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Relation between disaster losses and environmental degradation in the Peruvian Amazon

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1. INTRODUCTION

The aim of the study is to provide quantitative evidence concerning the correlation between Disaster Losses (DL) and Environmental Degradation (ED).

First a literature research was undertaken in order to 1) investigate scientific evidence of correlation between DL and ED in different countries around the world and to 2) examine different methodological approaches (see “bibliographic research”)
This research has supported selection of possible case study and benefitted the method of investigation.

The quantitative investigation was carried out by using remote sensing technologies such as: satellite images to identify and to obtain indicators for ED and Post Classification Comparison (PCC) to perform change detection. The purpose was to detect and quantify changes in land use (such as deforestation or urban growth) by comparing two satellite images acquired at different periods (with a time lag of ten to twenty years).

1.1. Environmental Degradation

Satellite images interpretation and quantification of land cover changes were carried out through a classification process which categorizes all pixels in a digital image into one of several classes. There are very well developed software packages that provide a range of sophisticated tools for the whole image-processing. For the present study, ERDAS imagine® and ArcGIS (ESRI) have been used (floating license allowing multiple users were provided at IGAR-UNIL).

In order to quantify the ED indicators, classification of land cover was needed. Different methods of image classification were tested and the optimal one, in terms of quality and time consuming, was chosen.

Land cover was classified by its different uses such as forest, urban areas, water bodies, etc. There are two main standard procedures that can be used to achieve this outcome, which are *supervised* and *unsupervised classification* techniques. In *supervised classification*, thematic classes are defined by the characteristics of pixels, within an image, that correspond to training areas in the field chosen to represent known features. Each pixel within the image is then assigned to a thematic class and the user can decide to accept or to correct the classification. In *unsupervised classification*, the software does most of the processing itself; generally it results in more categories than the user is interested in. Therefore, the semi-supervised classification can be a good compromise: this technique implies that the user makes decisions on which categories can be grouped together into a single land use category, following the unsupervised classification, and to assign them a class.

1.2. Disaster Losses

Disaster losses were estimated from data stored on DesInventar database. This part of the project has to be accomplished by a pool of experts. IGAR team has carried out some preliminary analyses in collaboration with members of UN/ISDR (Geneva). It involved the choice and selection of DL indicators and the correlation between DL and ED indicators.

2. DATA

Environmental Degradation was estimated using satellite images interpretation. Given that financial support to buy images was not available for the present project, only free images were used. Some images can be accessed and downloaded for free from different web sites. For this study, images were downloaded from the website of Global Land Cover Facility (GLCF) developed by the Department of Geography of University of Maryland. This site provides earth science data focusing on land cover and land cover change around the world. (For more information, address to: http://glcf.umiacs.umd.edu/index.shtml).

Six or seven bands are enough to detect and classify forest, agriculture, urban, water and bare soil. After an investigation of available free images and their characteristics, Landsat imagery was chosen to provide the support for image classification. In fact, Landsat represents the world’s longest continuously acquired collection of space-based land remote sensing data.

Landsat imagery is available since 1972 from six satellites in the Landsat series (major component of NASA's Earth observation program). For the present project Landsat 5 (launched in 1984) and 7 (launched in 1999) Earth observations were used. Both Landsat 5 and 7 carry TM sensor (ETM+ for Landsat 7, enhanced be panchromatic band). TM sensor has seven bands that simultaneously record reflected or emitted radiation from the Earth's surface in the blue-green (band 1), green (band 2), red (band

3), near-infrared (band 4), mid-infrared (bands 5 and 7), and thermal (band 6) portions of the electromagnetic spectrum. Spatial resolution is 30 meters for visible and IR bands, 60 meters for thermal band and 15 meters for panchromatic band.

Indicators for Disaster Losses were provided from DesInventar databases. DesInventar is a conceptual and methodological tool for the implementation of National Disaster Observatories and the construction of databases of damage, loss and the effects of disasters in general.
In agreement with ISRD team, three indicators were selected: flood, landslide and alluvium. For each one of them, the number of events, the number of victims and the number of houses destroyed and damaged were selected. Moreover, the sum of each variable was calculated: total number of events, total number of victims for all events, and total number of houses destroyed and damaged for all events (see PCCgar2011-descriptio.pdf). All the DesInventar data were selected for the frame-period 1985-2006, to include the overall couples of multitemporal satellite images.

3. CASE STUDY

Given the short time and limited human and financial resources, only one case study, selected among all the countries included on the list of DesInventar, was carried out. It corresponds to representative administrative areas of Peru.

This choice is due to different reasons:

- the exhaustiveness of the database for a wide range of years (10-20 years)
- the accessibility to satellite images for 2-3 periods within a range of 10-20 years, in order to detect and quantify land cover changes
- the well known environmental degradation in Peru due to deforestation of the Amazonian forest, urban growth and coastal erosion
- moreover one member of the IGAR team is Peruvian and is very familiar with the land characteristics of this country.

Different indicators were considered to quantify the environmental degradation occurring in the country: deforestation, urban growth, agricultural increase. The quality of the available images allowed detecting, classifying and then quantifying with an acceptable accuracy the changes due to the deforestation only. Therefore, after several efforts to quantify more indicators, only deforestation was retained.

At administrative level, Peru is organized in departments (first level), provinces (second level) and districts (third level). According to the data accuracy of the DesInventar, the change in forest cover was calculated as the difference in hectares between the oldest and the more recent period inside each considered district. The more representative

zones have been chosen in forest area, in the north-east part on the country. Major constraints in obtaining satellite images are represented from: 1) availability of free data sources and 2) images for the same path and row (covering the same area) need to be acquired in the same season and to have a gap of at least 10 years. Giving these limitations, twenty-eight images (corresponding to fourteen path-raw for two different periods) were downloaded. These images cover around three hundred districts and an overall time frame from 1986 through 2006 (fig.1)

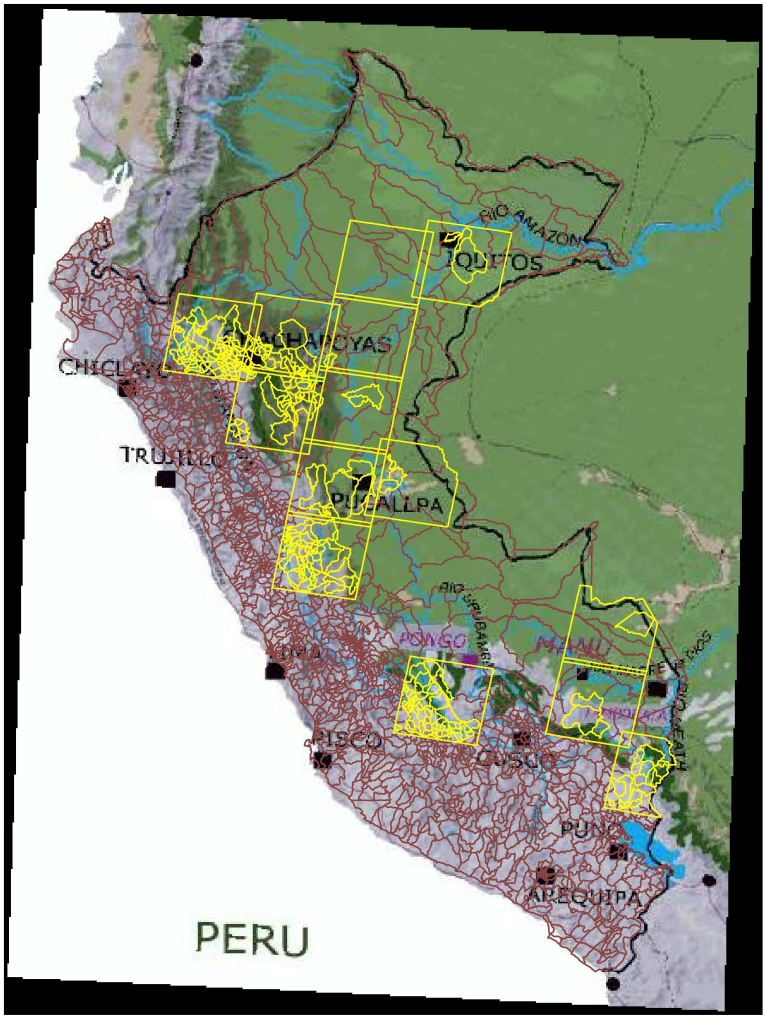

Figure1: satellite images and classified districts

4. IMAGE CLASSIFICATION AND PCC

Detection of land transition, or change detection, includes different methods. For the present study the Post Classification Comparison (PCC) was performed, mainly because of the quality of the available images. PCC consists in detecting changes in land cover by comparing two multitemporal images previously and independently classified.

As stated before, after several efforts to quantify more than one indicator, only deforestation was considered for detecting land use changes. To quantify the change in

forest cover, satellite images were completely classified providing interesting maps of land cover as byproduct of the present study (fig.2).

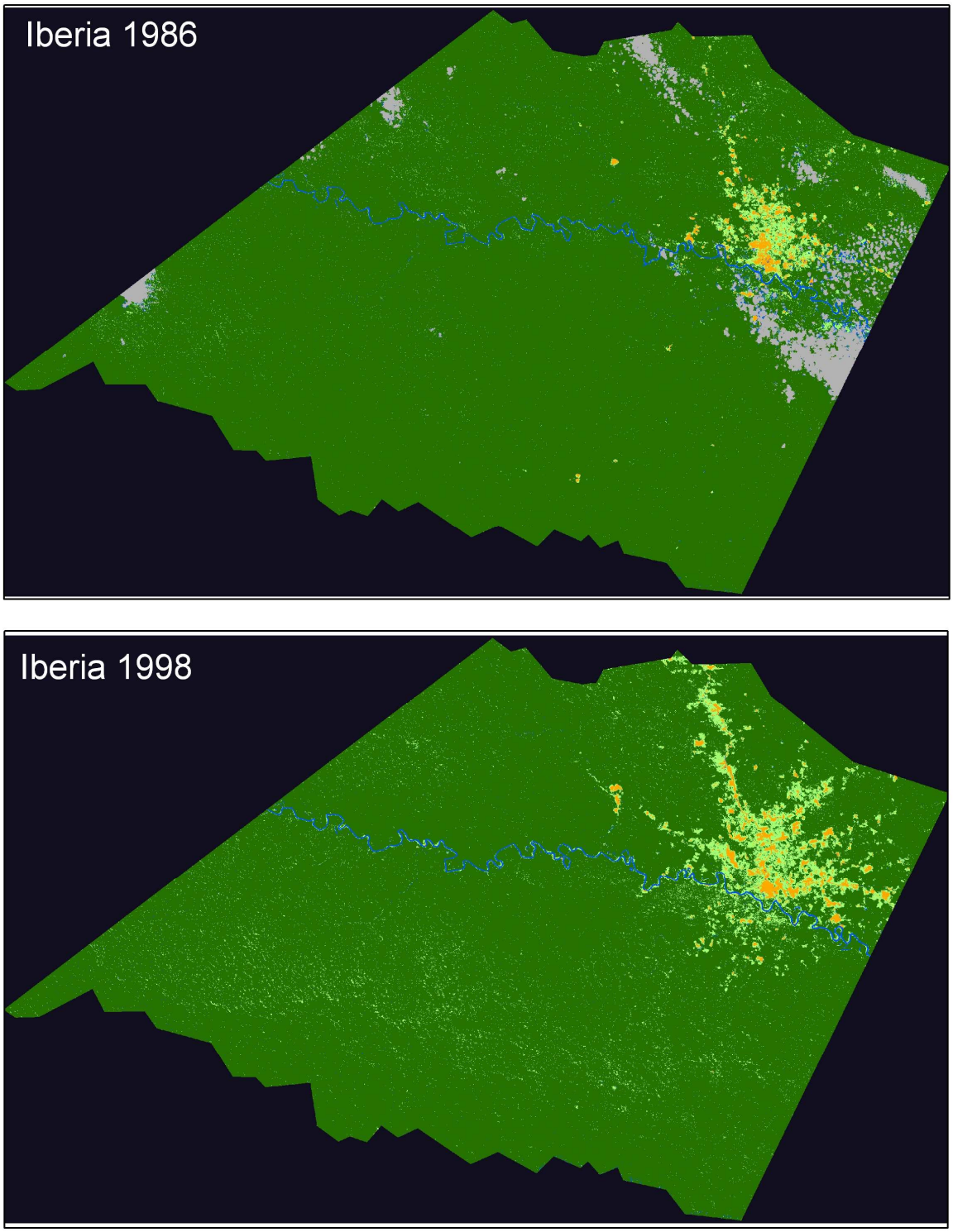

Figure 2: Classified Landsat images acquired on 1986 (up) and 1998(down)

Unclassified Forest Water Cloud Bare soil Agriculture

The following paragraph describes the methods employed. Three steps follow one after the other in satellite image analysis:

1. Image pre-processing
2. Image classification
3. Image post-processing

Finally, by working on the attribute tables, it was possible to calculate statistics and quantify the amount of change in forest cover between the two periods at district level.

4.1 Image pre-processing

This section allowed obtaining and preparing images for classification. The first step was to select path/row for the selected area of the country. Secondly, the availability and the quality of the images had to be verified. It had also been checked that they were acquired in the same period: this restriction is important because vegetation is affected by seasonality. Downloaded images needed to be decompressed and then the singles files (one for each band) stacked in a unique multiband image file. The polygon borders corresponding to each image were used to select the districts that fall inside; then each multiband image was cut around the overlapping districts borders. These operations involved both ERDAS and ArcGIS geotreatment's tools.

4.2 Image classification

Three classification methods were tested:

- NDVI (Normalized Difference Vegetation Index): it uses the red and near infrared bands to calculate an index that varies between -1.0 and +1.0. The NDVI of an area containing a dense vegetation canopy will tend to positive values (say 0.3 to 0.8). It was rejected because it was very difficult to separate agriculture from forest.
- Unsupervised classification: this method works well with a big number of classes (at lest 30). The user needs to aggregate the classes after the system attributes them to the image pixels.
- Supervised classification: the user attributes different classes for different objects detected on the images. A signature file is first generated and AOI (Areas Of Interest) are selected to this purpose. Then the signature is assigned the corresponding object. The recoding tool allows defining a specific quality class to each assigned value.

For supervise and unsupervised classification an accuracy report is then elaborated. This report contains the "Error Matrix" resulting from the classifying training set pixels (random points) and allows assessing the classification accuracy. These matrices

compare the relationship between known reference data and the corresponding results of the automated classification. The comparison is made category by category. Such matrices are square and the number of rows and columns are given by the number of categories whose classification accuracy is being assessed. Therefore, they determine how well a classification has categorized a representative subset of pixels.

In term of both accuracy and time consuming, the supervised classification was retained instead of unsupervised classification.
Finally, six classes were retained: forest, agriculture, urban, bare soil, water, ice and clouds. An image reclassification was needed to assign the six final classes (fig.2).

4.3. Image post-processing

In order to detect changes between the two images a *Post-Classification Comparison* (PCC) was adopted. This method performs change detection in land cover comparing images classified independently and acquired at two different periods. Effectively, the more recent image (image 1) is subtracted to the oldest image (image 2), once the class values of the two images are made equals:

*Difference Image = 10 * image 1 – image 2*

The pixel values of the image resulting from this operation can be interpreted as change in land cover between the two periods.

According to the classification table, the resulting image can have the following values:

			Image 1 (oldest image)						
			Forest	**Water**	**Bare Soil**	**Cloud**	**Agric**	**Urban**	**Ice**
			1	**2**	**3**	**4**	**5**	**6**	**7**
Image 2 (newest image)	**Forest**	**10**	**Forest 9 ⇒ 1**	8 ⇒ 2	7 ⇒ 3	**Forest 6 ⇒ 1**	5 ⇒ 5	4 ⇒ 6	3 ⇒ 7
	Water	**20**	19 ⇒ 1	**Water 18 ⇒ 2**	17 ⇒ 3	Cloud 16 ⇒ 4	15 ⇒ 5	14 ⇒ 6	13 ⇒ 7
	Bare soil	**30**	29 ⇒ 1	28 ⇒ 2	**B.Soil 27 ⇒ 3**	Cloud 26 ⇒ 4	25 ⇒ 5	24 ⇒ 6	23 ⇒ 7
	Cloud	**40**	39 ⇒ 1	38 ⇒ 2	37 ⇒ 3	**Cloud 36 ⇒ 4**	35 ⇒ 5	34 ⇒ 6	33 ⇒ 7
	Agric	**50**	49 ⇒ 1	48 ⇒ 2	47 ⇒ 3	46 ⇒ 4	**Agric 45 ⇒ 5**	44 ⇒ 6	43 ⇒ 7

	Urban	**60**	59 ⇒ 1	58 ⇒ 2	57 ⇒ 3	56 ⇒ 4	55 ⇒ 5	**Urban** **54** ⇒ 6	53 ⇒ 7
	Ice	**70**	69 ⇒ 1	68 ⇒ 2	67 ⇒ 3	66 ⇒ 4	65 ⇒ 5	64 ⇒ 6	**Ice** **63** ⇒ 7

- the red diagonal means that for each of these numbers the category is the same to the one they belong to
- the yellow column highlights those for which values indicate forest change
- the other values show the transition between the oldest and newest land cover.

This method was used to clean the clouds from the oldest image: if in the more recent image the corresponding soil cover is forest, it is reasonably to assign the same class to the oldest image (blue cell). Otherwise, a mask was applied to cover clouds and exclude the corresponding area to the computation of land change.
The resulting difference image was then reclassified according to the new values shown on the matrix (⇒ #). The reclassified image replaces the newest image, corrected for clouds.
The last operation of post-classification was to *mask* the clouds present to the oldest image and the ones that were not possible to remove from the newest image. For this purpose a specific tool in ArcMap was implemented: it reclassifies all classes different than clouds as value “1” and cloud class as value “0” for both images and uses the value “0” to mask the two images.

5. STATISTICS

The overall goal of the present project was to quantify the change in land cover for an area over two different periods of time using one or more indicators. The purpose was to correlate afterwards these values with losses indicators as registered on the DesInventar.

5.1 Quantification of land covers changes

The last step of the analysis was to calculate the proportion of forest change calculated as the difference in hectares in forest cover from the two satellite images acquired with a gap of 10-20 years. Since the documented and tested tendency is a regression in forest cover along the last fifty years, the term “deforestation” is used. Deforestation was detected and it was designated as indicator of environmental degradation. All the quantitative values were computed at district level.
As a result, a decrease in forest area is confirmed be the present study. Among the 197 districts analyzed, 186 show appreciable deforestation, that amount to a total of 848.813 hectares, corresponding to the 7% over the entire analyzed area and frame period.

Changes in the other land classes (agriculture, bare soil, urban, water and ice) were also estimated, but we recommend being careful to correlate these values with losses, since their accuracy was not highly achieved in the analysis. Urban is for instance often confused with bare soils since townships are frequently structured in isolate basic accommodations. Similarly, the quality of images didn't allow distinguishing agricultural land from pasture or wet agricultural soil from water.
Another important result is that globally agricultural land increase of about 672.000 hectares: from, this data it is possible to conclude that agriculture represent the major cause of deforestation.

5.2 Correlation analyses

The SPSS statistics program were used to perform the correlation between environmental and losses indicators. Results are shown in the table Bivariate_correlation.xls and partially on PCCgar2011.xls and discussed on the annexed document PCCgar2011-description.pdf.
A final result is that no statistical correlation can be found between the considered variables. Nevertheless, a trend between data can be delineating, in the sense of an increase in losses when deforestation increase.

6. CONCLUSIONS

Comparing with the previous report GAR2009, the novelty of the current study is to have identified and quantified land cover changes from satellite images. Deforestation in some districts of Peru, representing the case study, has been analyzed and correlated with losses indicators (landslide, flood and alluvium related data) registered on the DesInventar database. The quality and quantity of available data do not allow finding a statistical significant correlation between variables. Nevertheless, we consider the present study as a pilot project: this method of analyzes can be reproduced over other areas and using more consistent satellite images.
Statistical analyses can be furthermore carried out by a team of statisticians and others losses indicators can be selected by experts attempting to find data correlation.

Bibliographic research

The bibliographic research carried out by IGAR team focused on the following main topics:

- generalities on the use of the remote sensing applied to environmental analysis issues, like natural hazards
- remote sensing methodologies to identify vegetation from satellite images
- deforestation detection by remote sensing.

- correlation between deforestation and environmental degradation

As results from this list of references, deforestation is the subject of several studies, but only few of them treats the quantitative aspects of this problem. Specifically, no statistically significant correlation between deforestation and environmental degradation was found.

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