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Ecological Modelling

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https://doi.org/10.1016/0304-3800(95)00206-5

ELSEVIER

Ecological Modelling 93 (1996) 263–273

ECOLOGICAL MODELLING

Geo-Biosphere Processes

# A model analysis of the terrestrial vegetation model of IMAGE 2.0 for Costa Rica

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Received 15 May 1995; accepted 8 November 1995

**Abstract**

The Terrestrial Vegetation Model (TVM) of the Integrated Model to Assess the Greenhouse Effect (IMAGE 2.0) determines potential land cover for natural ecosystems and potential productivity for agrosystems. A model analysis of this TVM using Monte Carlo simulations is described for the eighteen Costa Rican (0.5° × 0.5° latitude–longitude) IMAGE 2.0 grid cells. It is demonstrated that the TVM is not overly sensitive to climate input variability. Much observed output variability is related to model parameters. These model parameter related effects can strongly determine the intra/inter grid variability for Costa Rican potential yields. The model analysis indicates that more model refinement is required to make any effort to improve data quality effective. It is therefore proposed to remove as many model criteria as possible or to replace them by more gradual criteria based on crop ecophysiological characteristics. A first tentative comparison of maize, rice and pulses yield potentials and their distribution in Costa Rica during 1973 and 1984, suggests that the assumption that the two are related, as assumed in the Land Cover Model (LCM) in IMAGE 2.0, has some validity.

*Keywords:* Climate; Land use planning; Model evaluation; Monte Carlo models; Vegetation dynamics

## 1. Introduction

The Integrated Model to Assess the Greenhouse Effect (IMAGE 2.0) is a multi-disciplinary and integrated model designed at the National Institute of Public Health and Environmental Protection, the Netherlands, to simulate the dynamics of the global society–biosphere–climate system (Alcamo et al., 1994). The objectives of the model are to investigate linkages and feedbacks in the system, and to evaluate consequences of climate policies. Dynamic calculations are performed with different time steps (1970–2050), on different geographical scales, depending on the sub-model (ranging from one day to five years and 0.5° latitude × 0.5° longitude to world region respectively).

IMAGE 2.0 links and integrates both complex models and Geographic Information Systems (GIS). One of the main dangers of integrated computer modelling as done with IMAGE 2.0 is that unskilled users may uncritically accept simulation results and as-

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SSDI 0304-3800(95)00206-5

sume that such a complex model performs adequately. Even experts may accept simulated results without sufficient validation. Model errors of integrated model–GIS systems are usually related to both the GIS data as the model relations (Burrough et al., 1993). Model predictions can thus be affected by uncertainty and errors in the geo-referenced data as well as in the applied model functions and boundary/threshold conditions. A direct and effective way to analyze these potential error sources is a model analysis. As extensive Monte Carlo simulations with IMAGE 2.0 would require years to complete, it was decided to make a model analysis for the different sub-models (Alcamo et al., 1994). A first analysis carried out for the Atmospheric Composition sub-model showed the existence of a strong contribution to output variability by model parameters (Krol, 1994).

Another relevant sub-model in IMAGE 2.0 is the Terrestrial Vegetation Model (TVM) which determines potential land cover for natural ecosystems and potential productivity for agrosystems (Leemans and van den Born, 1994). A sensitivity analysis of this sub-model for the whole global data set would still require an enormous computing effort. It was therefore decided to limit the first model analysis to a country with sufficient different climatic environments and sufficient data availability. Because the global climate data set is relatively more reliable for higher latitudes than for lower latitudes (Leemans and Cramer, 1991) a lower latitude country was selected, Costa Rica. This paper describes the model analysis of the TVM for the 18 Costa Rican grid cells (0.5° × 0.5° latitude–longitude) (Fig. 1).

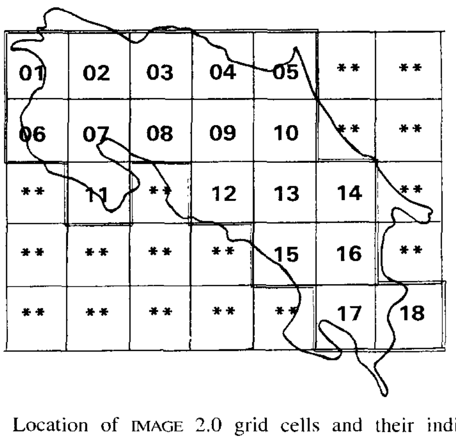



Fig. 1. Location of IMAGE 2.0 grid cells and their individual identification no. in Costa Rica.

## 2. Climate and crops in Costa Rica

Costa Rica's topography is dominated by a central spine of mainly volcanic mountains stretching from northwest to the southeast. Exceeding 2500 m at numerous places in a country only 260 km wide at maximum, the mountains divide the country into two distinct zones dominated by Atlantic and Pacific weather systems, creating tremendous variation in temperature and precipitation regimes (Herrera, 1985). Costa Rica contains 14 of the 31 of the world's tropical bio-climatic zones (Holdridge, 1967; Gómez, 1986). Soils, in addition to altitude and climate, influence the natural vegetation and the human land uses that replace it. Mountainous regions above 1000 m are generally cool and temperate, with abundant and moderately seasonal rainfall (2–5 m/yr). Extensional coastal plains lie to the east and west of the mountains. In the Atlantic and southern Pacific lowlands, rainfall is high (2–7 m/yr) and relatively a-seasonal. The northern half of the Pacific coastal plain forms a distinct, markedly drier (1–2 m/yr) region, where precipitation is more seasonal than in the rest of the country. Nowadays most of the natural vegetation in Costa Rica has been replaced by human land use (DGEC, 1987). Each decade the DGEC composes an agrarian census database containing detailed crop yields for each canton and province in Costa Rica. The 1973 and 1984 crop distributions for rice, maize and beans were aggregated into the (0.5° × 0.5°) grid cells to allow a qualitative comparison with the TVM calculated potential yield trends.

## 3. Terrestrial vegetation model of IMAGE 2.0

The Terrestrial Vegetation Model (TVM) of IMAGE 2.0 simulates the potential distribution of vegetation and major crops. A main assumption within the TVM is that there is a strong linkage between climate, vegetation and crop distribution (Leemans, 1992; Leemans and van den Born, 1994). Another important model assumption is that the vegetation and crop distribution exist under equilibrium conditions for completely rainfed conditions on well-drained soils, thus excluding irrigated agriculture and waterlogging. For natural ecosystems their potential is corresponding to a fully developed and not degraded system, while for crops it is defined as those conditions adequate for obtaining an economically feasible yield. The TVM is implemented with a high-resolution (0.5° × 0.5° latitude–longitude) gridded climate data base (Leemans and Cramer, 1991). Climate is described by 'normal' data of a station or region based on a long-term average of weather records. Such climatic normals are essential to describe the interactions between climate and other biosphere components such as vegetation and crops. Within IMAGE 2.0 the monthly patterns of temperature (mean, minimum and maximum), precipitation (mean and range) and cloudiness are used.

A water balance model yielding the daily available soil moisture for plant growth is used in combination with a temperature regime to define the characteristics of the growing season. The length of growing season is defined as that period during the year when warmth and soil moisture are adequate for vegetation/crop growth. Besides length of growing season, monthly precipitation and temperature of the coldest and warmest month are determined. Effective temperature sums are computed by using the interpolated daily temperature values. Furthermore, climatic requirements are defined for the 16 selected crop types of which some are listed in Table 1. If a crop can grow in a certain grid cell, its potential productivity or yield potential is determined using a simple photosynthetical model based on the crop models of de Wit (1965) and adapted from the specific approach by FAO (FAO, 1978). Photosynthesis is governed by the total amount of irradiance, which is dependent on latitude and cloudiness fraction during the growing season and is also a function of temperature. Evapotranspiration is calculated based on the Priestley–Taylor approach (Prentice et al., 1993; Leemans, pers. commun., 1995). Water-limited yields are thus calculated for all crops as listed in Table 1. Subsequently, some crops are aggregated into economic crop groups, roots (potatoes and cassava), sugar crops (sugar cane and sugar beet) and oil crops (oil palm, sunflower, rapeseed and cottonseed). For each economic group the highest yield potential is used, i.e. the simulated maximum under assumed climatic (temperature and rainfall) constraints assuming optimum management. More specific information is given by Leemans and van den Born (1994). These economic crop groups are used in the Land Cover Model (LCM), another sub-model of the terrestrial environment system of IMAGE 2.0 (Zuidema et al., 1994), together with a demand for agricultural products to calculate actual land cover.

Table 1
Climate corp requirements for the 16 major crop varieties in the TVM

| Crops | MTR | MR | Final crop group |
|---|---|---|---|
| Temperate maize | $-20 < \ < 15$ | – | Maize |
| Tropical maize | $\geq 5$ | – | Maize |
| Rice | $\geq -7.5$ | $\geq 0.95$ | Rice |
| Spring wheat | $< 5$ | – | Wheat |
| Winter wheat | $< 10$ | – | Wheat |
| Millet | $\geq -25$ | $< 0.95$ | Millet |
| Potatoes | $< 15$ | – | Roots |
| Cassava | $\geq 10$ | – | Roots |
| Pulses | $< 20$ | – | Pulses |
| Sugar beet | $< 15$ | – | Sugar |
| Sugar cane | $\geq 10$ | – | Sugar |
| Soy beans | $< 20$ | – | Oil |
| Oil palm | $\geq 10$ | – | Oil |
| Sunflower | $< 10$ | – | Oil |
| Rapeseed | $< 10$ | – | Oil |
| Cottonseed | $\geq -5$ | – | Oil |

MTR = temperature of the coldest month (°C); MR = moisture index (ratio of annual AET and PET); Final crop group = economic crop groups.

## 4. Materials and methods

A sensitivity analysis is performed in order to gain more insight in the crucial aspects of the model and its data, in particular with respect to parameter uncertainty and possible model errors. A common and effective technique is the Monte Carlo method using latin hypercube sampling (Janssen et al., 1990). The IMAGE 2.0 standard climate data set is derived from an extensive interpolation exercise of many meteorological stations. In case of Costa Rica only one national meteorological station (San José) was included within this interpolation exercise, making the standard IMAGE 2.0 data set less suitable for a sensitivity analysis. Based on more than one hundred Costa Rican meteorological stations (Herrera, 1985; Gómez, 1986) new climatological data and their variability were calculated. The model inputs and outputs were statistically analyzed using the SAS software package.

### 4.1. Inputs

The available Costa Rican meteorological stations (Herrera, 1985; Gómez, 1986) were grouped in the IMAGE 2.0 grids (0.5° × 0.5° latitude–longitude, Fig. 1). The long-term mean monthly precipitation and mean monthly temperature data were used to determine the variability within each grid unit. The amount of stations within a grid cell ranged from 2 to 12. These monthly precipitation and temperature data, their distributions and correlations were used for Monte Carlo sampling with the latin hypercube technique. This technique uses a stratified way of sampling from the separate source ranges, sampling each range only once (Janssen et al., 1990).

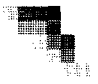
50 precipitation (mm) and 50 temperature (°C) input combinations were sampled, each consisting of 12 monthly temperatures and 12 monthly precipitation data for all 18 grid cells. The two different input data sets were combined and used for simulation with the TVM of IMAGE 2.0, resulting in $50 * 50 = 2500$ runs for each grid cell. Another standard input data set in the TVM describes monthly cloudiness (%). As the cloudiness data in Costa Rica are limited and of uncertain quality, no reliable statistical analysis could be made to support useful Monte Carlo simulations, consequently the standard IMAGE 2.0 cloudiness values were used.

Statistical analysis of the Costa Rican climate data demonstrated strong correlations between many data. An analysis of their variance and their interrelationships with ANOVA and factor analysis (principal component extraction and varimax rotation) indicated that the climatic variability (> 95% of total variance) of both temperature and precipitation can be sufficiently described by only three independent climatic variables, mean temperature in May (TMAY), mean precipitation in January (PJAN) and mean precipitation in October (POCT). The suitability and validity of these three independent input variables is also supported by the observation that they are able to explain up to 98% of the model output variability by multiple regression modelling. Grid means and coefficient of variance (CV) values of these three input variables are given in Fig. 2 and summarized in Table 2. The maps in Fig. 2 display the range of grid values between the minimum and maximum values. For each individual variable 15 equal interval classes were made ranging from its minimum (almost white) to its maximum (almost black) leaving many classes empty. The individual

Table 2
Descriptive statistics (means, standard deviations, minimum, maximum, intra- and inter-grid variance and coefficient of variance) of input and output variables

| Variable | *N* | Units | Mean | S.D. | Min. | Max. | Intra-grid variance | Inter-grid variance | Inter/intra var. coeff. | Coefficient of variance (%) |
|---|---|---|---|---|---|---|---|---|---|---|
| *Inputs* | | | | | | | | | | |
| TMAY | 46436 | °C | 24.8 | 35.5 | 12.2 | 31.7 | 274.1 | 1006.3 | 3.67 | 14.29 |
| PJAN | 46436 | mm | 135 | 119.4 | 0 | 534 | 2786.9 | 11704.1 | 4.20 | 88.02 |
| POCT | 46436 | mm | 410 | 141.8 | 99 | 783 | 7110.6 | 13273.2 | 1.87 | 34.58 |
| *Outputs* | | | | | | | | | | |
| LENGTH | 46436 | days | 349 | 28.0 | 259 | 365 | 178.7 | 619.7 | 3.47 | 8.03 |
| TEMP | 46436 | °C | 24.0 | 34.5 | 11.8 | 30.3 | 221.2 | 989.3 | 4.47 | 14.36 |
| RICE | 46436 | t/ha | 942 | 9.3 | 590 | 1100 | 25.6 | 63.2 | 2.47 | 9.93 |
| MAIZE | 46436 | t/ha | 1639 | 16.0 | 1210 | 2110 | 54.6 | 205.4 | 3.76 | 9.76 |
| MILLET | 46436 | t/ha | 461 | 51.0 | 0 | 1320 | 898.1 | 1745.1 | 1.94 | 110.75 |
| PULSES | 46436 | t/ha | 129 | 25.5 | 0 | 870 | 237.9 | 424.8 | 1.79 | 196.97 |
| ROOTS | 46436 | t/ha | 1875 | 17.7 | 1400 | 2190 | 56.5 | 263.4 | 4.66 | 9.46 |
| OIL | 46436 | t/ha | 1100 | 10.9 | 650 | 1280 | 35.9 | 86.2 | 2.40 | 9.98 |
| SUGAR | 46436 | t/ha | 5357 | 87.8 | 1820 | 6120 | 534.8 | 7323.0 | 13.69 | 16.40 |







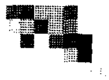




Fig. 2. Distribution of means and coefficient of variance (CV) of the input variables TMAY (mean temperature in May), PJAN (mean precipitation in January) and POCT (mean precipitation in October).

classification of each variable makes the given maps not directly comparable, but they illustrate the different grid values for Costa Rica.

### 4.2. Outputs

The 2500 simulation runs of the TVM sub-model yielded the following output variables: potential vegetation class, length of growing season (LENGTH), mean temperature of growing season (TEMP), water-limited yield levels for: rice, maize, millet, pulses, roots, oil and sugar crops. For each output variable descriptive statistics (see Fig. 3) and ANOVA were carried out in order to determine the inter and intra grid variances (Table 2). Regression was applied to model the output variables variability by the three independent input descriptive variables TMAY, PJAN and POCT both on grid and national level (Fig. 3). The Costa Rica grid maps in Fig. 3 indicate the range of grid values for regression model fits ($R^2$), coefficient of variance (CV) and output means. The minimum (almost white) and maximum (almost black) values are also divided into 15 equal interval classes, meaning that except for the $R^2$ maps (all ranging from 0 to 100%), the maps in Fig. 3 are not directly comparable.

## 5. Results

### 5.1. Water-limited yields

All calculated output variables are given in Fig. 3. Wheat is not presented because all simulations re-



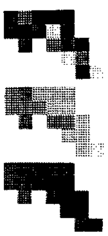







Fig. 3. Distribution of model fits of multiple regressions (see listed models), coefficient of variance (CV) and means of calculated model outputs for Costa Rica grids, LENGTH (length of growing season, (units: days)), TEMP (mean temperature of growing season (units: °C)) and potential water-limited yield levels (units: t/ha) for rice, maize, millet, pulses, roots, oil crops and sugar crops.

sulted in yields of 0 ton/ha for all Costa Rican grid cells. A first comparison of the input and output data by correlation showed changing correlations for each output variable with the three input variables for the entire Costa Rica data set. More detailed insight can be obtained from comparing the trends in Fig. 2 and Fig. 3. The coefficients of variance (CV) of the input data (ranging from about 14% for TMAY, 35% for POCT to about 88% for PJAN) are usually much larger than the CV of the output data (Fig. 3 and Table 2), suggesting a certain robustness of the TVM. However, this reduction of CV does not always occur. Especially millet and pulses outputs demonstrate considerably larger CVs, up to 700% for certain grids (Fig. 3). More detailed analysis of this high CV revealed that in both cases (millet and pulses) this was caused by many yield failures (0 kg/ha) during the simulations. This is in both cases directly related to model criteria/thresholds concerning crop requirements (as listed in Table 1). Millet requires a moisture index < 0.95, a condition not often met in the general humid climate of Costa Rica. Pulses on the other hand require a coldest month of < 20°C, a condition which is only found in the higher cooler grid cells. This strong model parameter related variability is confirmed by the observation that grids with higher mean water-limited yield levels for both millet and pulses (many years with a yield) have relatively low CVs. Another confirmation was obtained by regression modelling for each individual grid cell. These regression models attempt to explain calculated water-limited yield variability by the three independent input variables TMAY, PJAN and POCT. The model fits ($R^2$) are reported for each individual Costa Rica Grid (Table 3). The contributions of the three input variables to these regression models are listed in (Table 3) by +

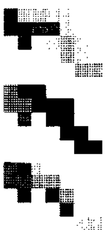


**Model: MAIZE = TMAY + PJAN + POCT**

Model fit for each individual grid ($R^2$), Min = 0.19 to Max = 0.96.

Coefficient of variance for each individual grid (CV), Min = 2.2 to Max = 6.6 %.

Mean values for each individual grid (ton/ha), Min = 1387 to Max = 1966 ton/ha.



**Model: MILLET = TMAY + PJAN + POCT**

Model fit for each individual grid ($R^2$), Min = 0 to Max = 0.92.

Coefficient of variance for each individual grid (CV), Min = 4.9 to Max = 625 %

Mean values for each individual grid (ton/ha), Min = 0 to Max = 1127 ton/ha.

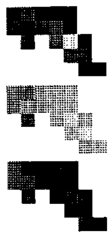
**Model: PULSES = TMAY + PJAN + POCT**

Model fit for each individual grid ($R^2$), Min = 0 to Max = 0.79.

Coefficient of variance for each individual grid (CV), Min = 3.6 to Max = 700 %

Mean values for each individual grid (ton/ha), Min = 0 to Max = 834 ton/ha.

Fig. 3 (continued).

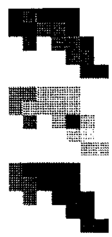


**Model: ROOTS = TMAY + PJAN + POCT**

Model fit for each individual grid ($R^2$), Min = 0.06 to Max = 0.97.

Coefficient of variance for each individual grid (CV), Min = 1.9 to Max = 6.1 %.

Mean values for each individual grid (ton/ha), Min = 1599 to Max = 2124 ton/ha.

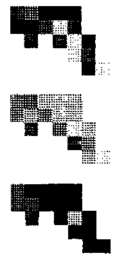


**Model: OIL = TMAY + PJAN + POCT**

Model fit for each individual grid ($R^2$), Min = 0.61 to Max = 0.96.

Coefficient of variance for each individual grid (CV), Min = 1.9 to Max = 16.6 %

Mean values for each individual grid (ton/ha), Min = 933 to Max = 1239 ton/ha.



**Model: SUGAR = TMAY + PJAN + POCT**

Model fit for each individual grid ($R^2$), Min = 0.04 to Max = 0.96.

Coefficient of variance for each individual grid (CV), Min = 2.1 to Max = 8.1 %.

Mean values for each individual grid (ton/ha), Min = 2037 to Max = 5952 ton/ha

Fig. 3 (continued).

and − for each individual grid cell. It can be observed that the higher coefficients of determination ($R^2$) are related to lower output CVs. The output variable, length of growing season (LENGTH), has many grids with a coefficient of determination ($R^2$) of 0 because no variance can occur when all calculated length of growing seasons are 365 days (the whole year). For some grid cells a very low coefficient of determination is found for water-limited yield levels of crops which have a reasonable small CV. Examples are found in certain grids for roots, oil and sugar crops. Detailed analysis of these grid cells shows that this was mainly due to the selection of different crops within the economical crop groups, roots, oil and sugar. For one cool grid cell (no. 13 in Fig. 1) a different sugar crop, sugar beet, was selected instead of the commonly selected sugar cane in the other Costa Rica grids. For this same grid cell potato instead of cassava was selected. The temperature-related crop requirement parameter

Table 3
Multiple regression models (significance level of 0.05) of output variables (coefficient of determination ($R^2$) and contributions of explaining variables (inputs)) for all 18 grids. Model: OUTPUT = TMAY + PJAN + POCT

| Output | Grid no. | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 |
| LENGTH | 0.71 | 0.54 | 0.0 | 0.0 | 0.0 | 0.66 | 0.63 | 0.23 | 0.12 | 0.0 | 0.75 | 0.54 | 0.07 | 0.0 | 0.27 | 0.0 | 0.17 | 0.03 |
| tmay | + | + | − | − | − | + | + | − | − | − | + | + | − | − | − | − | − | + |
| pjan | + | + | − | − | − | + | + | + | + | − | + | + | + | − | + | − | + | + |
| poct | + | + | − | − | − | + | + | + | + | − | + | + | − | − | − | − | − | + |
| TEMP | 0.97 | 0.97 | 0.97 | 0.97 | 0.98 | 0.96 | 0.97 | 0.98 | 0.98 | 0.98 | 0.97 | 0.98 | 0.96 | 0.98 | 0.98 | 0.98 | 0.98 | 0.98 |
| tmay | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + |
| pjan | + | + | − | − | − | + | + | + | − | − | + | − | − | − | − | − | − | − |
| poct | + | − | − | − | − | − | − | − | − | − | + | − | − | − | − | − | − | − |
| RICE | 0.87 | 0.68 | 0.97 | 0.97 | 0.97 | 0.89 | 0.91 | 0.80 | 0.77 | 0.96 | 0.86 | 0.61 | 0.64 | 0.97 | 0.70 | 0.85 | 0.91 | 0.93 |
| tmay | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + |
| pjan | + | + | − | − | − | + | + | + | + | − | + | + | − | − | + | − | + | − |
| poct | − | + | − | − | − | + | + | + | + | − | + | + | − | − | − | − | − | − |
| MAIZE | 0.87 | 0.59 | 0.96 | 0.96 | 0.96 | 0.89 | 0.91 | 0.80 | 0.26 | 0.90 | 0.85 | 0.59 | 0.82 | 0.92 | 0.15 | 0.64 | 0.91 | 0.19 |
| tmay | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + |
| pjan | + | + | − | − | − | + | + | + | + | − | + | + | + | − | + | − | + | − |
| poct | + | + | − | − | − | + | + | + | − | − | + | + | − | − | − | − | − | − |
| MILLET | 0.87 | 0.22 | 0.26 | 0.0 | 0.0 | 0.90 | 0.92 | 0.60 | 0.60 | 0.05 | 0.86 | 0.09 | 0.27 | 0.0 | 0.34 | 0.09 | 0.34 | 0.38 |
| tmay | + | + | − | − | − | + | + | − | − | + | + | + | + | − | − | − | + | + |
| pjan | + | + | + | − | − | + | + | + | + | − | + | + | + | − | + | + | + | + |
| poct | + | + | + | − | − | + | + | + | + | − | + | + | + | − | − | − | + | + |
| PULSES | 0.07 | 0.79 | 0.48 | 0.51 | 0.07 | 0.0 | 0.0 | 0.0 | 0.43 | 0.07 | 0.0 | 0.77 | 0.70 | 0.0 | 0.54 | 0.78 | 0.0 | 0.52 |
| tmay | + | + | + | + | + | − | − | − | + | + | − | + | + | − | + | + | − | + |
| pjan | − | + | − | − | − | − | − | − | − | − | − | + | + | − | − | − | − | − |
| poct | − | − | − | − | − | − | − | − | − | − | − | − | − | − | − | − | − | − |
| ROOTS | 0.88 | 0.69 | 0.97 | 0.97 | 0.97 | 0.90 | 0.92 | 0.80 | 0.75 | 0.97 | 0.86 | 0.61 | 0.06 | 0.96 | 0.71 | 0.85 | 0.92 | 0.95 |
| tmay | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + |
| pjan | + | + | − | − | − | + | + | + | + | − | + | + | + | − | + | − | + | + |
| poct | + | + | − | − | − | + | + | + | + | − | + | + | − | − | − | − | − | − |
| OIL | 0.87 | 0.69 | 0.96 | 0.98 | 0.97 | 0.89 | 0.91 | 0.79 | 0.76 | 0.96 | 0.86 | 0.61 | 0.64 | 0.96 | 0.70 | 0.85 | 0.91 | 0.93 |
| tmay | + | + | | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + + |
| pjan | + | + | − | − | − | + | + | + | + | − | + | + | − | − | + | − | + | + |
| poct | + | + | − | − | − | + | + | + | + | − | + | + | − | − | − | − | − | − |
| SUGAR | 0.85 | 0.54 | 0.96 | 0.96 | 0.96 | 0.87 | 0.89 | 0.75 | 0.14 | 0.86 | 0.83 | 0.62 | 0.06 | 0.90 | 0.21 | 0.70 | 0.89 | 0.04 |
| tmay | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + |
| pjan | + | + | − | − | − | + | + | + | + | − | + | + | + | − | + | − | + | + |
| poct | + | + | − | − | − | + | + | + | − | − | + | + | − | − | − | − | − | + |

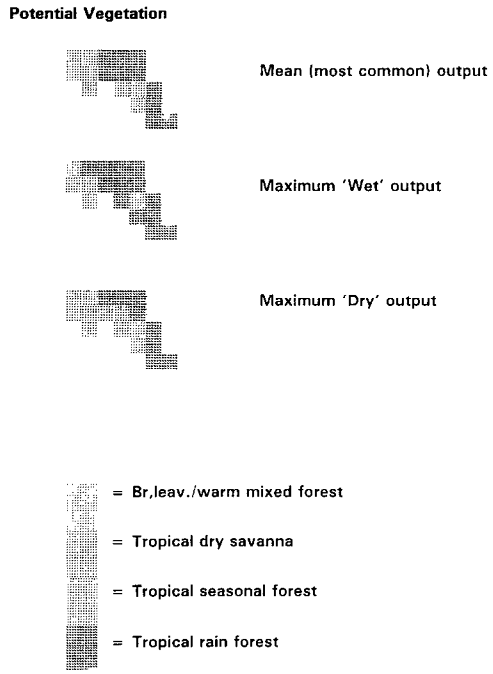



Fig. 4. Potential vegetation (see legend), the mean output with the wettest and driest outputs.

resulted in a considerable increase in the CV of the model outputs. A very similar observation applies for the oil crops were three different crops were selected for the Costa Rica grids causing changes in CV in the oil crop outputs. These examples clearly indicate that the role of model parameters and thresholds can considerably dominate the model output variability of the TVM.

When the Monte Carlo simulations are evaluated for Costa Rica as a whole, similar model effects can be observed (Table 4). The overall regression model fits are reasonable to good, ranging from 72% (millet) to 99% (mean temperature during growing season), indicating the important contribution of both temperature and precipitation in explaining model output variability. Independent of the three selected input variables, a so-called grid effect could be determined by regression modelling, ranging from 0.8% (TEMP) to 75% (sugar) of the total output variability. In other words, apart from the variability resulting from the input variables, the grid cells themselves created an additional source of variability. This grid effect could be attributed in part to the effect of cloudiness (which was not evaluated), but may almost certainly be due to the model parameters used for the selection of crops for the economical crop groups. This is corroborated by the observed effects in roots and sugar variability. This effect could also explain the detected differences in the calculated inter/intra grid variance coefficients (Table 2).

### 5.2. Potential vegetation

Potential vegetation as calculated by the TVM for each grid is presented by 15 classes. Of these classes only four are found in Costa Rica: broadleaved warm mixed forest (A), tropical dry savanna (B), tropical seasonal forest (C) and tropical rain forest (D) (Fig. 4). Of the 18 Costa Rica grids seven had tempera-

Table 4
Overall regression models of the output variables (of 18 aggregated grids) with partial coefficients of determination ($R^2$) in %, of input variables and grid-effects. Model: OUTPUT = TMAY + PJAN + POCT + GRID-effect

| Outputs | TMAY (%) part. $R^2$ | PJAN (%) part. $R^2$ | POCT (%) part. $R^2$ | GRID-effect (%) part. $R^2$ | Total (%) $R^2$ model | Unexpl. tot. var. (%) |
|---|---|---|---|---|---|---|
| LENGTH | 5.76 | 34.75 | 21.90 | 16.24 | 78.65 | 21.35 |
| TEMP | 98.59 | 0.00 | 0.03 | 0.80 | 99.42 | 0.58 |
| RICE | 40.50 | 7.60 | 5.30 | 24.67 | 78.07 | 21.93 |
| MAIZE | 57.51 | 11.34 | 5.81 | 8.78 | 83.44 | 16.56 |
| MILLET | 0.99 | 55.10 | 0.51 | 15.76 | 72.36 | 27.64 |
| PULSES | 65.09 | 0.06 | 0.34 | 8.89 | 74.38 | 25.62 |
| ROOTS | 27.98 | 8.27 | 5.41 | 52.11 | 93.77 | 6.23 |
| OIL | 39.58 | 7.49 | 5.31 | 24.78 | 77.16 | 22.84 |
| SUGAR | 11.38 | 4.93 | 2.34 | 75.86 | 94.51 | 5.49 |

ture/precipitation values near threshold values causing considerable changes in vegetation classes during the Monte Carlo simulations. These grids are found in the transition zone between the dry west part of Costa Rica and its humid east coast. The most humid and arid results are also given in Fig. 4. The observed threshold effects in the TVM for potential vegetation types seem less dominant than for the potential water-limited yield calculations. This may be due to the more refined and balanced classification boundaries use in TVM which are based on the BIOME model of Prentice et al. (1992).

## 6. General discussion and conclusions

### *6.1. Model sensitivity*

Although only a small country, but with considerable climatic and land use variability, was evaluated, the Monte Carlo simulations demonstrated that the model sensitivity of the TVM in respect to water-limited crop yield-potentials was mostly determined by model parameters rather than by input variability of climate data. The dominating model parameters are criteria related to crop requirements and clustering of crop types into economic crop groups. When climate inputs are not close to the specified crop requirements (Table 1) a rather limited CV can be observed for the calculated outputs compared to the CV of the input data, illustrating the robustness of the TVM in respect to its climate data. When model thresholds are met or crossed, a strong increase in the CV and the inter/intra grid variance coefficient can be observed. This suggests that the current model parameters and crop growth criteria are applied too rigorously in the TVM. Apparently the crop requirements used are too coarse.

### *6.2. Additional data needs*

Only when the model parameters have been made less dominant in the model performance of the TVM of IMAGE 2.0, it will become relevant to collect more detailed and realistic climate data as currently available in IMAGE 2.0. The overall performance of the TVM for Costa Rica seems rather satisfactory (Tables 2 and 4). The different climate environments

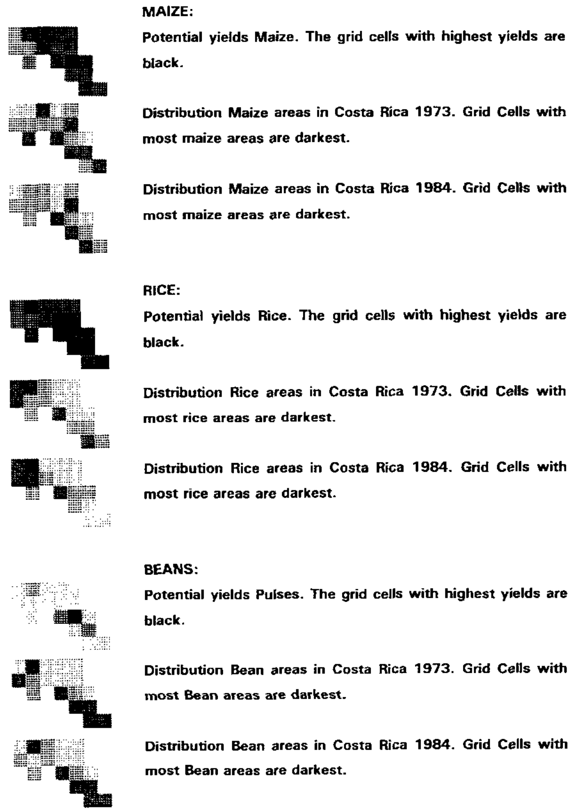



Fig. 5. Comparison potential yields of maize, rice and pulses and their distributions in 1973 and 1984 in Costa Rica.

yielded significantly different water-limited yields. The calculated TVM results are applied on world region scale in the Land Cover Model (LCM) to allocate crops to agricultural grids (Zuidema et al., 1994). The crop distribution in IMAGE 2.0 is assumed to be directly related to the calculated crop production potential. In order to check the validity of this assumption for Costa Rica the calculated yield potentials for each grid cell is compared with crop distributions of maize, rice and beans in 1973 and 1984 (DGEC, 1976, 1987). It has to be noted that in reality crop distributions are influenced by many other factors unrelated to biophysical potential. In Fig. 5 the high potential yields and the grid cells were most beans, maize and rice were grown in 1973 and 1984 are given in dark grey colours. The maps demonstrate that the crop distribution in Costa Rica tends to change somewhat in time, but in general a qualitative match between the calculated yield potentials and their general distributions can be observed, suggesting that the basic biophysical assumption in the LCM of IMAGE 2.0 has practical merit.

### *6.3. Model improvements and relevance*

Our first model analysis for the terrestrial vegetation model of IMAGE 2.0 demonstrates that the limitations to successful modelling are more caused by lack of scientific insight rather than data availability and quality. The refinement of the TVM of IMAGE 2.0 should be sought in model improvement instead of data quality improvement.

The application of the model requires further improvements. First, solutions with respect to model criteria may be envisaged. Model criteria could be limited as much as possible. But a more interesting solution may be found in applying more gradual threshold values, using overlapping domains. This corresponds with what is observed in reality, i.e. that crop distribution zones overlap and that farmers tend to exploit crop niches at the boundaries of their suitability zones. Furthermore, the grouping of crops into economic crop-groups leads to unnecessary errors, as is the case of the combination of sugar cane and sugar beet which have very different ecophysiological requirements. It may be concluded that a grouping of crops in phenological/physiological groups with gradual transition criteria from one crop to the other instead of the current economic groups with fixed boundaries would improve model results. Given the resolution of the model, and the adequacy of the predictions, there is not much point in further refinement of its subcomponents, such as the calculation procedures for dry matter accumulation or crop respiration. Similarly, improvement of the growth models with more crop-specific models is unlikely to yield more significant improvements than may be achieved by replacing the model criteria. However, after the TVM is thus improved, this could be re-evaluated.

Secondly, the overall performance of the model could be reviewed in the light of additional field level information. As it stands, the objective of the TVM is to determine potential vegetation and potential land cover/use. By definition (see e.g. de Wit, 1965) management practices or other realistic factors to downscale yields are not included in this type of modelling. For the current exploratory studies undertaken with IMAGE 2.0 this appears appropriate. However, policy makers will require much more realistic model outcomes that take into account current land cover/use and explain future land use by analysing previous trends and driving biophysical and socio-economic forces. A better linkage between IMAGE 2.0 and models of land use dynamics could be explored further.

## Acknowledgements

This research was supported partially by the Dutch National Programme on Global Air Pollution and Climate Change (NOP). The UNCSAM computer programme was developed by the RIVM, Box 1, 3720 BA Bilthoven, the Netherlands. The Dirección General de Estadística y Censos (DGEC) and the field team of the Programma Zona Atlantica (PZA) at Guapiles of the joint programma of CATIE, MAG and the Agricultural University Wageningen have been helpful in providing information and agronomic census data of 1973 and 1984.

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