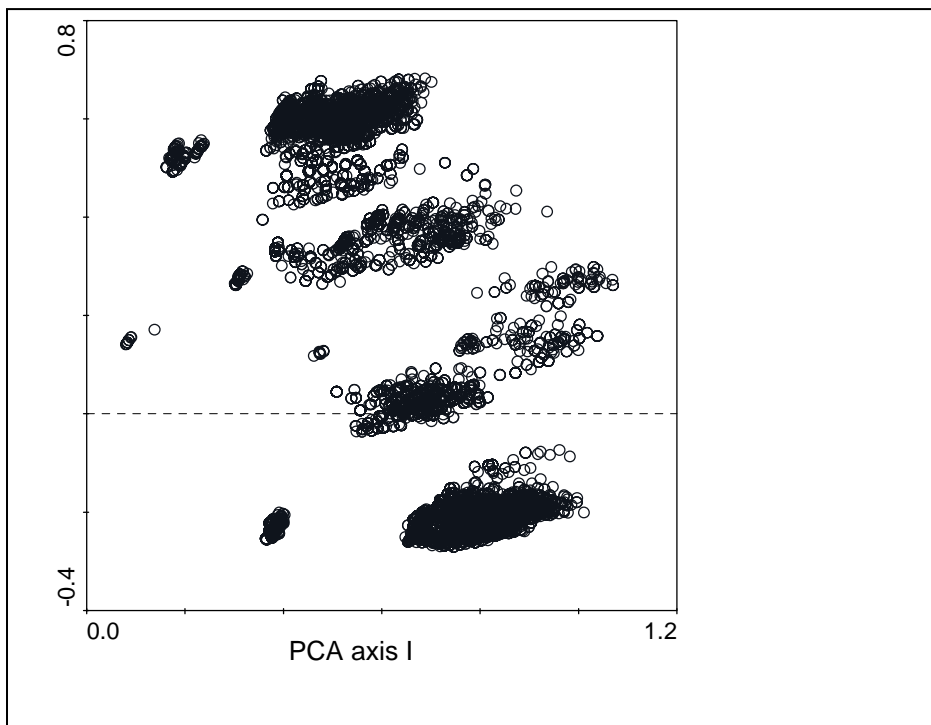

Figure A2 Grid cells ordination diagram based on PCA analysis (Axis I andn II) on 'overlay physical data' and vegetation macro –types

Table A3 59 species 'true' endemics of ACOSA that were included in the 'endemic species'
TARGET runs (see appendix 1, data set).

Endemic vascular plants

Aiouea obscura
Anthurium burgeri
Bourreria grandicalix
Bourreria rinconensis
Calathea hylaeanthoides
Calathea lasiophylla
Calathea nitidifolia
Calliandra grandifolia
Cavendishia linearifoli
Cavendishia osaensis
Coccoloba bejuco
Combretum graciliflorum
Coryanthes horichiana
Costus osae
Costus stenophyllus
Daphnopsis costaricensi
Dendropanax ravenii
Duroia costaricensis
Epiphyllum grandilobum
Faramea permagnifolia
Ficus osensis
Geonoma scoparia
Guatteria pudica
Hebeclinium hygrohylaeu
Heliconia wilsonii
Hoffmannia hammelii
Huberodendron allenii
Inga bella
Inga golfodulcensis
Inga tenuiloba
Justicia aurantiimutata
Justicia deaurata
Licania corniculata

Licania diegogomezii

Licaria pergamentacea

Macroclinium allemiorum

Maxillaria vittariifoli

Mormodes fractiflexum

Mouriri osaensis

Mouriri tuberculata

Ocotea multiflora

Ocotea patula

Ocotea rivularis

Oncidium stenobulbom

Osa pulchra

Ouratea rinconensis

Parathesis longipedicel

Pentaplaris doroteae

Peperomia trichomanoide

Piper sagittifolium

Pouteria triplarifolia

Prestonia hammelii

Rauvolfia amoena

Rudgea raveniana

Syngonium hastiferum

Syngonium oduberi

Thelypteris illicita

Trichilia skutchii

Zygia rubiginosa

7.1.3 Biodiversity and indicators for planning in ACOSA

The rainforests of the ACOSA area in southeastern Costa Rica belong to the most species-rich forests in Central America, with strong floristic affinities with the Columbian Choco-region (Weissenhofer et al. 2001). According to INBio (Atta information system, February 2001) 2659 species of vascular plants have been recorded in ACOSA, distributed among 203 families and 1029 genera. The ECOMAPAS Project recorded for the Area species of 794 vascular plant, representing this number, 7.1 % of the vascular flora known for Costa Rica (Kappelle et al. 2002). It is also remarkable, that the region harbours over 700 tree species – the highest tree species diversity in all of Central America (ref.? How is this comparison made?). In recent years, 57 species from ACOSA have been described as new to science (Weissenhofer et al. 2001). Until now, at least 70 species of marine crabs, 61 fresh-water fish species, 46 amphibians, 71 reptiles, 375 birds, 124 terrestrial mammals and 58 bats have been recorded (Soto & Jimenez 1992, Maldonado 1997).

Information about the distribution of biological diversity is the basis of conservation planning and priority-setting. For both biodiversity assessment and ecological monitoring it is necessary to relay on indicator taxa which serve as surrogates for the entire biota (Kremen 1992, Norton and Ulanowicz 1992, Pearson and Cassola 1992, Kremen et al. 1994) since taxa inventories generally represent only a portion of the total richness. This is especially true for invertebrates, which are estimated to make up as much as 90% of the biodiversity at the species level (Disney 1986, Kim 1993, Samways 1994).

Because of the need to use biodiversity surrogates in conservation planning, considerable effort has been dedicated to review the attributes of adequate indicator taxa (Noss1990, Kremen 1992, Pearson & Cassola 1992, Halffter & Favila 1993, Pearson 1994 and Spector and Forsyth 1998).

Species as indicators of human-induced biodiversity changes

Useful indicators of habitat alteration must be capable of displaying a gradient of responses to a gradient of environmental change. A wealth of life-history and ecological studies have assessed the degree to which a species is threatened by human activities. Based on ecologically empirical findings, Henle et al. (2004) identified , a series of life-history traits that confer susceptibility to fragmentation for a wide spectrum of organims , i.e.population size, population stochasticity and storage effect, traits related to competition and sensitivity to disturbance in plants, use of micro-habitats or habitat mosaics, rarity (as low abundance within a habitat) and biogeographical position (as location in the distributional range)

Trends in population numbers or the distribution of individual species with well-known life histories, ecological requirements and population dynamics, as for instance mammals, or groups of well-known taxa (e.g. birds and butterflies) can be useful as warning signals of expected biodiversity loss. However, the extrapolation of the effects of human activities to other organisms can be misleading. Needless to stress are the enormous differences among individual organisms regarding the life-traits that determine their abundance and their distributional ranges. It is therefore extremely unlikely that different species will show similar response to even major changes in habitat (Lawton et al. 1998). If species data are to be used as indicators of biodiversity change , an approach in which a wide range of taxa embracing species with different life history traits and ecological roles have to be considered. In contrast, individual species with well-known ecological characteristics, habitat requirements and showing high sensitivity (rapid response times) to specific changes in the environment are more reliable as indicators of the effects of human activities (Henle et al. 2004). For example, insects are promising as indicators of habitat change or loss because of their abundance, habitat specialisation, and their response to small-scale habitat heterogeneity (Hill 1996, Niemela et al. 1996) and because of their important role in ecosystem function (Didham et al. 1996). However, terrestrial surveys in the tropics rarely include insects other than butterflies.

The threats to human health by water and air pollution led to early research on bioindicators in order to map and monitor the effects of pollution on selected organisms. Because of their sensitivity to air pollution and acid rain, lichens are among the most widely used biomonitors in terrestrial environments (Nimis et al. 2002). Different species of lichens, beetles and birds have been used as indicators of forest continuity (late successional stages) (Kuusinen 1996, Nilsson et al. 1995, Jonsson & Jonsell 1999, Uliczka & Angelstam 2000). Due to their position in the trophic chain, raptors have proved their value as indicators of trends in pollutant levels (pesticides and heavy metals) in the environment (Newton 1979).

As a consequence of their dependence on a variety of habitats across large ranges neotropical migrant birds have become flagship indicators of the negative consequences of fragmentation and of large-scale source/sink population dynamics (Robinson 1998, Burke and Nol 1998).

Species as indicators of overall biodiversity

The use of indicator taxa to represent local richness relies on the premise that, across large areas, the number of species in one well-studied taxon is well correlated with the number of species in other less well-known taxa (Schall & Pianka 1987). Because of its potential use for conservation planning and management, there have been many attempts to explore these correlations, usually with limited degree of success. Instead, plants and birds are used as surrogates for overall biodiversity (Wege and Long 1995, Stotz et al. 1996). However, the need for testing and validation has been stressed (Noss 1990) and caution has been recommended about the sensitivity of biodiversity surrogates to conservation objectives and spatial scales (McGeogh 1998). For example, Basset et al. (1996), Gaston and Hudson (1994) suggest that plants and vertebrates do not accurately predict patterns of insect biodiversity, and that species richness of individual butterfly families did not correlate in any consistent way with

overall butterfly species richness. A Emberson (1985) found weak correlations between plant species richness and soil mite species richness in British grasslands, and Usher (1992) came to the same conclusion for plants and arthropods in the British heatlands. Similar disparity has been found in very different ecosystems and at different spatial scales. For example, Prendergast et al. (1993) and Prendergast and Eversham (1997) found that the relationship between species richness of certain higher taxa in Britain (birds, butterflies, dragonflies and plants) is spatially highly variable and unpredictable while in Norway, Sætersdal et al. (1993) found that in the same woods, there was no coincidence between locations with high species diversity of bird and plants.

This lack of coincidence has also been shown for tropical ecosystems. Howard et al. (1998) for example, found little spatial congruence in the species richness of woody plants, large moths, butterflies, birds and small mammals across 50 Ugandan forests. Also Lawton et al. (1998) concluded that assessing the effects of habitat modifications and disturbance on tropical biodiversity by using changes in species richness of familiar and well-studied groups such as birds or butterflies as indicators of changes in other taxa gives a highly misleading picture of overall faunal changes.

Species data not used and why

Generally, broadly distributed taxa are preferred as biodiversity surrogates as they are comparatively easy to identify, and allow comparisons between areas with different biophysical conditions and threats. Useful indicators of habitat alteration must be capable of displaying a gradient of responses to a gradient of environmental change. Indicator taxa for ecosystem viability should therefore have well-understood natural histories and be known to have key roles in ecosystem functioning such as nutrient cycling, biomass production, pollination, or seed dispersal.

However, our approach has had a different focus. The biodiversity value of a land unit has not been related to its richness but rather to the magnitude of the additional contribution that a specific unit of land makes to the overall representation of biodiversity in the area subject to conservation planning. Two concepts are central to our approach of prioritisation of areas for biodiversity conservation. The first one refers to the aspect of biodiversity that is targeted to conserve. TARGET maximises the *representation* of biodiversity. This implies that the more distinct an area is in terms of its biodiversity attributes, the higher its *representativity* value. Hence, the biodiversity value an area within a selected set is related to its contribution to the increment in *biodiversity representation* in relation to the overall biodiversity conservation targets, in other words the biodiversity value of an area corresponds to its *complementarity* value (Faith and Walker 1996).

Priority setting in conservation planning must be based on some knowledge about the biodiversity attributes of a target area and how these attributes relate to those of other areas. The procedure followed by TARGET is a formalisation of a selection procedure with the advantage of allowing documentation, repeated evaluation of the results and analyses of sensitivity. At each prioritisation step the areas are compared with each other and to the already selected set. Consequently, the knowledge of the distribution of the biodiversity attributes by which the areas are compared must be calculated under the same premise.

The INBio. through its inventory program has compiled an impressive data base of geo-referenced taxa in the country. However, complete maps of the biota of ACOSA, which would be necessary for species-based priority setting, do not exist. Models of species distribution can be used to predict occurrences in non-surveyed areas (Wielaard (2003) Kadmon et al. 2004, Otaviani et al. 2004, Rushton et al. 2004 (and references therein)). These models must are based on ecological knowledge about the species or the ecological communities, i. e. it is necessary to understand the main environmental and biological drivers that underlie the patterns of their distribution.

Ordination techniques is a family of methods used to reveal relationships between large number of species or ecological communities, e.g. the relationships of hundreds of species simultaneously (Palmer, 2004). Some direct ordination methods (as Canonical Correspondence Analysis) make possible the analysis of species and environmental variables and can be used to statistically predict species distributions. However, for statistical validity data collection has to conform a sampling design that is representative of the universe about which predictions are to be made. It will involve random, stratified random, or regular distribution of sampling sites (Palmer 2004). In other words, if there is any subjectivity involved in locating the sampling sites, the sampling effort, or the taxa or specimens collected the results are technically not valid for this kind of analysis.

Ordination techniques can also be used for "exploratory" purposes, where the aim is to describe the variation of the data set and to identify trends of main underlying factors that account for this variation and their relative importance.

The surveys of the 'Inventario' program at INBio pose restrictions to a formal statistical analysis of species distributions since the sampling design does not conform an objective representation of areas and of ecological (environmental explanatory) factors.

Topography, climate and substrate are fundamental determinants of biological activity and their spatial distributions strongly determine those of plants and animals (Faith et al. 2001a). We used an own compilation of cartographic data in digitized format together with a considerable amount of these data from the ECOMPAS project, at INBio to derive a series of environmental variables to describe the areas (grid cells) that where part of the prioritization exercise (Appendix 1 in Section 7, this report) in terms of their ecological features.

Based on these environmental data and species lists (insects and plants) from grid cells with records from the 'Inventario' survey, we performed Canonical Correspondence Analysis (CCA) to explore the relationship between species occurrences and classes of environmental variables. This was an attempt to understand the drivers of species distribution patterns and to associate these distributions to the areas in the conservation priority setting exercise.

The species data consisted of records of 10 families of well-known and ubiquitous vascular plants from the Atta database collected in 419 grid cells. The number of species per grid cells ranged between 236 (once) and 1 (116 times). The environmental variables used in the analyses had a poor explanatory value (total variation explained by the CCA axes 43.264 and variation explained by canonical axes 4.626) of the overall species distribution patterns.
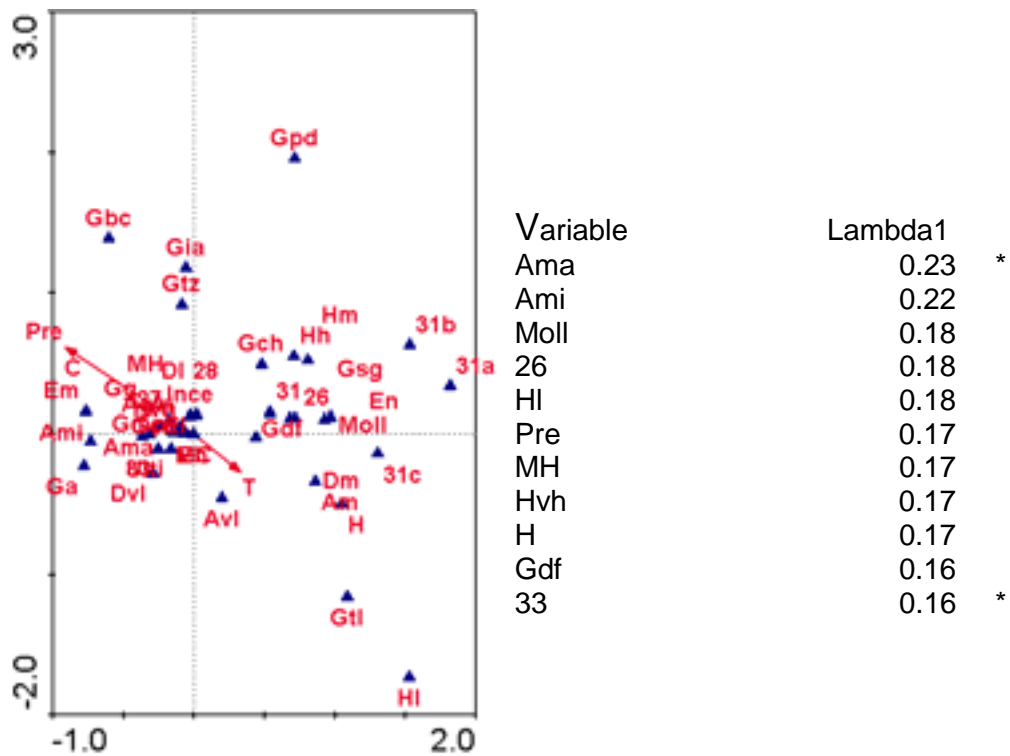
Variable	Lambda1	
Ama	0.23	*
Ami	0.22	
Moll	0.18	
26	0.18	
HI	0.18	
Pre	0.17	
MH	0.17	
Hvh	0.17	
H	0.17	
Gdf	0.16	
33	0.16	*

Figure A3 Canonical Correspondence Analysis (CCA) based on occurrences of vascular plants in grid cells (source geo-referenced data in the Atta base, INBio) and environmental variables and vegetation macro types.

Note: Elevation (Ama and Ami), Moll: molisol soil, Macro type 26: Lowland tropical rainforest on alluvial formations and flat topography, HI: hydric index, Pre: precipitation, MH and H: climate humidity, Hvh: humidity index, humidity, Gdf: fluvial deposits and vegetation macro type 33:lowland tropical rainforest on alluvial formations, undulating topography

We attributed this poor correlation to two main reasons. The first one is related to the fact that inventory surveys have had the purpose of compiling a collection of the plants and insects of Costa Rica as complete as possible being. An assessment of distribution patterns has been beyond the aims of the Inventario program. A more systematic survey could improve the predictability of species distributions in the future. Secondly, each grid cell contains a variety of habitat types and ecological conditions that are not fully represented in the cartographic material that is available. The scale of some of the maps is too small, and the mapping resolution and accuracy are rather coarse compared to the scales we expect these variables will affect the distributions of organisms. These data can be improved with more detailed climate data derived from e.g. models of rainfall and temperature based on accurate terrain models and by including records of key environmental/habitat data with specimen collections.

7.2 Appendix 2: TARGET model scenarios

Table A4. Target modell scenarios

Sensitivity Issue	Run #	Study area		TARGET parameters						Masked locations	TARGET data files			
		Scale	Resolution Grid=25ha Unit=100ha	Regional PP (%)	Protected PP (%)	Unprotected PP (%)	Cost weight (b)	Cost defin-	Preselected locations /committed location		Biodiversity surrogate	*.env file	*.loc file	*.att file
Reliability	0	ACOSA	unit	0.99	0.9	0	1	total	random location(#1, #500, #1000), natparks.sel, psa.sel	none	overlay$_{678}$	costa5-td.env	costa1.loc	cost1.att
Scale	1	Corridor	unit	0.99	0.9	0	1	total	none	non-corridor locations	overlay$_{678}$ masked	costa5-td.env	costa1.loc	cost1.att
	2	Osa Peninsula	unit	0.99	0.9	0	1	total	none	non-peninsula locations	overlay$_{678}$ masked	costa5-td.env	costa1.loc	cost1.att
	3	ACOSA	unit	0.99	0.9	0	1	total	none	none	overlay$_{678}$	costa5-td.env	costa1.loc	cost1.att
Resolution	4	Corridor	grid	0.99	0.9	0	1	total	none	none	overlay$_{86}$	corrg-td.env	corrg.loc	corrg.att
Surrogate definition	5	Corridor	unit	0.99	0.9	0	1	total	none	none	PCA$_{121}$	corru-td.env	curru.loc	cost1.att
	6	ACOSA	unit	0.99	0.9	0	1	total	none	none	PCA$_{573}$	pca-td.env	pca.loc	cost1.att
	7	ACOSA	unit	0.99	0.9	0	1	total	none	none	overlay$_{678+end}$	costa6-td.env	costa2.loc	cost1.att
	8	ACOSA	unit	0.99	0.9	0	1	total	none	none	k-means	kmean-td.env	lmeans1.loc	cost1.att
Cost definition	9	Osa Peninsula	unit	0.99	0.9	0	0.1	expect	none	non-peninsula locations	overlay$_{678}$	costa5-td.env	costa1.loc	cost1.att
	10	Osa Peninsula	unit	0.99	0.9	0	0.1	total	none	non-peninsula locations	overlay$_{678}$	costa5-td.env	costa1.loc	cost1.att

7.3 Appendix 3: Correspondance analysis of TARGET model results

Correspondance analysis (reciprocal averaging) was used as a method for comparing the results of TARGET model scenarios, both with respect to the locations and attributes selected.   Model scenarios refer to This standard method is briefly explained in the following[22].   TARGET produces a number of results files two of which contain (i) the number of replicates of attributes in the selected set of locations and (ii) the complementarity value within the set of each selected location.

When comparing the selected sets of locations and attributes between TARGET scenarios the following analogy is made to the more traditional use of correspondence analysis of site species lists.

Data matrix:	Comparing species lists by site:	Comparing TARGET output by scenarios
Rows	Observed occurences of species	Complementarity value of locations Recurrence of surrogate attributes
Columns	Sites	Scenarios

The species matrix Y, where the m species are arranged as rows and the n sites as columns, can be analysed with a technique called reciprocal averaging, RA (Palmer, 1993). This method, also called correspondence analysis, is an ordination technique with which sites (i.e. samples, localities) and/or species can be arranged along environmental gradients (Palmer, 1993). This method is based on the assumption that the data have a unimodal response to a gradient. In its basic form RA produces two vectors of so-called scores, one for sites (x) and one for species ($u;$ also called "species loadings"). These scores can directly be used in ordination. For example, the site scores (one value per site) characterise the species composition of a particular site with a single number, and the differences in the site scores indicate differences in species composition between the sites. In other words, site scores serve as an ordination index based on the species composition of the sites. Similarly, species which have similar species scores will exist in about the same selection of sites.

The RA algorithm is:

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[22] We are grateful to Tuomo Saloranta, NIVA, for editing this section and programming a MATLAB correspondance analysis Excel workbook which we used to analyse the TARGET output textfiles in Excel.

Inputs :

$Y = \begin{bmatrix} y_{ij} \end{bmatrix}$: Species by sites matrix $(m \times n)$

y_{ij} : Abundance of species i at site j

Outputs :

x : Site scores ($1 \times n$ vector)

u : Species loadings ($m \times 1$ vector)

Algorithm :

Set x to zero mean, unit variance random vector

Repeat

$$u_i = \frac{\sum_j x_j y_{ij}}{\sum_j y_{ij}} \qquad i = 1 \ldots m$$

$$x_j = \frac{\sum_i u_i y_{ij}}{\sum_i y_{ij}} \qquad j = 1 \ldots n$$

Until no change in x

The RA technique is related to detrended correspondance analyse (DCA) and canonical correspondance analyse (CCA) techniques, but as long as one considers only the first gradient axis, there should be no differences in the results of these three techniques. Results from RA can be sensitive to inclusion of very rare species and/or localities with very few species in the matrix Y. Therefore, these extremities should be removed from Y prior to RA analysis, in order to get a more balanced output from the RA analysis and to avoid clear outliers in the site or species scores. Also, the species included in Y should be identified to the same level of detail, i.e. a blend of e.g. single species and species groups should be avoided.

References (appendix 3)

Palmer, M. W. 1993. Putting things in even better order: the advantages of canonical correspondence analysis. *Ecology 74(8)*, 2215-2230.

7.4 Appendix 4 : Correlation between probability of deforestation and opportunity cost to agriculture and forestry

Figure A4 illustrates the correlation between total opportunity cost used in this study and deforestation probabilities calculated by Rosero-Bixby et al. (2002).
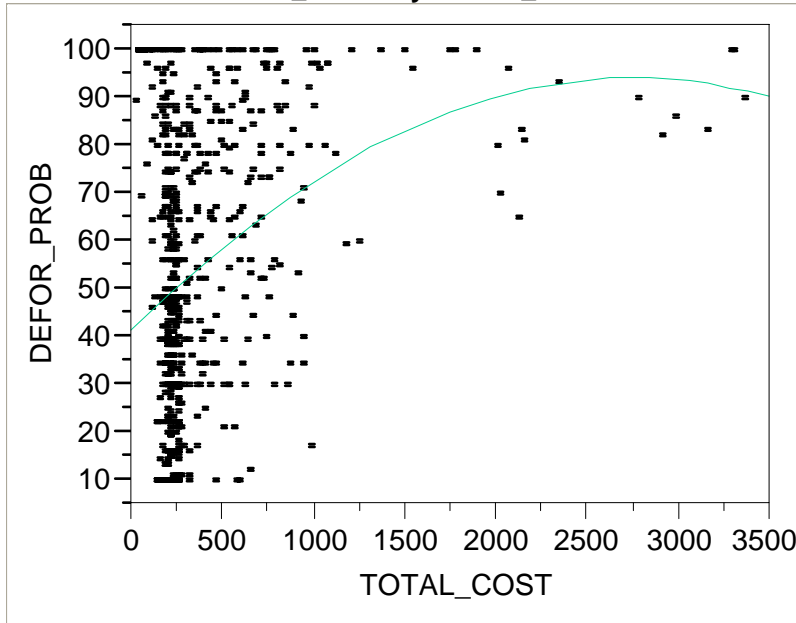
Bivariate Fit of DEFOR_PROB By TOTAL_COST

Figure A4. Probability of deforestation - total opportunity cost (forestry and agriculture)

Polynomial Fit Degree=2
DEFOR_PROB = 42,238676 + 0,0327963 TOTAL_COST - 0,0000069 (TOTAL_COST-401,138)^2

Summary of Fit

RSquare	0,102665
RSquare Adj	0,099766
Root Mean Square Error	27,90577
Mean of Response	54,11576
Observations (or Sum Wgts)	622

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	42,238676	2,007751	21,04	<.0001
TOTAL_COST	0,0327963	0,005116	6,41	<.0001
(TOTAL_COST-401,138)^2	-0,000007	0,000003	-2,74	0,0064

Probability of deforestation - forest opportunity cost.

Figure A5 illustrates the correlation between forestry opportunity costs used in this study and deforestation probabilities calculated by Rosero-Bixby et al. (2002). Predicted deforestation probability reflects current forest fragmentation implying less standing forest and lower returns to forestry per unit of area.
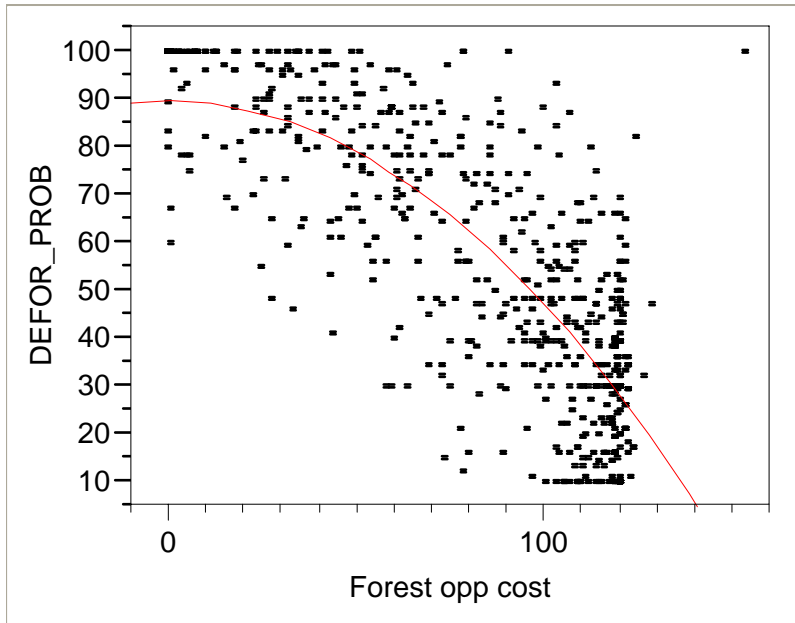

Figure A5 Forestry opportunity cost and deforestation probability

Transformed Fit to Square
DEFOR_PROB = 89,790157 - 0,0042605 Square(Forest opp cost)

Summary of Fit

RSquare	0,639252
RSquare Adj	0,63867
Root Mean Square Error	17,67943
Mean of Response	54,11576
Observations (or Sum Wgts)	622

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	89,790157	1,288758	69,67	<.0001
Square(Forest opp cost)	-0,00426	0,000129	-33,15	<.0001

7.5 Appendix 5: GIS accuracy – converting polygon to grid data

The 500mx500m grid used for calculating opportunity cost and biodiversity surrogate values uses an area-based weighting of polygons themes falling within any particular grid cell. The values in four adjacent 25 ha. cells are then averaged and assigned to 1000mx1000m (1 km2) cells used in the TARGET analysis. In **Figure A6** an illustration is provided of the grid overlay on forest polygons used to calculate forest opportunity cost. Some GIS based errors are introduced along the coastline border of the study area due to different interpretations of land area on mud-flats (see "manglar"= mangrove area), which in turn affects the weighted value of the 1 km2 grid cells. GIS data may have errors of interpretation of 400m-500m as illustrated in the figure – area based weighting averages errors across 1km2 cells used for analysis and imply that there should be no systematic bias across the study area. The sensitivity analysis og grid resolution is conducted to evaluate whether using 25 ha. and 100 ha cells for analysis affects the set of selected locations.
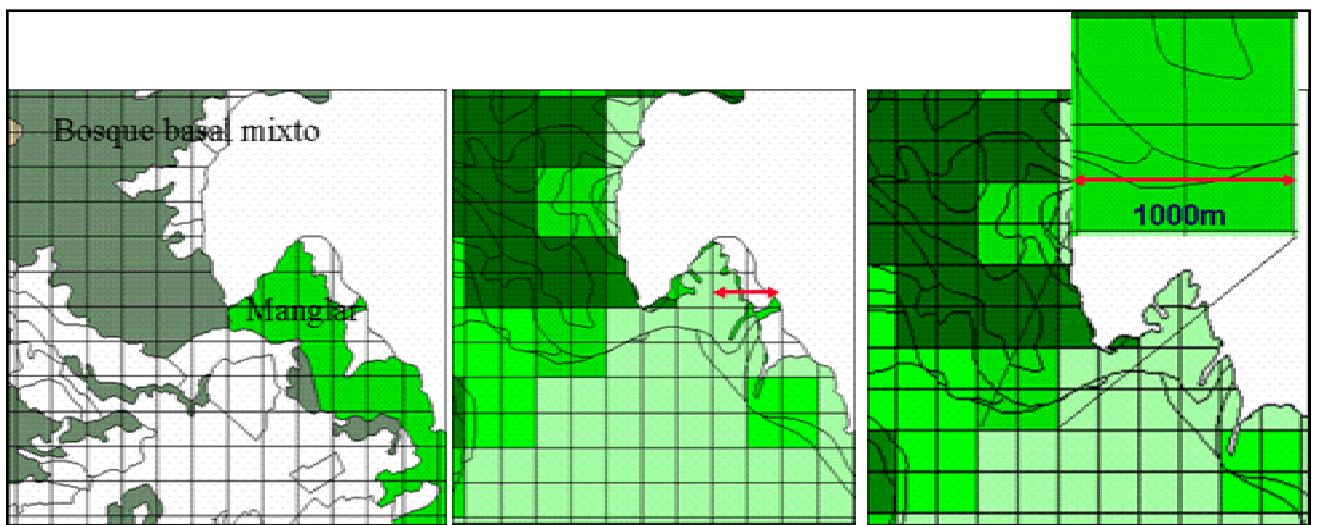

Figure A6 GIS errors in converting polygon to grid data.
Source: Ecomapas, INBio.

The use of TARGET for prioritising environmental service payments to land-owners depends on accurate and consistent georeferencing of property boundaries and areas under payment. **Figure A2** illustrates several practical GIS issues that must be overcome before TARGET can become an applied tool for priority setting:
- property boundaries and environmental service payment contract areas do not overlap
- PSA contracts for forest protection and plantation/reforestation have been assigned to the same locations within few years, raising doubts about the effectiveness of monitoring and enforcement of contract conditions for the different types of management.
-

Is TARGET algorithm normalised by area. If not large "resource units" will be prioritised over smaller ones.
Large polygons have large complementarity (larger probability of multiple attributes within polygon). Opportunity cost will vary with property size.
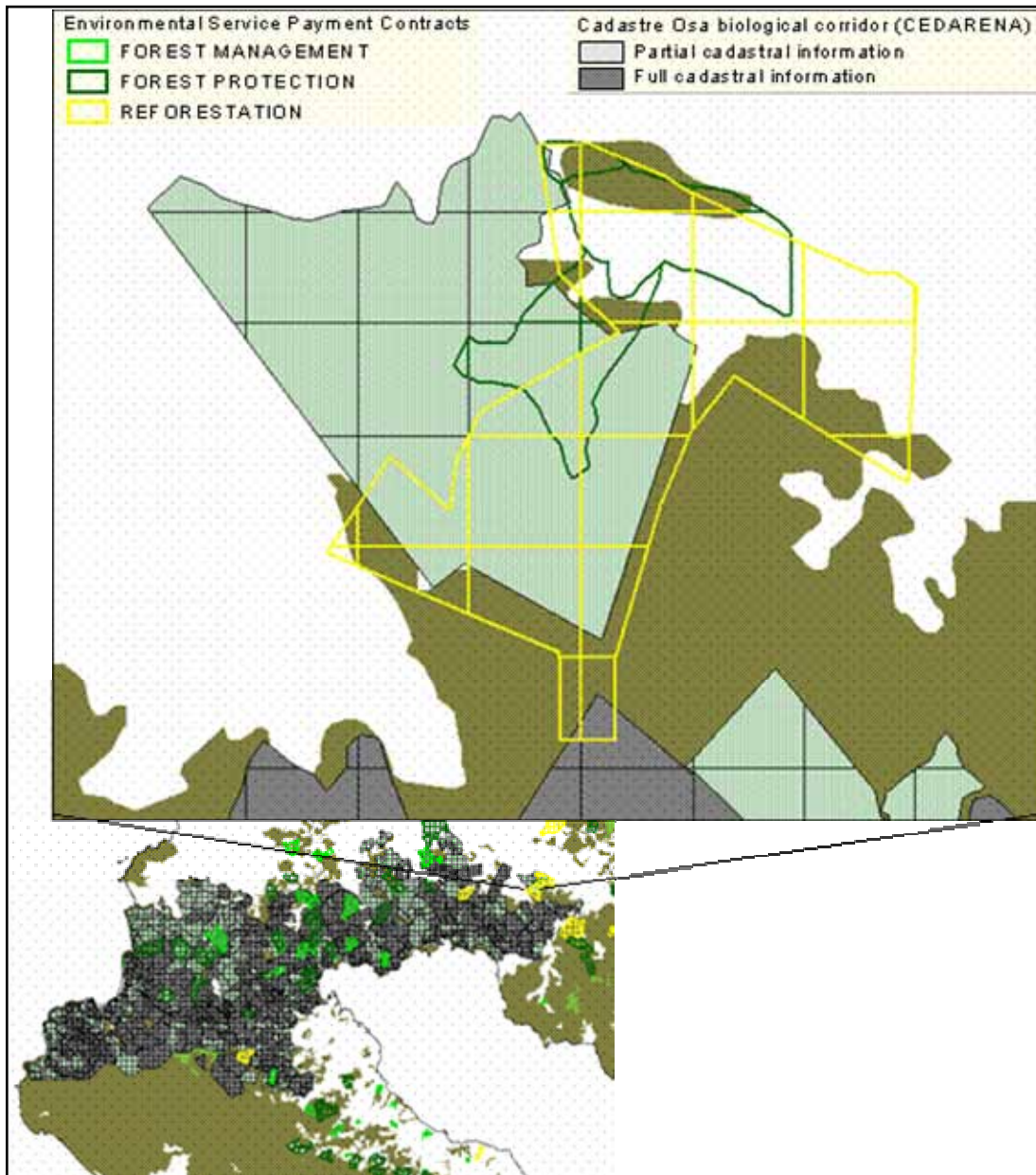
Figure A7 Georeferencing inaccuracies in cadastre information on PSA contracts
Source: Property cadastre data (CEDARENA), environmental service payment contract areas (1999-2001) FONAFIFO.

7.6 Appendix 6: Example of TARGET calculation of probabilities of persistence

The user typically (in the simple case) nominate a target for the overall regional probability of persistence, R, of each attribute. This overall probability is to be achieved by one minus the products of the probabilities of extinction of the attribute over the different places in the region.

The user nominates a base probability of persistence, B - this is the probability of persistence (one minus probability of extinction of an attribute in any place that is not selected - think of it as the default "do-nothing" value. Lastly the user nominates the probability of persistence, P, if a place is selected for protection.

If an attribute has T occurrences over all places in the LOC file, and N of these occurrences are represented in the course of selecting a set of places, then:

$$1 - R = (T - N) * (1 - B) * N * (1 - P)$$
in other words, we have multiplied up the probabilities of extinction for the attribute.

TARGET uses this formula to figure out ahead of time how big N has to be, given user defined values for R, B, and P and the count of the value T calculated from the LOC file for each attribute.

THE FOLLOWING SIMPLE CASE REQUIRES A BASIC KNOWLEDGE OF THE TARGET SOFTWARE INTERFACE

Suppose we have place 1 with 3 attributes, 1,2, and 3; place 2 with attributes 1 and 2; place 3 with attributes 2 and 3; and place 4 with attributes 1 and 3. T = 3 for all attributes.

So, in this example, let the probabilities be R = .99999, B = .9 and P = .99 .:

Then the distance to target is "6", because 2 copies of each of the 3 attributes must be selected (giving for each attribute a product of (1-B) times (1-P) times (1-P), or .1*.01*.01 = .00001 = 1 - .99999, which was the regional target):

```
[illegible text block]
```

when the best place, number 1, with all three attributes is selected, the distance to target goes down to "3":

```
[illegible text block]
```

when place number 1 and number 2 are selected, only attribute 3 still needs further representation, so the distance is now 1:

```
[illegible text block]
```

In the "attribute export" file:

Locations on select list
1 2

Committed to protection

Attribute	On list	No. repl	Dist to Target	Target set	Target on list
1	1	2	0.000	1.999	2.000
2	1	2	0.000	1.999	2.000
3	1	1	0.999	1.999	1.000

Current distance from target 0.999
Number of attributes fully represented...   2
Number of attributes partly represented..   1
Number of attributes not represented ..   0
Attribute furthest from target   ..   3
Maximum distance from target   ..   0.999

(note minor rounding errors; e.g. 1.999 instead of "2")

and finally after 3 places are selected we have reached the targets - in fact attribute 2 occurs 3 times:

Locations on select list
 1 2 3

  Committed to protection

Attribute   On list   No. repl   Dist to Target Target set   Target on list
    1   1   2   0.000   1.999   2.000
    2   1   3   0.000   1.999   3.000
    3   1   2   0.000   1.999   2.000

  Current distance from target 0.000
  Number of attributes fully represented...   3
  Number of attributes partly represented..   0
  Number of attributes not represented   ..   0
  Attribute furthest from target   ..   0
  Maximum distance from target   ..   0.000

Note that these gains against the effective need for "6" units mean that the complementarity value of a place is given by how many required units it contributes (much the same as when we are just counting up species in the simple case). It is these complementarity values that are compared to weighted costs when the analysis performs trade-offs.