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Title: Improving the efficiency of conservation policies with the use of surrogates derived from remotely sensed and ancillary data

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Abstract

Conservation policies are emerging in many places around the world, many of which involve payment for ecosystem services (PES) schemes. PES schemes provide economic incentives for forgoing land uses that reduce the provision of ecosystem services. The efficiency of such schemes depends not only on the ecosystem services provided by an area but also on the willingness of local people to forgo their land use activities. Targeting land for enrollment in PES schemes on the basis of the potential provision of ecosystem services and on the willingness to forgo certain economic activities, may therefore improve the efficiency of these schemes. The objective of this study was to develop a targeting approach, based on three surrogates derived from remotely sensed and ancillary data, for identifying land to be enrolled in one of the largest PES schemes in the world: China's Grain-to-Green Program (GTGP). The GTGP encourages farmers to return steep hillside cropland to forest by providing cash, grain and tree seedlings. The three surrogates used in the targeting approach were slope index, cropland probability, and GTGP enrollment probability. Combining these surrogates through Bernoulli trials allows targeting areas under cropland, with low opportunity costs for farmers and with potentially high soil erosion and landslide susceptibility. Results of applying the targeting approach in a case study area (Baoxing County, Sichuan province, China) show that around half of the land currently enrolled is placed in areas with gentle slopes and tend to be located distant from forest areas. This reduces the potential benefits obtained from the GTGP. Targeting land using the proposed approach may double the benefits obtained from the program under the same budget, thus improving its efficiency. The approach may be applied to the entire GTGP implementation area in China and with proper modifications it may also be applicable to similar PES programs around the world.

1. Introduction

The exponential growth of human population and its activities is threatening many ecosystems worldwide (Leakey and Lewin, 1995). This has prompted the development of a multitude of conservation policies and actions (Liu and Raven, 2010). However, one of the greatest challenges is that many conservation actions affect the livelihood systems of numerous people. Therefore, programs of payment for ecosystem services (PES) have emerged in many places around the world (Ferraro and Kiss, 2002). These programs provide incentives (usually as economic compensations in the form of land purchases, leases or easements) for forgoing economic activities that reduce the provision of ecosystem services (Ferraro, 2001; James et al., 1999).

As conservation resources are limited globally (James et al., 1999), it is important to improve the efficiency of conservation investments in PES programs. This requires targeting the land that provides crucial ecosystem services, while also fully compensating for the forgone economic activities of the local people managing such land (i.e., opportunity costs). In developing countries, many people managing land that provides crucial ecosystem services tend to be economically and politically marginal. Thus, the success and long-term sustainability of PES programs also depend on their contribution to poverty alleviation (Gauvin et al., 2010; Uchida et al., 2007). As a consequence, the economic incentives provided through PES programs need to reach the poorest people, while also fully compensating for their forgone economic activities. Targeting land parcels for inclusion in PES programs is thus needed for increasing the overall efficiency of these programs (Babcock et al., 1997). However, due mainly to the lack of information on the suitability of different land parcels to be enrolled in PES programs, targeting has rarely been used (Chen et al., 2010), particularly in developing nations such as China.

China is not only the most populated nation on earth, but also has exhibited the fastest economic growth over the last three decades, has shown drastic environmental degradation during the same time period (Liu and Diamond, 2008), and has a government with a demonstrated ability to enact wide-ranging policies with relative rapidity. For instance, the Grain-to-Green Program (GTGP; also referred to as the Sloping Land Conversion Program) is one of the largest forest restoration PES programs in the world (Liu et al., 2008; Uchida et al., 2005). Providing cash, grain and tree seedlings, this program encourages farmers to return steep hillside cropland to forest in order to reduce soil erosion and landslide susceptibility. By the end of 2005 more than 90 billion Yuan (1 USD ~ 8.2 Yuan in 2005) had been invested in the GTGP and by 2006 the net forest cover had increased ca. 2% within the areas of GTGP implementation (Liu et al., 2008). Despite the large areas of cropland involved, it has been shown that the effect of the program on China's grain production, food prices or food imports is small (Xu et al., 2006). While these reports suggest that the program has been successful, some studies indicate that there is room for improvement, since many enrolled areas are not necessarily located in steep slopes (Uchida et al., 2005; Xu et al., 2004). In addition, while the program has achieved moderate success in poverty alleviation since it has been implemented mostly in fairly poor areas of China (Uchida et al., 2007), many farmers complained that they were not consulted prior to their enrollment in the program, and that the actual payment received did not always compensate their opportunity costs (Xu et al., 2004). The program therefore needs to account for opportunity costs (Uchida et al., 2005) to reduce the likelihood of farmers reconverting the land back to cultivation.

Targeting land parcels for enrollment in the GTGP should then be based not only on the identification of cropland in the steepest slopes (i.e., exhibiting higher soil erosion and landslide susceptibility) but also in areas with the lowest opportunity costs for farmers, so that more land can be enrolled with the same GTGP budget. However, knowledge of the opportunity cost is very difficult to acquire, particularly when the costs to obtain ecosystems services are heterogeneous across the landscape (Babcock et al., 1996, 1997; Chan et al., 2006; Osborn et al., 1993). In addition, due to a lack of a robust land market in China, it is impractical to obtain a true value of opportunity cost for each parcel to be enrolled, and assigning opportunity costs based on grouping farmers using some pre-defined criteria can be highly inaccurate (Adams et al., 2010). However, opportunity costs can be correlated with the geographic location and the biophysical features of each parcel (Alix-Garcia et al., 2008; Cooper and Osborn, 1998; Ferraro, 2003; Khanna et al., 2003), although this correlation has seldom included information on land holders (Chen et al., 2010).

The overall objective of this article is to describe a targeting approach developed for identifying land parcels to be enrolled in PES programs. This approach overcomes the dearth of information on individual land parcels, because it is based on the use of three surrogates derived from readily available spatial data layers acquired by space-borne remote sensors, together with ancillary data. The surrogates are: a slope index (surrogate of soil erosion and landslide susceptibility), cropland probability (surrogate of the likelihood of a land parcel to be under cultivation) and the probability of enrollment in the PES program (surrogate of farmers' opportunity costs). While these surrogates do not provide a complete picture of all the environmental benefits of a PES program, their combination through the targeting approach can be used to enhance the benefits obtained under the same budget. This improves the overall efficiency of the PES program. Specific objectives of the study are to: (1) evaluate the efficiency of currently enrolled GTGP parcels in Baoxing County, China; and (2) propose the location of additional land parcels to be included in the program.

2. Study area

With a total area of ca. 3,114 km^2, Baoxing County is located at the center of the UNESCO World Heritage Sichuan Giant Panda Sanctuary, in Sichuan Province, Southwestern China (Fig. 1). This Sanctuary was established in August, 2006 (Li, 2010) mainly to promote the conservation of the habitat of giant pandas (*Ailuropoda melanoleuca*), which are recognized as a 'national treasure' of China and a symbol for global biodiversity conservation efforts (Loucks et al., 2001; Viña et al., 2010). The Sanctuary is home to more than 30% of the wild population of giant pandas (a total of approximately 1,600 individuals) (State Forestry Administration, 2006) and comprises the largest remaining contiguous area of giant panda habitat in the world (Li, 2010).

In addition to the giant pandas, Baoxing county has a diverse flora and fauna, owing to its strong elevational gradient (Fig. 1). Natural vegetation is dominated by evergreen and deciduous broadleaf forests at lower elevations (ca. 1,500 m) and subalpine coniferous forests at higher elevations (ca. 2,700 m). The dense understory of these forests is dominated by bamboo species (e.g., *Bashania faberi*), which are the staple food of giant pandas (State Forestry Administration, 2006). Baoxing County was the first place where the giant panda was discovered scientifically (Hu, 2001), but the county also supports many other endangered wildlife species (e.g., *Neofelis nebulosa*, *Budorcas taxicolor*, *Rhinopithecus roxellana*, *Panthera pardus*) that are listed as first-class national protected animals of China (Hu, 2001). In fact, the county is within one of the world's hottest biodiversity hotspots, the Southwest China hotspot (Mittermeier et al., 2004; Myers et al., 2000). By 2008 Baoxing County had ca. 58,700 people, distributed in ca. 16,000 households. Among them ca. 82% depend on agricultural activities for their subsistence (Statistics Bureau of Baoxing County, 2007).

3. Materials and methods

3.1. Currently enrolled GTGP parcels

We obtained a dataset with the geographic locations of more than 28,000 cropland parcels (belonging to ca. 11,600 households) enrolled in the GTGP between 2001 and 2004. Information on the year of enrollment and the size of each parcel was also obtained. Ranging in size from less than 0.01 ha to 2 ha, these parcels account for ca. 3,000 ha of cropland and correspond to ca. 98% of all land parcels enrolled in the GTGP in Baoxing County. Each GTGP parcel was planted with up to three tree species, for a total of 48 tree species planted in all parcels combined. However, *Cunninghamia lanceolata* (Lamb.) Hook. (38% of the parcels), *Magnolia officinalis* Rehder & Wilson (20% of the parcels), *Ligustrum lucidum* W.T.Aiton (4.7% of the parcels), *Cryptomeria japonica* (L.f.) D.Don (4.4% of the parcels), *Eucommia ulmoides* Oliv. (4.1% of the parcels) and *Alnus cremastogyne* Burkill (4% of the parcels) were the tree species used more often.

3.2. Surrogates for GTGP targeting

Slope Index. Since the main purpose of the GTGP is to reduce soil erosion and landslide susceptibility, land with steep slopes (i.e., ≥ 25°) should receive higher priority for enrollment in the GTGP (Uchida et al., 2007). However, this criterion has not been completely enforced as a significant amount of parcels enrolled in the program have lower slopes than the 25° threshold (Gauvin et al., 2010). Therefore targeting land with high slopes is necessary to improve the benefits obtained from the program.

To identify the land with the highest slopes we calculated a slope index as:

$$Slope\ Index_i = \left(\frac{slope_i - slope_{\min}}{slope_{\max} - slope_{\min}} \right)^2 \qquad (1)$$

Where $slope_i$ is the slope of land parcel *i*, and $slope_{min}$ and $slope_{max}$ are the minimum and maximum slopes among all land parcels in the study area, respectively. This index gives more weight to parcels with steeper slopes, thus assumes that a higher benefit could be obtained when cropland located at higher slopes is enrolled in the GTGP (Chen et al., 2010). A synoptic dataset of slopes in the study area was obtained from a digital elevation model (DEM) acquired at a spatial resolution of 90 m/pixel by the Shuttle Radar Topography Mission (SRTM) (Berry et al., 2007). The spatial resolution of these data was increased to 10 m/pixel through the use of the cubic convolution resampling method (Jensen, 1996). The vertical (i.e., elevational) accuracy of these resampled SRTM-DEM data was tested using elevation data collected with a differentially corrected Global Positioning System (GPS) receiver (i.e., with a sub-meter horizontal accuracy) in 216 locations throughout the Sichuan Giant Panda Sanctuary. Within the elevational range assessed in the field (ca. 1200-3500 m), the resampled SRTM-DEM data provided an elevational accuracy of 34.7 m (Fig. 2). While resampling the SRTM-DEM data to 10 m/pixel does not improve its elevation accuracy, nor the accuracy of the slope derived from these data, the accuracy obtained seems to be sufficient for developing the slope index used in the study.

Cropland probability. This surrogate evaluates if a particular area is under cultivation. We developed a procedure for estimating the probability of an area to be cropland, using a fuzzy classification algorithm based on the principle of maximum entropy (Jaynes, 1957). The algorithm was applied to remotely sensed multi-spectral data using the software MaxENT (Phillips et al., 2006). The multi-spectral data consisted of two Landsat Thematic Mapper (TM) images (28.5 m/pixel) acquired during the winter (December 9, 1999) and summer (June 13, 2001) seasons. The use of these two images acquired in different seasons provides valuable information on cropland phenology which, in addition to the multi-spectral information, is suitable for accurately separating cropland from other land cover types.

To calibrate and validate the maximum entropy classification procedure, we selected (from the parcels described in section 3.1 above) 9,738 parcels that were enrolled in the GTGP between 2003 and 2004. These parcels were selected since they were considered to have been cropland at the time of Landsat TM imagery acquisition (between 1999 and 2001). Two-thirds of these cropland parcels were randomly chosen for calibration, while the rest were used for validating the output cropland probability map. To reduce the dependence on a single random partition into calibration and validation, we generated 20 different random partitions to be used in 20 different cropland classifications that were averaged. Although the area of many of the calibration/validation parcels is smaller than the area comprised by a Landsat TM pixel, if at least one parcel fell within a Landsat TM pixel, the entire pixel was considered under cropland. This constitutes an approximation since not necessarily 100% of a Landsat TM pixel is under cropland, however it is a common procedure in many pixel-based imagery classification methods (Lu and Weng, 2007). Using the cubic convolution method (Jensen, 1996), we then resampled the resolution of the output cropland probability maps to 10 m/pixel, so that each cropland parcel occupied at least one pixel.

The 20 output cropland probability maps were validated by means of a receiver operating characteristic (ROC) curve (Hanley and Mcneil, 1982). The ROC curve is a plot of the sensitivity values (i.e., true positive fraction) vs. their equivalent 1-specificity values (i.e., false positive fraction) for all possible probability thresholds. The area under the ROC curve (AUC) is a measure of model accuracy, with AUC values ranging from 0 to 1, where a score of 1 indicates perfect classification, a score of 0.5 implies a classification that is not better than random, and values lower than 0.5 imply a worse than random classification. Due to a lack of reliable and representative field data (i.e., obtained concurrently with the Landsat TM imagery) under land cover types different from cropland, we calculated the ROC curve using the validation parcels together with 10,000 randomly selected locations to calculate 20 AUC values, respectively, which were averaged. It is important to note that the AUC values calculated in this way tend to be underestimated because some of the 10,000 random locations used as non-cropland in the validation may fall in cropland areas, thus artificially increasing the commission error (Phillips et al., 2006; Wiley et al., 2003).

Probability of enrollment in the GTGP. The costs of enrolling a cropland parcel in the GTGP program, related to the forgone economic benefits from cropping it, constitute the opportunity cost for farmers. For a parcel to be successfully enrolled in the GTGP, its opportunity cost should be lower than the compensation obtained from the GTGP. As farmers obtain different economic benefits from cropping different parcels, not all cropland parcels have the same probability to be enrolled in the GTGP. We developed a procedure for estimating the probability of a parcel to be enrolled in the GTGP, based on household information and on biophysical characteristics of the GTGP parcels. In this procedure, we assumed that if a parcel was enrolled the opportunity cost of enrollment was less than the GTGP payment, otherwise it was larger (Chen et al., 2010). The GTGP payment used was 3,450 Yuan/ha, which corresponds to the average payment given to farmers in the upper reaches of the Yangtze River basin (Liu et al., 2008), which includes the study area. While no household survey data were available for Baoxing county, we used a survey of 304 randomly selected households located in Wolong Nature Reserve (Chen et al., 2009a; Chen et al., 2009b; Chen et al., 2010). Details of this survey are given in the references cited. Although these data were not acquired in Baoxing county they are still suitable as the Wolong Nature Reserve is located immediately to the north of Baoxing County and within the Giant Panda Sanctuary (Fig. 1). Therefore, the two areas share similar topography, climate and ecosystems, and the GTGP was concurrently implemented in both areas during the early 2000s. In addition, culture, livelihoods and economic activities of the people in Baoxing are very similar to those in

Wolong, with agriculture being the main income source [e.g., similar to Baoxing, ca. 84% of the people in Wolong depend on agricultural activities for their subsistence (Statistics Bureau of Wenchuan County, 2007)]. The survey inquired about household's plans for their GTGP parcels when the annual GTGP payments cease (after 8 years). For those respondents that planned to re-convert their GTGP plots to cropland, stated choice methods (Louviere et al., 2000) were used to elicit whether they would re-enroll their parcels in GTGP under various payment levels (i.e., 1500, 3000, 3750 and 4500 Yuan/ha).

A logistic regression model was performed using GTGP parcel enrollment as the dependent variable (binary), and the different payment levels, distance of each parcel to roads, and topographic characteristics of the parcels, including elevation, aspect and the compound topographic index (CTI), as predictor variables. Elevation, aspect [converted into relative soil moisture classes, which in temperate mountain regions are related to differences in solar illumination with changes in aspect (Parker, 1982)] and the CTI [a measure of soil water accumulation potential (Gessler et al., 1995)] were all derived from the SRTM-DEM.

Similar to the probability of cropland, the output GTGP enrollment probability map (obtained by applying the coefficients estimated by the logistic regression to synoptic data in Baoxing) was validated by means of a receiver operating characteristic (ROC) curve (Hanley and Mcneil, 1982). For this, we used a random sample of 3800 points located in areas with a high probability of cropland that were not enrolled in the GTGP, against a sample of 3200 points located in areas enrolled in the GTGP. This procedure, however, assumes that the un-enrolled cropland has higher opportunity cost than the enrolled cropland, which may not be the case for many cropland areas. Nevertheless it provides a way of assessing if the model for obtaining the probability of enrollment performs better than random.

3.3. Targeting approach

Our targeting approach for identifying the cropland parcels most suitable to be enrolled in the GTGP (i.e., those with potentially high soil erosion and landslide susceptibility, and low opportunity costs for farmers), consists of four steps. First, we identified the areas suitable to be targeted for enrollment in the GTGP based on the probability to be cropland through a Bernoulli trial. For this, we selected the areas that had higher probability than a uniform random number ranging from 0 to 1. This included all the land currently enrolled in the GTGP as well as all other cropland currently not included in the GTGP. Second, among the areas selected in the first step, we identified the areas suitable to be targeted using a second Bernoulli trial in which we compared the probability of enrollment, obtained from the logistic regression model using the current GTGP payment level (i.e., 3,450 Yuan per ha), against a uniform random number ranging from 0 to 1. In other words, to determine if the opportunity cost of enrollment is higher or lower than the current payment level. This way, some of the selected cropland can be enrolled under the current payment level, but some cannot because of high opportunity cost. Third, among the identified cropland areas that can be enrolled in the GTGP under the current payment level, we then sorted them from high to low according to their slope index values, choosing areas with higher values first until all the GTGP budget for Baoxing county was exhausted. Because land parcels are selected with a stochastic process, the first three steps were performed 1000 times and the areas were ranked depending on the number of times (i.e., from 1000 to 0) they were selected by the targeting approach. Fourth, the areas with the highest ranking were gradually chosen until the total area of Baoxing County enrolled in the GTGP (ca. 3000 ha) was obtained. This constitutes the land area of Baoxing County that should have been enrolled by the GTGP with the highest priority.

3.4. Comparison between observed and targeted land parcels

Once the optimum areas for GTGP enrollment were obtained through the targeting approach, we compared them with the areas actually enrolled between 2001 and 2004 in terms of slope, elevation, distance to roads, distance to forests [with forest cover obtained using an unsupervised classification applied to Landsat TM data acquired on September 18, 2007 (Viña et al., 2011)] and probability of enrollment. In addition, to compare the total amount of overall regional benefits (i.e., potential reduction in soil erosion and landslide susceptibility once the land enrolled in the GTGP is converted to forest) obtained between the observed GTGP parcels and the GTGP parcels identified through the targeting approach, we calculated an Overall Benefit Index (OB) as the slope index multiplied by the area and integrated for all parcels, following the equation:

$$OB = \sum_{i=1}^{n}\left[\left(\frac{slope_i - slope_{\min}}{slope_{\max} - slope_{\min}}\right)^2 \times area_i\right] \qquad (2)$$

Finally, since forests restored through the GTGP could potentially become habitat for wildlife species we investigated the potential degree of forest fragmentation once the GTGP areas are completely converted into forest. The degree of fragmentation was assessed through the patch density calculated using FRAGSTATS (McGarigal et al., 2002), and compared it between the observed and the targeted GTGP areas.

4. Results

Maps of the three surrogates used for targeting the GTGP parcels in Baoxing County are shown in Fig. 3. These maps represent the spatial configuration of the values of the surrogates used in the targeting approach. While the maps showing the probability of cropland and the probability of enrollment in the GTGP exhibit similar spatial configurations in their values (e.g., both tend to have higher values at lower elevations), the spatial configuration of the slope index values are different and unrelated with elevation (Fig. 3).

The map of the probability of cropland corresponds to the average of 20 model runs using 20 different partitions into calibration and validation. The average AUC value obtained was 0.96, with a standard deviation of 0.002 (Fig. 4). Considering that errors of commission are overestimated in this AUC value, this average cropland probability map (Fig. 3) constitutes an accurate depiction of the probability of an area to be under cultivation.

The logistic regression that was used to predict the probability of enrollment is presented in Table 1. Among the predictors used only the payment level, the elevation and the CTI had a significant effect (Table 1) on probability of enrollment, with payment level exhibiting a positive coefficient, while elevation and CTI exhibited a negative coefficient. This means that the higher the payment, the higher the probability of enrollment, while higher values of elevation and of soil water accumulation potential (i.e., CTI) are related with lower probabilities of enrollment. As with the cropland probability map, the map of the probability of enrollment (Fig. 3) was validated using a ROC curve, and an AUC of 0.68 was obtained (Fig. 4). While low, as compared to the average AUC obtained for the probability of cropland, it is significantly higher ($p < 0.001$) than 0.5 (i.e., random prediction), thus it constitutes a fair surrogate, particularly if we consider the difficulty in obtaining a meaningful depiction of the true opportunity cost for farmers to enroll their cropland in the GTGP.

Through the targeting approach we obtained a map of the distribution of the optimal location of GTGP parcels (Fig. 5). Through the comparison of targeted vs. observed parcels enrolled in the GTGP we found that the overall regional benefit (as quantified by the OB; eq. 2) that may be obtained by the targeted parcels (OB = 20,931.5) more than doubles the OB of the observed parcels (OB = 9,106.2). In addition, we found dissimilar histogram distributions between the targeted and the observed parcels (Figs. 6 and 7). On one hand, the targeted parcels had a higher median value of slope than the observed parcels (Fig. 6A), reflecting the specific effect of targeting for higher slopes. Also, while the surrogate of the probability of enrollment was inversely related with elevation, the targeted parcels exhibited a higher median elevation (Fig. 6B) than the observed parcels, reflecting that the optimal selection is based on the combined effect of probability of cropland, probability of enrollment and slope, and not on a single surrogate. With respect to distance to roads, the targeted parcels exhibited a median value that more than doubled the median value of the observed GTGP parcels (Fig. 7A), with ca. 14.7% of the targeted parcels located farther away from roads than any observed GTGP parcel. Opposite to this pattern was the proximity to forest, with the observed

GTGP parcels exhibiting an almost twice as large median distance to the nearest forest edge as the targeted parcels (Fig. 7B). Finally, no difference in the probability of enrollment between targeted and observed parcels was obtained (Fig. 7C), denoting that both targeted and observed parcels may have similar opportunity costs, and thus farmers are equally prone to enroll them in the GTGP.

5. Discussion

The targeting approach developed in this study is suitable for two main reasons. First, it allows establishing the optimal location of GTGP parcels based on the original intended purpose of increasing soil retention and reducing soil erosion and landslide susceptibility, as well as placing them in areas under cropland and with a higher probability for enrollment (i.e., where payment level is above the opportunity cost for farmers). This is of importance at a time when the contracts of many GTGP parcels are maturing, as they have been running for 8 years, and therefore decisions to re-enroll them, as well as procedures for determining which new parcels to enroll, are needed.

Second, the approach can be used to evaluate the efficiency of current conservation investments in the GTGP. On the one hand, as has been reported for other GTGP areas (Gauvin et al., 2010), many parcels (ca. 39% in Baoxing county) enrolled in the GTGP program are below the 25° slope threshold, while most of the targeted parcels were above this threshold. Considering that more than 3,000 ha of cropland in Baoxing County not enrolled in the GTGP are located in areas with slopes higher than 25°, this suggests that the efficiency of the current GTGP program implementation can be substantially improved through our targeting approach. On the other hand, many enrolled parcels are located at lower elevations, but perhaps more important, they are located more distant from forest areas than the parcels targeted by the approach. In fact, comparing the patch density that could be obtained (once the forest is established in the GTGP parcels) between the observed and the targeted parcels, we found that while the total forest area is similar, the latter will exhibit less patch density (i.e., less fragmentation) than the former (Table 2). Thus, once the trees planted become established and the current GTGP parcels are completely converted from cropland to forest, their usefulness as habitat for wildlife is comparatively lower than if the parcels enrolled were targeted due to their higher degree of fragmentation. Therefore, successfully converted GTGP parcels into forest will be used less likely by wildlife species under the current parcel distribution than if they would have been targeted. While habitat for wildlife species was not necessarily an intended goal during the establishment of the GTGP, such an outcome is welcomed, particularly if the newly formed forest areas become habitat for endangered species such as the giant panda (Liu et al., 2008).

Finally, it was found that the observed GTGP parcels tended to be located more often in the proximity of roads, while the targeting approach allowed reaching parcels that are located further away from roads. While at higher hierarchical levels (e.g., countries) road development is correlated with economic development (Queiroz and Gautam, 1992), at local levels this relationship is less clear. However, due to a higher access to public amenities (e.g., schools, hospitals) as well as to commercial and industrial enterprises it is hypothesized that the proximity to a road constitutes a proxy of economic development, even at household levels. Using household survey data obtained from a random sample of 165 households in Wolong Nature Reserve (Fig. 1) before [i.e., 1998; (An et al., 2001)] and after (i.e., 2007; Liu, W., unpublished data) the implementation of GTGP, we tested this hypothesis by comparing the distance to the nearest road between households above and below the international absolute poverty threshold [US$1.25 per capita per day; (Gillie, 1996; Ravallion et al., 2008)]. To ensure the comparability of income data during 1998 and 2007, we defined three household income categories (i.e., agricultural income, non-agricultural income and government subsidies), which covered all income sources in these 165 households. Agricultural income included crop cultivation, animal husbandry and traditional Chinese medicinal herb collection. Non-agricultural income mainly consisted of wage labor (both permanent and temporary) and income from businesses (e.g., tourism activities). Government subsidies included (but were not limited) to those from the GTGP. Results from this analysis showed that poor (i.e., below the international poverty threshold) households are located significantly more distant from roads than richer (i.e., above the international poverty threshold) households (Fig. 8). This result was more pronounced in 2007 than in 1998, which could be explained by the striking economic development experienced by China during the last decade (Liu, 2010). Therefore, we hypothesize that by reaching parcels further away from roads, the targeting approach developed in this study may allow to reach poorer people, and thus may help the GTGP to fulfill the dual goal of poverty alleviation (Gauvin et al., 2010).

6. Conclusions

The pace of current environmental degradation worldwide is acerbating the need for conservation actions, particularly the implementation of PES programs (Ferraro, 2008; Jack et al., 2008). Therefore, it is becoming increasingly important to improve the efficiency of investments in PES programs. In this study we developed an approach for targeting land to be enrolled in one of the biggest PES program in the world. However, this approach does not account for the cost of operation of the program (i.e., transaction cost). For instance, parcels located further from roads may increase the transaction costs of the program, as managers will be required to travel farther distances to check for program compliance. Therefore, some of these transaction costs may be partly responsible for the differences in the distribution of targeted and observed parcels, as well as for the relatively high proportion of GTGP parcels below the 25° slope threshold. Another reason that may explain these differences is that the GTGP program also aims at "…seriously degraded lands, as well as ecologically important but agriculturally less-productive lands…" (State Council of the People's Republic of China, 2002), which are not necessarily located in areas with slopes higher than 25°. For these reasons, the targeting approach constitutes an approximation. Thus, policy makers will need to weigh in the transaction costs and other considerations for further selecting the most suitable land parcels to be included in PES programs.

The targeting approach described is general enough to be applicable across broad geographic regions. Therefore, while it was tested in a single county, it can be applied to the entire GTGP implementation area across China. With proper modifications, it may also be applicable to similar PES programs around the world.

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Table 1. Maximum likelihood estimates of the coefficients of the predictor variables obtained in the logistic regression model to predict the probability of parcel enrollment in the GTGP (i.e., a surrogate of opportunity cost).

Parameter	Unit	Coefficient	Standard Error	z-value	P-value
Intercept	Unitless	5.3806	1.2268	4.39	<.0001
Payment level	Yuan/ha	0.00043	0.00006	6.78	<.0001
Distance to road	km	-2.92e-06	0.00047	-0.01	0.995
Elevation	m	-0.00167	0.00052	-3.23	0.001
Aspect*	Unitless	0.00121	0.02442	0.05	0.961
CTI**	Unitless	-0.10054	0.04885	-2.06	0.040

*Converted into soil moisture classes (Parker, 1982)
**CTI – Compound Topographic Index

Table 2. Patch density of forest in Baoxing considering the GTGP (observed and targeted) parcels alone or together with the entire forest cover in Baoxing county during 2007. Patch density was calculated on the map shown in Fig. 4, using the software FRAGSTATS (McGarigal et al., 2002).

	Patch Density (Patches/ha)
Observed GTGP parcels alone	4.41
Targeted GTGP parcels alone	0.88
Baoxing forest cover with no GTGP parcels	1.68
Baoxing forest cover with Observed GTGP parcels	1.93
Baoxing forest cover with Targeted GTGP parcels	1.74

Figure Legends

Figure 1. Baoxing County is located at the center of the UNESCO Giant Panda Sanctuary in Sichuan Province, China. The elevation and location of main roads are also shown.

Figure 2. Relationship between elevations obtained from a digital elevation model (DEM) acquired by the Shuttle Radar Topography Mission (SRTM) vs. their respective elevations obtained in the field. The Root Mean Squared Error (RMSE) was obtained using the 1-to-1 relationship (i.e., dotted line), while the R^2 was obtained from the linear regression (i.e., continuous line).

Figure 3. Maps of the spatial configuration of surrogate values in Baoxing County, China developed for targeting the optimal location of GTGP parcels. Colors correspond to the range of values in the three surrogates (i.e., cropland probability, probability of enrollment in the GTGP, and slope index).

Figure 4. Results of the validation of the maps of the probability of cropland and the probability of GTGP enrollment, depicted in Fig. 3. The values of the areas under the ROC curve (AUC) for each map are also shown. The 45-degree line represents an AUC = 0.5 (i.e., random prediction).

Figure 5. Location of the targeted and enrolled GTGP parcels comprising the total area (ca. 3000 ha) enrolled in Baoxing County. Overlapping parcels account for around ca. 9.3 % of the enrolled parcels. The area of forest was obtained using an unsupervised classification applied to Landsat TM data acquired on September 18, 2007. Details on this forest classification are given in Viña et al. (2011).

Figure 6. Frequency distribution of (A) slopes, and (B) elevations of the observed and targeted GTGP parcels.

Figure 7. Frequency distribution of (A) distances to main roads, (B) distances to forest, and (C) probabilities of GTGP enrollment, of the observed and targeted GTGP parcels.

Figure 8. Average distance to the main road among households with incomes above and below the international poverty line (i.e., US$1.25 per capita per day) in Wolong Nature Reserve (located immediately to the north of Baoxing County; Fig. 1) during 1998 and 2007. Error bars correspond to 1 SEM.

Figure 1
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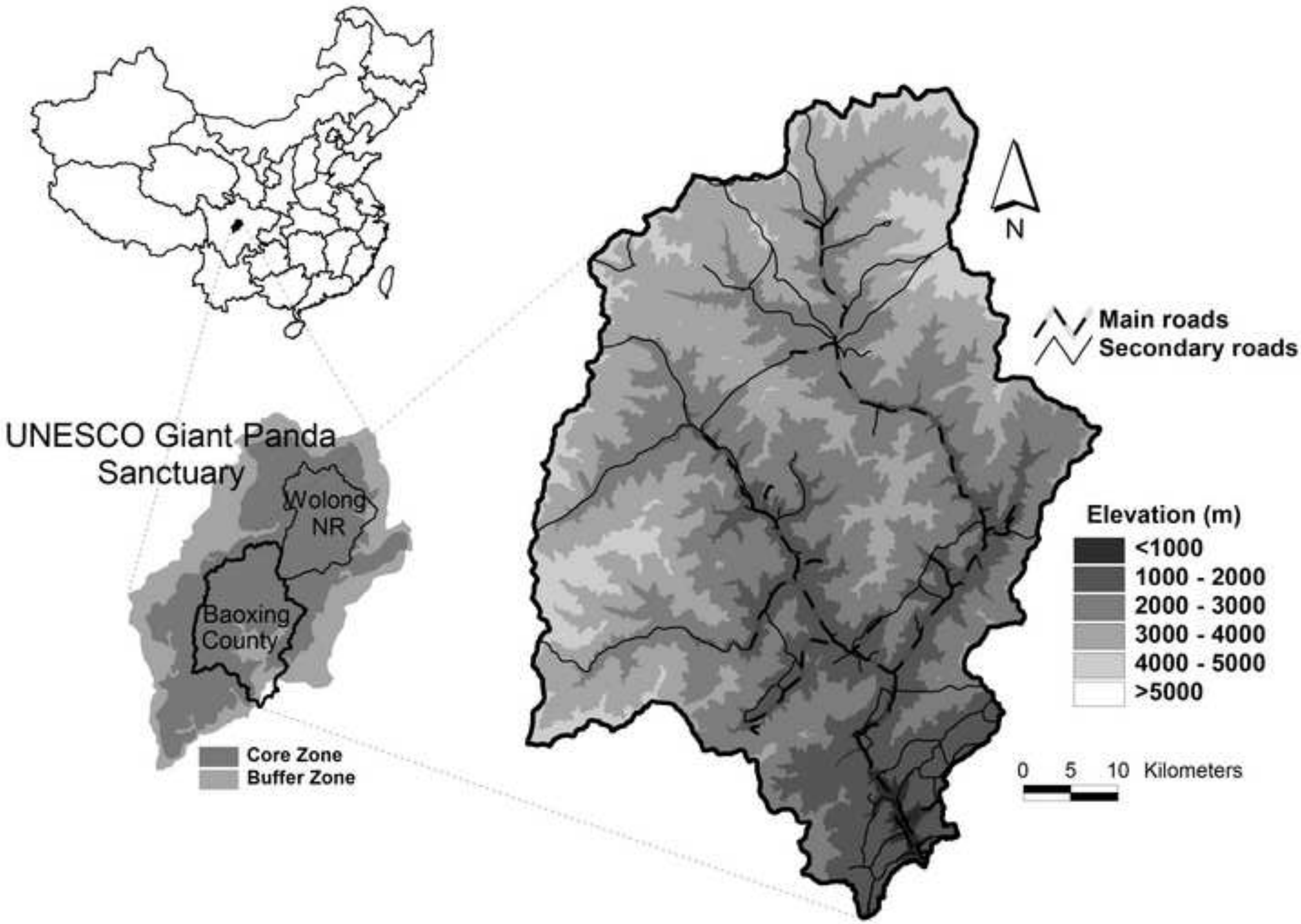

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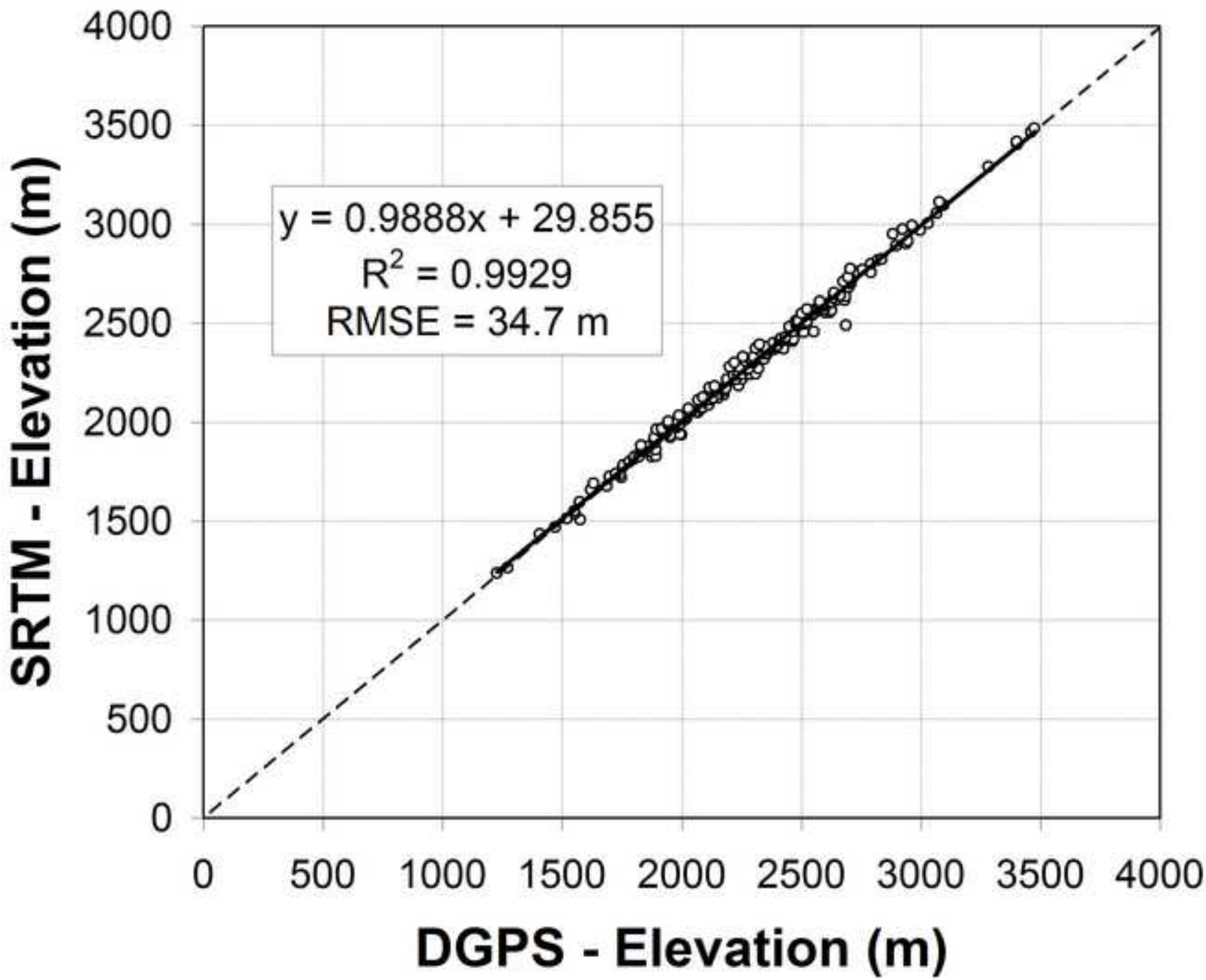

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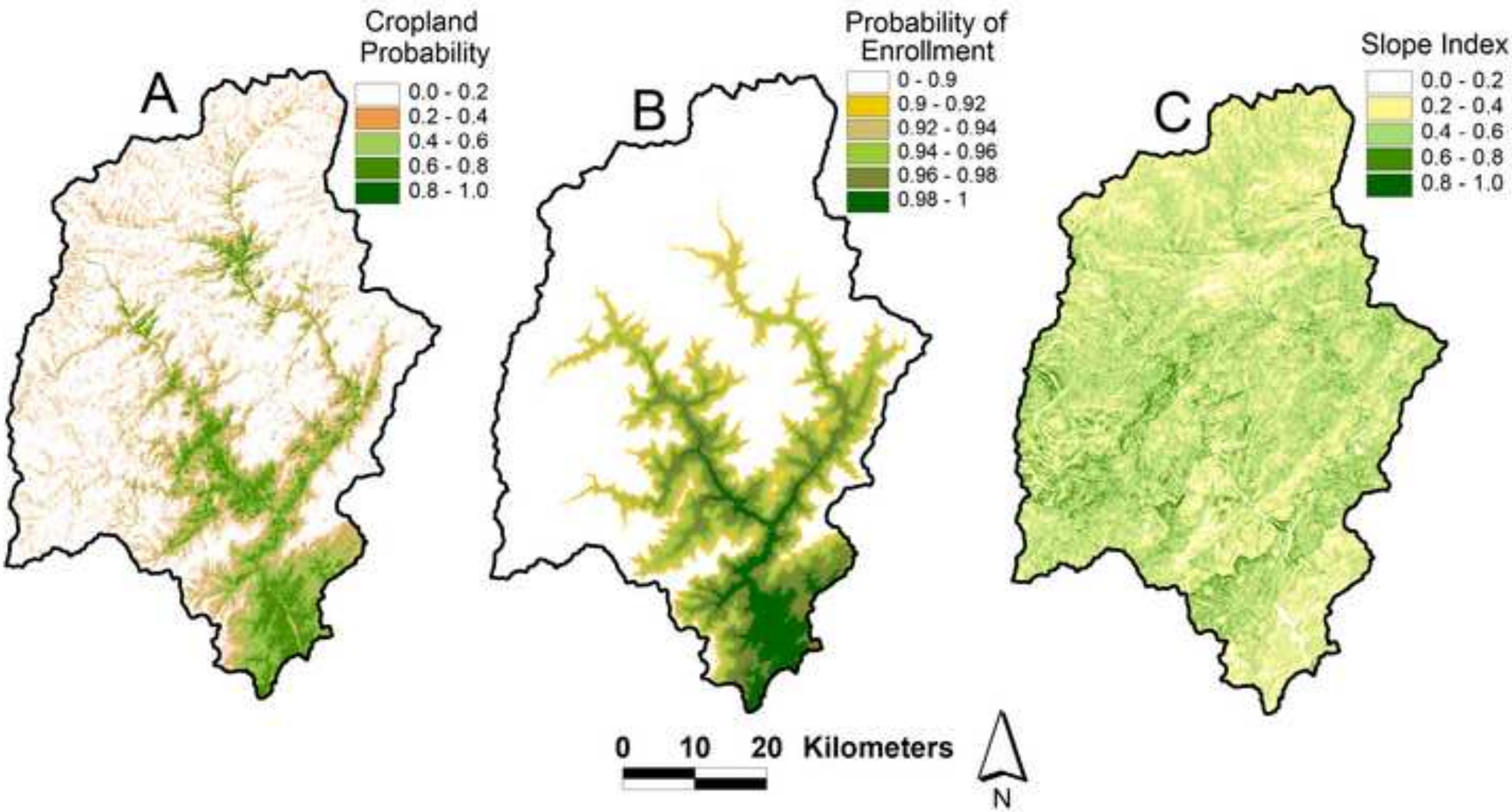

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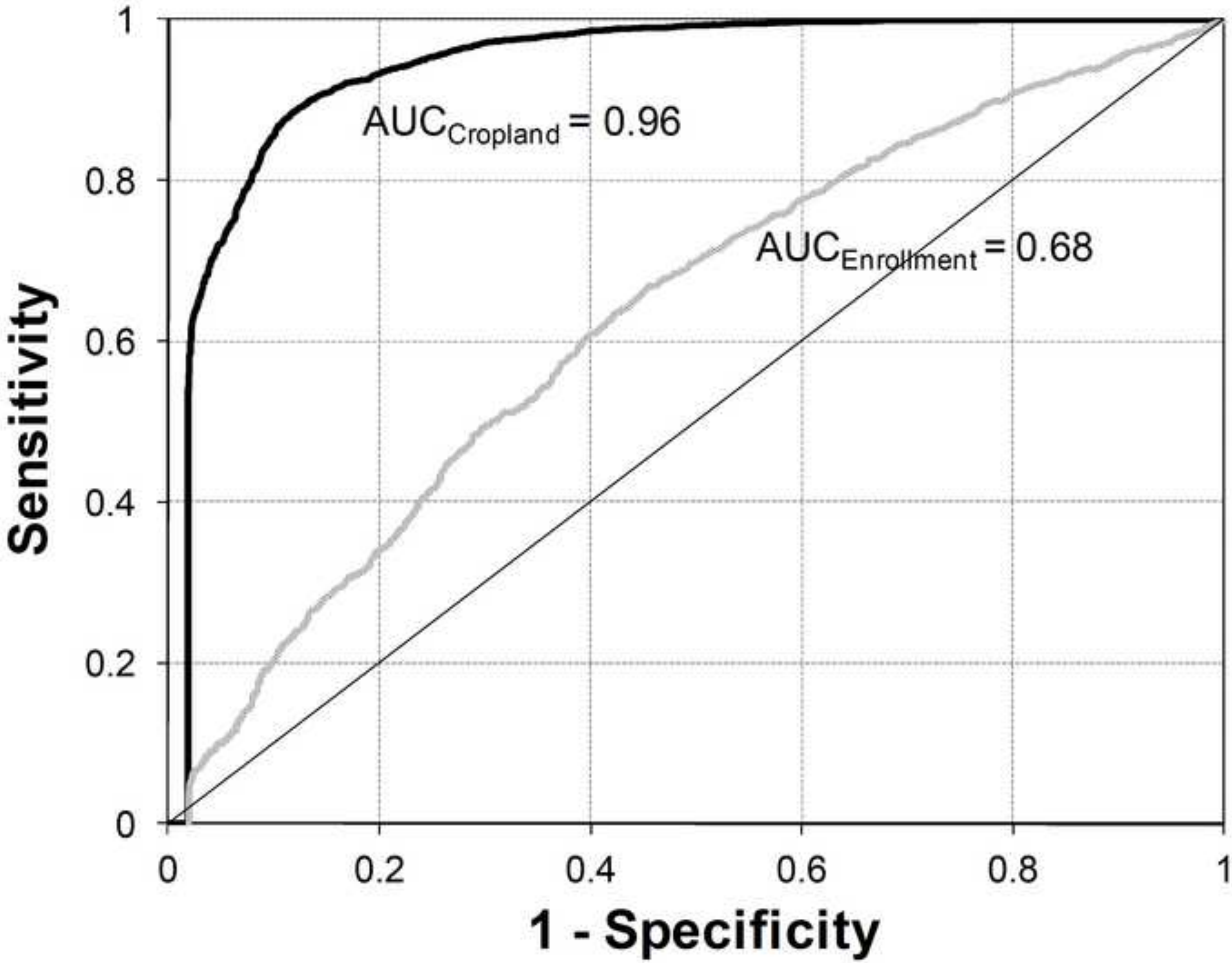

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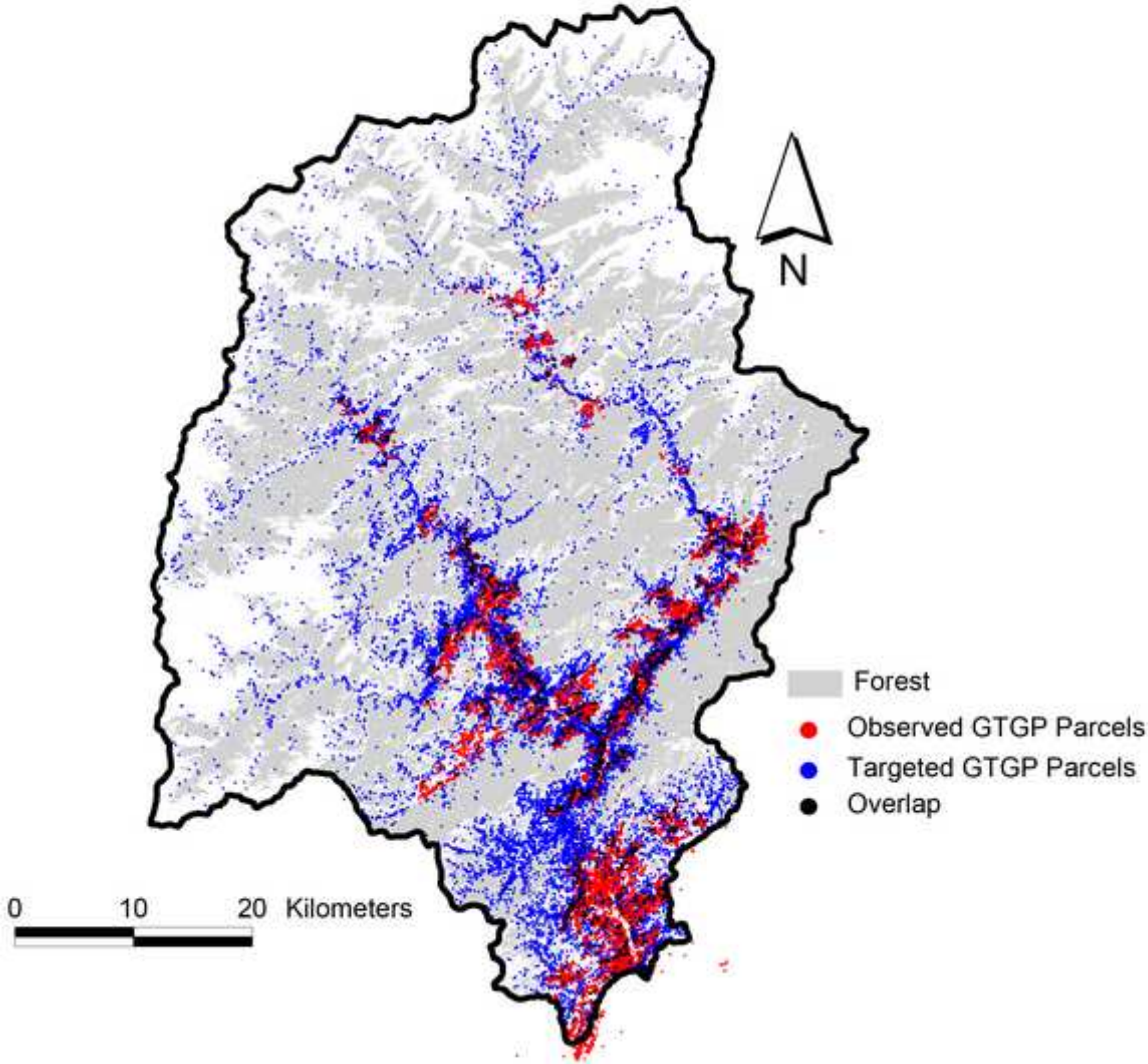

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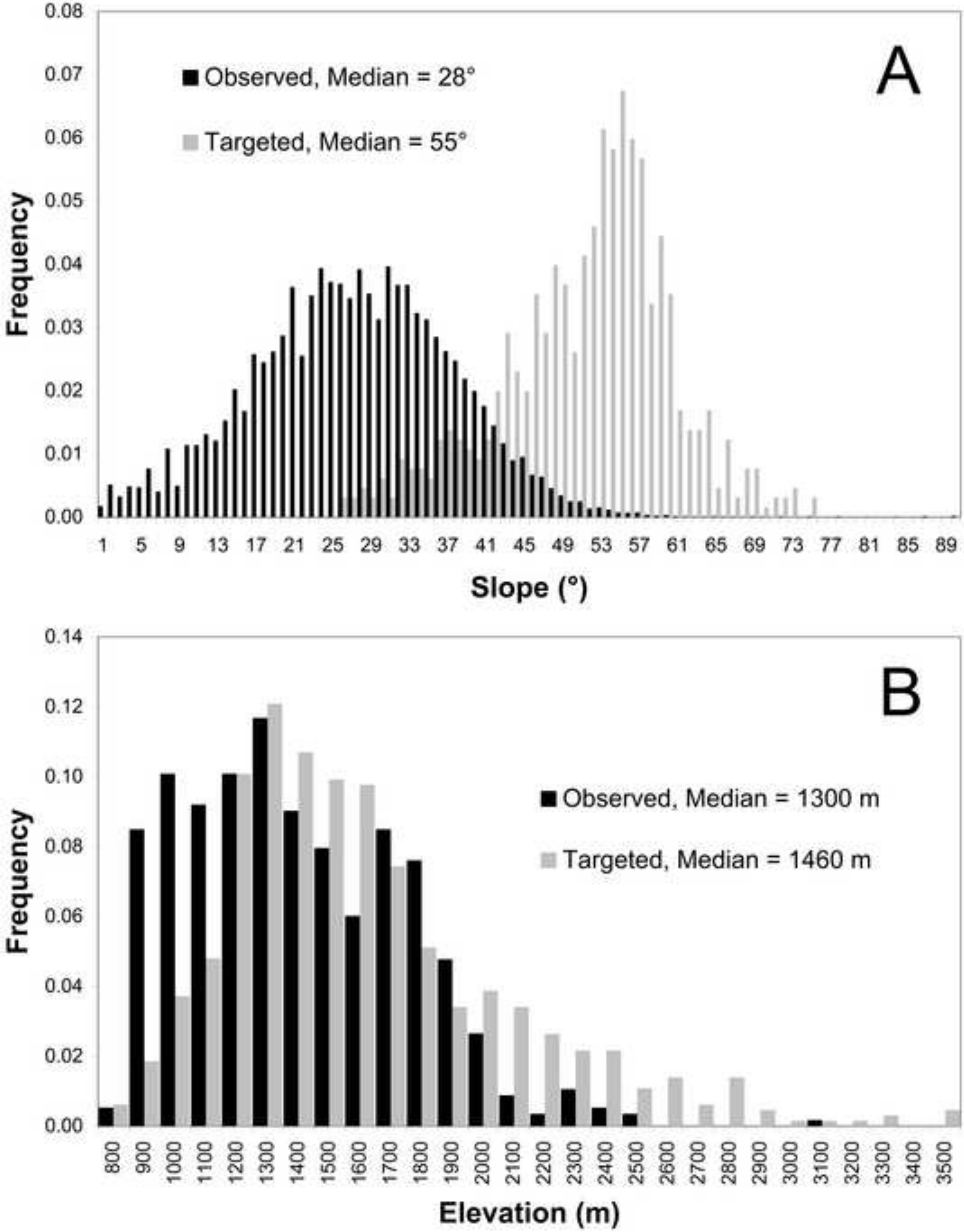

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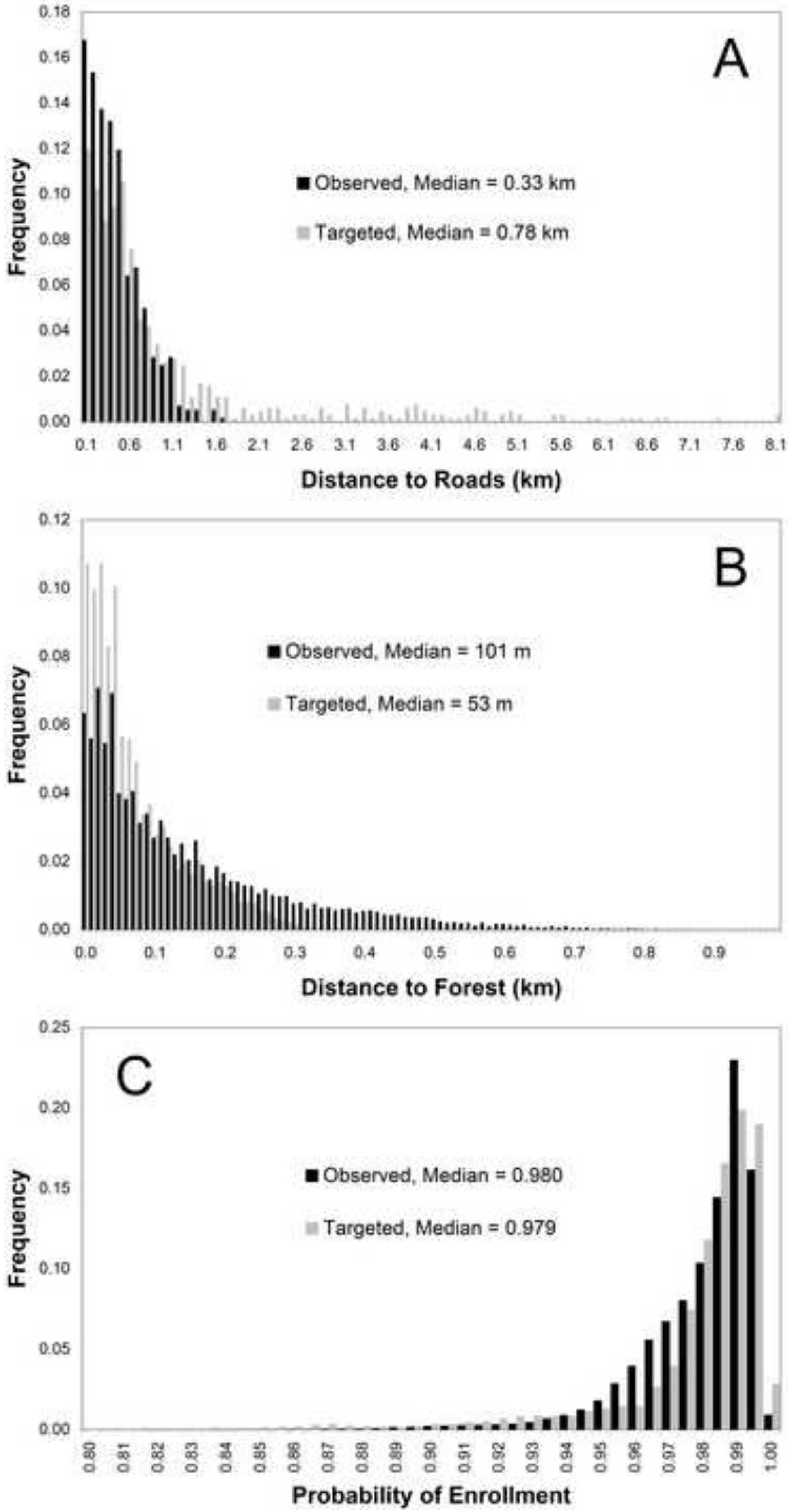

Figure 8

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