ABSTRACT

Title of Dissertation: ADDRESSING THE IMPACT ON SOIL DEGRADATION OF CHANGE FROM GRASSLAND TO CROPLAND: A CASE STUDY IN THE URUGUAYAN GRASSLANDS

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Globally, there has been large-scale conversion of natural grassland to cropland ecosystems which this has led to land degradation that could reduce future food security, other ecosystem services and even climate. Currently, there is a dearth of quantitative information assessing the severity, distribution, and causes of this land degradation. For practical purposes, this information is needed to develop improved methods of land use (LU) conversion. Uruguay, in contrast with many other regions, still has a high proportion of unimproved grasslands but, during the last 15 years, there has been extensive conversion to grow grain crops.

The fundamental goal of this dissertation was to quantify soil degradation resulting from this LU change. Two aspects of soil degradation were studied, soil organic carbon (SOC) and erosion by water. The Environmental Policy Integrated Climate biophysical simulation model (EPIC) was used to model the grassland and cropping systems. The study consisted of three steps: (1) calibration and validation of the model for the Uruguayan agroecosystems, and development of a spatial version, (2) identification of the LU change areas, and (3) quantification of soil degradation as a result of the LU changes.

The EPIC model adequately reproduced the field-scale SOC dynamics and erosion in field validation sites. Further, the spatial version of the model was found to simulate spatial and temporal performance adequately. LU change areas during 2000-2013 were mapped and found to cover an area of 410,000 ha, about 13% of potential area for commercial agriculture. LU greatly affected soil degradation. It was greatest for continuous Soybean cultivation with no crop rotation, and lowest for grassland (no conversion to cropping). In addition to LU, slope and initial SOC had significant effects on degradation.

The main conclusions were that the recent and continuing conversion from grassland to cropland has caused significant soil degradation, but that some modifications of LU can reduce the risk of degradation.

ADDRESSING THE IMPACT ON SOIL DEGRADATION OF CHANGE FROM GRASSLAND TO CROPLAND: A CASE STUDY IN THE URUGUAYAN GRASSLANDS

by

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Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park, in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2017

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Dedication

To my wife and daughters,

Lucía, Catalina and Victoria….

For love & support during my Graduate Studies

Acknowledgements

I would like to thank the National Agricultural Research Institute of Uruguay for sponsoring my PhD program. I also would like to thank the Department of Geographical Sciences of the University of Maryland, College Park for providing an additional sponsoring during the first three years of my PhD program.

I would like to thank José Terra, Andrés Berreta and Daniel Formoso for providing unpublished data from field experiments. A special thank you to Ritvik Sahajpal, Curtis Jones, Xuesong Zhang and Taras Lychuk for their helping during the continued development of the EPIC model for the Uruguayan conditions. I also thank the members of my committee, Professor Matthew Hansen, Professor George Hurtt and Professor Adel Shirmohammadi for their guidance.

I am particularly grateful to my co-advisors, Professor Stephen Prince and Research Professor R. César Izaurralde, for their mentorship and guidance during the course of my PhD studies. The combination of their insight and wealth of knowledge produced a learning experience that fostered my academic growth.

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Chapter 1: Introduction

1.1 __Background__

Human alteration of Earth is substantial and growing; conversion of land to grow crops, raise animals, obtain timber, and build cities is one of the foundations of human civilization. Between one-third and one-half of the land surface has been transformed by human action (Vitousek et al., 1997). Until 1000, croplands occupied roughly less than 1% of the global ice-free land area and pasture a similar area. In the centuries that followed, the share of global cropland increased to 2% in 1700 (c. 300 Mha) and 11% in 2000 (1,500 Mha), while the share of pasture area grew from 2% in 1700 to 24% in 2000 (3,400 Mha) change. Rapid increase in population, especially between 1700 and 2000, caused large scale conversion of natural ecosystems to agricultural land uses, 42-68% of the land surface was impacted by land-use activities, this land-use change involved conversion of 1,135 million hectares (Mha) of forest and woodland, and 669 Mha of savanna, grassland, and steppe to croplands. Similarly, the area under grazing land increased from 530 Mha to 3,300 Mha (Hurtt et al., 2006; Lal, 2007). As a result, between 1700 and 2000, the terrestrial biosphere made the critical transition from mostly wild to mostly anthropogenic, passing the 50% mark early in the 20th century. At present, and ever more in the future, the form and process of terrestrial ecosystems in most biomes will be predominantly anthropogenic, the product of land use and other direct human interactions with ecosystems (Ellis et al., 2010).

Land use and land cover change (LULCc) is an important driver of global change. These profound land-use changes have had, and will continue to have, quite considerable consequences for global and regional climates, global biogeochemical cycles such as carbon, nitrogen, and water, and biodiversity (Klein Goldewijk et al., 2011; Meiyappan and Jain, 2012). While land use provides essential ecosystem goods (food, fiber, energy), it alters a range of other ecosystem functions, such as the provisioning of freshwater, regulation of climate and biogeochemical cycles, and maintenance of soil fertility. It also alters habitat for biological diversity (DeFries et al., 2004).

Global croplands, pastures, plantations, and urban areas have expanded in recent decades, accompanied by large increases in energy, water, and fertilizer consumption, along with considerable losses of biodiversity. Such changes in land use have enabled humans to appropriate an increasing share of the planet’s resources, but they also potentially undermine the capacity of ecosystems to sustain food production, maintain freshwater and forest resources, regulate climate and air quality, and ameliorate infectious diseases. Modern land-use practices, while increasing the short-term supplies of material goods, may undermine many ecosystem services in the long run, even on regional and global scales (Foley et al., 2005). As was pointed by (Lal, 2007) agricultural expansion and its intensification, by plowing and irrigation along with use of chemicals: (1) exacerbated the problems of soil, mainly is caused by water and wind erosion, (2) increased irrigated land area to about 280 Mha or 19% of the total cropland area consuming 18,200 km3 of water in evapotranspiration or 26% of the total terrestrial evapotranspiration, (3) disrupted global biogeochemical cycling of carbon leading contributing to the increase in atmospheric abundance of CO_2 by 37.5% from 280 ppm in ~1750 to 385 ppm in 2006, (4) accentuated the use of fertilizers and pesticides to increase food production, and (5) caused mass extinction of plant and animal species.

Grasslands occur on every continent (excluding Antarctica) occupying 52 x 106 km^2, covering 40.5% of the earth's surface based on the Pilot Analysis of Global Ecosystems (PAGE) Classification (White et al., 2000). This biome is one of the most modified on Earth, as a large portion of it has been replaced by crop fields or subject to livestock grazing (Piñeiro et al., 2006). Globally, there has been large-scale conversion of grassland to human-dominated uses; of the world's 13 terrestrial biomes, 45.8% of temperate grasslands, savannahs and shrublands, 23.6% of tropical/subtropical grasslands, savannahs, and shrublands, 26.6% of flooded grasslands and savannahs, and 12.7% of montane grasslands and shrublands have been converted (Hoekstra et al., 2005).

One type of grasslands are Temperate, which accounts for a large fraction of the vegetation of the Earth (Coupland, 1992). Large expanses of temperate grasslands and derivative croplands are located at mid-latitudes in Asia, North, and South America (Sala et al., 1996). In South America, temperate grasslands encompass large units, such as the Pampa grasslands at the mesic end to the Patagonian steppe on the xeric end of the gradient (Soriano et al., 1992).

1.2 Main effects of Land use conversion on soil degradation

Conversion from grassland to cropland ecosystems often degrades soil quality.

Soil is a critically important component of the earth's biosphere, functioning not only in the production of food and fiber but also in ecosystems function and the maintenance of local, regional, and global environmental quality (atmosphere, hydrology) (Doran, 2002). Soil is the foundation for nearly all land uses and soil quality concepts are commonly used to evaluate sustainable land management in agro-ecosystems (Carter, 2002). When soils are degraded to the level that they can no longer perform their ecosystem functions, restoration is slow, expensive, and uncertain (Arshad and Martin, 2002; Scherr, 1999).

Karlen, D.L. and a committee for the Soil Science Society of America cited by Arshad and Martin (2002) defined the soil quality as : "the fitness of a specific kind of soil, to function within its capacity and within natural or managed ecosystem boundaries, to sustain plant and animal productivity, maintain or enhance water and air quality, and support human health and habitation". Maintenance and improvement of soil quality in continuous cropping systems is critical to sustaining agricultural productivity and environmental quality for future generations (Reeves, 1997). Quantitative, measurable properties are needed to study the effects of specific changes of soil quality and as a result soil degradation. These properties, soil quality indicators, are measurable soil attributes that influence the capacity of soil to perform crop production or environmental functions, attributes that are most sensitive to management are most desirable as indicators (Doran and Zeiss, 2000). In a given agro-climatic region, the measurable soil attributes that are primarily influenced are: soil-depth, organic matter, respiration, aggregation, texture, bulk density, infiltration, nutrient availability and retention capacity. Many of these soil indicators interact with each other (Arshad and Martin, 2002).

Soil organic Carbon (SOC) or Soil Organic Matter (SOM) is one of the principal indicators of sustainability and soil quality, given it influence on many other soil properties (Causarano et al., 2007). Without doubt, SOM is the most used quality indicator (or organic carbon), although it is strange that this property is not more widely used in establishing the quality of non-agricultural soils too, since soil organic matter is related with crop growth but also with plant growth in natural conditions, where vegetation is essential for avoiding degradative processes or where it may have a buffering effect on some contaminants (Bastida et al., 2008).

Soil organic matter (carbon) influences numerous soil properties relevant to ecosystem functioning and crop growth. Soil organic matter in croplands is a key to water-holding capacity, nutrient availability, and carbon sequestration (Foley et al., 2005). Total SOM influences soil compactibility, friability, and soil water-holding capacity while aggregated SOM has major implications for the functioning of soil in regulating air and water infiltration, conserving nutrients, and influencing soil permeability and erodibility (Carter, 2002). Even small changes in total C content can have disproportionately large impacts on key soil physical properties; practices to encourage maintenance of soil C are important for ensuring sustainability of all soil functions (Powlson et al., 2011). Soil microorganisms decompose dead roots and above-ground residues of plants and animals. Decomposition results in the release of carbon as CO_2 or, under highly anaerobic conditions, as CH_4, but also in the formation of soil humus or organic matter, the principal store of organic C in soils

(Wood et al., 2000). Storage of C compounds in grasslands soils are an effective way for carbon sequestration (Lal, 2002).

Conversion of natural to agricultural ecosystems in the USA has depleted the SOC pool by 3 to 5 Pg (Lal, 2002). Soils of the world's agroecosystems (croplands, grazing lands, rangelands) are depleted of their soil organic carbon (SOC) pool by 25–75% depending on climate, soil type, and historic management. The magnitude of loss may be 10 to 50 tons C ha^{-1}). Soils with severe depletion of their SOC pool have low agronomic yield and low use efficiency of added input. Conversion to a restorative land use and adoption of recommended management practices, can enhance the SOC pool, improve soil quality, increase agronomic productivity, advance global food security, enhance soil resilience to adapt to extreme climatic events, and mitigate climate change by off-setting fossil fuel emissions (Lal, 2011).

One of the management practices that most influence the soil quality is tillage technology. The adoption of no-till practices has resulted in greater storage of precipitation and water use efficiency, which has led to higher productivity, more diverse crop rotations, and improvements in soil properties. In Colorado (USA), for example, a no-till rotation of winter wheat–maize–fallow increased total annualized grain yield by 75% compared to winter wheat–summer fallow. Soil erosion was reduced to just 25% of that from a conventional tillage wheat–summer fallow system. A risk of reducing fallow frequency is the increase in yield variability and risk of crop failure (Hansen et al., 2012). But, even though without tillage, there are some findings, as presented by DuPont et al.

(2010), that conversion from perennial grassland species to annual crops reduced belowground root biomass to 43% of prior biomass. These authors also found that, three years after conversion, readily decomposable C and microbial biomass in the top 40 cm soil depth were significantly lower in annual never-tilled cropland than in perennial grassland.

Soil erosion is a major environmental threat to the sustainability and productive capacity of agriculture. During the last 40 years, nearly one-third of the world's arable land has been degraded and abandoned because of erosion processes that continue even today at annual rates larger than 10 million hectares. Croplands are the most susceptible to erosion because the soil is repeatedly tilled and often left without sufficient protective cover (Pimentel et al., 1995). Erosion results when rainfall, runoff, and wind carrying kinetic energy impact and destroy soil aggregates. Raindrops hit exposed soil with an explosive effect, launching soil particles into the air. In most areas, raindrop splash and sheet erosion are the dominant forms of erosion. Erosion increases dramatically on steep cropland. Living and dead plant biomass left on fields reduce soil erosion and water runoff by intercepting and dissipating raindrop and wind energy. Both the texture and the structure of soil influence its susceptibility to erosion; additionally slope of the land, soil composition, and extent of vegetative cover influence the rate of erosion. Soils with medium to fine texture, low organic matter content, and weak structural development have low infiltration rates and experience increased water runoff (Pimentel et al., 1995).

On-site effects: When erosion occurs, the amount of water runoff increases, so that less water enters the soil matrix and becomes available for the crop. In addition to creating water deficiencies, soil erosion causes shortages of basic plant nutrients, such as nitrogen, phosphorus, potassium, and calcium, which are essential for crop production. Finally, due to most of the organic matter is near the soil surface in the form of decaying leaves and stems, erosion of topsoil results in a rapid decrease in levels of soil organic matter. Several studies have demonstrated that the soil removed by either wind or water erosion is 1.3 to 5 times richer in organic matter than the soil left behind (Pimentel et al., 1995). As a result of this negative effects the crops yields are affected, as reported by Izaurralde et al. (2006a) where they found grain yield reductions due to simulated soil erosion were either linear or curvilinear functions of nutrient removal.

Off-site effects: erosion not only damages the immediate agricultural area where it occurs but also negatively affects the surrounding environment. Off-site problems include roadway, sewer, and basement siltation, drainage disruption, undermining of foundations and pavements, gullying of roads, earth dam failures, eutrophication of waterways, siltation of harbors and channels, loss of reservoir storage, loss of wildlife habitat and disruption of stream ecology, flooding, damage to public health, plus increased water treatment costs (Pimentel et al., 1995).

Secondary soil biophysical and biochemical indicators. Bulk density affects plant growth because of its effect on soil strength and soil porosity; with increasing bulk density, strength tends to increase and porosity tends to decrease; both tend to be limiting to root growth at some critical values (Kwong, 2007). Other indicator is the available water capacity (AWC) is defined as the amount of water (cm3 water=100 cm3 soil) retained in the soil between the ‘‘field capacity’’ (FC) and the ‘‘permanent wilting point’’ (PWP); field capacity and permanent wilting point are defined as the volumetric fraction of water in the soil at soil water potentials of 10–33 and 1500 kPa, respectively (Tom, 2007); often there is a linear relationship between plant available water and yield and between plant available water and leaf growth, within limits (Ritchie and Argyrios, 2007). Finally, plant nutrients, apart from water shortages, is the major constraint on the plant growth and yield, increased crop production can be achieved through enhanced soil fertility, which can only be sustained if the nutrients removed from the soil are replenished through addition (Kanwar, 2007).

1.4 Study area: Uruguayan grasslands

The Río de la Plata grasslands in South America are one of the largest temperate grassland regions of the world, occupying more than 700,000 km^2 distributed across eastern Argentina, Uruguay and southern Brazil (Soriano et al., 1992). This region is the most extensive biogeographic unit of the prairie biome in South America; it has been extensively modified by human activities (Guerschman et al., 2003). Finally, this region plays a key role in national crop and animal production as well as international trade resulting in land-use change rates among the highest within the historical record.

Uruguay is in the southeast of South America, between 30º and 35º south and 54º and 59° west. The total land area is 176,215 km^2. The topography is rolling plains with a maximum height of 514 meters. The climate is temperate, with a range of rainfall between 1,100 – 1,300 mm year^{-1}, the mean temperatures are 11C° in winter and 27C° in summer, and the extreme temperatures are maximum 40C ° and minimum - 4C°. The main ecosystem is Grasslands associated with riverside bush forest and the soils are Prairie Soils slightly acid (Mollisols) (Berreta, 2003; Castaño et al., 2011).

This region has a long history of land use change. For the last 10,000 years, soils developed under prairie vegetation where the trees were almost absent only restricted to riparian areas and some isolated rocky soils. The first European settlers introduced domestic herbivores (cattle, horses and sheep) in the mid-1500s, but their density became significantly by 1600 (Soriano et al., 1992). Cattle and horses were the first large domestic herbivores introduced to the region in 1611 and sheep increased in number by the mid-nineteenth century. This human action, through the introduction of domestic animals to the natural grassland system, has caused changes in vegetative life forms so grazing is the main factor which keeps the grasslands in a herbaceous pseudo-climax phase (Berreta, 2003).

Historic LU change of Uruguay. Livestock density rapidly increased and became stable by 1900, once all land was fenced, at high stocking rates (currently ranging 178–302 kg/ha), consuming from 30% to 60% of annual ANPP (Piñeiro et al., 2006). The present state of natural pastures is far from its potential. Under climax conditions, there would be a prevalence of bushes and tall grasses of low palatability and nutritive value; though they can be biologically productive, they would be poorly suited to feeding cattle and horses; therefore, the present situation of pastoral disclimax seems to be more suitable for feeding grazing animals (Berreta, 2003). During the XX century the commercial agriculture was developed in the better soils using traditional tillage technics. Finally, since 2000 there has been a change from traditional to no-tillage agriculture (García-Préchac et al., 2004)

Currently, the Uruguayan agro-ecosystem is composed of two main sub-systems, which usually coexist in the same farm, one is the Natural Grasslands and the other is the Croplands. The Natural Grassland sub-ecosystem is characterized by domestic herbivores grazing the evolved natural pasture during all year (continuously), the herbivores are bovine and also ovine grazing together and the grassland is defined as a vegetative cover formed by grasses along with herbs and associated shrubs, where trees are scarce. This grassland is an environment with great richness in grass species (~400) of summer (C4) and winter (C3) habits with perennials predominating over annuals. Of this great number of species only 10 (mostly C4) are the main contributors of the annual forage production, which averages 3-4 DM ton/year (Berreta, 2003). The Cropland sub-ecosystem is a commercial rainfed crop production system where the main crops are soybean in summer and wheat in winter all produced with no-tillage, based on (MGAP-DIEA, 2015) about half of the crop area rotate summer-winter and the other half only make summer-summer rotation (Figure 1.1). Finally, the land tenure of Uruguayan agro-ecosystem is all private lands, but a high percent of the crop areas are rented and the average farm size is 775 ha (MGAP-DIEA, 2015).

The main reasons to select Uruguay as the study area are: it still has a high percentage of grasslands in contrast with other regions, but this area is threatened by the recent LULC change. Previous studies in the Río de la Plata region, within the period between 1985 and 2003, found that the area covered by grassland decreased from 67.4 to 61.4% between the study periods (MGAP-DIEA, 2012). During the last 12 years there was an expansion of the cropland area in Uruguay, mainly soybean and wheat, from 200,000 ha in 1999 to more than 1,400,000 ha in 2010 (Figure 1.1), and this process has been more intensive since 2002. As a result of this expansion, grasslands were converted to croplands. Additionally, another reason for this selection is the available data to perform this research.

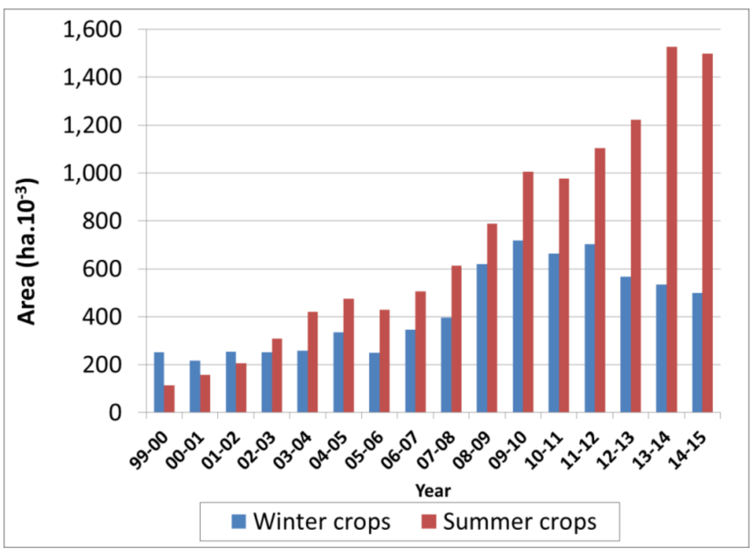


Figure 1.1 Crop area evolution from 2000 to 2015 extracted from (MGAP-DIEA, 2015).

This research was conducted using the natural grassland regions of the Republic of Uruguay (Uruguay) as the study area. The research was conducted in two of the Agro-ecological regions of Uruguay (Ferreira, 2001) that historically were mainly natural grasslands due to their specific capabilities: Zone 2 East “Sierras” and

Zone 4 Granitic (Crystaline) also called "Southern Campos" sub-region (Soriano and Paruelo, 1992), it is located in the Middle South of Uruguay where soils support natural grassland and have limited crop use capabilities (marginal lands) (MGAP-RENARE-DSA, 2003). The main reasons to select this study area are: (1) Uruguay still has a high percentage of natural grasslands in contrast with other regions of the world; (2) this area was being used for grazing beef cattle more than 100 years, one of the main exported products of this country, but nowadays this area is threatened by a recent LULC change from grasslands to croplands and 3) the availability of the data to perform this research.

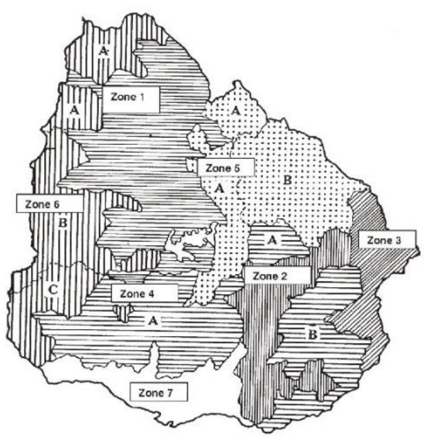


Figure 1.2 Uruguayan Agroecological zones (Ferreira, 2001)

1.5 Research Objectives

The overall goal of this research was to temporally and spatially identify and quantify the possible impacts on the soil degradation (quality) resulting from the conversion of natural grassland to cropland ecosystem under different land use. Even though, the land use change from one ecosystem to the other, as was mentioned before, could impact on: soil, plants, atmosphere, geology and hydrology, the focus of this research will be in the soil component, which is the most affected by the anthropogenic processes (management) (Sands and Podmore, 2000), with a main focus in the soil quality or health as quantitative indicators of degradation. The following issues, even though could be related to the main question, are not addressed in this research: the economic sustainability, the social impacts, possible chemical contamination (ex: pesticides) and the impacts on biodiversity and on climate.

Assessing the soil degradation or loss soil health or of agricultural systems in a quantitative manner requires the identification and integration of diverse phenomena or ‘indicators’ of environmental effects. Although selection of soil indicators will vary with societal goals, as presented by (Arshad and Martin, 2002) the followings seem to be suitable indicators for crop production in most cases: organic matter, topsoil-depth, infiltration, aggregation, pH, electrical conductivity, suspected pollutants and soil respiration. Crop yield can be used as an integrator of the foregoing soil indicators. For this research, based on previous researches, the scale (regional) and the available soil data, the two following quality indicators were selected as the main indicators: soil carbon and topsoil loss (erosion).

Previous research had been focused on different aspects of the soil degradation of each type of ecosystems grassland (Piñeiro et al., 2006) and croplands (Baethgen, 2003) but there are no previous studies that address the impacts of the transition of the first one to the second one. Additionally, previous researches did not address the effect of LUC in marginal lands and also did not consider the impact of erosion on the soil degradation. Finally, most of the previous research was conducted at a field scale or small regions.

The main hypothesis is: as a result of the conversion of grassland to cropland is expected during medium to long-term a soil degradation which could include soil C and N losses, degradation of physical proprieties, soil loss (erosion) and finally negative effects on NPP at a regional to country level scale. These expected impacts could be different as a result of the influence of the biophysical and the anthropogenic drivers.

To test this hypothesis the following research, with two main steps, was done. The first step was the identification of the LUC of the study area based on remote sensing since there are no quantitative data on the patterns and rates of land cover changes available (Chapter 3). The second step was the quantification of the potential impact on the soil quality in the medium-term of this LUC changes using a bio-physical simulation model, analyzing how the biophysical and anthropogenic drivers could affect these potential impacts (Chapter 2 and Chapter 3). The biophysical drivers to study was geomorphology (soils, slope) and the anthropogenic drivers to study were: land use change scenarios and land use management (crop rotation, tillage, crop management)

1.6 Outline of Dissertation

The dissertation consists of four chapters. Chapter 1 (a) reviews the topic of soil degradation as a result of conversion from grassland to cropland ecosystem, (b) presents research questions and objective, and (c) describes the study area.

Chapter 2 presents and tests a data-modeling system designed to simulate field-scale crop productivity and soil processes under grassland and cropland covers in South-Central Uruguay. This is achieved through the calibration and testing of the terrestrial ecosystem model EPIC using local data (e.g., plant productivity, crop yields, soil erosion, and soil carbon dynamics). Also, it describes the development and testing of a spatial EPIC, calibrated and validated for Uruguayan agroecosystem conditions. Finally, addresses the potential impact on C fluxes due to LULC from grassland to cropland during a 15-year period at regional scales.

Chapter 3 utilizes the temporal and spatial results to quantify soil degradation (loss of soil quality) resulting from the conversion of grazed grassland to cropland under different land use change including the influence of anthropogenic (management) and geomorphological processes.

Finally, Chapter 4 summarizes the findings, discusses the main implications and limitations of the findings, and how these limitations may be addressed in future research.

Chapter 2: Simulating field-scale carbon dynamics of natural grassland and cropland ecosystems of Uruguay using the EPIC model

2.1 Introduction

Temperate grasslands, a major type of grasslands, account for a large fraction of the Earth's vegetation (Coupland, 1992). Large expanses of temperate grasslands and derivative croplands are located at mid-latitudes in Asia, North America, and South America (Sala et al., 1996). In South America, temperate grasslands encompass large units, such as the Pampa grasslands, one of the largest temperate grassland regions of the world, occupying more than 700,000 km^2 distributed across eastern Argentina, Uruguay and southern Brazil (Soriano et al., 1992). This region, the most extensive biogeographic unit of the prairie biome in South America, has been extensively modified by human activities (Guerschman et al., 2003).

Currently, this region contributes significantly to the domestic and international trade of crop commodities and thus it has been experiencing extensive and intensive changes in land use and cover (Altesor et al., 2006; Vega et al., 2009). These ongoing changes in land use and cover are presumably impacting carbon cycling dynamics and soil erosion processes. This conversion from grassland to cropland ecosystems is achieved through the use of tillage implements to prepare seedbeds, control weeds and apply nutrients. Often, this tillage disturbance enhances soil organic matter oxidation (loss of soil carbon), soil structure deterioration, and soil erosion all negatively impacting soil quality and ecosystem services (Lal, 2002).

Uruguay, in contrast with other regions, still has a high percentage of grasslands vulnerable to land-use change. During 1999-2010, Uruguay expanded its cropland area from 200,000 to >1,000,000 ha, mainly due to soybean (*Glycine max* (L.) Merr.) and wheat (*Triticum aestivum* L.) cropping. During the same period, the area under grassland cover decreased from 67.4 to 61.4% (MGAP-DIEA, 2012). This process mainly took place in the South-Central Uruguay region (MGAP Uruguay et al., 2011). However, a quantification of the intensity and extent of the impacts of the land-use and management changes on soil quality is currently lacking.

To address this important topic, the EPIC (Environmental Policy Integrated Climate) model was selected to simulate key agro-ecological processes associated with grassland-cropland conversions such as: plant growth, plant yield, water balance, soil erosion, soil carbon dynamics, nutrient cycling, and greenhouse-gas emissions (Izaurralde et al., 2006b; Williams et al., 1984). Previous studies in Uruguay used the Century model (Baethgen, 2003; Parton et al., 1988), but Century was not deemed appropriate for this study since it does not explicitly simulate land degradation processes such as soil erosion (Caride et al., 2012; Baethgen, 2003).

Globally, there is a need to better quantify carbon budgets and fluxes (stock, emission and sequestration) of managed ecosystems at different spatial scales using the best available technology (UNFCCC, 2003). There is a lack of a systematic and extensive collection of C budget field data and, consequently, the spatial estimations are suggested to be obtained using process-based agroecosystem models (Smith et al., 2012). The EPIC model (Williams, 1995), was used to simulate C fluxes over the US croplands regions (Causarano et al., 2008; Zhang et al., 2015) and other regions of the world (Billen et al., 2009).

The objectives of this research were to: 1) develop and test a data-modeling system to simulate field-scale crop productivity and soil processes under grassland and cropland covers in South-Central Uruguay. This was achieved through the calibration and testing of EPIC using local data (e.g., plant productivity, crop yields, soil erosion, and soil carbon dynamics), 2) develop a spatial version of the EPIC model adapted to Uruguayan agro-ecosystems, following the point scale calibration and validation of the model, and 3) address the potential C-flux impacts of Land Use (LU) change from grassland to cropland during a 15-year period, evaluating the capability of the EPIC model to simulate regional-scale grassland and cropland C fluxes on the Uruguayan Agro-ecosystem.

These steps were necessary to run EPIC at a regional scale in South-Central Uruguay to evaluate crop and soil productivity under contemporary grassland-cropland conversions and future climate, land-use, and management scenarios. To our knowledge, this is an original contribution in which the EPIC model is employed to simulate grassland productivity and soil quality under conditions of the Rio de la Plata grasslands.

2.2 Materials and methods

2.2.1 Study are area

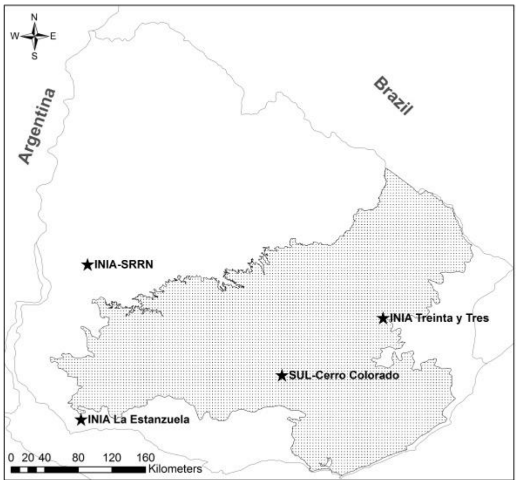


Figure 2.1 Map of Uruguay, showing the study area (gray zone) and the study sites

Uruguay is located in the southeast of South America, between 30º and 35º South and 54º and 59° West. The total land area is 176,215 km^2. The region is dominated by rolling plains reaching a maximum elevation of 514 m. The climate is temperate, with a range of rainfall between 1,100 – 1,300 mm yr^{-1}, mean temperatures of 11°C in winter and 27°C in summer, and extreme temperatures of - 4°C and 40°C. The main ecosystem is Grasslands associated with riverside bush forest. Soils are slightly-acidic Prairie Soils (Mollisols) (Berreta, 2003; Castaño et al., 2011). The "Southern Campos" sub-region (Soriano and Paruelo, 1992) was selected as the study area (Figure 2.1), it is located in the Center-South of Uruguay where soils support natural grassland and have limited crop use capabilities (MGAP-RENARE-DSA, 2003).

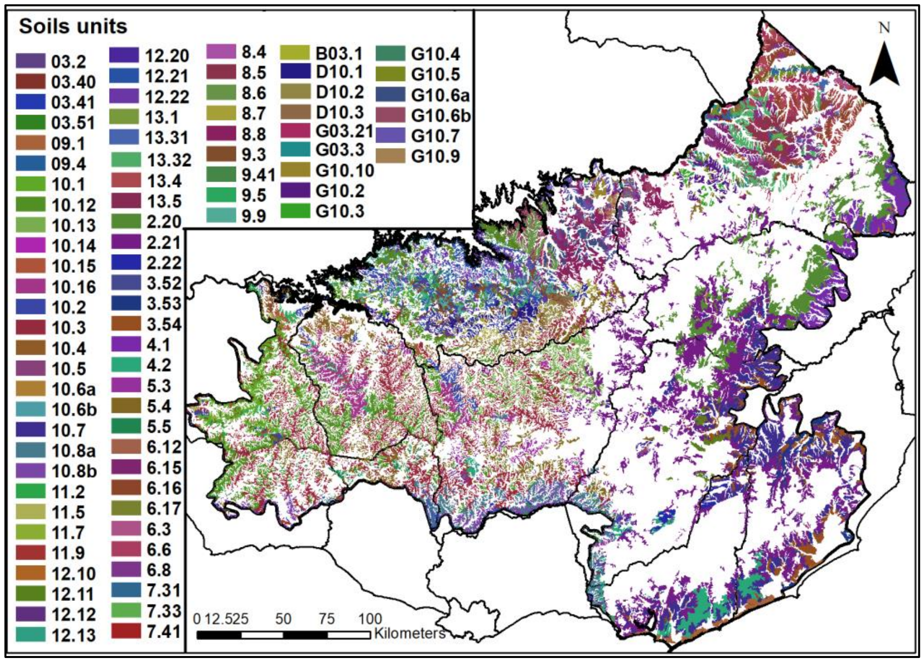


Figure 2.1 Map of the study area showing the soils units (CONEAT) suitable to grow cash crops.

As the final objective of the this research was to address the potential impacts of LU change on land (soil units) that was deemed suitable for growing cash crops (Figure 2.2) according to soil classification made by MGAP-RENARE-DSA (2003) of the CONEAT soil maps (Capurro Etchegaray, 1977), which classified soil units as suitable, less suitable, marginal and no suitable for crops.

2.2.2 Uruguayan agro-ecosystem

Currently, the Uruguayan agro-ecosystem is composed of two main sub-systems, which usually coexist in the same farm: a) Natural Grasslands and b) Croplands. The Natural Grassland sub-ecosystem is characterized by domestic herbivores continuously grazing the evolved natural pasture; the herbivores are bovine and also ovine grazing together. The grassland (natural pasture) is defined as a vegetative cover formed by grasses along with herbs and associated shrubs, where trees are scarce; it is an environment rich in grass species (>400 species) with a high proportion of summer species (C_4) in comparison to winter species (C_3). Several perennials of different botanical families predominate over annual species. However, of this great diversity of species, only 10 are the main contributors to the annual forage production, which averages 3 - 4 Mg DM yr^{-1} with the most frequent being: *Andropogon ternatus, Rottboellia selloana*, *Paspalum notatum*, *Paspalum plicatulum*, *Paspalum dilatatum*, *Bothriochloa laguroides*, *Axonopus affinis, and Aristida murina* (Berreta, 2003).

The Cropland sub-ecosystem is a commercial rain-fed crop production system where the main crops are soybean in summer and wheat in winter all produced with no-tillage; based on MGAP-DIEA (2012) about half of the crop area rotates summer-winter and the other half supports a summer-summer rotation. In the study area, the main winter crop planted is wheat and the main summer crop planted is soybean followed by sorghum (*Sorghum bicolor* (L.) Moench). All land in the Uruguayan agro-ecosystem is under private tenure with a high percentage being rented. The average farm size is 775 ha (MGAP-DIEA, 2012).

2.2.3 Description of the EPIC model and inputs

The Environmental Policy Integrated Climate (EPIC) Model is a computer model originally developed to simulate the impacts of water and wind erosion on crop and soil productivity throughout the United States during the 1980's (Williams et al., 2008a). Since its first development and application, EPIC has evolved into a comprehensive agro-ecosystem model capable of simulating the growth of crops grown in complex rotations and management operations, such as tillage, irrigation, fertilization and liming (Izaurralde et al., 2006b). EPIC has been continuously improved through the additions of algorithms to simulate water quality, climate change and the effect of atmospheric CO_2 concentration, as well as nitrogen, carbon, and phosphorus cycling (Izaurralde et al., 2012). Operating at field / small watershed spatial scales and at daily time step, EPIC contains physically-based algorithms to simulate soil and crop processes such as crop growth, erosion, nutrient balance, and related processes. It is designed to simulate homogeneous areas that are characterized by a common weather, soil, landscape, crop rotation, and management. The processes simulated include leaf interception of solar radiation, conversion to biomass, division of biomass into roots, above ground biomass, and economic yield, root growth, water use, and nutrient uptake (Gassman et al., 2005). The main inputs needed to run EPIC are: daily weather (maximum and minimum temperature and rain), soil-layer properties (soil layer depth, texture, bulk density, and C concentration among others), and site characteristics (latitude, longitude, elevation and slope) (Williams et al., 2006).

This study was focused on three main EPIC sub-models/process: 1) crop sub-model, 2) Carbon-Nitrogen sub-model, and 3) (water) erosion process. EPIC uses a single plant growth model to simulate about 100 plant species, including crops (annual and perennial), native grasses, and trees; each characterized by a unique set of parameter values. It uses the concept of radiation-use efficiency (Williams et al., 2008b) by which a fraction of daily photosynthetically active radiation is intercepted by the plant canopy and converted into plant biomass. Plant phenology is controlled via heat-unit calculations where each crop/plant species has base and optimal air temperatures for growth. Potential daily gains in biomass are affected by environmental stresses such as water, temperature, nutrients (primarily N and P), and aeration (Parton et al., 1988). The coupled carbon-nitrogen C:N sub-model follow the approach used in the Century model (Izaurralde et al., 2006b), where the C and N in soil organic matter are distributed among three pools or compartments: active (microbial), slow and passive; these pools differ in size and function while their turnover times range from days to hundreds of years (Izaurralde et al., 2006b). The EPIC module for water-induced erosion simulates erosion caused by rainfall and runoff and by irrigation (furrow, sprinkler, and drip). Five USLE-based erosion models (USLE, RUSLE, AOF, MUSLE and MUSL), are used in EPIC to simulate water erosion caused by rainfall and runoff as regulated by topography, soil properties, and management (Apezteguía et al., 2009).

2.2.4 Calibration and validation of the EPIC model at a field scale

Even though EPIC is flexible enough to perform under a variety of environments, there was no prior experience using the model to simulate the Uruguayan agroecosystem. Consequently, there was a need to calibrate and validate the model. Usually the calibration process includes a successive modification of the model parameters using the weather, soils, land-use and agronomic conditions of the study area until the desired reproduction of this environment is achieved (Bernardos et al., 2001). This process was performed independently for the grassland and the cropland ecosystems because these ecosystems have very different management and development conditions. Sources of data for field calibration are given in the next section in Tables 2.1 and 2.2.

Two approaches were used to evaluate the model performance during calibration and validation steps. In the first approach, when replicated observational data were available, two standard statistical tests were conducted: 1) t-test to evaluate the probability that modeled and observed means were the same and 2) regression analysis to test if the modeled and field data were correlated (significance of the coefficient of determination and of the slope). The second approach, in few instances when observational data were insufficient, a “semi-quantitative” analysis (without statistical significance) was performed combining comparisons of modeled data against quantitative sparse data (e.g. data from sparse bibliographic sources, national statistics, databases) and finally expert assessment of modeled results by local researchers; with this sources combined a “semi-quantitative” evaluation of the reliability of these results was done.

2.2.4.1 Sources of data for field calibration

Table 2.1 Study sites for field calibration.

Site	Latitude	Longitude	Altitude (m)	Dominant soils
INIA* Treinta y Tres Research Station (INIA-TyT-RS)	33°:15’36"S	54°:29’26"W	60	Abruptic Argiaquolls and Oxiaquic Vertic Argiudolls
INIA La Estanzuela Research Station (INIA-LE-RS)	34°20'33"S	57°43'25"W	80	Typic, mesic, Argiudoll
INIA-SRRN**	32°40'53"S	57°39'29"W	70	Argiudolls and Hapludolls
SUL** Cerro Colorado Research Station (SUL-CC-RS)	33°52'11"S	55°34'19"W	205	Hapludolls and Argiudolls
*INIA: National Agricultural Research Institute of Uruguay. **SRRN: Rural Society of Río Negro. ***SUL: Uruguayan Wool Secretariat				

Table 2.2 Sources of data for field calibration.

Class	Variable	Description	Sources	Temporal Coverage	Temporal resolution
Grassland	Forage yield	Historical	Centro-Sur: (Formoso, 2005; Risso and Scavino, 1978) Este: (Mas, 1978) (Ayala et al., 1993)	1970-2000	Seasonal and annual averages
	Forage yield	INIA TyT Grassland experiment	(Bermudez and Ayala, 2005)	1992-2004	Seasonal and Yearly
	Forage yield	Cerro Colorado experiment	Formoso, D. (pers. com.)		Seasonal and Yearly
	Soil carbon	INIA Treinta y Tres grasslands experiments.	Terra et al. (pers. com. (Salvo et al., 2008) (Ayala, W. pers.com.)		
Cropland	Crop grain yield	Historic	(MGAP-DIEA, 2012)		Yearly averages
	Crop grain yield	INIA LE crop evaluation experiments	(Castro and Coutiño, 2014)		
	Crop grain yield	INIA-SRRN crop evaluation experiments	(Castro and Coutiño, 2014)		
	Crop grain yield	INIA TyT crop rotation experiment	Terra et al. (pers. com.)		
Erosion	Soil loss	Outputs of RUSLE equations database	(García Préchac et al., 2009)		
Climatic	Precipitation, Temperature, solar radiation, wind		(INIA Uruguay - GRAS Unit, 2016) and INUMET (pers. com.)	1970-2015	Daily
Soil profiles	Layer depth, soil carbon, pH, CIC,		Department of Agriculture and Fishery (MGAP) pers. com.		

2.2.4.2 Simulation of the Grassland ecosystem

In order to simulate the grassland ecosystem the following calibration / validation steps were performed according to guidelines provided in the EPIC user's guide (Williams et al., 2006) for 1) grass forage yields, 2) water erosion, and 3) soil carbon. The first objective was to achieve the mean historic annual and seasonal forage yield extracted from published literature (Table 2.2). The strategy to achieve this objective was to select and adapt a grass species from the crop database available in EPIC to build the "Grassland Uruguay crop". Summer grass crop (SPAS) was selected from this database, based on that the composition of the Uruguayan grassland species is dominated by summer grasses, with a C_4 photosynthetic pathway (Berreta, 2003). The main modifications, to reflect the characteristics of the dominated species on the study area, were made in the following crop parameters: WA, DMLA, PP, HMX and HU based on the experience of previous researches where the adaptation of EPIC model crops were made (Adejuwon, 2005; Causarano et al., 2008) (Table 2.3).

Table 2.3 EPIC crop parameters of “Grassland Uruguay crop”.

Parameter	Description	Original value *	Modified value
WA	Biomass-Energy Ratio (kg ha^{-1} MJ^{-1})	35.0	30.0
DMLA	Maximum potential leaf area index (m^2 m^{-2})	5	2
HMX	Maximum crop height (m)	1.0	0.5
PP	Plant population (no. m^{-2})	---	10
HU	Potential heat units (°C)	---	1500

* Source: EPIC crop database.

The model was parameterized and tested with forage field data measured seasonally from two sites. One is INIA-TyT-RS, located in Treinta y Tres in the South-East and the other is a SUL-CC-RS located in Cerro Colorado, Florida in the South-Center (Table 2.1).

After the model was able successfully to simulate forage production, the next step to complete the carbon cycle of this ecosystem was the addition of the grazing component. Although the EPIC has a grazing routine, it was found that the best option was to use a simulated grazing, using two EPIC’s operations: “hay cut” to simulate the grazing by animals (C output) and “manure addition” to emulate the nutrient return to the soil (C return) by dung. This process was done monthly and the input and output values were taken from the following computation: the animal dry matter intake (hay cut) was based on an average animal stock of 0.75 beef cow of 400 kg per hectare (MGAP-DIEA, 2012), the animal requirement of forage dry matter (DM) is 2% of the body weight (bw) per day (INIA Uruguay et al., 2012; IPA Uruguay, 2012); resulting in a daily consumption is 6 kg of DM ha^{-1} or about 2.20

Mg ha^{-1} $year^{-1}$. However, given than the average animal forage utilization (net consumption) is 65% of the consumed (IPA Uruguay, 2012), the required cut forage is 9.2 kg of DM ha^{-1}, from which 6 are consumed (output) and 3.2 kg of DM ha^{-1} are returned to the soil as litter. Based on this computation, the required dry matter is 3.32 Mg ha^{-1} $year^{-1}$ which agrees with the reported forage production of this area (Formoso, 2005; Risso and Scavino, 1978). Finally, the manure added (C return) was 1.1 kg ha^{-1} considering that there is an 18% of the dry matter forage intake that is returned with the manure (Piñeiro et al., 2006).

The last step was to test the model's capability to reproduce soil losses caused by water erosion and soil carbon dynamics as affected by residue additions, microbial respiration, and carbon losses with soil sediments, runoff, and leaching. As described before, the EPIC model has several equations available to simulate water erosion. Based on previous research conducted in Uruguay (Clérici C., 2001), the equation selected was the Revised Universal Soil Loss Equation (RUSLE). Due to the lack of available measured data, the model outputs were compared against local estimates obtained by the RUSLE equation (Clérici C., 2001) previously incorporated into a computer program called Erosion UY (García Préchac et al., 2009). Finally, the soil carbon model in EPIC was tested with measured soil carbon from two experiments at the INIA-TyT-RS (Table 2.1). Data from these experiments consisted of temporal measurements of soil carbon stocks in the top 15-cm soil depth.

2.2.4.3 Simulation of the Cropland ecosystem

As described above, the cropland ecosystem consisted of a rotation of winter and summer crops. Consequently, the model calibration was made using the three main crops (wheat, soybean and sorghum) in a 2-year rotation, following the general modeling procedures applied by Causarano (2007) and Apezteguía (2009). Considering the best agronomic practice in order to conserve the soil, the crop sequence in the study region (independent agronomy consultants pers. com.) consists of wheat planted in late autumn, harvested in late spring, then soybean planted immediately and harvested in early autumn, then a second wheat planted in late autumn, harvested in late spring, finally sorghum planted in late spring and harvested in mid-autumn.

Similar to the process applied to calibrate the grassland system, the first step in the calibration of the model in cropland conditions in the study area was to simulate historical grain yields using data available from national statistics (MGAP-DIEA, 2012) and crop-cycle details of the three crops (Castro and Coutiño, 2014). It was taken from the EPIC crop database the three study crops (spring wheat, soybean and sorghum) and the EPIC´s crop parameters were modified based on the experience of previous research (Causarano et al., 2007), the main adjustments at this stage were the crop heats units and PARM7 (Table 2.4).

Table 2.4 EPIC's cropland parameters.

EPIC global parameters:				
Parameter	Description	Original value*	Modified value	
PARM7	N fixation			
PARM12	Soil evaporation coefficient	2.50	2.35	
PARM35	Water stress weighting coefficient	1.00	0.58	
PARM61	Weighting factor for estimating soil evaporation	0.80	0.83	
EPIC crop parameters				
Parameter	Description	Crop	Original value	Modified value
WA	Biomass-Energy Ratio (kg ha^{-1} MJ^{-1})	Soybean	30.0	20.2
		Sorghum	37.0	30.0
HI	Harvest index	Soybean	0.35	0.30
		Sorghum	0.50	0.45

* EPIC crop database

In order to obtain a better adjustment, as a second stage, an automatic calibration using a parameter optimization algorithm was performed. It was done with the HydroPSO package (Zambrano-Bigiarini and Rojas, 2013) of the R statistical software (R Development Core Team, 2013); this package is model-independent R package, which the main focus is the calibration of environmental and other real-world models. It implements a modified version of the Particle Swarm Optimisation

(PSO) algorithm to meet specific user needs and optimizes based on a user defined goodness-of-fit measure until a maximum number of iterations or a convergence criterion is met. It allows the user to perform model calibration and assessment of the results (Zambrano-Bigiarini and Rojas, 2013).

To perform this calibration step, measured data of grain yield from a 10-year crop yield experiment (sorghum, soybean and wheat) from the site INIA-LE-RS (Table 2.1) was used. Five EPIC variables were utilized in the process, three EPIC Parameters: PARM12, PARM35 and PARM61 and two crop parameters from the soybean and sorghum crops: WA and HI (Table 2.4).

The validation of the crop grain yield modeled was performed using data from two experiments. A crop yield experiment in the INIA-SRRN (Table 2.1), this experiment is a replication of the INIA-LE-RS experiment conducted in another site. The other experiment that it was used is a two year no tillage crop rotation (wheat-soybean, wheat-sorghum) located in the INIA-TyT-RS (Table 2.1).

Similar to the model calibration and testing performed for grassland systems, the last step was to test the capability of EPIC to reproduce soil erosion and soil carbon dynamics in cropland systems. To test the model performance on the soil erosion in croplands the local calibrated equations were used (García Préchac et al., 2009). Finally, the modeled soil carbon was tested with measured soil carbon from a crop rotation experiment located in the INIA-TyT-RS, the available data were carbon measurements made up to 15 cm depth.

2.2.5 Development, calibration and validation of EPIC model at a regional scale

The next step was the development, calibration and validation of EPIC model at a regional scale. The development included the following steps: 1) building of a geospatial database with the required data, 2) building of the Homogenous spatial modeling units (HSMU) and 3) building of faster computation environment using a parallel model running environment.

2.2.5.1 Geospatial database

2.2.5.1.1. Soils layer

The CONEAT soil groups (CONEAT) was used as a base layer of soils. These CONEAT groups are not strictly basic cartographic soil units, but are homogeneous areas defined by its production capacity (productivity), which is considered as the initial capacity of the soil to produce a certain yield per hectare per year (MGAP-RENARE-CONEAT, 1994). These groups were characterized by aerial photo interpretation at scale 1:40,000 together with field verifications and physical and chemical soil analyses (Capurro Etchegaray, 1977).

The defining characteristics of the CONEAT soil groups (properties of soils and associated landscape features) were based on the dominant and associated soils according to the Soil Classification of Uruguay (MGAP-RENARE-DSA, 1976a), where each CONEAT group was related to the units of the Soil Survey of Uruguay at 1: 1,000,000 (MGAP-RENARE-DSA, 1976b). The last step was the overlap of the Soil Groups with the rural lots and represented it in CONEAT mapping at 1:20,000 (Capurro Etchegaray, 1977).

Recently, by expert assessment, each CONEAT soil group was associated with a surveyed soil profile (Molfino, 2009). This soil profile database has the soil properties required to run EPIC for each soil group, including the number of soil layers; layer depth; albedo; bulk density; pH; sum of bases; percent of sand, silt, clay and coarse fragments; and percent of organic C.

2.2.5.1.2. Climate layer

EPIC model requires daily weather information, including daily temperature (maximum and minimum), precipitation, solar radiation, wind speed, and relative humidity. This layer was built using point-weather stations (Figure 2.3), these points were interpolated to a grid of 10 by 10 km using Ordinary Kriging geostatistical method (Castaño et al., 2011; Grimes and Pardo-Igúzquisa, 2010; Zhang and Srinivasan, 2009).

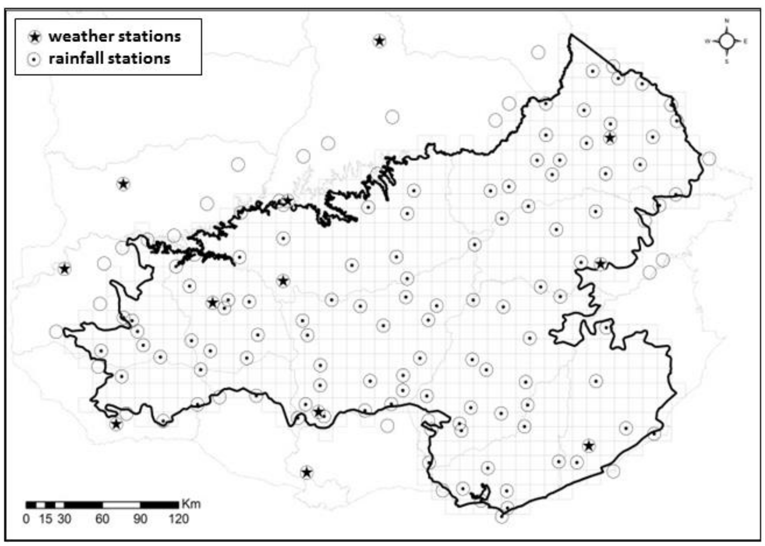


Figure 2.3 Map of climate grid and weather stations.

Based on the climate characteristics of this study region (Castaño et al., 2011) the following variables were identified as having less spatial variability: temperature, wind, radiation, relative humidity and, as a result, they required fewer stations (11) to represent the region but, on the other hand, the rainfall had high spatial variability, which required more stations to improve the spatial distribution. 132 points were used

(108 inside the study area and 25 outside), with an average distance of 37 km between each rain gauge with the four nearest. Also, in an attempt to improve the spatial distribution of the rainfall data, a remote-sensing option to estimate rainfall was evaluated. However, as shown by Salio et al. (2015) and Vila et al. (2009) for SS America, this option can lead to overestimations of rainfall. Further, the resulting spatial resolution was lower than the interpolated, as shown by De Vera and Terra (2012) for this region when comparing remote sensing (RS) rainfall estimations and rain gauge observations. In summary, even after statistical adjustments, the RS estimations did not produce a spatial improvement when the distance between points was less than 50km.

Table 2.5 Data sources of the Geospatial database.

Data		Source	Type of data			Temporal coverage	Temporal resolution	Spatial resolution/ Scale/ Points
Class	Variables		Point	Polygon	Raster			
Climate	precipitation	INIA Uruguay and INUMET Uruguay	X			1995-2015	daily	132 points
	temperature, wind, solar radiation	INIA Uruguay and INUMET Uruguay	X			1995-2015	daily	11 points
Soils map	Layer depth, soil carbon, pH, CIC, Sand, Silt; Productivity Index	(MGAP-RENARE-CONEAT, 1994)		X			-	1:40,000
Topography	elevation and slope gradient	MGAP-RENARE Uruguay (Dell'Acqua, 2004)			X			30m
Agro-stats	crop yields	(MGAP-DIEA, 2015)					yearly	Country
Admin boundaries	departments (counties), country limits	SGM Uruguay		X				

2.2.5.1.3. Topography layer

The required topographical information was extracted from the Uruguayan digital elevation model (Dell'Acqua, 2004). It is a raster file with a spatial resolution of 30 meters with two layers: elevation and slope gradient.

2.2.5.2 Building of the Homogenous spatial modeling units (HSMU)

As mentioned above, in the present study, only the land that is suitable for growing cash crops was modeled (Figure 2.2) (MGAP-RENARE-DSA, 2003). This cash-crop area, covering ~50% of the total study area, is assumed to be the total area that could be potentially dedicated to growing cash crops when all the suitable land is used.

To build the homogenous spatial modeling units (HSMU), considering the maximum potential area, the approach presented by Zhang et al. (2010) was adapted to this region using the available data sources. A conceptual diagram of the geospatial EPIC simulation system is presented in Fig. 3.4. The following layers were intersected:

- CONEAT soils (polygons)
- Slope (from DEM)
- Elevation (from DEM)

Finally, at each HSMU a grid point of daily data was assigned.

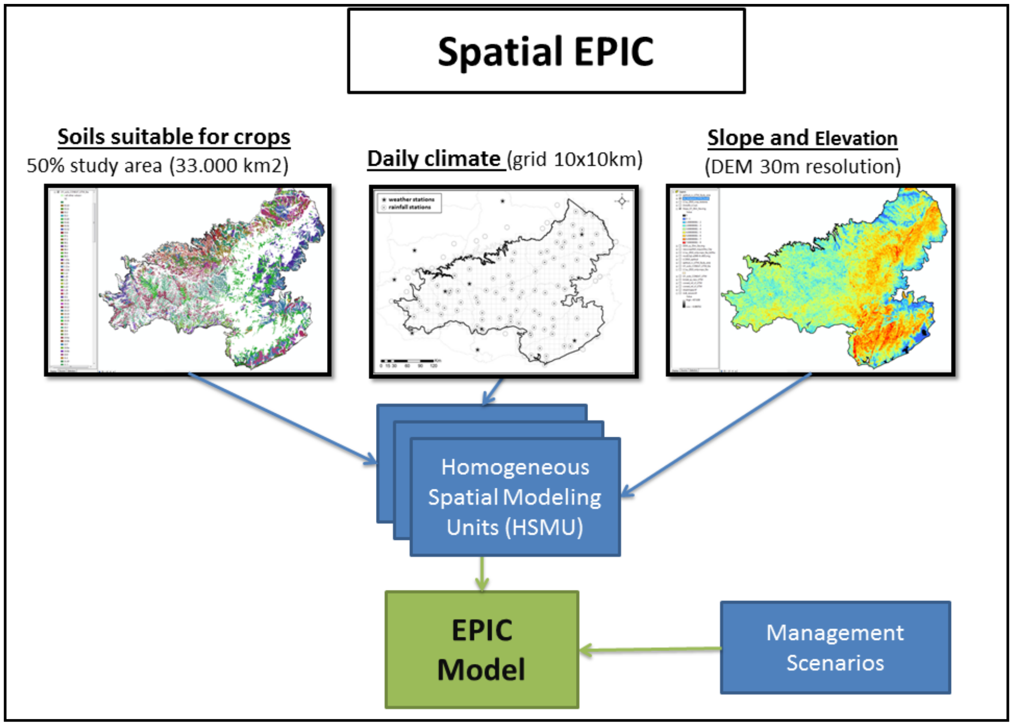


Figure 2.4 Conceptual diagram of geospatial EPIC

2.2.5.3 Parallel model running

Each run of the EPIC spatial involved about 7,500 HSMU. To reduce the time required for each run, a parallel computing software developed by Zhang et al. (2014) was adapted, which implement a parallel-EPIC in a Linux server using a Python (python.org) script. Finally, a script of R Statistic soft (R Development Core Team, 2013) was used to extract the study variables (grassland production and crop yield) from the EPIC's output files to a spreadsheet.

2.2.5.4 Spatial EPIC validation

The EPIC model was previously validated at a point scale for the Uruguayan agro-ecosystems (Section 2.2.4). After the development of a spatial version of the EPIC model for these conditions, the next step was to validate it for both agro-ecosystems with the available data at this scale.

2.2.5.4.1 Simulation of the Grassland ecosystem

Due to the lack of spatially distributed grassland forage yield field records, the model was validated with the average of the grassland production (NPP) over 15 years using the spatial version of the EPIC model. The outputs were compared with the CONEAT Productivity Index (CONEAT PI), as an indirect validation.

The CONEAT PI, created by Act 13.695 (October 1968) of the Uruguayan government, is an index of the potential production capacity of the soils in terms of production of cattle meat, sheep meat, and wool per hectare per year. Using an expert assessment approach, productivity rates were assigned to the 188 CONEAT soil groups according to their similarities. The index values range from 0 (lowest) to 263 (highest) while the average value at a country scale is the index of 100 (Capurro Etchegaray, 1977). It was considered that this index could be used as an indirect measure of the grassland productivity, given that under conditions of grazed animal production, the productivity index is directly related to forage availability.

This definition of productivity implies a potential capacity of agricultural goods production and covers all agricultural sectors, even though it is expressed on animal products, during the development was taking in account the potential crop productivity and crop limitations (MGAP-RENARE-CONEAT, 1994). This index, even though, was developed almost 50 years ago, it still captures well the current land productivity / capability, as confirmed by Lanfranco Crespo and Sapriza Fraga (2011) who found a positive correlation between the CONEAT PI and the unit price of farmland.

2.2.5.4.2 Simulation of the Cropland ecosystem

The soybean crop was selected to validate the EPIC spatial model on croplands since it is the dominant crop (90% of summer crops) and also most of the crop production it is exported (MGAP-DIEA, 2015), which means a risk in terms of environmental threat of exporting limited available natural resources (water and soil carbon). In this ecosystem in order to have a good representation of the crop productivity the EPIC annual yield outputs, for the whole region, were compared against the National crop yield averages (MGAP-DIEA, 2016). Although these statistics cover an area bigger than the study area, it was found it was useful because it allows for the examination of trends in inter-annual variability.

2.2.6 Potential carbon fluxes

The net ecosystem exchange (NEE) is the net CO_2 flux between the terrestrial ecosystem and the atmosphere; a negative sign of NEE indicates C uptake into the biosphere, while a positive value denotes net emission to the atmosphere (Chapin et al., 2006). Recent studies (Schwalm et al., 2010; Zhang et al., 2015) showed that the C algorithm in EPIC simulated well NEE of diverse agroecosystems in the US Midwest, where NEE was calculated as heterotrophic soil respiration (RSPC) minus the net C sequestration from the atmosphere into plant biomass (i.e. NPP) (Chapin et al., 2006).

Here, an analysis of the potential impact of the land use change from grassland to cropland on the carbon fluxes was performed. To this effect, the pertinent variables (NEE, RSPC, NPP) were extracted from the outputs of the EPIC runs over 15 years obtained previously during the validation process. Here, the focus was on the biogenic-related C processes included in the NEE calculation but do not consider fossil fuel C emission from agronomic practices and heterotrophic respiration by humans and livestock (West et al., 2011).

2.3 Results and discussion

2.3.1 Field scale calibration and validation

2.3.1.1. Simulation of the Grassland ecosystem

The first step of the calibration and validation process was to modify parameters in order to best mimic the observed forage yields; this was an important verification step in order to capture the C inputs into the soil system (Apezteguía et al., 2009). The model was calibrated comparing the historic yearly averages (Table 2.2) and the model's outputs of a run using a representative soil profile of the study area with 30 years of recorded daily weather data (precipitation and air temperature). During this process, different values of the crop parameters were tested based on the model developer's guidelines and the characteristics of the Uruguayan grassland, until the best adjustment of the model was achieved. The final values of these parameters are shown in Table 2.3.

The EPIC model simulated reasonably well the mean response of historic forage yields, based on a "semi-quantitative" comparison (Section 2.2.4). It was found that the simulated average of 30 years was 3.56 Mg ha^{-1} where the average reported on selected bibliography (Table 2.2) was 3.46 Mg ha^{-1}; the minimum and maximum simulated yields were 1.77 Mg ha^{-1} and 4.55 Mg ha^{-1} respectively; these values were within the reported observed values that ranged between 1.19 and 5.25 Mg ha^{-1} (Table 2.2). Additionally, these maximum and minimum yields agreed well with those recorded in dry and wet years (Castaño et al., 2011). The average seasonal distribution of simulated forage yields was 27% in spring, 51% in summer, 20% in fall and 2% in winter while the historic records were 25-29% in spring, 38-48% in summer, 19-23% in fall and 9-13% in winter. Thus, the model tended to over predict in summer and under predict in winter. The forage yield under prediction in winter is not significant for the objective of this research due to the reported low production in winter, about 400 Mg ha^{-1} (Berreta, 2003) .

The next step was the validation of the modeled results; the model´s forage yield production was tested using 12 years of data, seasonally measured from 1992 to 2003 in the INIA-TyT-RS grassland experiment (Figure 2.2). Analyzing the average yearly production over this period, the modeled average was 3.55 Mg ha^{-1} while the measured average was 3.39 Mg ha^{-1}, this difference was not statistically significant ($p<0.05$); however, both were significantly correlated with an R^2 was 0.60 ($p<0.05$), with a slope significantly close to 1 ($p<0.05$) (Appendix 1.1.1). This model adjustment is similar to other reports (Apezteguía et al., 2009; Causarano et al., 2008) where EPIC had been calibrated for other cropping conditions because of the lack of published EPIC calibrations under natural grassland environments.

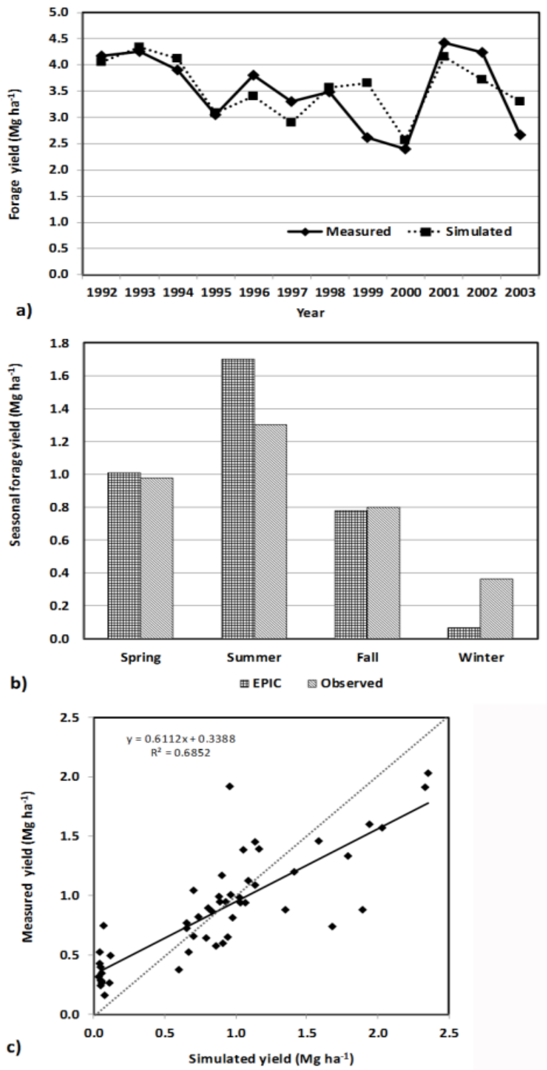


Figure 2.5 Comparison of simulated vs observed forage yield in INIA-TyT-RS: a) yearly, b) seasonal averages and c) all seasonal data

Analyzing the inter-annual variation, the model adjusted reasonably well to the measured data (Figure 2.5a), also representing well the dry-wet periods. In some years, however, the model slightly under predicted (1996, 1997 and 2002) or over predicted (1999) ; this last event may have been because it was a dry year (Castaño et al., 2011). Considering the seasonal distribution of the forage yields (Figure 2.5b), it was found that the model overestimated in summer and underestimated in winter conditions, as it had been noted before during the calibration process.

Finally, comparing all the seasonally measured data (Figure 2.5c) and modeled results, it was found that both were significantly correlated the R^2 was 0.69 ($p<0.05$) and the slope 0.61 was significantly different from the 1:1 line ($p<0.05$) (Appendix 1.1.2); the main cause of the departure from 1 was the bias in the winter production, as mentioned before.

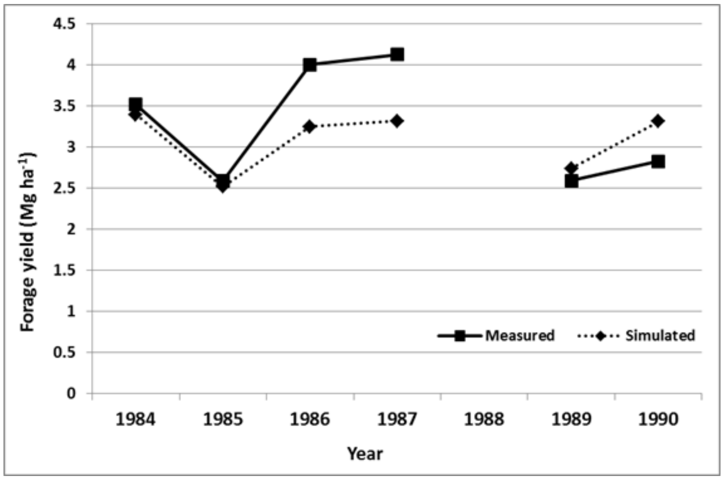


Figure 2.6 Comparison of simulated vs observed yearly forage yield in SUL-CC-RS.

Secondly, it was tested the model´s forage yield production using 6 years of data, from 1984 to 1990, of the SUL-CC-RS grassland experiment (Table 2.1). Analyzing the yearly production during this period, the model average was 3.09 Mg ha^{-1} while the measured was 3.24 Mg ha^{-1}, this difference was not statistically significant ($p<0.05$) (Appendix 1.1.3). Analyzing the inter-annual variation, the model adjusted reasonably well to the measured data (Figure 2.6) and it represents well the dry-wet periods. With exception of some years were the model under predict (1986, 1987, 1990).

The last step was to test the simulated erosion and soil carbon dynamics. Uruguayan grazing conditions (animal stock, forage intake, etc.) were reproduced in the model management instructions. The outputs of modeled grazing runs (30 years) were compared with the outputs of the locally validated erosion equations stored in an available database (Table 2.2). Again, based on a “semi-quantitative” comparison, good model behavior was found; the average modeled soil loss was 2.24 Mg ha^{-1} year^{-1} while the output of the Erosion UY was 2.50 Mg ha^{-1} year^{-1} in the INIA-TyT-RS site and 3.72 Mg ha^{-1} year^{-1} and 3.40 Mg ha^{-1} respectively, in the SUL-CC-RS site.

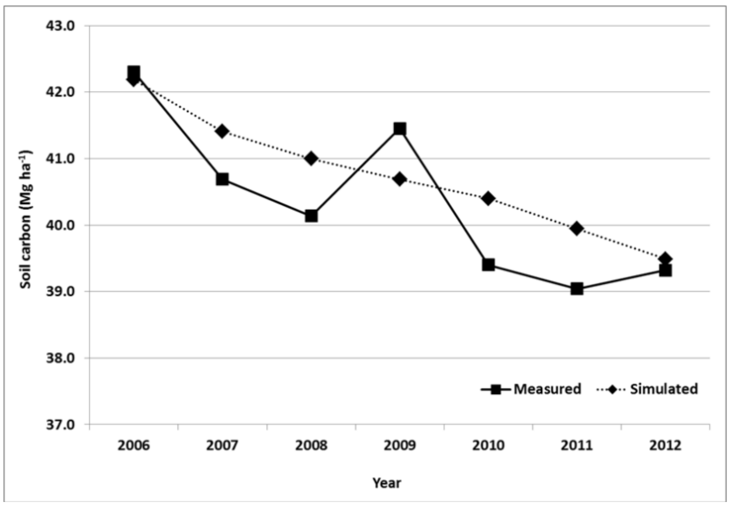


Figure 2.7 Comparison of simulated vs yearly measured soil carbon of INIA-TyT-RS grassland experiment at top 15cm soil depth.

Finally, it was simulated soil carbon changes during a seven year period (2006-2012) and compared the results against measured soil carbon in the top 15-cm soil depth from two experiments conducted at INIA-TyT-RS on similar conditions (Table 2.2). The results showed a good agreement between the modeled and measured loss of soil carbon during the study period. On average, the modeled soil carbon loss was and 0.496 Mg ha^{-1} year^{-1} while the average measured loss was 0.446 Mg ha^{-1} year^{-1} this difference was not statistically significant ($p<0.05$) (Appendix 1.1.4). Also, it was compared the simulated outputs with yearly measurements (Figure 2.7). Overall, there was a significant correlation (R^2 = 0.72, $p<0.05$) between observed and simulated values of SOC stocks. Analyzing the inter-annual behavior of the data presented in Figure 2.7, it can be observed that measured soil carbon was more variable than modeled soil carbon, which could be likely as a result of expected spatial variability and errors inherent to the soil sample process. In spite of simulated soil carbon being higher than observed soil carbon during some years, there were significant negative trends in both observed and simulated soil carbon. The simulated and measured loss of soil carbon of the grassland ecosystem presented here agrees with that reported by Piñeiro et al. (2006) for the Pampa grasslands.

2.3.1.2. Simulation of the Cropland ecosystem

The first step of the model calibration and validation process, as with the grassland, was to achieve the measured historic grain yield (national statistics, Table 2.2) and the length of the crop cycle (Table 2.2). The model was run comparing the historic yearly averages and the model's outputs using 30 years of recorded weather data. During this process, different values of the crop parameters were tested based on the model developer's guidelines and the characteristics of the Uruguayan cropland management (planting date, plant population, fertilization, etc.). After this process, a reasonable behavior of the model outputs was obtained, a realistic agreement of the length of crop cycle and an acceptable crop yield average, but the model still over predicted by more than 20% the measured yields which required a further step to improve it.

After the first approach to the calibration modifying manually the parameters, an automatic calibration using the HydroPSO package was performed, with 10 years of recorded crop yields from one site (INIA-LE-RS). The objective was to analyze the three crops together. The best adjustment of the model was achieved with the values of the model parameters showed in Table 2.4.

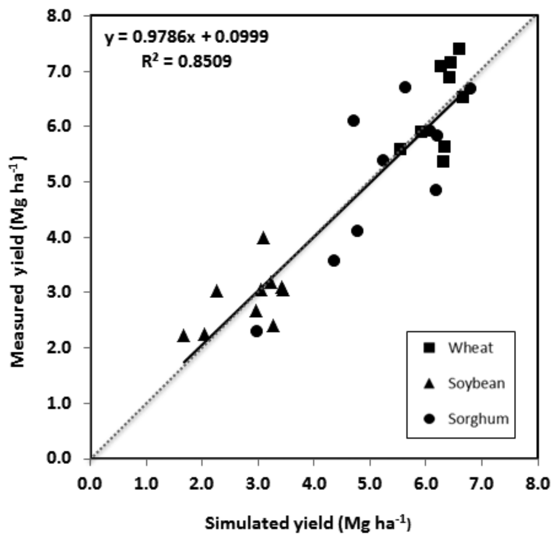


Figure 2.8 Comparison of simulated vs observed crop yield of INIA-LE-RS crop evaluation experiment after HydroPSO calibration.

The agreement between modeled and measured crop yields was excellent; the modeled yield was 4.76 Mg ha^{-1} while the measured yield was 4.76 Mg ha^{-1}, this difference was not statistically significant ($p<0.05$) (Appendix 1.2.1). Both were significantly correlated with an R^2 equal to 0.85 ($p<0.05$), with a with a slope significantly close to 1 ($p<0.05$) and the interception closed to 0 (Figure 2.8), this agreement is similar to previous EPIC calibration exercises (Apezteguía et al., 2009; Causarano et al., 2008). Analyzing the results by crop, the agreement between simulated and observed average yields remained outstanding without significant difference ($p<0.05$) on the three crops (6.28 and 6.39 Mg ha^{-1} for wheat, 2.84 and 2.90 Mg ha^{-1} for soybean, and 5.31 and 5.14 Mg ha^{-1} for sorghum).

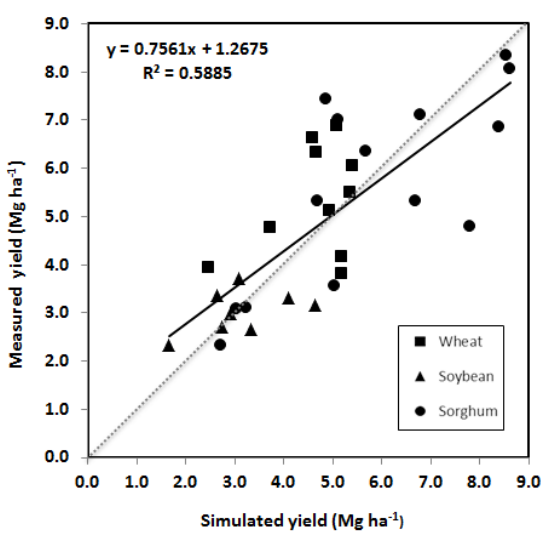


Figure 2.9 Comparison of simulated vs observed crop yield of INIA-SRRN crop evaluation experiment.

Then the model was tested with data from two locations. The first is the INIA-SRRN research station, 10 years of crop yield evaluation. The results showed a good agreement between simulated and measured crop yields; the modeled was 4.78 Mg ha^{-1} while the measured was 4.88 Mg ha^{-1}, this difference was not statistically significant ($p<0.05$) and both were significantly correlated with an R^2 equal to 0.59 ($p<0.05$) (Figure 2.9) (Appendix 1.2.2.). Analyzing the results of the crop individually the average yields were very close for the soybean which was 3.14, 3.03 Mg ha^{-1} and sorghum which was 5.80, 5.62 Mg ha^{-1} simulated and measured respectively, the wheat crop were less closed where simulated was 4.66 vs 5.39 Mg ha^{-1} of the observed, but all these differences were not statistically significant ($p<0.05$).

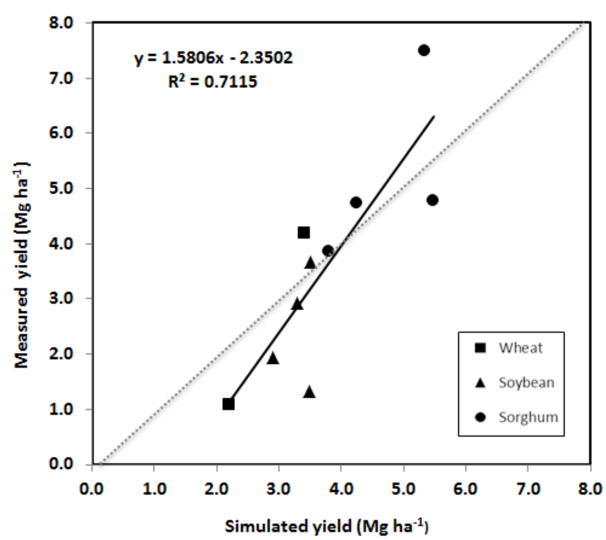


Figure 2.10 Comparison of simulated vs observed crop yield of INIA-TyT-RS crop rotation experiment

The other data set that it was used was a two year crop rotation (1-wheat-soybean, 2-sorghum) from an experiment located in the INIA-TyT-RS; the aim was to evaluate the performance of the model to mimic a crop rotation (management) that was commonly used in the study region. The results showed a good agreement between simulated and measured average crop yields; the modeled was 3.76 Mg ha^{-1} while the measured was 3.60 Mg ha^{-1}, this difference was not statistically significant ($p<0.05$) and both were significantly correlated (Appendix 1.2.3.) with an R^2 equal to 0.71 ($p<0.05$) (Figure 2.10).

The last step was to test the soil lost by water erosion and soil carbon evolution. To perform this step, the management of the crop rotation experiment of the INIA TyT RS was reproduced again. To test soil erosion, the model was run with 30 years of recorded weather, the outputs were compared with the outputs of the local validated erosion model equations database (Table 2.1) in two sites: INIA-TyT-RS and INIA-LE-RS; based on a "semi-quantitative comparison" , it was found a good model behavior in both sites, the average modeled soil loss was 22.9 Mg ha^{-1} year^{-1} and the output of the Erosion UY was 21.8 Mg ha^{-1} year^{-1} in INIA-TyT-RS and 15.6, 16.2 Mg ha^{-1} year^{-1} respectively in INIA-LE-RS site.

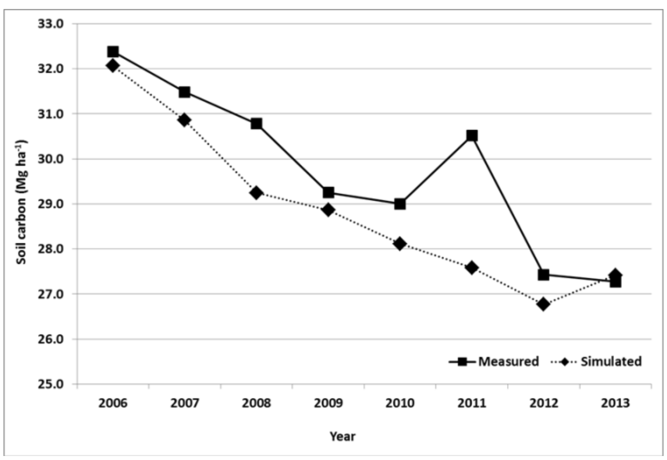


Figure 2.11 Comparison of simulated vs yearly measured soil carbon of INIA-TyT-RS crop rotation experiment at top 15cm soil depth.

As with the grassland data presented above, it was also simulated soil carbon changes during an eight year period (2006-2013) and it was compared the output with measured soil carbon in the top 15-cm soil depth from the crop rotation experiment conducted at INIA-TyT-RS (Table 2.2). As before with the grassland data, there was a good agreement between simulated and measured soil organic carbon during the study period. It was modeled an average soil carbon loss in the top 15-cm soil depth of 0.664 Mg ha^{-1} yr^{-1} while the average measured loss was 0.729 Mg ha^{-1} yr^{-1}, this difference was not statistically significant ($p<0.05$) (Appendix 1.2.4.). It was also found a significant correlation ($R^2 = 0.75$, $p<0.05$) between yearly values of simulated and measured soil carbon (Figure 2.11). As with the grassland dataset, the inter-annual values of measured soil carbon showed more variation than the simulated values. In spite of modeled values being lower than observations in some years, they showed a good agreement when considering the whole study period. The higher soil carbon loss simulated in cropland than in grassland ecosystems, even under no tillage, agrees with previous research of grassland conversion to cropland (Culman et al., 2010; DuPont et al., 2010).

2.3.2 Regional scale development, calibration and validation

2.3.2.1 Grassland

The EPIC model was run on all HSMU for a period of 15 years (1996-2015) using the locally adapted-calibrated grassland and the simulated grazing. The modeled forage production yearly average for the whole region over this period was 2.67 Mg DM ha^{-1} year^{-1} with a maximum of 2.17 Mg DM ha^{-1} year^{-1} and a minimum of 2.92 Mg DM ha^{-1} year^{-1} (Figure 3.5a) these values agree with the values presented by (Ayala and Bermudez, 2005; Bermudez and Ayala, 2005; Formoso, 2005).

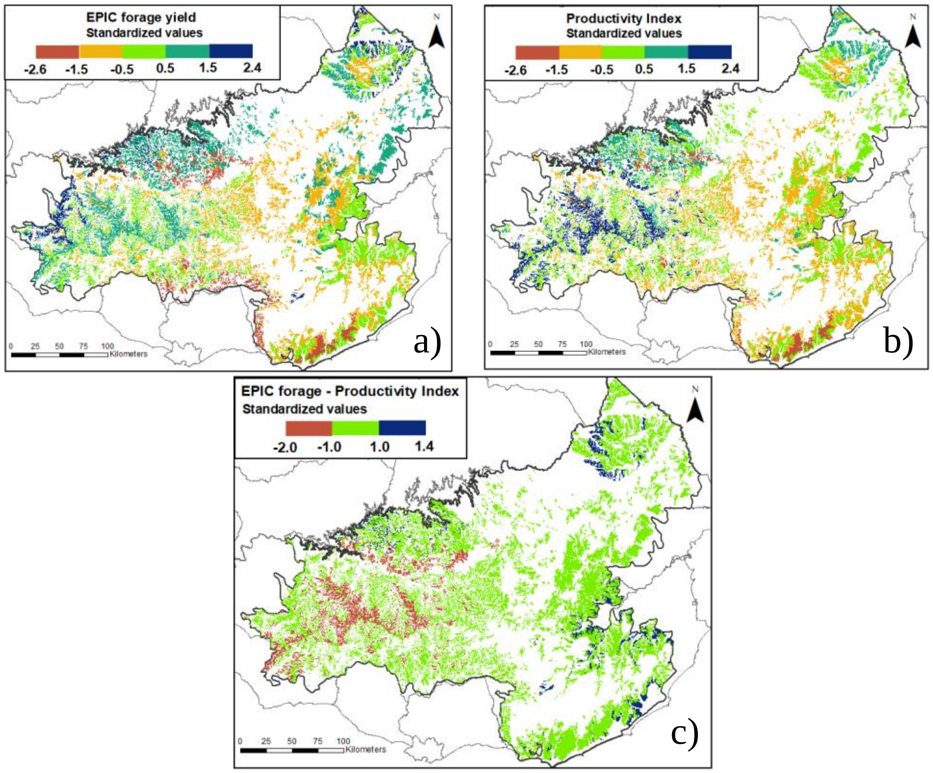


Figure 2.12 Standardized* maps of (a) EPIC grassland production yearly average (15 years), (b) CONEAT productivity index and (c) EPIC subtracted Productivity Index (* standard value is the original value minus the media and divided by the standard deviation)

Comparing the modeled forage production (Figure 2.12b) with the CONEAT PI (Figure 2.12a) a good agreement could be observed, where the higher forage yield values agree with the higher PIs and vice versa (Figure 2.12c).

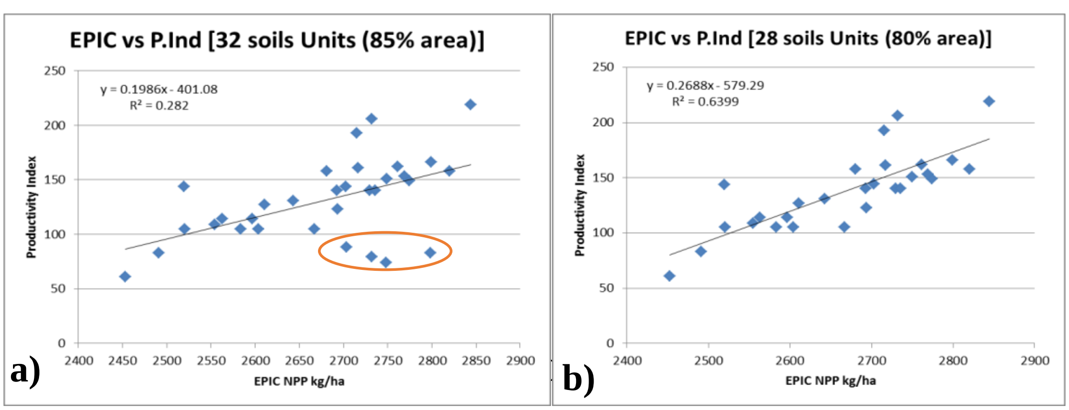


Figure 2.13 Comparison between EPIC grassland production (average 15 years) and Productivity Index (CONEAT) (a) with outliers and (b) without outliers

Next, the average grassland production by soil units with the CONEAT PI was compared. Here, 32 of the 80 units were used, which together cover 85% of the study area (Figure 2.13a). Even though there was a good agreement between both, it was found that four soil units (in red) have high grassland productivity but low CONEAT PI. These units were identified as outliers; mainly sandy soils, and soils with other limitations that newer agricultural techniques, arising after the creation of CONEAT, such as direct sowing with herbicide application, allow the crop plantation with good production results on soils that still have low index, as was noted on the rain-fed summer crops zoning made by MGAP-RENARE-DSA (2003), due to this improvement on the potential productivity of these units were not update since its creation. Finally, these outliers were removed keeping the 80% of the area (28 soils units) and still maintained a good correlation between both (R^2=0.64) (Figure 2.13b).

3.3.2.2 Cropland

The EPIC annual soybean grain yield outputs for the whole region were compared against the Uruguayan country crop yield yearly averages. First, comparing

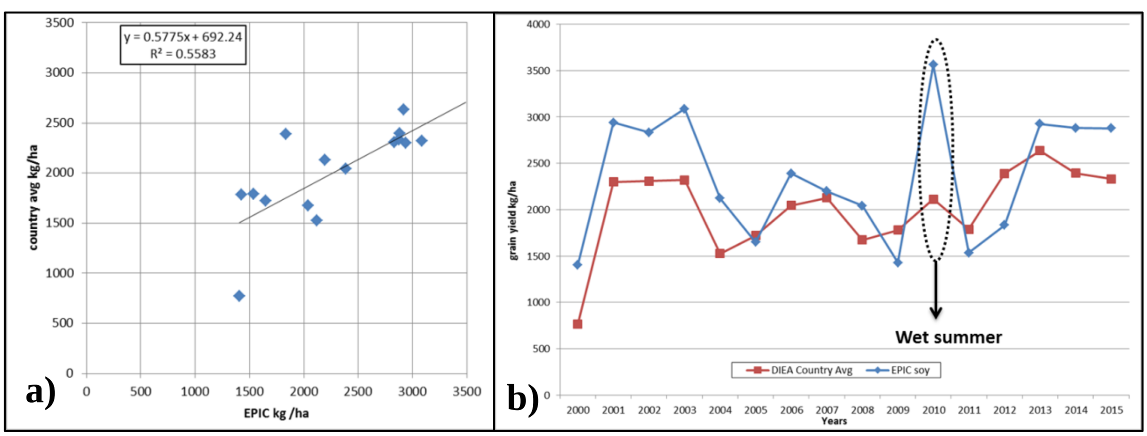


Figure 2.14 Comparison between modeled annual crop yield (average 15 years) and Productivity Index (CONEAT). (a) correlation considering all years and (b) annually over the time

the annual crop yield modeled against the country average (Figure 2.14a) it was found a good agreement, with an R^2=0.56. Second, it was analyzed the inter-annual behavior (Figure 2.14b), overall it was found that the model best represents the inter-annual variation in the crop yields. The main exception was on 2010 where the model overestimates the production, this could be related to this year was a wet summer-fall (INIA Uruguay - GRAS Unit, 2016) in this case the model expresses the crop potential, but in the fields usually it could not have reached due to harvest problems for the wet conditions.

2.3.3 Potential carbon fluxes

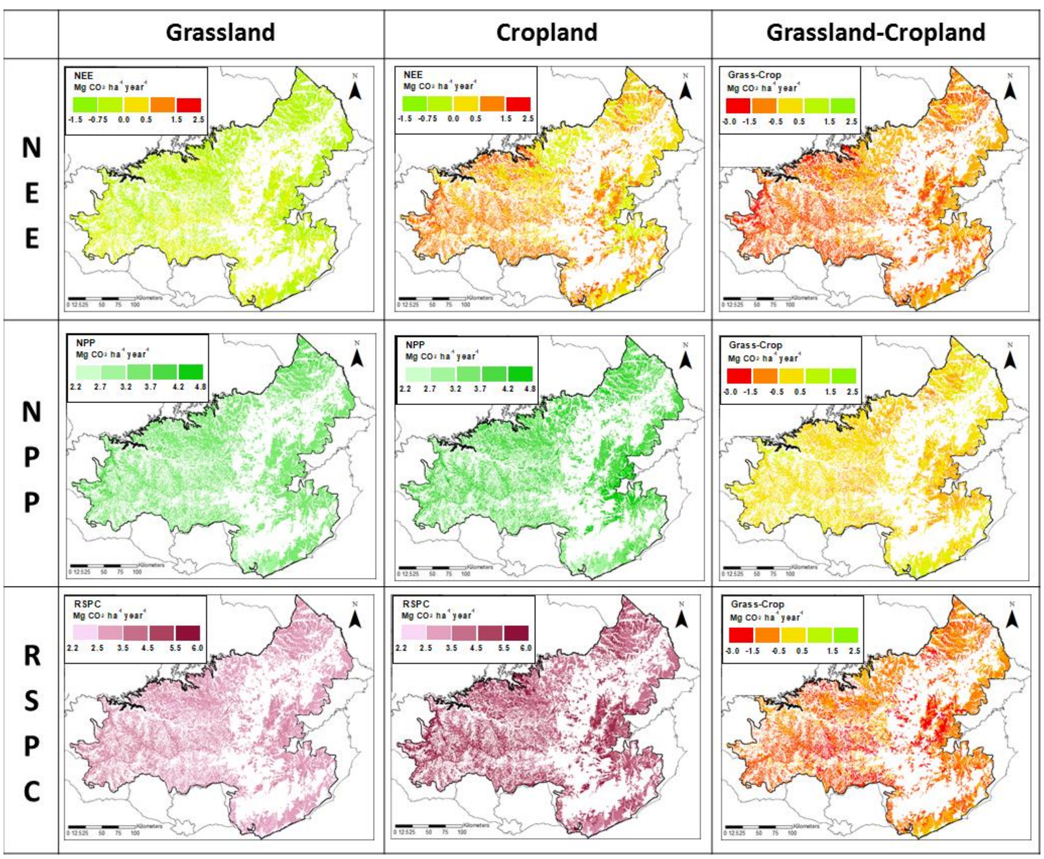


Figure 2.15 Maps of carbon fluxes (NEE, NPP, RSPC) of Grassland, Cropland and Grassland minus Cropland.

An analysis of the potential impact of the land use change from grassland to cropland on the carbon fluxes was performed, the related variables (NEE, RSPC, NPP) from the outputs of the EPIC runs over 15 years (Figure 2.15) were extracted.

The modeled results show that the average values NEE of the grassland were -573 kg CO_2 ha^{-1} $year^{-1}$ and of the cropland 703 kg CO_2 ha^{-1} $year^{-1}$, which means that grassland was mainly removing CO_2 from the atmosphere while the cropland mainly emitted CO_2 the atmosphere. Also, the grassland results of NEE were less variable than the cropland results (Figures 2.15 and 2.16).

Analyzing the NEE components (NPP, RSCP) it could be observed that these results of NEE are mainly related to the amount of RSPC who were much bigger on cropland than grassland (grassland =2,924, cropland =4,491 kg CO_2 ha^{-1} $year^{-1}$) even though the NPP were bigger on cropland than grassland (grassland=3,498, cropland=3,787 kg CO_2 ha^{-1} $year^{-1}$) it was not enough to compensate the loss by RSPC.

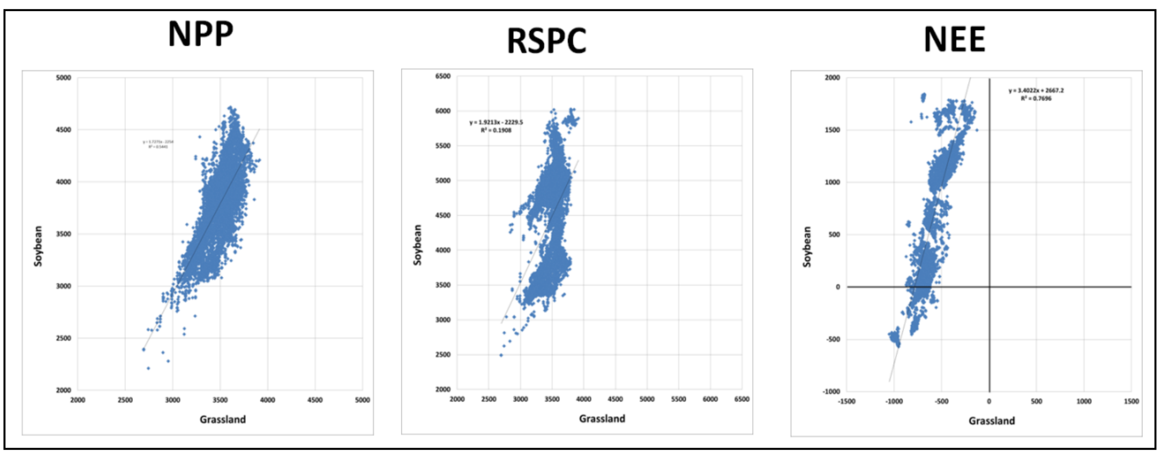


Figure 2.16 Comparison of the carbon fluxes (NPP, RSPC, NEE) between grassland and cropland.

2.4 Conclusions

EPIC model successfully simulated the field-scale crop productivity and soil processes under grassland and cropland covers in South-Central Uruguay. After calibration and testing of EPIC using local data, it was found an acceptable agreement firstly in the grass and crop yields; and secondly in the soil loss by erosion and the soil carbon stock evolution.

After building, testing, and calibrating the spatial version of EPIC to the Uruguayan agroecosystem conditions, an analysis of the potential impact of the land use change from grassland to cropland on the carbon fluxes was performed, extracting the related variables (NEE, RSPC, NPP) from the outputs of the EPIC runs over 15 years. The modeled results show that the average values NEE of the grassland was -573 kg CO_2 ha^{-1} $year^{-1}$ and of the cropland 703 kg CO_2 ha^{-1} $year^{-1}$, which means that grassland were mainly taking CO_2 from the atmosphere where the cropland mainly emitted CO_2 the atmosphere; also, the grassland results of NEE were less variable that the cropland results.

One of the limitations encountered with this research was the scarcity of measured data required to perform the calibration/validation process in the study area. This lack of data suggests a need to conduct field campaigns dedicated to collect weather, agronomic, and soil data to improve field- and regional-scale model predictions. In the next chapter, the spatially-explicit EPIC modeling system validated for South-Central Uruguay conditions will be deployed to evaluate the evolution of crop and soil productivity under contemporary grassland-cropland conversions and future climate, land-use, and management scenarios.

Chapter 3: The effects of change from grassland to cropland on soil carbon and erosion: Uruguay case study

3.1 Introduction

Global croplands, pastures, plantations, and urban areas have expanded in recent decades, accompanied by large increases in energy, water, and fertilizer consumption. Such changes in land use have enabled humans to appropriate an increasing share of the planet's resources, but they also potentially undermine the capacity of ecosystems to sustain food production, maintain freshwater and forest resources, maintain biodiversity, regulate climate and air quality, and attenuate the impact of infectious diseases. Modern land-use practices, while increasing the short-term supplies of material goods, may undermine many ecosystem services in the long run, even on regional and global scales (Foley et al., 2005). Agricultural expansion and intensification, at the expense of forest and grassland conversion, plowing, irrigation, and agrochemicals have led to (Lal, 2007): (1) deterioration of soil quality, mainly due to water and wind erosion, (2) increased irrigated land area (~280 Mha or 19% of the total global cropland area) and water use (18,200 km^3 of water in evapotranspiration or 26% of the global terrestrial evapotranspiration), (3) disrupted global carbon cycle contributing to a ~38% increase in atmospheric CO_2 (from 280 ppm in ~1750 to 385 ppm in 2006), (4) accentuated use of fertilizers and pesticides to increase food production, and (5) caused mass extinction of plant and animal species

Expanding croplands to meet the needs of a growing population, changing diets, and biofuel production also comes at the cost of reduced carbon stocks in natural vegetation and soils (West et al., 2010). Soil Organic Carbon (SOC), is one of the principal indicators of sustainability and soil quality due to its positive influence on many soil physical, chemical, and biological properties (Reeves, 1997). Undoubtedly, SOC is the most useful quality indicator; SOC it is strongly linked not only with crop growth but also with plant growth under natural conditions. Healthy natural vegetation is essential to avoid degradative processes and maintain buffering effect on some contaminants (Bastida et al., 2008). Conversion of natural to agricultural ecosystems in the USA has depleted the SOC pool by 3 to 5 Pg C. Worldwide, agro-ecosystem's soils (croplands, grazing lands, rangelands) have been depleted of their SOC pool by 25–75% depending on climate, soil type, and historical management (Lal, 2002).

Soil erosion is a major environmental threat to the sustainability and productive capacity of agriculture (Pimentel et al., 1995) and the most widespread form of soil degradation (Lal, 2003). Erosion results from kinetic energy transmitted from water (rainfall and runoff) and wind to soil. Raindrops hit exposed soil with an explosive effect, launching soil particles into the air. In most areas, raindrop splash and sheet erosion are the dominant forms of erosion. Erosion increases dramatically on steep fields used for agriculture. Living and dead plant biomass left on fields reduce soil erosion and water runoff by intercepting and dissipating raindrop and wind energy. Both soil texture and structure influence the susceptibility of soils to erosion. Other factors such as slope gradient and length, SOC, and vegetative cover influence the rate of erosion. Soils with medium to fine texture, low SOC, and weak structural development have low infiltration rates and experience increased water runoff (Pimentel et al., 1995). Erosion causes on-site and off-site effects. When water erosion occurs, on-site effects become evident through the formation of rills and gullies, increased water runoff, and reduced water availability for crop growth. Examples of off-site effects include sediment deposition, blockage of waterways, damage to infrastructure, and pollution of water bodies.

The overall goal of this research is to identify temporally and spatially and quantify the possible degradation (loss of soil quality) resulting from the conversion of natural grassland to cropland. As mentioned before, even though, the land use change from one ecosystem to the other, could impact on: soil, plants, atmosphere, geology and hydrology, the focus of this research will be in the soil component, which is the most affected by anthropogenic processes (management) (Sands and Podmore, 2000), with the main focus on soil quality ("health") as a quantitative indicator of degradation (West and Wali, 2002). Even though they could be related to the main question, issues such as economic sustainability, social impacts, chemical contamination, biodiversity losses, and climate impacts are not addressed in this research.

This research was conducted using the natural grassland regions of the Republic of Uruguay (Uruguay) as the study area. The rationale for selecting this study area includes: 1) Uruguay still has a high percentage of natural grasslands in contrast with other regions of the world; 2) this area has been used for grazing beef cattle for more than 100 years, one of the main exported products of this country, but nowadays this area is threatened by a recent LU change from grasslands to croplands; and 3) the availability of the data to perform this research.

3.2 Materials and methods

3.2.1 Study area

Uruguay is located in the southeast of South America, between 30º and 35º South and 54º and 59° West. The total land area is 176,215 km^2. The region is dominated by rolling plains reaching a maximum elevation of 514 m. The climate is temperate, with a range of rainfall between 1,100 – 1,300 mm yr^{-1}, mean temperatures of 11°C in winter and 27°C in summer, and extreme temperatures of - 4°C and 40°C. The main ecosystem is Grasslands associated with riverside bush forest. Soils are slightly-acidic, Prairie Soils (Mollisols) (Berreta, 2003; Castaño et al., 2011). The "Southern Campos" sub-region (Soriano and Paruelo, 1992) was selected as the study area (Figure 3.1), it is located in the Center-South of Uruguay where soils support natural grassland and have crop use capabilities but restricted by their intrinsic biophysical characteristics (MGAP-RENARE-DSA, 2003). In the past, this area was considered "marginal" to grow cash crops; historically, the crops were located West of this area in soil more suitable, but it is almost full covered; as a consequence the expansion to more "marginal" lands was

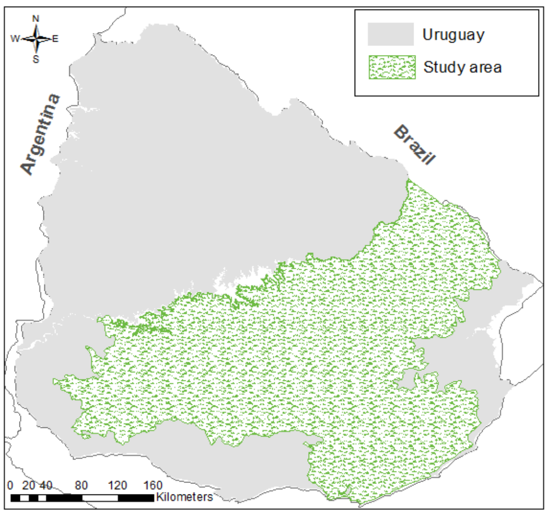


Figure 3.1 Map of Uruguay, showing the study area.

been done recently.

Currently, the Uruguayan agro-ecosystem is composed of two main sub-systems, which usually coexist in the landscape: a) Natural Grasslands and b) Croplands. The Natural Grassland sub-ecosystem is defined as a vegetative cover formed by grasses along with herbs and associated shrubs, where trees are scarce. It is used by domestic herbivores throughout the year (continuously), the herbivores are bovine and also ovine, grazing together. This grassland is an environment with great richness in grass species (~400) of summer (C4) and winter (C3) habits, with perennials predominating over annuals. Of this great number of species, 10 (mostly C4) are the main contributors of the annual forage production, which averages 3-4 Mg year^{-1} of dry matter (DM) (Berreta, 2003). The Cropland sub-ecosystem is rainfed where the main crops are soybean in summer and wheat in winter all produced with no-tillage (MGAP-DIEA, 2015). About half of the crop area rotates from summer to winter and the other half is only a summer-summer rotation (Fig. 3). Finally, the land tenure of Uruguayan agro-ecosystem is entirely private of which a high percent is rented. The average farm size is 775 ha (MGAP-DIEA, 2015).

3.2.2 Description of the EPIC model

The Environmental Policy Integrated Climate (EPIC) Model is a computer model originally developed during the 1980's to simulate the impacts of water and wind erosion on crop and soil productivity throughout the United States (Williams et al., 2008a). Operating at field / small watershed spatial scales and at a daily time step, EPIC contains physically-based algorithms to simulate soil and crop processes such as crop growth, erosion, nutrient balance, and related processes (Figure 3.2). It is designed to simulate homogeneous areas that are characterized by a common weather, soil, landscape, crop rotation, and management. The processes simulated include leaf interception of solar radiation, conversion to biomass, a division of biomass into roots, above ground biomass, and economic yield, root growth, water use, and nutrient uptake (Gassman et al., 2005). The main inputs needed to run EPIC are daily weather (maximum and minimum temperature and rain), soil-layer properties (soil

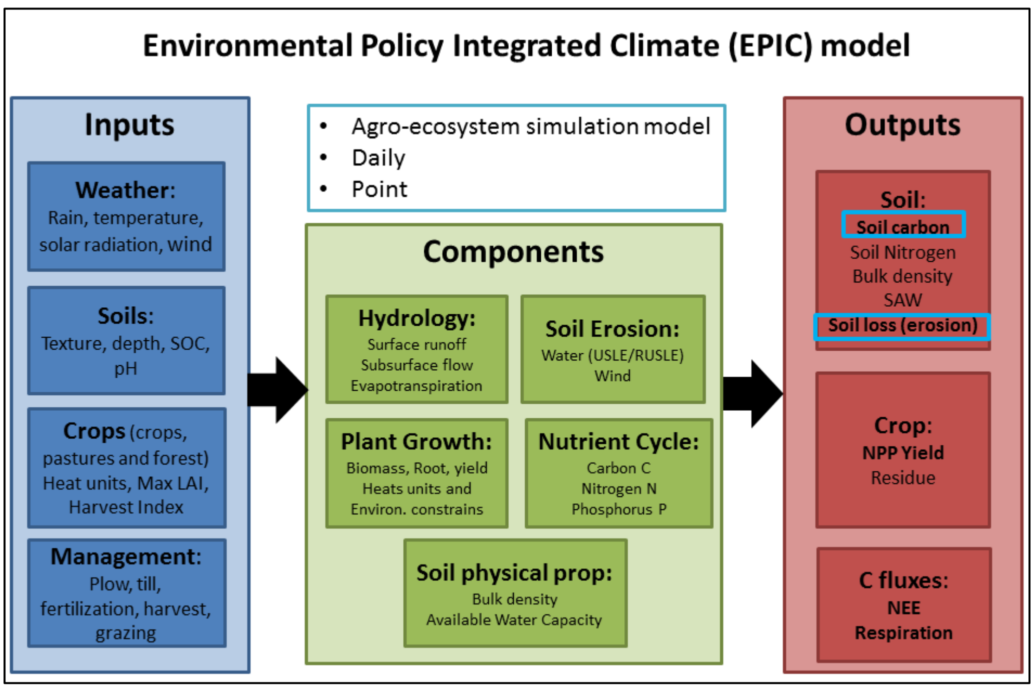


Figure 3.2 Diagram of main components, inputs and outputs the EPIC model.

layer depth, texture, bulk density, and C concentration among others), and site characteristics (latitude, longitude, elevation and Slope) (Williams et al., 2006).

Since its first development and application, EPIC has evolved into a comprehensive agro-ecosystem model capable of simulating the growth of crops grown in complex rotations and management operations, such as tillage, irrigation, fertilization and liming (Izaurralde et al., 2006b). EPIC has been continuously improved through the additions of algorithms to simulate, for example, water quality, climate change and the effect of atmospheric CO_2 concentration, and nitrogen, carbon, and phosphorus cycling (Izaurralde et al., 2012).

This study was focused on three main EPIC sub-models/process: 1) crop sub-model, 2) Carbon-Nitrogen sub-model, and 3) (water) erosion processes. EPIC uses a single plant growth model with parameters to simulate about 100 plant species, including crops (annual and perennial), native grasses, and trees; each characterized by a unique set of parameter values. It uses the concept of radiation-use efficiency (Williams et al., 2008b) by which a fraction of daily photosynthetically active radiation is intercepted by the plant canopy and converted into plant biomass. Plant phenology is controlled via heat-unit calculations where each crop/plant species has base and optimal air temperatures for growth. Potential daily gains in biomass are affected by environmental stresses such as water, temperature, nutrients (primarily N and P), and aeration (Parton et al., 1988). The coupled carbon-nitrogen C:N sub-model follow the approach used in the Century model (Izaurralde et al., 2006b), where the C and N in soil organic matter are distributed among three pools or compartments: active (microbial), slow and passive. These pools differ in size and function while their turnover times range from days to hundreds of years (Izaurralde et al., 2006b). The EPIC module for water-induced erosion simulates erosion caused by rainfall and runoff and by irrigation (furrow, sprinkler, and drip) (Apezteguía et al., 2009), although the later capability was not used here.

3.2.3 Homogenous Spatial Modeling Units (HSMU).

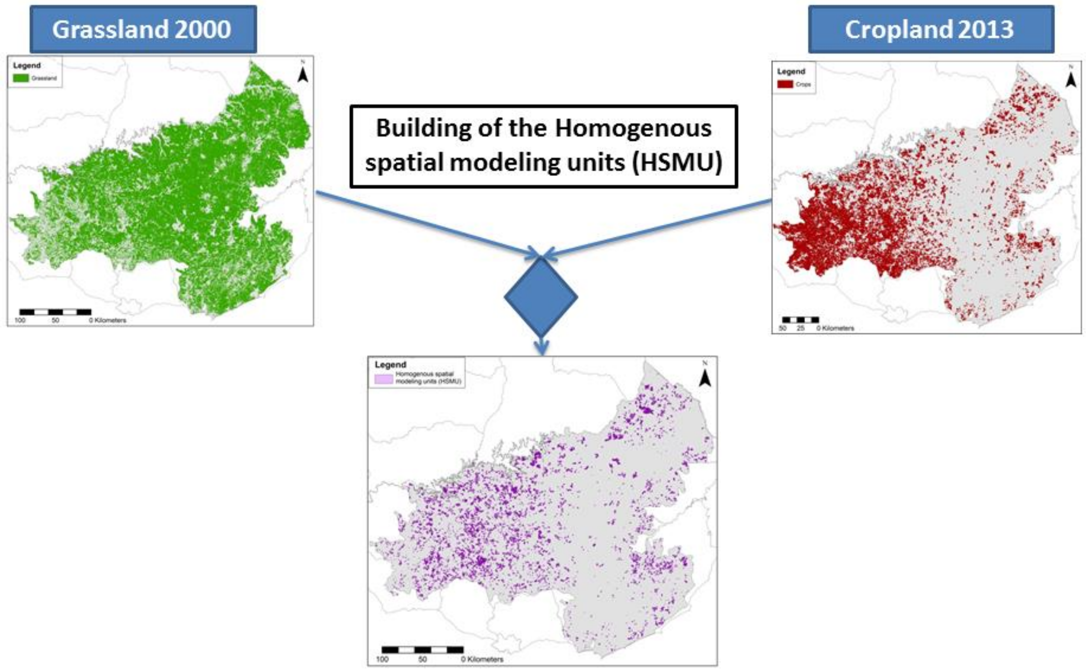


Figure 3.3 Building of the Homogeneous spatial modeling units (HSMU).

The identification of the LU change areas that occurred during 2000 to 2013 was made using LCCS-FAO products for Uruguay for the years 2000 and 2013 (MGAP Uruguay et al., 2011; MVOTMA-DINOT, 2015). These products were made using Landsat-TM images based on the FAO LCCS classification (Di Gregorio, 2016; Di Gregorio and Leonardi, 2016). The ESRI shapefiles were downloaded from MVOTMA – SIT (http://www.mvotma.gub.uy/ambiente-territorio-y-agua/item/10002809-sistema-de-informacion-territorial.html). The process consisted in overlapping the 2013 Cropland classes with the 2000 Grassland class (Figure 3.3).

This resulted in one ESRI shapefile containing polygons with areas that had experienced changes in land use. Subsequently, each of these polygons was used as

Homogenous Spatial Modeling Units (HSMU). Finally, using the same methodology and data that was presented in the previous chapter, each HSMU was assigned the appropriate data needed to run the EPIC model at this scale (soil, Slope, elevation and daily weather data).

3.2.4 Detection of changes in winter and summer crop cover from 2000 to 2015

Once the new crop areas were identified, the next step was to identify when this transition had occurred and what type of crop rotation prevailed in these new areas. Due to insufficient temporal coverage of Landsat images to address this issue, the identification was done using MODIS Vegetation Indexes (VI) (MOD13Q1) (Huete et al., 2002) to trace crop/pasture phenologies. The MODIS VI were used to describe plant phenology at a regional scale using farm-plot level data (Zhang et al. (2003). In order to identify the date of the LU change and the crop rotation for each HSMU, a yearly land cover product of winter (wheat) and summer crops (soybean) from 2000 to 2015, based on MODIS-EVI images using the methodology proposed by (Tan et al., 2011) and (Araya et al., 2013), was used, as implemented by A. Cal (pers. com., 9/15/2016). These products were intersected with the HSMUs to derive crop rotations and LU change dates for each polygon (Figure 3.4).

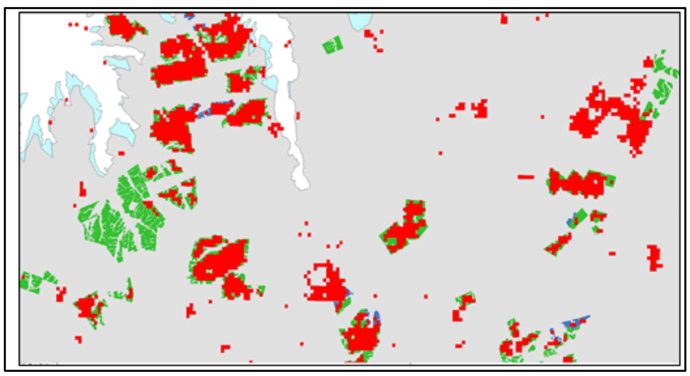


Figure 3.4 Example of summer crop cover estimated with MODIS images (red) over the HSMUs (green).

3.2.5 Building the EPIC model management scenarios

Management scenarios for the period 2000 – 2015 were developed, with the objective of reproducing the recent LU conversion (1) and also other hypothetical situations (3) Four scenarios were considered (Figure 3.5): 1) Grass-Crop, this scenario was intended to mimic the land use changes in this period, which starts with grassland followed by conversion to crops, 2) Grassland: continuous grassland, with no LU change, 3) Soy-Soy: soybean crop in the summer and fallow in winter, repeated every year and, 4) Soy-Wheat: soybean in the summer and wheat in the winter season, also repeated every year.

To construct the scenario Grass-Crop, an R script (R Development Core Team, 2013) was used to build a management file for each HSMU, using the data of LU change year and the crop rotation estimated with MODIS images (Section 3.2.5). The conversion from Grassland to Cropland was made using no-tillage technology that is using herbicides to kill the grassland, followed by direct seeding without plowing. Note that both cropping scenarios included soybean.

3.2.6 Parallel version of model

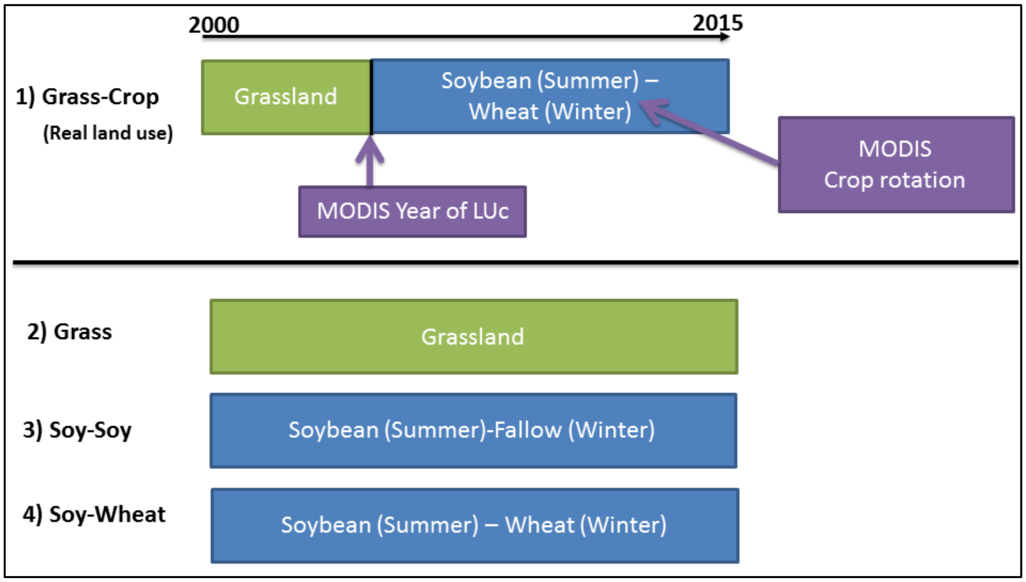


Figure 3.5 Diagram of the four management scenarios simulated with EPIC.

The EPIC spatial model was run for each HSMU, which required about 7,000 individual model runs To reduce the time required parallel computing software developed by Zhang et al. (2014) was used in a Linux server using a Python (python.org) script. An R Statistic soft script (R Development Core Team, 2013) was used to extract the study variables (grassland production and crop yield) from EPIC output files and to place them in Excel spreadsheets.

3.2.7 The effects of grassland to cropland change on soil degradation

In order quantify the degradation (loss of SOC) resulting from the conversion of natural grassland to cropland with different crop rotations, the modeled soil erosion by water and the changes in SOC results were examined, both temporally and spatially.

First, the SOC change (complete soil profile) and the soil loss by erosion were estimated for the Grass-Crop LU change; second, the impact on SOC and erosion for each Soil Unit; and, finally, the impact of the management and the biophysical environment (Slope, initial SOC and the combined effect of initial SOC and Slope) were analyzed.

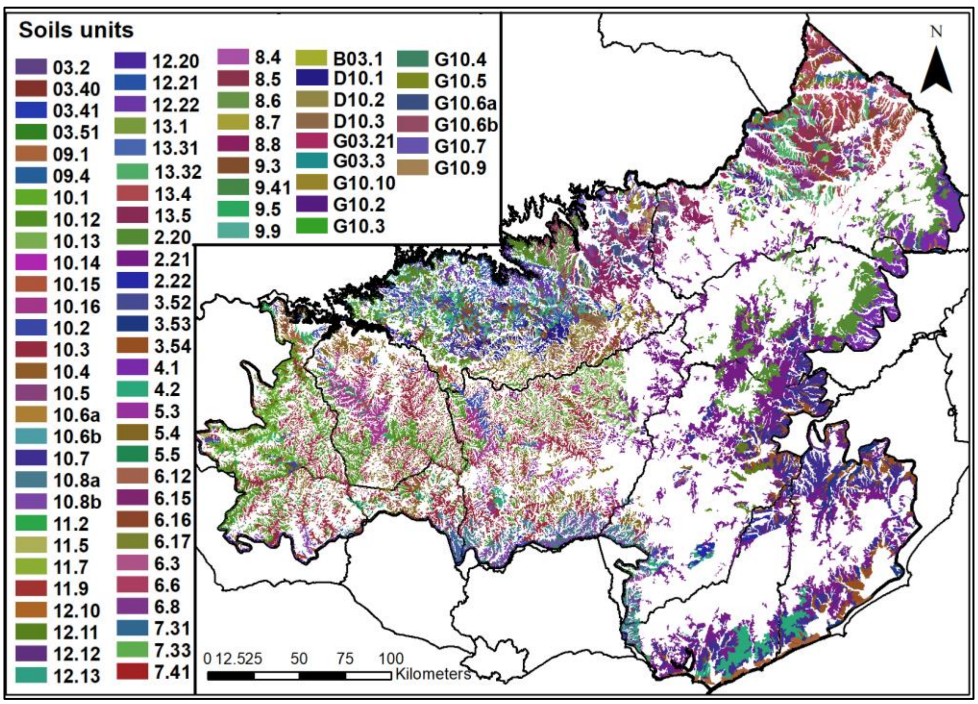


Figure 3.6 Soils units map.

Many of the characteristic properties used to group soils into spatial units (SOC content, texture (clay, sand and silt), pH, bulk density, water holding capacity, and soil depth) affect SOC dynamics and soil erosion (Hassink, 1994, 1992, Wang et al., 2013, 2010). The study area is covered by 84 soil units (Figure 3.6), from which 32 units cover 93% of the total area (Table 3.1)

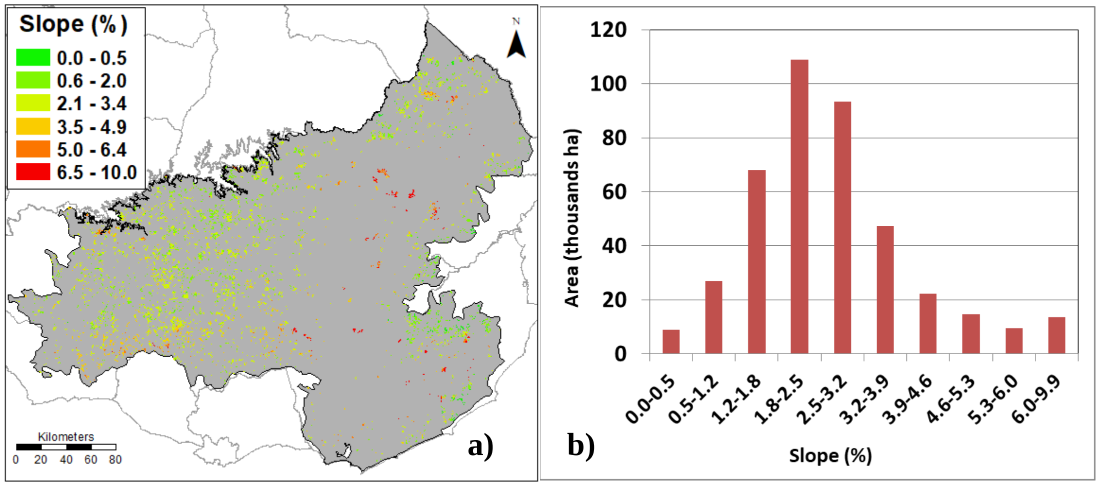


Figure 3.7 Slope map (a) and frequency graph (b) of the HSMUs

The Slope gradient (%) of the HSMUs are spatially distributed within the study area (Figure 3.7a), ranged from 0% to 10%, with an average of 2.7%.Where the 50% of the area has a Slope of 1.8% to 3.2% (Figure 3.7b).

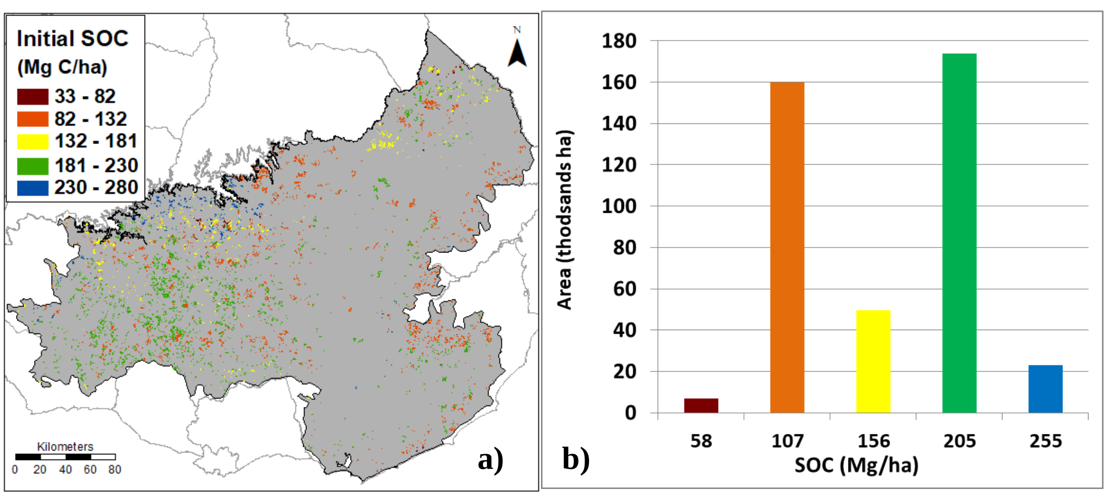


Figure 3.8 Initial SOC map (a) and frequency graph (b) of the HSMUs

The Initial SOC content of the HSMUs are also spatially distributed within the study area (Figure 3.8a), ranged from 33 to 280 Mg C ha^{-1}, with an average of 143 Mg C ha^{-1}. The Initial SOC content is mainly concentrated in two distribution bins averaged 107 and 205 Mg ha^{-1} (Figure 3.8b); these two bins were selected for the analysis.

Finally, the EPIC model has several equations available to simulate water erosion, based on previous research conducted in Uruguay (Clérici C., 2001; Puentes, 1981), the equation selected was the Revised Universal Soil Loss Equation (RUSLE) (Renard et al., 1991):

$$A = R * K * LS * C * P \qquad \text{(Equation 3.1)}$$

Where:
A= estimated average soil loss in tons per ha per year
R= rainfall-runoff erosivity factor
K= soil erodibility factor
L= slope length factor
S= slope steepness factor
C= cover-management factor
P= support practice factor

The following standard statistical tests were conducted: 1) when the impact of the management was addressed, Tukey's HSD was used to evaluate the probability that the means of the model outputs of the different scenarios were the same and, 2) when the combined effect of initial SOC and Slope was analyzed, multiple regression analysis of the standardized values of the modeled outputs for each scenario was performed in order to determine the weight of each factor in the final results.

3.3. Results

3.3.1 Grassland to cropland changes from 2000 to 2013

The LCCS-FAO map of Uruguay was used to measure changes in the 410,000 ha study area from 2000 to 2013. The 7,239 HSMU polygons had an average area of 57 ha (Figure 3.3). 90% of the area changed after 2005 (Figure 3.9), so the transitions in the period from 2006 to 2015 were studied.

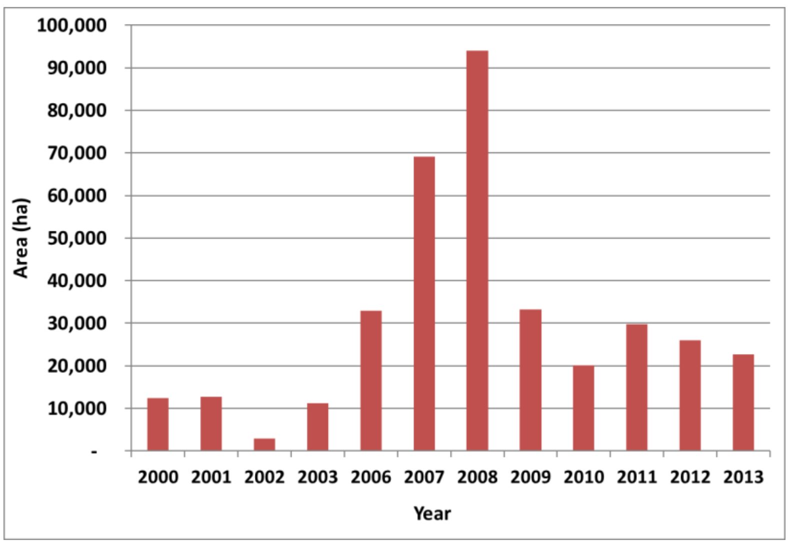


Figure 3.9 Estimated yearly area of LU change.

3.3.2 Winter and summer crop cover from 2000 to 2015

The locations of LU change estimated with the MODIS LU product agreed with the increment of the crop area in the national statistics from 2000 to 2015 (MGAP-DIEA, 2016) (Figure 3.9). Also, the ratio of winter to summer crops of 1:3 agreed with that derived from the yearly average national statistics (MGAP-DIEA, 2016).

3.3.3 Soil degradation of the study area

The recent LU changes simulated by EPIC (Grass-Crop scenario) revealed a soil degradation associated with these changes, with losses of soil by erosion and SOC. The simulated average yearly soil loss due to water erosion was 12.54 Mg ha^{-1} year^{-1} (Figure 3.10a) with a minimum of 3.52 Mg ha^{-1} in 2008 and a maximum of 23.49 Mg ha^{-1} in 2013. These values were similar to those reported by García Préchac and Durán (2001), Hill et al. (2008), Clérici (2001) and Puentes (Puentes, 1981) for different soil and management conditions in Uruguay. Considering the distribution of the yearly average values per HSMU over the study area, the 90th percentile of simulated soil erosion ranged from 2.09 to 32.75 Mg ha^{-1} (Figure 3.10a). The annual total soil loss due to water erosion averaged 5,142 Gg year^{-1} over the whole study area during the study period.

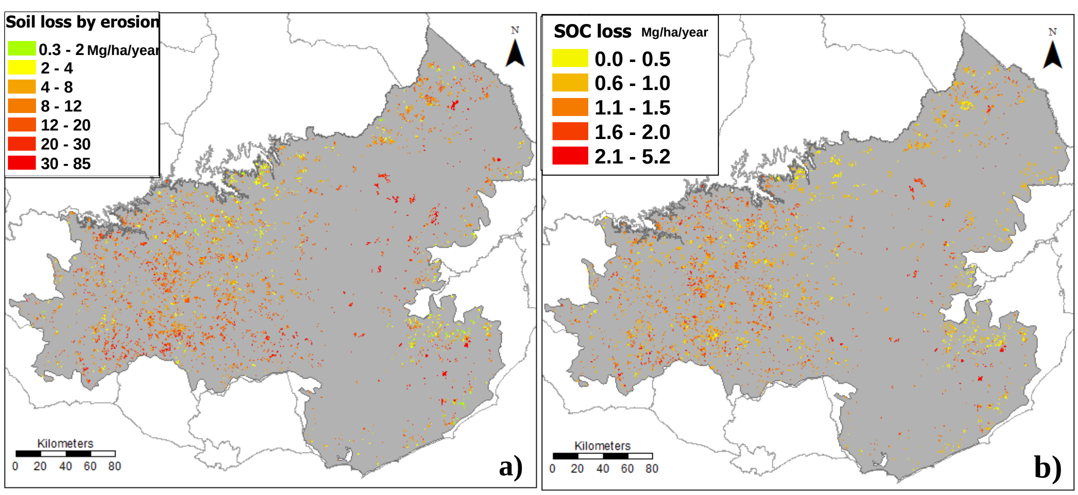


Figure 3.10 Maps of average yearly soil loss by erosion (a) SOC loss (b) and of Grass-Crop scenario.

Soil organic C losses are closely linked to erosion, as demonstrated by (Lal, 2005, 2003) when comparing SOC pools between severe and slightly eroded soils. In this study, the simulated average yearly SOC loss per hectare for the whole study area for the study period was 1.08 Mg ha^{-1} $year^{-1}$ with a minimum of 0.50 Mg ha^{-1} in 2008 and a maximum of 1.02 Mg ha^{-1} in 2006. Again, considering the 90th percentile of the distribution of the yearly average values per HSMU over the study area, the simulated spatial distribution in SOC loss ranged from 0.39 to 1.96 Mg ha^{-1} (Figure 3.10b). Overall, the study area lost an average of 441 Gg C $year^{-1}$.

3.3.4 Soil types and soil degradation

The relation between the characteristic properties used to group soils into spatial units and SOC dynamics and soil erosion were clearly present in our study (Table 3.1). For example, soil units 2.21 and 10.7 (Table 3.2, red rectangle), which cover similar areas and have the same depth (Table 3.1), but differ in texture (unit 10.7 has more silt and less sand) and initial SOC (unit 10.7 has almost double), differed two to three fold in erosion and almost the same for SOC (Table 3.2).

Table 3.1 Description of soil unit 2.21 (left) and 10.7 (right).

	Soil Unit 2.21					Soil Unit 10.7		
Description	**Layer1**	**Layer2**	**Layer3**	**Layer4**		**Layer1**	**Layer2**	**Layer3**
Depth to bottom of layer (m)	0.21	0.32	0.59	0.80		0.20	0.40	0.85
Organic carbon concentration (%).	3.19	2.03	1.74	1.04		1.73	1.25	0.69
% sand.	31.0	26.0	18.0	24.0		20.0	13.0	12.0
% silt.	44.0	42.0	20.0	26.0		57.0	42.0	43.0
Bulk Density (T/m^3)	1.17	1.28	1.53	1.38		1.29	1.33	1.38
soil pH	5.5	6.5	6.7	8.0		5.7	6.5	7.3
Sum of bases (cmol/kg)	10.2	14.7	20.9	30.6		9.2	19.7	21.7
Cation exchange capacity (cmol/kg)	18.5	21.1	29.0	34.0		12.8	22.5	22.8

Table 3.2 Average SOC loss and soil loss by erosion by soil units.

Soil Unit	area (ha)	Percentage Accumulated	Average SOC loss Mg ha^{-1} $year^{-1}$ Grass-Crop	Grass	Soy-Wht	Soy-Soy	Average soil loss erosion Mg ha^{-1} $year^{-1}$ Grass-Crop	Grass	Soy-Wht	Soy-Soy
10.3	81056.2	20%	-1.4	-1.0	-1.2	-2.2	12.9	2.5	8.0	33.5
5.4	38765.4	29%	-0.8	-0.4	-0.5	-1.1	15.8	3.1	15.5	39.5
10.12	36764.9	38%	-1.2	-0.9	-1.0	-1.8	11.0	2.2	8.2	29.9
10.7	28873.9	45%	-0.6	-0.3	-0.3	-0.7	7.7	1.4	7.6	20.1
2.21	28777.8	52%	-1.7	-1.1	-1.4	-2.3	23.6	4.4	17.5	57.7
10.2	13722.4	55%	-1.2	-0.8	-1.0	-1.5	10.7	2.2	6.7	29.3
2.20	9902.6	58%	-0.9	-0.4	-0.6	-1.0	27.1	5.1	30.2	75.2
12.11	9813.3	60%	-1.5	-1.2	-1.2	-2.3	9.1	1.6	7.0	25.6
12.22	9013.8	62%	-1.6	-1.2	-1.2	-2.2	8.3	1.4	5.4	23.2
4.1	8390.4	64%	-0.7	-0.3	-0.3	-0.7	7.0	1.2	5.6	21.6
5.3	8252.2	66%	-0.7	-0.3	-0.4	-0.9	13.9	2.7	11.9	32.4
5.5	8199.7	68%	-1.4	-0.9	-1.1	-2.2	16.5	3.3	11.9	41.7
13.32	6761.2	70%	-1.3	-0.9	-1.0	-1.6	10.3	2.0	4.4	33.5
6.16	6394.8	71%	-1.3	-0.6	-0.8	-1.7	20.6	3.8	12.6	57.1
3.54	5942.2	73%	-0.6	-0.3	-0.4	-0.7	5.9	1.1	6.2	14.2
D10.1	5844.7	74%	-0.6	-0.4	-0.5	-0.7	5.3	1.1	4.3	13.5
10.13	5831.3	76%	-0.6	-0.3	-0.4	-0.8	11.4	2.3	10.8	30.2
G10.2	5775.4	77%	-0.9	-0.5	-0.6	-1.4	10.7	1.8	7.2	33.6
13.4	5278.1	78%	-1.4	-0.8	-0.9	-1.9	12.0	2.0	6.4	37.7
G10.6b	5206.8	80%	-0.6	-0.3	-0.4	-0.5	3.4	0.6	2.8	10.0
12.21	5184.8	81%	-1.1	-0.7	-0.8	-1.5	12.0	2.1	9.6	34.6
8.5	4935.2	82%	-0.5	-0.4	-0.4	-0.5	9.7	1.9	5.7	26.4
G10.6a	4673.9	83%	-0.6	-0.3	-0.4	-0.7	7.2	1.3	6.1	22.0
8.6	4612.4	84%	-0.6	-0.3	-0.4	-0.5	4.6	0.9	3.9	13.0
8.8	4530.5	85%	-0.6	-0.3	-0.3	-0.6	10.3	1.8	7.7	26.4
10.1	4142.0	86%	-1.6	-1.3	-1.4	-2.5	12.0	2.6	5.0	33.4
10.16	4085.7	87%	-1.3	-0.8	-1.0	-1.7	10.5	1.9	7.2	25.2
10.8a	3920.8	88%	-1.1	-0.9	-1.0	-1.7	11.3	2.2	7.9	28.5
10.4	3730.0	89%	-1.0	-0.8	-1.0	-1.2	6.8	1.5	4.3	18.9
10.8b	3672.8	90%	-1.3	-1.0	-1.1	-1.9	11.3	2.4	9.5	29.3
9.3	3527.8	91%	-0.4	-0.2	-0.2	-0.3	4.2	0.7	3.8	10.1
6.15	3483.6	92%	-1.0	-0.4	-0.6	-1.2	13.6	2.4	10.2	41.5
9.5	3184.2	93%	-0.8	-0.5	-0.6	-0.9	8.2	1.4	6.4	19.1
Average			-1.0	-0.6	-0.7	-1.3	11.1	2.1	8.4	29.9
Std. Dev.			0.4	0.3	0.3	0.6	5.1	1.0	5.1	13.7

3.3.5 Effects of anthropogenic and biophysical drivers on soil degradation

3.3.5.1 Anthropogenic (Management)

Farmers select cultivation method, cultivar selection, planting date and method, nutrient and pest management, and harvest and post-harvest treatments. These choices, when combined with seasonal weather and soil-landscape characteristics, determine the extent of soil degradation. Here, the focus was on the crop rotation of winter and summer crops and also fallow period; i.e., after a summer crop, it could be planting a winter crop, or keeping the land fallow.

The address the impact of this management practice, comparisons between scenarios (Grass, Grass-crop, Soy-Wheat and Soy-Soy) were done, using the grassland condition (Grass) (no LU change) as a baseline scenario. On Grass scenario, the average simulated yearly loss for the whole study area for the study period of soil by water erosion was 2.4 Mg ha^{-1} year^{-1}, while the average yearly SOC loss was 0.7 Mg ha^{-1} year^{-1} (Figure 3.11).

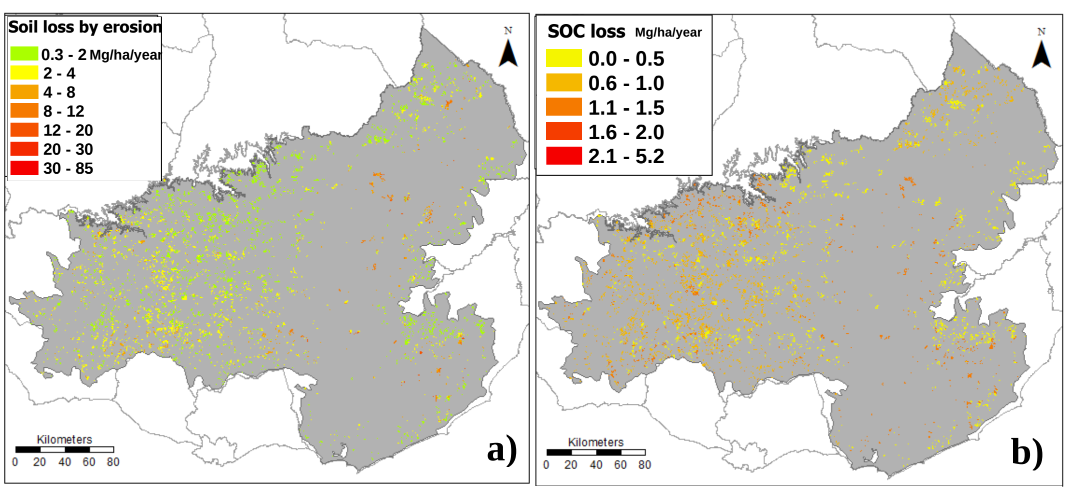


Figure 3.11 Maps of average yearly SOC loss (a) and soil loss by erosion (b) of Grass scenario.

The simulated crop rotation scenarios had large effects in erosion losses, the Grass scenario (baseline) produced the minimum soil loss, followed in increasing order by Soy-Wheat and Grass-Crop (medium), and finally Soy-Soy (maximum) (Table 3.3), all these different were statistically significant ($p<0.05$). The loss in the Grass-crop scenario was 5.3 times more that for Grass, 4.0 times more with Soy-Wheat and 13.9 times more with the Soy-Soy. There was a notable spatial variability in the average soil loss by erosion between the different scenarios (Figure 3.12).

Table 3.3 Soil loss by erosion under the different scenarios.

	Average† (Mg ha^{-1} year^{-1})	**Study area (Gg year^{-1})**	**Compared with Grassland (times)**
Grass	**2.4a††**	**964**	
Grass-Crop	**12.5c**	**5,142**	**5.3**
Soy-Wheat	**9.4b**	**3,841**	**4.0**
Soy-Soy	**32.6d**	**13,365**	**13.9**

† Averages of yearly values for all HSMUs
†† Within columns, means followed by the same letter are not significantly different according to Tukey's HSD ($p<0.05$)

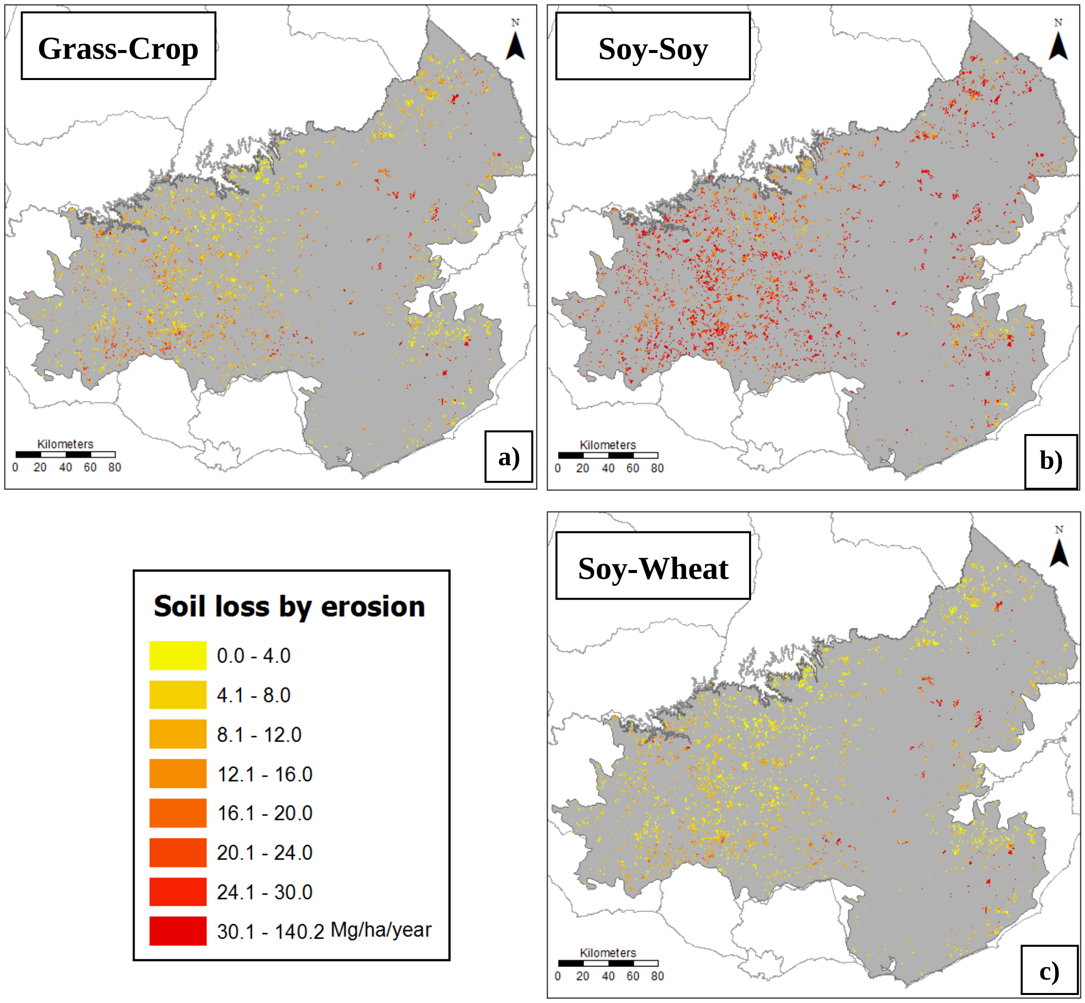


Figure 3.12 Maps of yearly soil loss by erosion for each scenario after subtraction of the Grass scenario: a) Grass-crop, b) Soy-Soy and c) Soy-Wheat.

Similarly to the erosion losses, the effect of crop rotation scenarios greatly affected SOC loss. The losses were lowest on the Grass scenario (minimum), followed in increasing order by Soy-Wheat, and Grass-Crop and Soy-Soy (Table 3.4), all these different were statistically significant ($p<0.05$). Compared with the Grass scenario, the losses were 1.2 times greater for Grass-crop, 1.5 times more for Soy-Wheat and 13.9 times more for the Soy-Soy scenarios. As with the erosion results, there was a significant spatial variability of SOC losses (Figure 3.13).

Table 3.4 Average yearly SOC loss under the different scenarios.

	Average† (Mg ha^{-1} year^{-1})	Study area (Gg year^{-1})	Compared with Grassland (times)
Grass	0.7a††	285	
Grass-Crop	1.1c	441	1.5
Soy-Wheat	0.8b	340	1.2
Soy-Soy	1.5d	622	2.2

† Averages of yearly values for all HSMUs
†† Within columns, means followed by the same letter are not significantly different according to Tukey's HSD ($p<0.05$)

The differences in soil and SOC losses between scenarios were similar to the results of Duval et al. (2016), Novelli et al., (2017, 2013, 2011) and Havlin et al. (1990). For example, the greater plant cover in the Grass and Soy-Wheat scenarios were inversely correlated with soil erosion and SOC losses; and residues left after wheat harvest were also inversely correlated too. The simulation results also suggested that, in spite of using No-Tillage, in all scenarios the soils lost SOC, as reported by others Milesi et al. (2013), and Maraseni and Cockfield (2011).

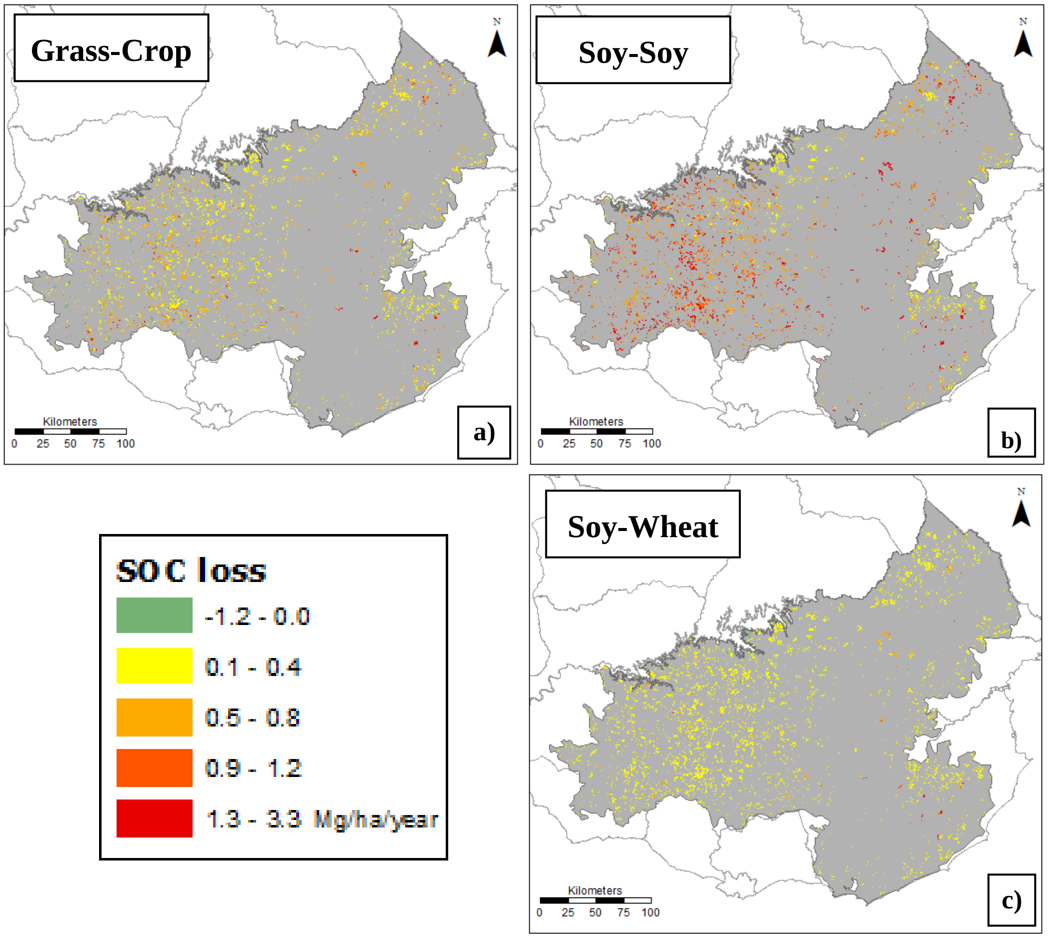


Figure 3.13. 2006-2015 yearly average SOC loss compared with Grass scenario a) Grass-crop, b) Soy-Soy and c) Soy-Wheat.

3.3.5.2 Biophysical factors

Slope had a significant impact on simulated soil loss (Figure 3.14a), as expected since slope steepness and length are key components of the soil erosion equation (García Préchac et al., 2009; García Préchac and Durán, 2001) (Equation 3.1).

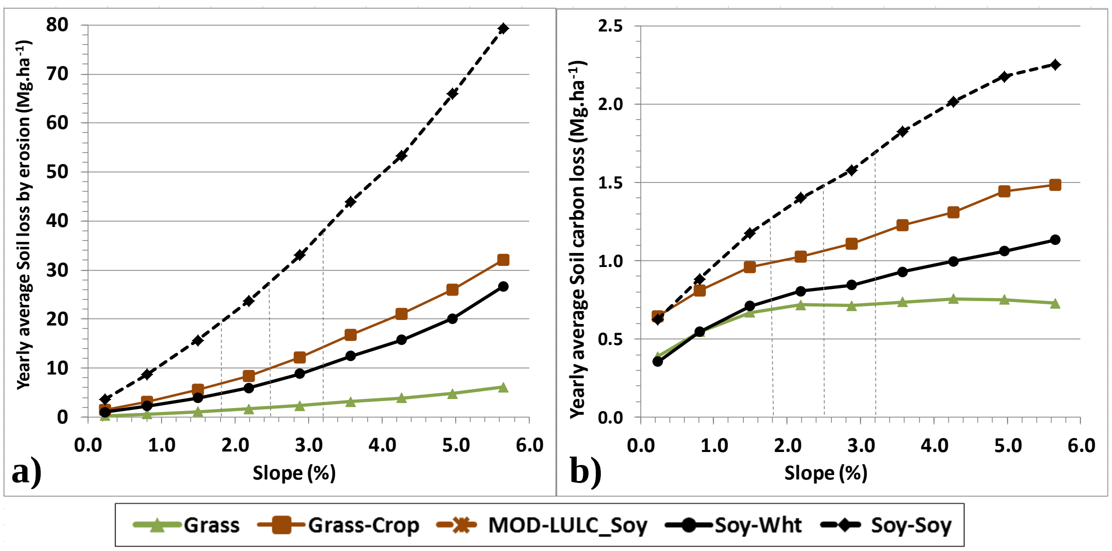


Figure 3.14 Impact of slope on average loss of soil by erosion (a) and SOC (b) for each LU scenario.

Slope was also related to SOC loss in all four scenarios (Figure 3.14b); of these, Grass-Crop and Soy-Soy were most affected. For example, for an average slope of 2.2%, the SOC loss was 0.72, 0.81, 1.03 and 1.40 Mg ha^{-1} for the Grass, Soy-Wheat, Grass-Crop and Soy-Soy scenarios, respectively.

Initial SOC content had a lower correlation with soil erosion than C loss (Figure 3.15). Average soil loss across the study area during the study period was 13.3 Mg ha^{-1} year^{-1} when initial SOC stock was 107 Mg ha^{-1}, and 15.6 Mg ha^{-1} year^{-1} when initial SOC stock was 205 Mg ha^{-1}. Considering the average of all scenarios, the yearly average SOC loss for the whole study area during the modeled period was 6.2 Mg ha^{-1} year^{-1} when initial SOC stock was 107 Mg ha^{-1} (a 6% loss with respect to its initial value) and 14.6 Mg ha^{-1} year^{-1} when initial SOC stock was 205 Mg ha^{-1} (a 7% loss with respect to its initial value). Differences between scenarios were consistent across the study area, i.e., initial SOC 205 Mg ha^{-1}always lost more carbon than initial SOC 107 Mg ha^{-1} (1 - 1.75 fold more). These results agree with Mann (1986) who found low-C soils gained C after cultivation while high C soils lost at least 20%.

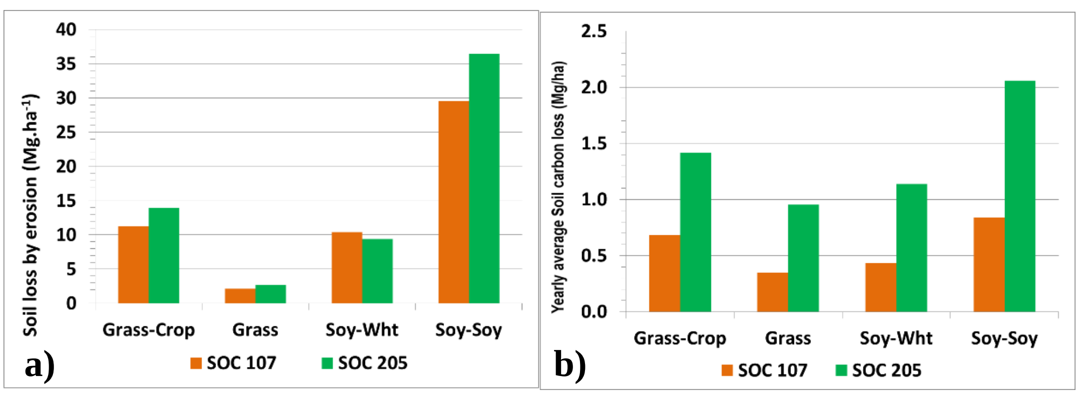


Figure 3.15 Impact of initial SOC on (a) soil loss by erosion and (b) on average SOC of each LU scenario.

Finally, the combined effect of initial SOC and slope on the soil degradation was analyzed. As was presented above in this section, the loss of SOC was related to both, in order to determine the importance of each factor, multiple-regression analyses of the standardized values of the model outputs for each scenario was used (Appendix 2.1.1.). For all scenarios, the initial SOC had the highest coefficients for soil losses (Table 3.5); in the Grass scenario, this accounted for about 84% of the variance, while in scenarios that included crops (Grass-Crop, Soy-Wheat, and Soy-Soy) it ranged from 60% to 66%. This less weight of the slope on Grass scenario, is explained due to its SOC loss has the less correlation with slope (Figure 3.14b).

Table 3.5 Relative contribution of the Initial SOC and Slope on the SOC loss (see Appendix 2.2.1).

	Initial SOC	**Slope**
Grass	**84%**	**16%**
Grass-Crop	**65%**	**35%**
Soy-Wheat	**66%**	**34%**
Soy-Soy	**60%**	**40%**

The simulated average values of SOC loss in the four scenarios, and their average for sites with two initial SOC levels and five different slopes (Table 3.6) indicated the same strong influence of slope as was found in the regression analyses. For example, with an initial SOC of 107 Mg ha^{-1}, the fields with slopes of 2.2% and 5.0%, lost 0.71 and 0.52 Mg ha^{-1} year^{-1}, respectively, that is 5.0% and 38% C of their initial values. The same trend was observed with initial SOC of 205 Mg ha^{-1}, and the effect of slope was greater: 1.79 and 1.18 Mg ha^{-1} year^{-1}, respectively, which is 51% more C loss with 5.0% than 2.2% slope. For the HSMUs with 2.2% slope (average of the study area) those with initial SOC 205 Mg ha^{-1} lost 1.18 and those with 107 Mg ha^{-1} lost 0.52 Mg ha^{-1} year^{-1}, respectively, that is 130% more C.

Table 3.6 Impact of initial SOC and slope on average SOC loss (Mg ha^{-1} year^{-1}) for each LU scenario.

Initial SOC	Slope (%)	Grass-Crop	Grass	Soy-Wheat	Soy-Soy	Average scenarios
SOC 107	Average slope	**0.68**	**0.35**	**0.43**	**0.84**	
	0.8	0.56	0.30	0.28	0.55	0.42
	2.2	0.62	0.34	0.38	0.71	0.52
	3.6	0.70	0.36	0.46	0.92	0.61
	5.0	0.81	0.38	0.54	1.11	0.71
	7.9	1.03	0.41	0.75	1.43	0.91
SOC 205	Average slope	**1.41**	**0.95**	**1.14**	**2.06**	
	0.8	1.11	0.86	0.85	1.22	1.01
	2.2	1.20	0.91	0.99	1.63	1.18
	3.6	1.47	0.97	1.17	2.23	1.46
	5.0	1.82	1.05	1.41	2.86	1.79
	7.9	2.28	1.12	1.84	3.42	2.17

As was done with loss of SOC, to quantify the effect of soil loss by erosion, a multiple-regression analysis was used to determine the weight of each factor (Appendix 2.1.2.). The results (Table 3.7) show that for all scenarios the Slope was the dominant factor related to the soil losses by erosion (about 90%) and the Initial SOC only weight for 10%.

Table 3.7 Relative contribution of the initial SOC and slope on the soil loss by erosion.

	Initial SOC	Slope
Grass	**10%**	**90%**
Grass-Crop	**9%**	**91%**
Soy-Wheat	**8%**	**92%**
Soy-Soy	**10%**	**90%**

3.4 Discussion

Based on the results, it can be concluded that the recent land conversion from grassland to cropland in the study area has significantly reduced soil quality. The loss of soil by erosion greatly exceeds tolerable limits for maintenance of soil quality in the medium to long term both in the Uruguayan environment (García Préchac and Durán, 2001) and elsewhere (Pimentel et al., 1995; Verheijen et al., 2009). The main drivers that could affect the erosion processes during the crop stage are the biomass and during fallow periods the amount, type of residue and how long it last over the soil (Montgomery, 2007). With this management that was common practice leave as fallow during winter (management scenarios Grass-Crop and Soy-Soy) with no cover, and due to amount of rain are more than 300 mm per season (Castaño et al., 2011) is expected that these combined effects could be the main drivers of the loss by erosion estimated.

The main driver of SOC loss is the respiration of soil organisms and the harvested portion of the crops that remain over the soils (residue) (Izaurralde et al., 2007; Mazzilli et al., 2012). In this study the crops management scenarios include two crops soybean and wheat, the first one has less biomass and when harvesting less residue (input) is left, and in addition, the residue have a different composition (more degradable) which in fact is discomposed (carbon respiration) much quicker than the wheat residue. Finally, less C is incorporated to the soils (inputs) on soybean than in wheat, and it could be the main reason of why it loss more soil C than wheat.

One limitation of our research it was assumed that the entire soil C was lost to the atmosphere or runoff but in fact, there is a redistribution of C across the landscape with deposition of carbon in the lower areas from higher areas (Gregorich et al., 1998; Lal, 2005). The Spatial EPIC model developed here does not include lateral transport of materials between adjacent HSMUs.

The results presented above (Section 3.3.5.2) show that in order to preserve the soils under different crop managements, farmers or conservation lawmakers need to consider the combined effects of biophysical drivers on soil degradation instead of taking each one independently. Also, the results could help farmers to select crop rotations based on how crop sequence and slope gradient impact on soil degradation.

Finally, in the mid-term, a change in the current land use could be necessary in order to ameliorate the current soil degradation. Many technological solutions could be adopted such as those proposed by Lal (2002) and by studies conducted in other regions of Uruguay (Alvarez et al., 1995; Morón et al., 2012). These options could be (1) introduction of winter cover crops (grass) to protect the soil and also as a soil C input; and (2) rotation with grass and leguminous plants (e.g. *Trifolium repens*, *Trifolium pratense*) and lotus (*Lotus spp*) that have been used in the past in Uruguay to restore the soils, also grazed by livestock that increases the soil carbon, as reported by Guo and Gifford (2002); and (3) rotate the summer crop (soybean) with a crop that leaves more residues such as Sorghum (*Sorghum bicolor* (L.) Moench) or Maize (*Zea mays L.)*.

3.5 Conclusions

The main findings of the study of the impacts of the recent conversion of natural grassland to cropland ecosystem in the Center-South of Uruguay, with the main focus on soil erosion by water and the changes in soil C stock, were: first, analyzing the impact of management (crop rotation), for the whole study period, on average the soil by erosion as a consequence of the recent LU change was higher than the Grass and the Soy-Wheat scenario, and lower than the Soy-Soy scenario. Almost the same trend was observed when the loss of SOC stock is analyzed, in this case, the higher loss was Soy-Soy, followed by Grass-Crop and the less loss was Soy-Wheat and Grass scenarios. Second, analyzing the impact by drivers on soil loss by erosion, the highest impact was the Management (crop rotation) followed by Slope and finally Initial SOC and the impact on SOC stock the order of the drivers was Management, followed by Slope and the less impact was Initial SOC.

Finally, it could be concluded that based on the results of this study that the recent conversion from Grassland to Cropland has impacted negatively on the soil quality and or soil degradation that could be mitigated with improved crop management practices.

Chapter 4: Synthesis, discussion and significance

4.1 Synthesis of research

Globally, during the last decades there was a conversion at a high rate of natural lands to human managed agricultural lands to grow crops, raise animals, and obtain timber; as a consequence, this conversion produced a land degradation that could impact negatively on future food security, climate and other ecosystem services. Currently, there is a demand for quantitative information assessing the severity, distribution, and causes of this land degradation in order to mitigate these impacts.

The focus of this research was on grasslands, one of the most modified biomes, which have been converted mainly to croplands to produce food, biofuels and fiber. A region of natural grassland in Uruguay was selected that had a notable LU change during the last 15 years to assess the impact on soil degradation of these changes.

The main goals of this dissertation were: (1) the calibration and validation of a bio-physical simulation model to reproduce to simulate key agro-ecological processes of this agro-ecosystem, (2) the identification of the LU change from Grassland to Cropland and the yearly land use (crop rotation) of the study area, and (3) the quantification of the potential impact on the soil quality (degradation) in the medium-term of this LU changes, at a regional scale, using the adapted bio-physical simulation model, analyzing how the biophysical and anthropogenic drivers affect these impacts. This chapter synthesizes the main findings and discusses their significance.

To address the first goal, the EPIC (Environmental Policy Integrated Climate) model was selected to simulate key agro-ecological processes associated with grassland-cropland (Izaurralde et al., 2006b; Williams et al., 1984). This model was, first developed to run at a point scale, typically one simulation per field, but lately, it has been extended to a spatial domain to simulate regional to country scale processes (Zhang et al., 2010).

In order to simulate at a regional scale, first the model was calibrated and validated at a field scale and after that extended to a spatial version, even though EPIC is flexible enough to perform under a variety of environments, there was no prior experience using the model to simulate Uruguayan agroecosystems. Consequently, there was a need to calibrate and validate the model for these conditions. This process was performed independently for the grassland and the cropland ecosystems because these ecosystems have very different management and development conditions.

It was found that EPIC model consistently reproduced the field-scale crop productivity and soil processes under grassland and cropland covers in South-Central Uruguay. An acceptable agreement was achieved after calibration and testing of EPIC using local data, firstly on the grass and crop yields and, secondly, on the soil loss by erosion and the loss of soil carbon. These results allow to running EPIC at a regional scale in the study region.

The next step was the development of a spatial version of the EPIC model adapted to the main Uruguayan agroecosystems, and after that, the validation for Grasslands and Croplands was done. There was good spatial and temporal agreement between modeled productivity (NPP) and the indirect indicators used.

To achieve the second goal, changes in LULC areas during 2000 - 2012 were identified with the product LCCS-FAO of Uruguay (MGAP Uruguay et al., 2011; MVOTMA-DINOT, 2015) covering an area of 410,000 ha about 13% of potential area to grow cash crops (MGAP-RENARE-DSA, 2003) were converted during this quite short period. Next, when this transition had occurred and what type of crop rotation were used in these new areas (winter and summer crops) was identified using MODIS' Vegetation Indexes (MOD13Q1) (Huete et al., 2002) and vegetation phenologies. The findings agreed with the increment of the crop area based on national statistics (MGAP-DIEA, 2016) and also the ratio of winter to summer crops (1:3) agreed with that derived from yearly average national statistics (MGAP-DIEA, 2016).

Finally, the impact on soil degradation was addressed, with the main focus on soil erosion by water and the changes in soil C stock, caused by conversion of natural grassland to cropland. The main finding was that crop rotation affected the loss of soil by erosion and loss of SOC. The soil loss by erosion was greatest for Soy-Soy, followed by Grass-Crop, and Soy-Wheat and the least effect was continuous Grass, almost the same trend was observed when the loss of SOC stock is analyzed, in this case, the higher loss was Soy-Soy, followed by Grass-Crop and the less loss was Soy-

Wheat and Grass. The effects of drivers on soil loss by erosion and on SOC found that the type of crop rotation was most important, followed by Slope and finally Initial SOC and the impact on SOC stock the order of the drivers was the highest Management, followed by Slope and the less impact was Initial SOC.

The main conclusion, based on the results of this study, was that the recent conversion from Grassland to Cropland has impacted negatively on the soil degradation (soil quality); it could be mitigated with improved crop management practices on the current modified areas and selecting new areas with less potential degradation risk (Slope).

4.2 Relevance to climate, global carbon budget, water quality and food security

The research was focused on soil degradation, a major aspect of the land degradation. "Land" was defined by the United Nations Convention to Combat Desertification (UNCCD) as "the terrestrial bio-productive system that comprises soil, vegetation, other biota, and the ecological and hydrological processes that operate within the system" (UNCCD/Science-Policy-Interface, 2016). In the context of land degradation resulting from land use changes, even though some of them were not directly addressed in this research, relevant effects of this conversion are the change of the carbon cycle, the climate, water, ecosystem services and biodiversity.

4.2.1. Impact in the carbon cycle

Between 1850 and 1990, changes in land use are calculated to have added 124 Pg C to the atmosphere over this period, about half as much as released from combustion of fossil fuels; where about 108 Pg C are estimated to have been transferred from forests to the atmosphere as a result of human activity, and another 16 Pg C were lost as a result of cultivation of mid-latitude grassland soils (Houghton, 1999). Shevliakova et al. (2009) using a dynamic land model (LM3V), estimated that during the 1990s, globally, a net terrestrial carbon source due to land use activities ranges from 1.10 to 1.30 Pg C year^{-1}, where the range is due to the difference in the historic cropland distribution, the estimates for the pastures' carbon flux vary from a source of 0.37 to a sink of 0.15 Pg C year^{-1}, and for the croplands shows a carbon source of 0.60 to 0.90 Pg C year^{-1}.

In this context, the findings, presented in Chapter 3, shows that the estimated impact of the land use change in Uruguay from grassland to cropland on the carbon stock was a loss of 0.441 x10^{-3} Pg C year^{-1} (Grass-Crop scenario). It could be assumed that most of this carbon was released to the atmosphere, due to the main proportion of this loss is from heterotrophic respiration; as a result, even if all this C was released to the atmosphere, the impact of the LC change of this study region is almost insignificant compared to the global emissions of land use activities for croplands (between 0.074% and 0.049% of the global) (Shevliakova et al., 2009).

The findings of this research in part of Uruguay could be related to a global scale applying the Uruguayan findings to regions of the world that have similar conditions. An attempt to project the Uruguayan SOC loss at global scale was done; basically, it was made mapping the Uruguayan conditions at the global scale and after that applying the found Uruguayan SOC loss to this global area.

Table 4.1 Mapping Uruguayan conditions at the global scale, data sources.

Class - Variable	Description	Source	Spatial resolution and coverage
Climate	Koeppen-Geiger climate region dataset representative for the 50-year period 1951-2000.	(Kottek et al., 2006)	0.5 degree (30 arc minutes) global
Soil - SOC	SOC (0-20cm depth)	International Soil Science Society - World Inventory of Soil property Estimates (WISE) project, (Batjes, 2012)	5 by 5 arc-minutes global grid
Grassland cover	The data is presented as a percentage share of the total grid-cell	Harmonized World Soil Database v 1.2 – FAO Land Use and Land Cover (Fischer et al., 2008)	5 by 5 arc-minutes global grid

In order to find the regions of the world similar to the study area, it was identified those that have a similar climate, SOC at 20cm and grassland cover. The data available at the global scale (Table 4.1) was used. The criteria used for each variable was (1) Koeppen-Geiger climate region Cfa (Humid subtropical, mild with no dry season, hot summer and year around rainfall but highly variable) (Kottek et al., 2006), (2) SOC (20cm) between 1 and 2% (Batjes, 2012), and (3)) Natural, potential Grassland cover more than 60% for each grid cell (Fischer et al., 2008); the regions that meet each criterion is presented in Figure 4.1 (red areas). Intersecting the areas that meet the three criteria a map of the global UY conditions was made (Figure 4.2), the resulted area covers 107,992,500 ha (purple areas) while the UY Study area was 400,000 ha (0.4% of the global); and was located mainly in Southern-East of South America and South-Central US, and spotted areas in Australia, China, Madagascar and Mid-East.

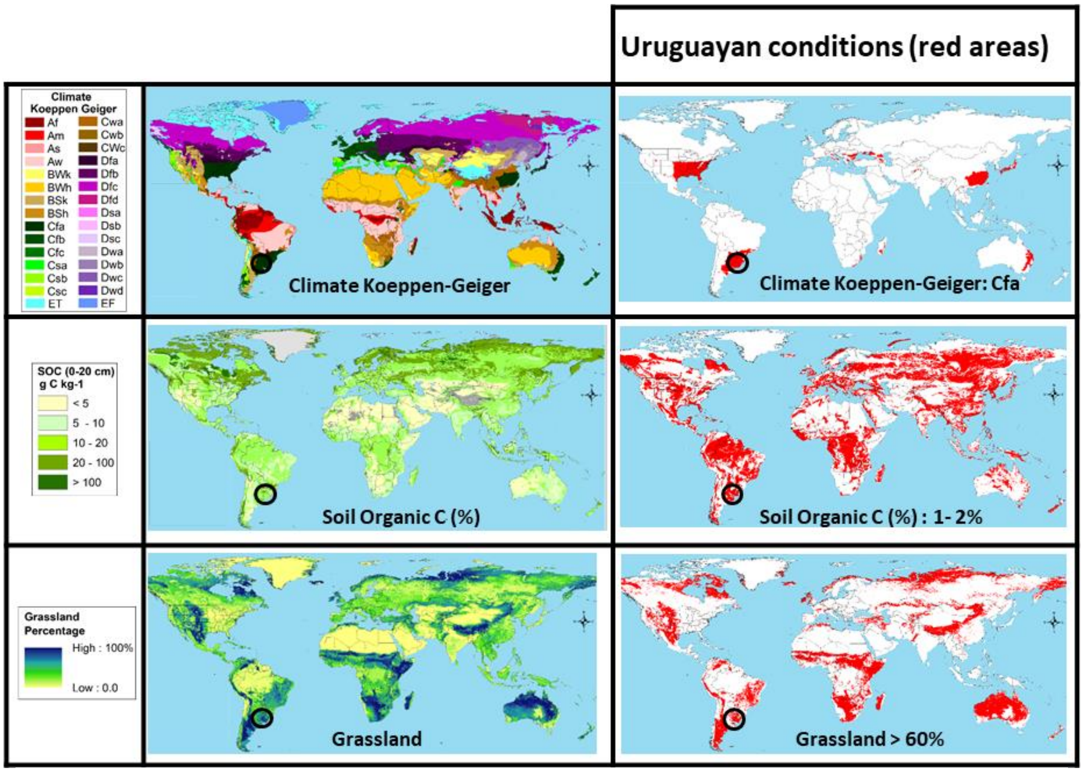


Figure 4.1 Global maps of three components of the Uruguayan environment.

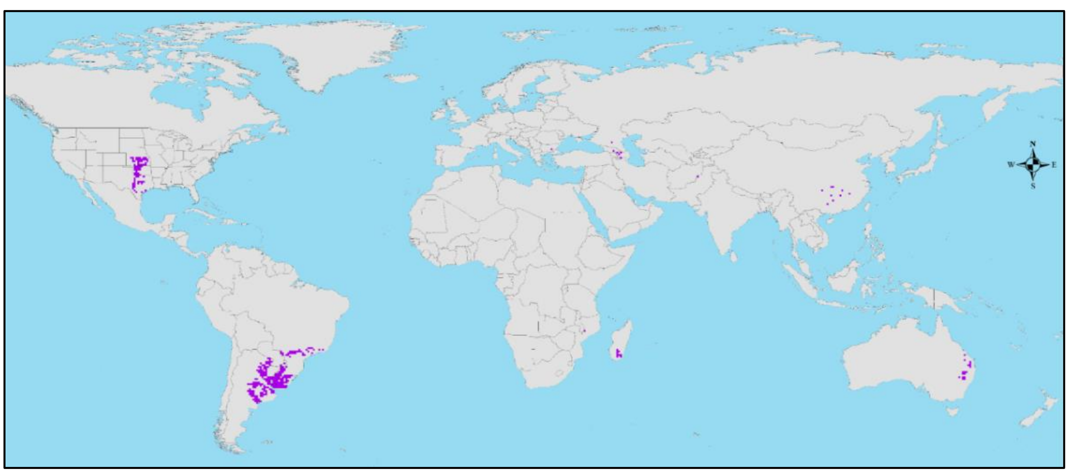


Figure 4.2. Intersection of three aspects of Uruguayan conditions at the global scale. See Fig. 4.1 for maps of each component.

The last step was to apply the UY estimations of SOC loss after LU change to the global UY conditions, the results are presented in Table 4.2. The estimated potential global C losses, if all this area was converted from Grassland, were under the different LU change scenarios: 54.0 Tg year^{-1} on Grass-Crop, 10.8 Tg year^{-1}on Soy-Wheat and 86.4 Tg year^{-1} on Soy-soy. These results could be compared to the global soil respiration, where the CO_2 is released into the atmosphere at an average rate of about 60 PgC year^{-1} (Houghton, 2007).

Table 4.2 Global net SOC loss after conversion to cropping from Grassland to each of the three crop rotations.

	UY estimations	Global UY conditions	
	Mg ha^{-1} year^{-1}	Tg year^{-1}	% of global soil respiration
Grass-Crop	**0.5**	**54.0**	**0.09%**
Soy-Wheat	**0.1**	**10.8**	**0.02%**
Soy-Soy	**0.8**	**86.4**	**0.14%**

4.3.2. Impact on climate and water

Land conversion can alter regional climates through its effects on net radiation, the division of energy into sensible and latent heat, and the partitioning of precipitation into soil water, evapotranspiration, and runoff (Foley et al., 2005). Snyder, Delire, and Foley (2004) using CCM3-IBIS model studied the influence of different vegetation biomes on the global climate; in one simulation they completely removed the vegetation cover of a particular biome and compared it to a control simulation where the biome was present, thereby isolating the climatic effects of each biome. They found that removal of the grassland and steppe vegetation has the largest effect on the central United States with warming and drying of the atmosphere in summer. The area that changed from grassland to cropland under this study was 5.6% of the total area of the study region, which could not be relevant to produced changes in the whole region. But it is expected to produce an impact on the climate at local scale (microclimate) as a result of the changes in evapotranspiration, albedo, etc. and, also it could affect water catchments on quantity (less runoff) and quality (runoff of fertilizers and pesticides).

4.3.3. Impact on Ecosystem services.

Agricultural ecosystems provide humans with food, forage, bioenergy and pharmaceuticals and are essential to human well-being relying on services provided by natural ecosystems, including pollination, biological pest control, maintenance of soil structure and fertility, nutrient cycling and hydrological (Millennium Ecosystem Assessment, 2005; Power, 2010). Current trends in land use allow humans to appropriate an ever-larger fraction of the biosphere's goods and services while simultaneously diminishing the capacity of global ecosystems to sustain food production, maintain freshwater and forest resources, regulate climate and air quality, and mediate infectious diseases. Furthermore, modern land-use practices, while increasing the short-term supplies of material goods, may undermine many ecosystem services in the long run, even on regional and global scales (Foley et al., 2005).

In this regional research was found a loss of soil quality, loss of carbon and soil loss by erosion, these losses could produce a risk on food security as a result of future diminishment of crop yields as was pointed by Lal (2007, 2006) and Izaurralde et al. (2006a). Even though this impact could be at a local scale, due to the almost all the harvested soybean are exported (Simoes and Hidalgo, 2011), in the future could produce loss of food that is required by a high populated country (e.g. China) and this could be a link between a local impact (degradation) with a global impact (food security).

4.3.4. Impact on Biodiversity

In the Rio de la Plata region, the change from a grassland with a rich number of native species (2,000 to 4,000), with about 100 species categorized as endangered species which have been categorized as likely to become extinct as was presented by many authors (Altesor et al., 2005; Lezama et al., 2014; Paruelo et al., 2007; Soriano et al., 1992) to a system with few crops would produce a biodiversity loss of endemic species, not only vegetal species also this change would affect soil microbiomes, insects and small animals (birds, mammals). The estimated LU changed area in this study area from 2000 to 2013, and as a resulting loss of habitat from the grassland environment, was 410,000 ha which represents a 5.6% of the total area of the study region. Even though not cover an important percentage of the total area, it was concentrated in few soil units as was described in the Section 3.3.4 and due to each of these units have as a described characteristic a number of vegetal species (Capurro Etchegaray, 1977) there is a risk of loss of these species on the high intensify land use areas; as an example, the soil unit 10.3 on 2000 has cropland on 25% of its area while in 2013 has 50% or the soil unit 10.12 who has 50% and 67% respectively, both losses a considerable amount of their grassland habitat. Also, a process of landscape fragmentation was detected with about 7,300 HSMU (polygons), this process, as was reported by Baldi et al. (2006) in the same region, has negative consequences on biodiversity.

4.3 Potential beneficiaries and future research

The findings of this original research containing a detailed identification of the impact on land degradation of a contemporary LU change could serve as a base for future researches and could have many potential beneficiaries such as farmers, local government, national policy, international programs and for Earth system science research.

Users clearly include the Uruguayan government. The national soil conservation laws and acts currently are based only on erosion as an indicator of soil degradation in order to ensure crop rotations are used that erode soils below a fixed threshold. The result of this research could allow developing new policies to ameliorate the soil degradation using the loss of soil carbon also as an indicator to preserve the soils.

Uruguay, as one of the Non-Annex I countries parties of the United Nation Framework Convention on Climate Change (UNFCCC), reports national statistics to the Secretariat. In October 2016, the 4th report was published (MVOTMA-SNRCC, 2016) In this document was reported the National Greenhouse Gas Emissions Inventory (NGHGI) using methodologies included on the “Tier 1” as was defined by UNFCCC (2003), and also was stated that “A projected future improvement is to estimate the emission/removal on account of biomass change in grassland to cropland conversion, as well as carbon stock changes in soils”. The results and also the developed methodology (EPIC model) presented here could avoid using “Tier 2” or “Tier 3” methodologies in future reports, ideally extended to the country as a whole, including the traditional crop areas (South-West) and also others “marginal” lands to grow cash crop that remains less impacted by the LU change (North).

The results of this research could be also a contribution for the next Uruguayan national report to the United Nations Convention to Combat Desertification (UNCCD) - PRAID2, the last of which was for the 5th cycle (2014-2015) (UNCCD, 2015).

Farmers could be another potential beneficiary; the results could help them when they plan to change grassland to crops, taking into account the possible impact on land degradation of this transition, and the best types of land management (crop rotation) to adopt. The comprehensive outputs of the modeling also allow the economic consequences of the different rotations to be assessed. This could be applied immediately as a decision support system (Figure 4.3) (INIA Uruguay - GRAS Unit, 2014, 2012). Simple presentations of the results are possible, especially with the spatial products.

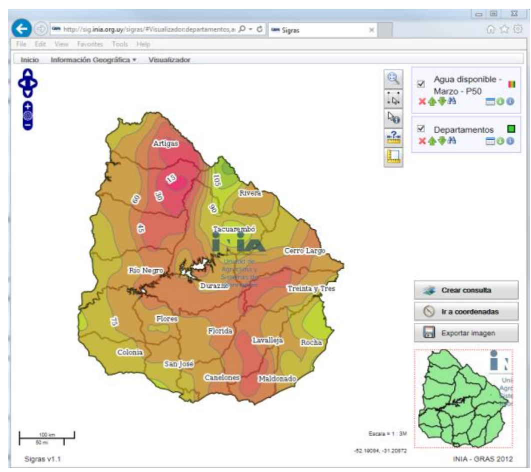


Figure 4.3 SIGRAS - INIA GRAS Unit Geographic Information System.

Finally, this research could contribute to future scientific investigations. For example: to enhance an existing use of the EPIC model to assess the effects on eutrophication and water quality of phosphorus losses from grasslands fertilized with broiler litter (Pierson et al., 1997); assessment of risks to food security (Aggarwal et al., 2010) of land degradation associated with climate changes. The modeling methodology (EPIC model) used in this research, makes it possible to assess the future effects on soil degradation as a consequence of the different possible climate change scenarios (IPCC, 2013); and to expand the scope of existing studies of the impact of climate change on Rio de Plata region, which was focussed on crop yields (Travasso et al., 2006) and grasslands production (Lauenroth et al., 2004) alone, without consideration of land degradation.

Appendix 1. Field scale validation statistical tests

The data analysis for this paper was generated using the Real Statistics Resource Pack software (Release 4.3). Copyright (2013 – 2015) Charles Zaiontz. www.real-statistics.com

1.1. Field scale validation of Grassland ecosystem

1.1.1. Yearly forage yields of INIA-TyT-RS site

Yearly Simulated (EPIC) vs Measured forage yield (DM Mg ha^{-1})

T Test: Two Paired Samples

SUMMARY			Alpha	0.05		Hyp Mean	0	
Groups	*Count*	*Mean*	*Std Dev*	*Std Err*	*t*	*df*	*Cohen d*	*Effect r*
Simulated	12	**3.548**	0.530					
Measured	12	**3.394**	0.836					
Difference	12	0.154	0.585	0.16221	0.948918	11	0.263183	0.264196

T TEST	*p-value*	*t-crit*	*lower*	*upper*	*sig*
One Tail	0.180691	1.782288			**no**
Two Tail	0.361382	2.178813	-0.1995	0.50735	**no**

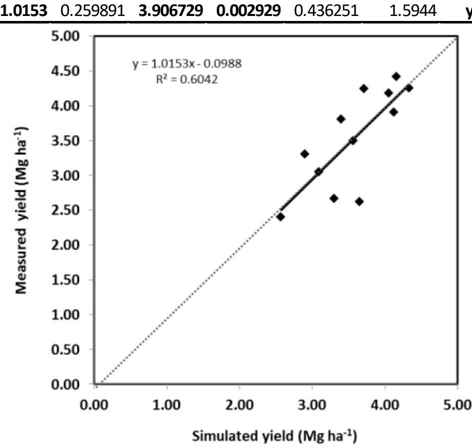
Regression Analysis

OVERALL FIT	
Multiple R	0.777
R Square	0.604
Adjusted R Square	0.565
Standard Error	0.471
Observations	12

AIC	-16.2407
AICc	-13.2407
SBC	-15.2709

ANOVA				**Alpha**	**0.05**	
	df	*SS*	*MS*	*F*	*p-value*	*sig*
Regression	1	3.390562	3.390562	15.26253	0.002929	**yes**
Residual	10	2.221494	0.222149			
Total	11	5.612057				

	coeff	*std err*	***t stat***	***p-value***	*lower*	*upper*	*sig*
Intercept	**-0.0988**	0.938184	**-0.10532**	**0.918201**	-2.18922	1.99159	
Slope	**1.0153**	0.259891	**3.906729**	**0.002929**	0.436251	1.5944	**yes**



1.1.2. Seasonal forage yields of INIA-TyT-RS site

Seasonal Simulated (EPIC) vs Measured forage yield (DM Mg ha^{-1})

T Test: Two Paired Samples

SUMMARY			**Alpha**	**0.05**		Hyp Mean	0	
Groups	*Count*	*Mean*	*Std Dev*	*Std Err*	*t*	*df*	*Cohen d*	*Effect r*
Measured	51	0.915	0.463					
Simulated	51	0.872	0.627					
Difference	51	0.044	0.356	0.050	-0.00243	50	0.00034	0.000344

T TEST

	p-value	*t-crit*	*lower*	*upper*	***sig***
One Tail	0.499035	1.675905			**no**
Two Tail	0.99807	2.008559	-0.10026	0.100017	**no**

Regression Analysis

OVERALL FIT

Multiple R	0.828
R Square	**0.685**
Adjusted R Square	0.679
Standard Error	0.262
Observations	51

AIC	-134.557
AICc	-134.046
SBC	-130.693

ANOVA				**Alpha**	**0.05**	
	df	*SS*	*MS*	*F*	*p-value*	***sig***
Regression	1	7	7	106.6382	6.85E-14	**yes**
Residual	49	3	0			
Total	50	11				

	coeff	*std err*	*t stat*	*p-value*	*lower*	*upper*	***sig***
Intercept	**0.339**	0.063	5.34983	2.31E-06	0.211558	0.466114	
Slope	**0.611**	0.059	10.32658	6.85E-14	0.492267	0.730153	**yes**

1.1.3. Yearly forage yields of SUL-CC-RS site

Yearly Simulated (EPIC) vs Measured forage yield (DM Mg ha^{-1})

T Test: Two Paired Samples

SUMMARY		**Alpha**	**0.05**		Hyp Mean	0			
Groups	*Count*	**Mean**	*Std Dev*	*Std Err*	*t*	*df*	*Cohen d*	*Effect r*
Simulated	6	**3.089**	0.367					
Measured	6	**3.277**	0.701					
Difference	6	-0.188	0.507	0.207	-0.90651	5	0.37008	0.375702

T TEST

	p-value	*t-crit*	*lower*	*upper*	***sig***
One Tail	0.203116	2.015048			**no**
Two Tail	0.406232	2.570582	-0.72033	0.34474	**no**

1.1.4. Yearly SOC loss and stock (15cm) of INIA-TyT-RS site

Simulated (EPIC) vs Measured SOC loss (15cm depth) (Mg ha^{-1} year^{-1})

T Test: Two Paired Samples

SUMMARY — Alpha 0.05 — Hyp Mean Diff 0

Groups	*Count*	***Mean***	*Std Dev*	*Std Err*	*t*	*df*	*Cohen d*	*Effect r*
Measured	6	**0.496**	1.2316					
Simulated	6	**0.449**	0.1766					
Difference	6	**0.047**	1.1835	0.4831805	0.09812715	5	0.04006024	0.0438416

T TEST

	p-value	*t-crit*	*lower*	*upper*	***sig***
One Tail	0.46282185	2.01504837			**no**
Two Tail	0.9256437	2.57058184	-1.1946419	1.28946815	**no**

Yearly Simulated (EPIC) vs Measured SOC (15cm depth) (Mg ha^{-1})

Regression Analysis

OVERALL FIT

Multiple R	0.846
R Square	**0.716**
Adjusted R Square	0.660
Standard Error	0.528
Observations	7

AIC	-7.30813916
AICc	0.69186084
SBC	-7.41631887

ANOVA — Alpha 0.05

	df	*SS*	*MS*	*F*	*p-value*	***sig***
Regression	1	3.5145	3.51448413	12.6273989	0.01632665	**yes**
Residual	5	1.3916	0.2783221			
Total	6	4.9061				

	coeff	*std err*	*t stat*	*p-value*	*lower*	*upper*	***sig***
Intercept	15.313	7.15542691	2.14005172	0.08531176	-3.08062676	33.70659412	
Slope	0.630	0.17733283	3.55350516	0.01632665	0.17430457	1.08600166	**yes**

1.2 Field scale calibration and validation of Cropland ecosystem

1.2.1. Crop grain yield of INIA-LE-RS site after HydroPSO automatic calibration

Simulated (EPIC) vs Measured crop grain yield (Mg ha^{-1})

T Test: Two Paired Samples

SUMMARY			Alpha	0.05		Hyp Mean	0	
Groups	*Count*	***Mean***	*Std Dev*	*Std Err*	*t*	*df*	*Cohen d*	*Effect r*
Simulated	29	**4.76**	1.652					
Measured	29	**4.76**	1.753					
Difference	29	**0.00**	0.678	0.12583	0.015072	28	0.002799	0.002848

T TEST

	p-value	*t-crit*	*lower*	*upper*	***sig***
One Tail	0.494041	1.701131			**no**
Two Tail	0.988081	2.048407	-0.25585	0.259648	**no**

Regression Analysis

OVERALL FIT

Multiple R	0.922
R Square	**0.851**
Adjusted R Square	0.845
Standard Error	0.689
Observations	29

AIC	-19.6686
AICc	-18.7086
SBC	-16.934

ANOVA — Alpha 0.05

	df	*SS*	*MS*	*F*	*p-value*	***sig***
Regression	1	73.17494	73.17494	154.0925	1.14E-12	**yes**
Residual	27	12.82167	0.474877			
Total	28	85.99661				

	coeff	*std err*	*t stat*	*p-value*	*lower*	*upper*	***sig***
Intercept	**0.099864**	0.396433	0.251908	0.80302	-0.71355	0.913277	
Slope	**0.978619**	0.078836	12.4134	1.14E-12	0.816862	1.140376	**yes**

Wheat: Simulated (EPIC) vs Measured crop grain yield (Mg ha^{-1})

T Test: Two Paired Samples

SUMMARY			Alpha	0.05		Hyp Mean	0	
Groups	*Count*	***Mean***	*Std Dev*	*Std Err*	*t*	*df*	*Cohen d*	*Effect r*
Measured	9	**6.4**	0.776945					
Simulated	9	**6.3**	0.343662					
Difference	9	**0.1**	0.64338	0.21446	0.515507	8	0.171836	0.179305

T TEST					
	p-value	*t-crit*	*lower*	*upper*	***sig***
One Tail	0.310069	1.859548			**no**
Two Tail	0.620138	2.306004	-0.38399	0.605101	**no**

Soybean: Simulated (EPIC) vs Measured crop grain yield (Mg ha^{-1})

T Test: Two Paired Samples

SUMMARY			Alpha	0.05		Hyp Mean	0	
Groups	*Count*	***Mean***	*Std Dev*	*Std Err*	*t*	*df*	*Cohen d*	*Effect r*
Measured	10	**2.9**	0.534413					
Simulated	10	**2.8**	0.622122					
Difference	10	**0.1**	0.558215	0.176523	0.322904	9	0.102111	0.107017

T TEST					
	p-value	*t-crit*	*lower*	*upper*	***sig***
One Tail	0.377072	1.833113			**no**
Two Tail	0.754144	2.262157	-0.34232	0.456323	**no**

Sorghum: Simulated (EPIC) vs Measured crop grain yield (Mg ha^{-1})

T Test: Two Paired Samples

SUMMARY			Alpha	0.05		Hyp Mean	0	
Groups	*Count*	***Mean***	*Std Dev*	*Std Err*	*t*	*df*	*Cohen d*	*Effect r*
Measured	10	**5.1**	1.436906					
Simulated	10	**5.3**	1.127759					
Difference	10	**-0.2**	0.839036	0.265327	-0.61057	9	0.193079	0.199434

T TEST					
	p-value	*t-crit*	*lower*	*upper*	***sig***
One Tail	0.278294	1.833113			**no**
Two Tail	0.556588	2.262157	-0.76221	0.43821	**no**

1.2.2. Crop grain yield of INIA-SRRN-RS site

Simulated (EPIC) vs Measured crop grain yield (Mg ha^{-1})

T Test: Two Paired Samples

SUMMARY			Alpha	0.05		Hyp Mean	0	
Groups	*Count*	***Mean***	*Std Dev*	*Std Err*	*t*	*df*	*Cohen d*	*Effect r*
Measured	32	**4.9**	1.811632					
Simulated	32	**4.8**	1.838124					
Difference	32	**0.1**	1.245561	0.220186	0.463695	31	0.081971	0.082995

T TEST

	p-value	*t-crit*	*lower*	*upper*	***sig***
One Tail	0.323053	1.695519			**no**
Two Tail	0.646106	2.039513	-0.34697	0.551172	**no**

Regression Analysis

OVERALL FIT

Multiple R	0.767159
R Square	**0.588533**
Adjusted R Square	0.574818
Standard Error	1.181293
Observations	32

AIC	12.59777
AICc	13.45491
SBC	15.52924

ANOVA				Alpha	0.05	
	df	*SS*	*MS*	*F*	*p-value*	***sig***
Regression	1	59.87872	59.87872	42.90989	3.03E-07	**yes**
Residual	30	41.86358	1.395453			
Total	31	101.7423				

	coeff	*std err*	*t stat*	*p-value*	*lower*	*upper*	***sig***
Intercept	**1.267532**	0.589755	2.149251	0.039803	0.063091	2.471972	
Slope	**0.756103**	0.115426	6.550564	3.03E-07	0.520372	0.991833	**yes**

Wheat: Simulated (EPIC) vs Measured crop grain yield (Mg ha^{-1})
T Test: Two Paired Samples

SUMMARY			Alpha	0.05		Hyp Mean	0	
Groups	*Count*	***Mean***	*Std Dev*	*Std Err*	*t*	*df*	*Cohen d*	*Effect r*
Measured	10	**5.3**	1.134					
Simulated	10	**4.7**	0.918					
Difference	10	**0.7**	1.176	0.3719565	1.782867	9	0.563792	0.510881

T TEST

	p-value	*t-crit*	*lower*	*upper*	***sig***
One Tail	0.054142	1.83311293			**no**
Two Tail	0.108285	2.26215716	0	1.5045728	**no**

Soybean: Simulated (EPIC) vs Measured crop grain yield (Mg ha^{-1})
T Test: Two Paired Samples

SUMMARY			Alpha	0.05		Hyp Mean	0	
Groups	*Count*	***Mean***	*Std Dev*	*Std Err*	*t*	*df*	*Cohen d*	*Effect r*
Measured	8	**3.0**	0.448					
Simulated	8	**3.1**	0.913					
Difference	8	**-0.1**	0.802	0.2836783	-0.39245	7	0.138752	0.146727

T TEST

	p-value	*t-crit*	*lower*	*upper*	***sig***
One Tail	0.353201	1.89457861			**no**
Two Tail	0.706401	2.36462425	-0.782122	0.559463	**no**

Sorghum: Simulated (EPIC) vs Measured crop grain yield (Mg ha^{-1})
T Test: Two Paired Samples

SUMMARY			Alpha	0.05		Hyp Mean	0	
Groups	*Count*	***Mean***	*Std Dev*	*Std Err*	*t*	*df*	*Cohen d*	*Effect r*
Measured	14	**5.6**	1.993					
Simulated	14	**5.8**	2.058					
Difference	14	**-0.2**	1.429	0.381838	-0.46274	13	0.123672	0.127296

T TEST

	p-value	*t-crit*	*lower*	*upper*	***sig***
One Tail	0.325601	1.7709334			**no**
Two Tail	0.651202	2.16036866	-1.001602	0.6482199	**no**

1.2.3. Crop grain yield of INIA-TyT-RS site crop rotation experiment

Simulated (EPIC) vs Measured crop grain yield (Mg ha^{-1})

T Test: Two Paired Samples

SUMMARY			Alpha	0.05		Hyp Mean	0	
Groups	*Count*	***Mean***	*Std Dev*	*Std Err*	*t*	*df*	*Cohen d*	*Effect r*
Simulated	10	**3.76**	1.022023					
Measured	10	**3.60**	1.915184					
Difference	10	**0.17**	1.187624	0.37556	0.440184	9	0.139198	0.145174

T TEST

	p-value	*t-crit*	*lower*	*upper*	***sig***
One Tail	0.335093	1.833113			**no**
Two Tail	0.670186	2.262157	-0.68426	1.01489	**no**

Regression Analysis

OVERALL FIT

Multiple R	0.843485	AIC	3.513223
R Square	**0.711467**	AICc	7.513223
Adjusted R Square	0.6754	SBC	4.118393
Standard Error	1.091151		
Observations	10		

ANOVA				Alpha	0.05	
	df	*SS*	*MS*	*F*	*p-value*	***sig***
Regression	1	23.48648	23.48648	19.72642	0.002164	**yes**
Residual	8	9.524881	1.19061			
Total	9	33.01136				

	coeff	*std err*	*t stat*	*p-value*	*lower*	*upper*	***sig***
Intercept	-2.35024	1.382947	-1.69944	0.127661	-5.53932	0.838843	
Slope	1.580618	0.355879	4.441444	0.002164	0.759959	2.401278	**yes**

1.2.4. Yearly SOC loss and stock (15cm) of INIA-TyT-RS site crop rotation experiment

Simulated (EPIC) vs Measured SOC loss (15cm depth) (Mg ha^{-1} year^{-1})

T Test: Two Paired Samples

SUMMARY			Alpha	0.05		Hyp Mean	0	
Groups	*Count*	***Mean***	*Std Dev*	*Std Err*	*t*	*df*	*Cohen d*	*Effect r*
Measured	7	**0.729**	1.402118					
Simulated	7	**0.664**	0.711743					
Difference	7	**0.065**	1.438758	0.5438	0.119725	6	0.045252	0.048819

T TEST

	p-value	*t-crit*	*lower*	*upper*	***sig***
One Tail	0.4543	1.94318			**no**
Two Tail	0.9086	2.446912	-1.26552	1.395736	**no**

Yearly Simulated (EPIC) vs Measured SOC (15cm depth) (Mg ha^{-1})

Regression Analysis

OVERALL FIT

Multiple R	0.865	AIC	1.723024
R Square	**0.748**	AICc	7.723024
Adjusted R Square	0.706	SBC	1.881908
Standard Error	1.002		
Observations	8		

ANOVA				Alpha	0.05	
	df	*SS*	*MS*	*F*	*p-value*	***sig***
Regression	1	17.86376	17.86376	17.80918	0.005561	**yes**
Residual	6	6.018389	1.003065			
Total	7	23.88215				

	coeff	*std err*	*t stat*	*p-value*	*lower*	*upper*	***sig***
Intercept	4.356145	6.031018	0.72229	0.49729	-10.4012	19.11351	
Slope	0.880239	0.208583	4.220092	0.005561	0.369855	1.390623	**yes**

Appendix 2. LU change degradation statistical tests

The data analysis for this paper was generated using the Real Statistics Resource Pack software (Release 4.3). Copyright (2013 – 2015) Charles Zaiontz. www.real-statistics.com

1.1. Contribution of the Initial SOC and Slope using multi-regression analysis

1.1.1. Impact on Soil SOC loss using multi-regression analysis with standardized* values

Grass scenario

Multiple Regression Analysis

OVERALL FIT			
Multiple R	0.974452	AIC	-38146.5
R Square	0.949557	AICc	-38146.5
Adjusted R Square	0.949543	SBC	-38125.8
Standard Error	0.071615		
Observations	7235		

ANOVA				Alpha	0.05	
	df	*SS*	*MS*	*F*	*p-value*	*sig*
Regression	2	698.2051	349.1025	68068.69	0	yes
Residual	7232	37.09062	0.005129			
Total	7234	735.2957				

	coeff	*std err*	*t stat*	*p-value*	*lower*	*upper*	*Relative contribution*
Intercept	0.694246	0.000842	824.2858	0	0.692595	0.695897	
Slope	**0.057031**	0.00082	69.53909	0	0.055424	0.058639	**16%**
Initial SOC	**0.306999**	0.000844	363.7125	0	0.305345	0.308654	**84%**

Soy-Wheat scenario

Multiple Regression Analysis

OVERALL FIT			
Multiple R	0.932287	AIC	-27754
R Square	0.869159	AICc	-27754
Adjusted R Square	0.869123	SBC	-27733.4
Standard Error	0.146864		
Observations	7235		

ANOVA				Alpha	0.05	
	df	*SS*	*MS*	*F*	*p-value*	*sig*
Regression	2	1036.207	518.1034	24020.66	0	yes
Residual	7232	155.9875	0.021569			
Total	7234	1192.194				

	coeff	*std err*	*t stat*	*p-value*	*lower*	*upper*	*Relative contribution*
Intercept	0.82393	0.001727	477.0255	0	0.820544	0.827316	
Slope	**0.176673**	0.001682	105.0441	0	0.173376	0.17997	**34%**
Initial SOC	**0.336671**	0.001731	194.4972	0	0.333277	0.340064	**66%**

Grass-crop scenario

Multiple Regression Analysis

OVERALL FIT			
Multiple R	0.816613	AIC	-17936.3
R Square	0.666857	AICc	-17936.3
Adjusted R Square	0.666765	SBC	-17915.6
Standard Error	0.289455		
Observations	7235		

ANOVA				Alpha	0.05	
	df	*SS*	*MS*	*F*	*p-value*	*sig*
Regression	2	1212.887	606.4435	7238.186	0	yes
Residual	7232	605.9252	0.083784			
Total	7234	1818.812				

	coeff	*std err*	*t stat*	*p-value*	*lower*	*upper*	*Relative contribution*
Intercept	1.070183	0.003404	314.3728	0	1.06351	1.076857	
Slope	**0.191818**	0.003315	57.86637	0	0.18532	0.198316	**35%**
Initial SOC	**0.363878**	0.003412	106.6594	0	0.35719	0.370566	**65%**

Soy-Soy scenario

Multiple Regression Analysis

OVERALL FIT			
Multiple R	0.916564	AIC	-17078
R Square	0.84009	AICc	-17078
Adjusted R Square	0.840046	SBC	-17057.3
Standard Error	0.307143		
Observations	7235		

ANOVA				Alpha	0.05	
	df	*SS*	*MS*	*F*	*p-value*	*sig*
Regression	2	3584.191	1792.095	18996.73	0	yes
Residual	7232	682.2454	0.094337			
Total	7234	4266.436				

	coeff	*std err*	*t stat*	*p-value*	*lower*	*upper*	*Relative contribution*
Intercept	1.50708	0.003612	417.2171	0	1.499999	1.514161	
Slope	**0.393046**	0.003517	111.7429	0	0.38615	0.399941	**40%**
Initial SOC	**0.586376**	0.00362	161.9792	0	0.57928	0.593473	**60%**

* Standard value is the original value minus the media and divided by the standard deviation.

1.1.2. Impact on soil loss by erosion using multi-regression analysis with standardized* values

Grass scenario

Multiple Regression Analysis

OVERALL FIT			
Multiple R	0.890933	AIC	-2073.13
R Square	0.793761	AICc	-2073.12
Adjusted R Square	0.793703	SBC	-2052.52
Standard Error	0.864175		
Observations	7111		

ANOVA				Alpha	0.05	
	df	*SS*	*MS*	*F*	*p-value*	*sig*
Regression	2	20430.11	10215.06	13678.47	0	yes
Residual	7108	5308.242	0.746798			
Total	7110	25738.35				

	coeff	*std err*	*t stat*	*p-value*	*lower*	*upper*	*Relative contribution*
Intercept	2.303761	0.010251	224.7388	0	2.283666	2.323855	
Slope	**1.646173**	0.00999	164.7838	0	1.62659	1.665757	**90%**
Initial SOC	**0.180384**	0.010281	17.54587	1.67E-67	0.160231	0.200538	**10%**

Soy-Wheat scenario

Multiple Regression Analysis

OVERALL FIT			
Multiple R	0.835387	AIC	23497.26
R Square	0.697872	AICc	23497.27
Adjusted R Square	0.697787	SBC	23517.87
Standard Error	5.217228		
Observations	7111		

ANOVA				Alpha	0.05	
	df	*SS*	*MS*	*F*	*p-value*	*sig*
Regression	2	446902	223451	8209.234	0	yes
Residual	7108	193476	27.21947			
Total	7110	640378				

	coeff	*std err*	*t stat*	*p-value*	*lower*	*upper*	*Relative contribution*
Intercept	9.167604	0.061887	148.1352	0	9.046287	9.28892	
Slope	**7.683897**	0.060311	127.4038	0	7.565669	7.802125	**92%**
Initial SOC	**-0.68997**	0.062067	-11.1165	1.79E-28	-0.81164	-0.5683	**8%**

Grass-crop scenario

Multiple Regression Analysis

OVERALL FIT			
Multiple R	0.836613	AIC	25027.92
R Square	0.699921	AICc	25027.93
Adjusted R Square	0.699836	SBC	25048.53
Standard Error	5.810068		
Observations	7111		

ANOVA				Alpha	0.05	
	df	*SS*	*MS*	*F*	*p-value*	*sig*
Regression	2	559657.5	279828.8	8289.53	0	yes
Residual	7108	239944	33.75689			
Total	7110	799601.5				

	coeff	*std err*	*t stat*	*p-value*	*lower*	*upper*	*Relative contribution*
Intercept	12.07342	0.068919	175.1828	0	11.93832	12.20852	
Slope	**8.624788**	0.067165	128.4127	0	8.493126	8.756451	**91%**
Initial SOC	**0.83022**	0.06912	12.0113	6.45E-33	0.694725	0.965716	**9%**

Soy-Soy scenario

Multiple Regression Analysis

OVERALL FIT			
Multiple R	0.882814	AIC	34647.06
R Square	0.779361	AICc	34647.07
Adjusted R Square	0.779299	SBC	34667.67
Standard Error	11.42665		
Observations	7111		

ANOVA				Alpha	0.05	
	df	*SS*	*MS*	*F*	*p-value*	*sig*
Regression	2	3278243	1639122	12553.74	0	yes
Residual	7108	928080.2	130.5684			
Total	7110	4206324				

	coeff	*std err*	*t stat*	*p-value*	*lower*	*upper*	*Relative contribution*
Intercept	32.01621	0.135543	236.2072	0	31.7505	32.28191	
Slope	**20.84643**	0.132093	157.8168	0	20.58749	21.10537	**90%**
Initial SOC	**2.35715**	0.135938	17.33988	5.29E-66	2.090671	2.623629	**10%**

* Standard value is the original value minus the media and divided by the standard deviation

Bibliography

Adejuwon, J., 2005. Assessing the suitability of the EPIC crop model for use in the study of impacts of climate variability and climate change in West Africa. Singap. J. Trop. Geogr. 26, 44–60. doi:10.1111/j.0129-7619.2005.00203.x

Aggarwal, P.K., Baethgen, W.E., Cooper, P., Gommes, R., Lee, B., Meinke, H., Rathore, L.S., Sivakumar, M.V.K., 2010. Managing climatic risks to combat land degradation and enhance food security: Key information needs. Procedia Environ. Sci. doi:10.1016/j.proenv.2010.09.019

Altesor, A., Oesterheld, M., Leoni, E., Lezama, F., Rodríguez, C., 2005. Effect of grazing on community structure and productivity of a Uruguayan grassland. Plant Ecol. 179, 83–91. doi:10.1007/s11258-004-5800-5

Altesor, A., Piñeiro, G., Lezama, F., Jackson, R.B., Sarasola, M., Paruelo, J.M., 2006. Ecosystem changes associated with grazing in subhumid South American grasslands. J. Veg. Sci. doi:10.1111/j.1654-1103.2006.tb02452.x

Alvarez, R., Díaz, R.A., Barbero, N., Santanatoglia, O.J., Blotta, L., 1995. Soil organic carbon, microbial biomass and CO2-C production from three tillage systems. Soil Tillage Res. 33, 17–28. doi:10.1016/0167-1987(94)00432-E

Apezteguía, H., Izaurralde, R.C., Sereno, R., 2009. Simulation study of soil organic matter dynamics as affected by land use and agricultural practices in semiarid Córdoba, Argentina. Soil Tillage Res. 102, 101–108. doi:10.1016/j.still.2008.07.016

Araya, S., Ostendorf, B., Lyle, G., Lewis, M., 2013. Crop phenology based on MODIS satellite imagery as an indicator of plant available water content. 20th Int. Congr. Model. Simulations, Adelaide, Aust. 1–6.

Arshad, M.A., Martin, S., 2002. Identifying critical limits for soil quality indicators in agro-ecosystems. Agric. Ecosyst. Environ. 88, 153–160. doi:10.1016/S0167-8809(01)00252-3

Ayala, W., Bermudez, R., 2005. Estrategias de manejo en campos naturales sobre suelos de lomadas en la región Este, in: Seminario de Actualización Técnica En Manejo de Campo Natural, Serie Técnica 151. INIA Uruguay, Montevideo - Uruguay, pp. 41–50.

Ayala, W., Carriquiry, E., Carámbula, M., 1993. Características y estrategias de utilización de pasturas naturales en la región Este [Features and strategies for using natural pastures in the eastern region], in: Campo Natural, Estrategia Invernal, Manejo Y Suplementación, Serie Actividades de Difusión No 49. INIA Uruguay, Treinta y Tres, Uruguay, pp. 1–28.

Baethgen, W.E., 2003. Utilización del modelo Century para estudiar la dinámica de carbono y nitrógeno [Using the Century model to study the dynamics of carbon and nitrogen], in: 40 Años de Rotaciones Agrícolas-Ganaderas (40 Years of Agricultural-Livestock Rotations), Serie Técnica No 134 (Technical Series).

National Agricultural Research Institute - Uruguay, Montevideo, pp. 9–18.

Baldi, G., Guerschman, J.P., Paruelo, J.M., 2006. Characterizing fragmentation in temperate South America grasslands. Agric. Ecosyst. Environ. 116, 197–208. doi:10.1016/j.agee.2006.02.009

Bastida, F., Zsolnay, a., Hernández, T., García, C., 2008. Past, present and future of soil quality indices: A biological perspective. Geoderma. doi:10.1016/j.geoderma.2008.08.007

Batjes, N.H., 2012. ISRIC-WISE derived soil properties on a 5 by 5 arc-minutes global grid (ver. 1.2), ISRIC report.

Bermudez, R., Ayala, W., 2005. Producción de forraje de un campo natural de la zona de Lomadas del Este [Forage production of a natural grassland field of the hilly Eastern], in: Seminario de Actualización Técnica En Manejo de Campo Natural, Serie Técnica 151. INIA Uruguay, Montevideo, Uruguay, pp. 33–39.

Bernardos, J.N., Viglizzo, E.F., Jouvet, V., Lértora, F. a., Pordomingo, a. J., Cid, F.D., 2001. The use of EPIC model to study the agroecological change during 93 years of farming transformation in the Argentine pampas. Agric. Syst. doi:10.1016/S0308-521X(01)00027-0

Berreta, E., 2003. Uruguay in Country Pasture Profiles [WWW Document]. Food Agric. Organ. URL http://www.fao.org/ag/AGP/AGPC/doc/Counprof/uruguay/uruguay.htm (accessed 2.9.16).

Billen, N., Röder, C., Gaiser, T., Stahr, K., 2009. Carbon sequestration in soils of SW-Germany as affected by agricultural management—Calibration of the EPIC model for regional simulations. Ecol. Modell. 220, 71–80. doi:10.1016/j.ecolmodel.2008.08.015

Capurro Etchegaray, M., 1977. CONEAT, reseña de la metodología adoptada para determinar la productividad a nivel predial [CONEAT, a review of the methodology adopted to determine productivity at the farm level]. Fundación de la Cultura Universitaria, Montevideo.

Caride, C., Piñeiro, G., Paruelo, J.M., 2012. How does agricultural management modify ecosystem services in the argentine Pampas? The effects on soil C dynamics. Agric. Ecosyst. Environ. 154, 23–33. doi:10.1016/j.agee.2011.05.031

Carter, M.R., 2002. Soil Quality for Sustainable Land Management. Agron. J. doi:10.2134/agronj2002.3800

Castaño, J.P., Gimenez, A., Ceroni, M., Furest, J., Aunchayna, R., Bidegain, M., 2011. Caracterización Agroclimática del Uruguay (1980-1989) [Agroclimatic characterization of Uruguay (1980-2009)], Serie Técnica 193. INIA Uruguay, Montevideo, Uruguay.

Castro, M., Coutiño, M.J., 2014. Evaluación de cultivares de cultivos de verano e invierno (2000-2014) [Varieties of Winter and Summer crop evaluation].

Montevideo, Uruguay.

Causarano, H.J., Doraiswamy, P.C., McCarty, G.W., Hatfield, J.L., Milak, S., Stern, A.J., 2008. EPIC modeling of soil organic carbon sequestration in croplands of Iowa. J. Environ. Qual. 37, 1345–1353. doi:10.2134/jeq2007.0277

Causarano, H.J., Shaw, J.N., Franzluebbers, A.J., Reeves, D.W., Raper, R.L., Balkcom, K.S., Norfleet, M.L., Izaurralde, R.C., 2007. Simulating field-scale soil organic carbon dynamics using EPIC. Soil Sci. Soc. Am. J. 71, 1174–1185. doi:10.2136/sssaj2006.0356

Chapin, F.S., Woodwell, G.M., Randerson, J.T., Rastetter, E.B., Lovett, G.M., Baldocchi, D.D., Clark, D.A., Harmon, M.E., Schimel, D.S., Valentini, R., Wirth, C., Aber, J.D., Cole, J.J., Goulden, M.L., Harden, J.W., Heimann, M., Howarth, R.W., Matson, P.A., McGuire, A.D., Melillo, J.M., Mooney, H.A., Neff, J.C., Houghton, R.A., Pace, M.L., Ryan, M.G., Running, S.W., Sala, O.E., Schlesinger, W.H., Schulze, E.D., 2006. Reconciling carbon-cycle concepts, terminology, and methods. Ecosystems 9, 1041–1050. doi:10.1007/s10021-005-0105-7

Clérici C., G.P.F., 2001. Aplicaciones del modelo USLE/RUSLE para estimar pérdidas de suelo por erosión en Uruguay y la región sur de la cuenca del Río de la Plata [Applications of the USLE / RUSLE model to estimate soil loss by erosion in Uruguay and the south of the Rio de la P]. Agrociencia Uruguay V, 92–103.

Coupland, R.T., 1992. Overview of South American Grasslands, in: Coupland, R.T. (Ed.), Ecosystems of the World. Elsevier, New York, pp. 363–366.

Culman, S.W., DuPont, S.T., Glover, J.D., Buckley, D.H., Fick, G.W., Ferris, H., Crews, T.E., 2010. Long-term impacts of high-input annual cropping and unfertilized perennial grass production on soil properties and belowground food webs in Kansas, USA. Agric. Ecosyst. Environ. 137, 13–24. doi:10.1016/j.agee.2009.11.008

De Vera, A., Terra, R., 2012. Combining CMORPH and Rain Gauges Observations over the Rio Negro Basin. J. Hydrometeorol. 13, 1799–1809. doi:Doi 10.1175/Jhm-D-12-010.1

DeFries, R.S., Foley, J. a., Asner, G.P., 2004. Land-use choices: balancing human needs and ecosystem function. Front. Ecol. Environ. 2, 249–257. doi:10.1890/1540-9295(2004)002[0249:LCBHNA]2.0.CO;2

Dell'Acqua, M., 2004. Metodología e Información utilizada para la elaboración de el Modelo Digital de Terreno de Uruguay [Methodology and Data used for the development of the Uruguayan Digital Terrain Model], MGAP - RENARE. MGAP Uruguay - RENARE, Uruguay.

Di Gregorio, A., 2016. Land Cover Classification System : Classification concepts. Software version 3. FAO, Rome.

Di Gregorio, A., Leonardi, U., 2016. Land Cover Classification System - User

Manual. Software version 3. FAO, Roma.

Doran, J.W., 2002. Soil health and global sustainability: translating science into practice. Agric. Ecosyst. Environ. doi:Doi 10.1016/S0167-8809(01)00246-8

Doran, J.W., Zeiss, M.R., 2000. Soil health and sustainability: Managing the biotic component of soil quality. Appl. Soil Ecol. doi:10.1016/S0929-1393(00)00067-6

DuPont, S.T., Culman, S.W., Ferris, H., Buckley, D.H., Glover, J.D., 2010. No-tillage conversion of harvested perennial grassland to annual cropland reduces root biomass, decreases active carbon stocks, and impacts soil biota. Agric. Ecosyst. Environ. 137, 25–32. doi:10.1016/j.agee.2009.12.021

Duval, M.E., Galantini, J.A., Capurro, J.E., Martinez, J.M., 2016. Winter cover crops in soybean monoculture: Effects on soil organic carbon and its fractions. Soil Tillage Res. 161, 95–105. doi:10.1016/j.still.2016.04.006

Ellis, E.C., Klein Goldewijk, K., Siebert, S., Lightman, D., Ramankutty, N., 2010. Anthropogenic transformation of the biomes, 1700 to 2000. Glob. Ecol. Biogeogr. 19, no-no. doi:10.1111/j.1466-8238.2010.00540.x

Ferreira, G., 2001. Tecnologías forrajeras para sistemas ganaderos de Uruguay [Forage technologies for livestock systems in Uruguay]. National Agricultural Research Institute, Montevideo, Uruguay.

Fischer, G., Nachtergaele, F., Prieler, S., Van Velthuizen, H.T., Verelst, L., Wiberg, D., 2008. Global agro-ecological zones assessment for agriculture (GAEZ 2008), IIASA, Laxenburg, Austria and FAO, Rome, Italy.

Foley, J.A., Defries, R., Asner, G.P., Barford, C., Bonan, G., Carpenter, S.R., Chapin, F.S., Coe, M.T., Daily, G.C., Gibbs, H.K., Helkowski, J.H., Holloway, T., Howard, E.A., Kucharik, C.J., Monfreda, C., Patz, J. a, Prentice, I.C., Ramankutty, N., Snyder, P.K., 2005. Global Consequences of Land Use. Science (80-.). 309, 570–574. doi:10.1126/science.1111772

Formoso, D., 2005. La investigación en utilización de pasturas naturales sobre cristalino desarrollada por el SUL [Reseach in natural pastures over granite soils made by SUL], in: Seminario de Actualización Técnica En Manejo de Campo Natural, Serie Técnica 151. INIA Uruguay, Montevideo, Uruguay, pp. 51–59.

García Préchac, F., Durán, A., 2001. Estimating Soil Productivity Loss Due to Erosion in Uruguay in Terms of Beef and Wool Production on Natural Pastures †, in: Stott, D.E., Mothar, R.H., Steinhardt, G.C. (Eds.), Sustaining the Global Farm. International Soil Conservation Organization in cooperation with the USDA and Purdue University, West Lafayette, IN., pp. 40–45.

García Préchac, F., Hill, M., Clérici, C., 2009. Erosion.

García-Préchac, F., Ernst, O., Siri-Prieto, G., Terra, J.A., 2004. Integrating no-till into crop–pasture rotations in Uruguay. Soil Tillage Res. 77, 1–13. doi:10.1016/j.still.2003.12.002

Gassman, P.W., Williams, J., Benson, V., Izaurralde, R.C., Hauck, L.M., Jones, C.A., Atwood, J.D., Kiniry, J.R., Flowers, J.D., 2005. Historical development and applications of the EPIC and APEX models, Director. Center for Agricultural and Rural Development, Iowa State University. doi:10.13031/2013.17074

Gregorich, E.G., Greer, K.J., Anderson, D.W., Liang, B.C., 1998. Carbon distribution and losses: erosion and deposition effects. Soil Tillage Res. doi:10.1016/S0167-1987(98)00117-2

Grimes, D.I.F., Pardo-Igúzquisa, E., 2010. Geostatistical Analysis of Rainfall. Geogr. Anal. 42, 136–160.

Guerschman, J.P., Paruelo, J.M., Bella, C. Di, Giallorenzi, M.C., Pacin, F., 2003. Land cover classification in the Argentine Pampas using multi-temporal Landsat TM data. Int. J. Remote Sens. 24, 3381–3402. doi:10.1080/0143116021000021288

Guo, L.B., Gifford, R.M., 2002. Soil carbon stocks and land use change: a meta analysis. Glob. Chang. Biol. 8, 345–360. doi:10.1046/j.1354-1013.2002.00486.x

Hansen, N.C., Allen, B.L., Baumhardt, R.L., Lyon, D.J., 2012. Research achievements and adoption of no-till, dryland cropping in the semi-arid U.S. Great Plains. F. Crop. Res. doi:10.1016/j.fcr.2012.02.021

Hassink, J., 1994. Effects of soil texture and grassland management on soil organic C and N and rates of C and N mineralization. Soil Biol. Biochem. 26, 1221–1231. doi:10.1016/0038-0717(94)90147-3

Hassink, J., 1992. Effects of soil texture and structure on carbon and nitrogen mineralization in grassland soils. Biol. Fertil. Soils. doi:10.1007/BF00336262

Havlin, J.L., Kissel, D.E., Maddux, L.D., Claassen, M.M., Long, J.H., 1990. Crop Rotation and Tillage Effects on Soil Organic Carbon and Nitrogen. Soil Sci. Soc. Am. J. doi:10.2136/sssaj1990.03615995005400020026x

Hill, M., García Préchac, F., Terra, J. a., Sawchik, J., 2008. Incorporación del efecto del contenido de agua en el suelo en el modelo USLE / RUSLE para estimar erosión en Uruguay [Soil water content effect in the USLE / RUSLE model to estimate erosion in Uruguay]. Agrociencia Uruguay XII, 57–67.

Hoekstra, J.M., Boucher, T.M., Ricketts, T.H., Roberts, C., 2005. Confronting a biome crisis: Global disparities of habitat loss and protection. Ecol. Lett. doi:10.1111/j.1461-0248.2004.00686.x

Houghton, R.A., 2007. Balancing the Global Carbon Budget. Annu. Rev. Earth Planet. Sci. 35, 313–347. doi:10.1146/annurev.earth.35.031306.140057

Houghton, R.A., 1999. The annual net flux of carbon to the atmosphere from changes in land use 1850-1990*. Tellus B 51, 298–313. doi:10.1034/j.1600-0889.1999.00013.x

Huete, a., Didan, K., Miura, T., Rodriguez, E.P., Gao, X., Ferreira, L.G., 2002. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sens. Environ. doi:10.1016/S0034-4257(02)00096-2

Hurtt, G.C., Frolking, S., Fearon, M.G., Moore III, B., Shevliakova, E., Malyshev, S., Pacala, S.W., Houghton, R.A., 2006. The Underpinnings of Land-use History: Three Centuries of Global Gridded Land-Use Transitions, Wood Harvest Activity, and Resulting Secondary Lands. Glob. Chang. Biol. doi:10.1111/j.1365-2486.2006.01150.x

INIA Uruguay - GRAS Unit, 2016. INIA Agroclimatic Data Base [WWW Document]. URL http://www.inia.uy/en/Paginas/Banco-datos-agroclimatico.aspx (accessed 1.26.16).

INIA Uruguay - GRAS Unit, 2014. SIGRAS - Android App Google Play [WWW Document]. URL https://play.google.com/store/apps/details?id=uy.inia.sigras.app&hl=es_419 (accessed 3.17.17).

INIA Uruguay - GRAS Unit, 2012. SIGRAS - GRAS Geographic Information System [WWW Document]. URL http://sig.inia.org.uy/sigras/ (accessed 3.17.17).

INIA Uruguay, UDELAR-Fagro, UDELAR-Fvet, CREA Uruguay, MGAP Uruguay, IPA Uruguay, SUL Uruguay, 2012. Revisión y análisis de las bases históricas y científicas del uso de la equivalencia ovino:bovino [Review and analysis of historical and scientific basis for the use of equivalence sheep:cattle]. Montevideo, Uruguay.

IPA Uruguay, 2012. Herramienta Calculadora de Carga [Stock calculator tool] [WWW Document]. URL http://www.planagropecuario.org.uy/Herramientas/CalculadoraDeCarga/ (accessed 2.29.16).

IPCC, 2013. Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA. doi:10.1017/CBO9781107415324.Summary

Izaurralde, R.C., Malhi, S.S., Nyborg, M., Solberg, E.D., Quiroga Jakas, M.C., 2006a. Crop Performance and Soil Properties in Two Artificially Eroded Soils in North-Central Alberta. Agron. J. 98, 1298. doi:10.2134/agronj2005.0184

Izaurralde, R.C., McGill, W.B., Williams, J.R., 2012. Development and application of the EPIC model for carbon cycle, greenhouse-gas mitigation, and biofuel studies, in: Managing Agricultural Greenhouse Gases: Coordinated Agricultural Research through GRACEnet to Address Our Changing Climate. Academic Press, New York, NY, USA, pp. 293–308.

Izaurralde, R.C., Williams, J.R., McGill, W.B., Rosenberg, N.J., Jakas, M.C.Q., 2006b. Simulating soil C dynamics with EPIC: Model description and testing against long-term data. Ecol. Modell. doi:10.1016/j.ecolmodel.2005.07.010

Izaurralde, R.C., Williams, J.R., Post, W.M., Thomson, a. M., McGill, W.B., Owens, L.B., Lal, R., 2007. Long-term modeling of soil C erosion and sequestration at the small watershed scale. Clim. Change. doi:10.1007/s10584-006-9167-6

Kanwar, L.S., 2007. Plant Nutrients: Sufficiency and Requirements, in: Lal, R. (Ed.), Encyclopedia of Soil Science, Second Edition. Taylor & Francis, pp. 1306–1310.

Klein Goldewijk, K., Beusen, A., Van Drecht, G., De Vos, M., 2011. The HYDE 3.1 spatially explicit database of human-induced global land-use change over the past 12,000 years. Glob. Ecol. Biogeogr. doi:10.1111/j.1466-8238.2010.00587.x

Kottek, M., Grieser, J., Beck, C., Rudolf, B., Rubel, F., 2006. World map of the Köppen-Geiger climate classification updated. Meteorol. Zeitschrift. doi:10.1127/0941-2948/2006/0130

Kwong, Y.C., 2007. Bulk Density, in: Lal, R. (Ed.), Encyclopedia of Soil Science, Second Edition. CRC Press, pp. 191–193. doi:10.1081/E-ESS-120042638

Lal, R., 2011. Sequestering carbon in soils of agro-ecosystems. Food Policy 36, S33–S39. doi:10.1016/j.foodpol.2010.12.001

Lal, R., 2007. Anthropogenic Influences on World Soils and Implications to Global Food Security, in: Donald, L.S. (Ed.), Advances in Agronomy. Academic Press, pp. 69–93. doi:10.1016/S0065-2113(06)93002-8

Lal, R., 2006. Enhancing crop yields in the developing countries through restoration of the soil organic carbon pool in agricultural lands. L. Degrad. Dev. 17, 197–209. doi:10.1002/ldr.696

Lal, R., 2005. Soil erosion and carbon dynamics. Soil Tillage Res. 81, 137–142. doi:10.1016/j.still.2004.09.002

Lal, R., 2003. Soil erosion and the global carbon budget. Environ. Int. 29, 437–450. doi:10.1016/S0160-4120(02)00192-7

Lal, R., 2002. Soil carbon dynamics in cropland and rangeland. Environ. Pollut. 116, 353–362. doi:10.1016/S0269-7491(01)00211-1

Lanfranco Crespo, B., Sapriza Fraga, G., 2011. El índice CONEAT como medida de productividad y valor de la tierra [The CONEAT index as a measure of land productivity and value], Serie Técn. ed. INIA Uruguay.

Lauenroth, W.K., Epstein, H.E., Paruelo, J.M., Burke, I.C., Aguiar, M.R., Sala, O.E., 2004. Potential effects of climate change on the temperate zones of North and South America. Rev. Chil. Hist. Nat. 77, 439–453. doi:10.4067/S0716-078X2004000300004

Lezama, F., Baeza, S., Altesor, A., Cesa, A., Chaneton, E.J., Paruelo, J.M., 2014. Variation of grazing-induced vegetation changes across a large-scale productivity gradient. J. Veg. Sci. doi:10.1111/jvs.12053

Mann, L.K., 1986. Changes in soil carbon storage after cultivation. Soil Sci.

Maraseni, T.N., Cockfield, G., 2011. Does the adoption of zero tillage reduce greenhouse gas emissions? An assessment for the grains industry in Australia.

Agric. Syst. 104, 451–458. doi:10.1016/j.agsy.2011.03.002

Mas, C., 1978. Región Este [Easter region], in: Pasturas IV. MAP-CIABB, Montevideo, Uruguay, pp. 37–64.

Mazzilli, S., Piñeiro, G., Kemanian, A., 2012. Priming effects on soil organic carbon decomposition induced by high C:N crop inputs. Agrociencia Uruguay 16, 191–198.

Meiyappan, P., Jain, A.K., 2012. Three distinct global estimates of historical land-cover change and land-use conversions for over 200 years. Front. Earth Sci. doi:10.1007/s11707-012-0314-2

MGAP-DIEA, 2016. Series Historicas de Estadísticas Agropecuarias [Historical Series of Agricultural Statistics] [WWW Document]. URL http://www.mgap.gub.uy/portal/page.aspx?2,diea,diea-series-historicas,O,es,0, (accessed 7.12.16).

MGAP-DIEA, 2015. Anuario estadístico Agropecuario 2015 [Agricultural Statistical Yearbook 2015]. MGAP, Montevideo, Uruguay.

MGAP-DIEA, 2012. Anuario estadístico Agropecuario 2012 [Agricultural Statistical Yearbook 2012]. MGAP, Montevideo, Uruguay.

MGAP-RENARE-CONEAT, 1994. Indice de Productividad grupos CONEAT.

MGAP-RENARE-DSA, 2003. Zonificación de cultivos de verano de secano [Zoning rainfed summer crops]. Montevideo, Uruguay.

MGAP-RENARE-DSA, 1976a. Soil Classification of Uruguay. MGAP (Department of Agriculture and Fishery).

MGAP-RENARE-DSA, 1976b. Soil Survey of Uruguay at 1: 1,000,000. MGAP (Department of Agriculture and Fishery).

MGAP Uruguay, MVOTMA Uruguay, FAO, 2011. Mapa de Cobertura del Suelo de Uruguay - Land Cover Classification System. Montevideo, Uruguay.

Milesi Delaye, L. a., Irizar, A.B., Andriulo, A.E., Mary, B., 2013. Effect of Continuous Agriculture of Grassland Soils of the Argentine Rolling Pampa on Soil Organic Carbon and Nitrogen. Appl. Environ. Soil Sci. 2013, 1–17. doi:10.1155/2013/487865

Millennium Ecosystem Assessment, 2005. Ecosystems and human well-being (Vol. 1). World Resources Institute., Washington, D.C.:

Molfino, J.H., 2009. Estimación del agua potencialmente disponible en los grupos CONEAT. Montevideo.

Montgomery, D.R., 2007. Soil erosion and agricultural sustainability. Proc. Natl. Acad. Sci. 104, 13268–13272. doi:10.1073/pnas.0611508104

Morón, A., Quincke, A., Molfino, J., Ibáñez, W., García, A., 2012. Soil quality assessment of Uruguayan agricultural soils. Agrociencia Uruguay 16, 135–143.

MVOTMA-DINOT, 2015. Atlas de Cobertura del Suelo de Uruguay. Cobertura de

Suelo y Cambios 2000-2011. FAO office in Uruguay, Montevideo, Uruguay.

MVOTMA-SNRCC, 2016. Fourth National Communication to the Conference of the parties in the United Nations Framework Convention On Climate Change. Montevideo, Uruguay.

Novelli, L.E., Caviglia, O.P., Melchiori, R.J.M., 2011. Impact of soybean cropping frequency on soil carbon storage in Mollisols and Vertisols. Geoderma 167–168, 254–260. doi:10.1016/j.geoderma.2011.09.015

Novelli, L.E., Caviglia, O.P., Piñeiro, G., 2017. Increased cropping intensity improves crop residue inputs to the soil and aggregate-associated soil organic carbon stocks. Soil Tillage Res. 165, 128–136. doi:10.1016/j.still.2016.08.008

Novelli, L.E., Caviglia, O.P., Wilson, M.G., Sasal, M.C., 2013. Land use intensity and cropping sequence effects on aggregate stability and C storage in a Vertisol and a Mollisol. Geoderma 195–196, 260–267. doi:10.1016/j.geoderma.2012.12.013

Parton, W.J., Stewart, J.W.B., Cole, C. V., 1988. Dynamics of C, N, P and S in grassland soils: a model. Biogeochemistry 5, 109–131. doi:10.1007/BF02180320

Paruelo, J.M., Jobbagy, E.G., Oesterheld, M., Galluscio, R.A., Aguiar, M.R., 2007. The Grassland and Steppes of Patagonia and Río de la Plata Plains, in: T. Veblen, Young, K., Orme, A. (Eds.), The Physical Geography of South America. Oxford University Press, New York, NY, USA, pp. 233–249.

Pereira, H.M., Leadley, P.W., Proenca, V., Alkemade, R., Scharlemann, J.P.W., Fernandez-Manjarres, J.F., Araujo, M.B., Balvanera, P., Biggs, R., Cheung, W.W.L., Chini, L., Cooper, H.D., Gilman, E.L., Guenette, S., Hurtt, G.C., Huntington, H.P., Mace, G.M., Oberdorff, T., Revenga, C., Rodrigues, P., Scholes, R.J., Sumaila, U.R., Walpole, M., 2010. Scenarios for Global Biodiversity in the 21st Century. Science (80-.). 330, 1496–1501. doi:10.1126/science.1196624

Pierson, S.T., Cabrera, M.L., Evanylo, G.K., Schroeder, P.D., Radcliffe, D.E., Kuykendall, H. a, Benson, V.W., Williams, J.R., Hoveland, C.S., McCann, M. a, 1997. Phosphorus losses from grasslands fertilized with broiler litter: EPIC simulations. J. Environ. Qual. 30, 1790–5. doi:10.2134/jeq2001.3051790x

Pimentel, D., Harvey, C., Resosudarmo, P., Sinclair, K., Kurz, D., McNair, M., Crist, S., Shpritz, L., Fitton, L., Saffouri, R., Blair, R., 1995. Environmental and Economic Costs of Soil Erosion and Conservation Benefits. Science (80-.). 267, 1117–1123. doi:10.1126/science.267.5201.1117

Piñeiro, G., Paruelo, J.M., Oesterheld, M., 2006. Potential long-term impacts of livestock introduction on carbon and nitrogen cycling in grasslands of Southern South America. Glob. Chang. Biol. 12, 1267–1284. doi:10.1111/j.1365-2486.2006.01173.x

Power, A.G., 2010. Ecosystem services and agriculture: tradeoffs and synergies. Philos. Trans. R. Soc. Lond. B. Biol. Sci. doi:10.1098/rstb.2010.0143

Powlson, D.S., Gregory, P.J., Whalley, W.R., Quinton, J.N., Hopkins, D.W., Whitmore, a. P., Hirsch, P.R., Goulding, K.W.T., 2011. Soil management in relation to sustainable agriculture and ecosystem services. Food Policy. doi:10.1016/j.foodpol.2010.11.025

Puentes, R., 1981. A framework for the use of the universal soil loss equation in Uruguay. Texas A&M University.

R Development Core Team, 2013. R Software. R A Lang. Environ. Stat. Comput.

Reeves, D.W., 1997. The role of soil organic matter in maintaining soil quality in continuous cropping systems. Soil Tillage Res. doi:10.1016/S0167-1987(97)00038-X

Renard, K.G., Foster, G.R., Weesies, G.A., Porter, J.P., 1991. Journal of soil and water conservation., Journal of Soil and Water Conservation. Soil Conservation Society of America].

Risso, D.F., Scavino, J., 1978. Región Centro-Sur [South-Central region], in: Pasturas IV. MAP-CIABB, Montevideo, Uruguay, pp. 025–036.

Ritchie, J.C., Argyrios, G., 2007. Plant Available Water, in: Lal, R. (Ed.), Encyclopedia of Soil Science, Second Edition. Taylor & Francis, pp. 1294–1298.

Sala, O.E., Lauenroth, W.K., Burke, I.C., 1996. Carbon Budgets of Temperate Grasslands and the Effects of Global Change. Glob. Chang. Eff. Conifer. For. Grasslands.

Salio, P., Hobouchian, M.P., García Skabar, Y., Vila, D., 2015. Evaluation of high-resolution satellite precipitation estimates over southern South America using a dense rain gauge network. Atmos. Res. 163, 146–161. doi:10.1016/j.atmosres.2014.11.017

Salvo, L., Terra, J.A., Ayala, W., Bermudez, R., Correa, J., Avila, P., Hernandez, J., 2008. Long-term phosporus fertilization and perennial legumes addition impacts on temperate natural grassland: II Total and particulate organic carbon, in: Multifunctional Grasslands in a Changing World Volume I. Organizing Committe of IGC/IRC Congress, Guangzhou, China, p. 282.

Sands, G.R., Podmore, T.H., 2000. A generalized environmental sustainability index for agricultural systems. Agric. Ecosyst. Environ.

Scherr, S.J., 1999. Soil degradation: A threat to developing country food security by 2020? [Policy Brief]. A 2020 Vis. Food, Agric. Environ.

Schwalm, C.R., Williams, C.A., Schaefer, K., Anderson, R., Arain, M.A., Baker, I., Barr, A., Black, T.A., Chen, G., Chen, J.M., Ciais, P., Davis, K.J., Desai, A., Dietze, M., Dragoni, D., Fischer, M.L., Flanagan, L.B., Grant, R., Gu, L., Hollinger, D., Izaurralde, R.C., Kucharik, C., Lafleur, P., Law, B.E., Li, L., Li, Z., Liu, S., Lokupitiya, E., Luo, Y., Ma, S., Margolis, H., Matamala, R., McCaughey, H., Monson, R.K., Oechel, W.C., Peng, C., Poulter, B., Price, D.T., Riciutto, D.M., Riley, W., Sahoo, A.K., Sprintsin, M., Sun, J., Tian, H., Tonitto, C., Verbeeck, H., Verma, S.B., 2010. A model-data intercomparison of CO2 exchange across North America: Results from the North American Carbon Program site synthesis. J. Geophys. Res. 115, G00H05. doi:10.1029/2009JG001229

Shevliakova, E., Pacala, S.W., Malyshev, S., Hurtt, G.C., Milly, P.C.D., Caspersen, J.P., Sentman, L.T., Fisk, J.P., Wirth, C., Crevoisier, C., 2009. Carbon cycling under 300 years of land use change: importance of the secondary vegetation sink. Global Biogeochem. Cycles. doi:10.1029/2007GB003176

Simoes, A., Hidalgo, C., 2011. The Economic Complexity Observatory: An Analytical Tool for Understanding the Dynamics of Economic Development - Export destinations of Soybeans from Uruguay (2015) [WWW Document]. Work. Twenty-Fifth AAAI Conf. Artif. Intell. URL http://atlas.media.mit.edu/en/visualize/tree_map/hs92/export/ury/show/1201/2015/ (accessed 3.3.17).

Smith, P., Davies, C.A., Ogle, S., Zanchi, G., Bellarby, J., Bird, N., Boddey, R.M., McNamara, N.P., Powlson, D., Cowie, A., Noordwijk, M., Davis, S.C., Richter, D.D.B., Kryzanowski, L., Wijk, M.T., Stuart, J., Kirton, A., Eggar, D., Newton-Cross, G., Adhya, T.K., Braimoh, A.K., 2012. Towards an integrated global framework to assess the impacts of land use and management change on soil carbon: current capability and future vision. Glob. Chang. Biol. 18, 2089–2101. doi:10.1111/j.1365-2486.2012.02689.x

Snyder, P.K., Delire, C., Foley, J.A., 2004. Evaluating the influence of different vegetation biomes on the global climate. Clim. Dyn. doi:10.1007/s00382-004-0430-0

Soriano, A., León, R.J.C., Sala, O.E., Lavado, R.S., Deregibus, V.A., Cahuépé, M.A., Scaglia, O.A., Velázquez, C.A., Lemcoff, J.H., 1992. Río de la Plata Grasslands, in: Coupland, R.T. (Ed.), Ecosystems of the World. Elsevier, New York, pp. 367–407.

Soriano, A., Paruelo, J.M., 1992. Biozones: Vegetation Units Defined by Functional Characters Identifiable with the Aid of Satellite Sensor Images. Glob. Ecol. Biogeogr. Lett. 2, 82. doi:10.2307/2997510

Tan, B., Morisette, J.T., Wolfe, R.E., Gao, F., Ederer, G.A., Nightingale, J., Pedelty, J.A., 2011. An Enhanced TIMESAT Algorithm for Estimating Vegetation Phenology Metrics From MODIS Data. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 4, 361–371. doi:10.1109/JSTARS.2010.2075916

Tom, G.H., 2007. Available Water Capacity and Soil Organic Matter, in: Lal, R. (Ed.), Encyclopedia of Soil Science, Second Edition. Taylor & Francis, pp. 139–143.

Travasso, M.I., Magrin, G.O., Baethgen, W.E., Castaño, J.P., Rodriguez, G.R., Pires, J., Fernandes, M., Travasso, M., South America, S., 2006. Adaptation Measures for Maize and Soybean in Southeastern South America. AIACC Work. Pap.

UNCCD, 2015. UNCCD - Reports [WWW Document]. URL http://www.unccd.int/en/programmes/Reporting-review-and-assessment/Reports/Pages/default.aspx (accessed 3.18.17).

UNCCD/Science-Policy-Interface, 2016. Land in Balance The Scientific Conceptual Framework for Land Degradation Neutrality The principles of LDN, Science-Policy Brief 02. September 2016. United Nations Convention to Combat Desertification (UNCCD), Bonn, Germany.

UNFCCC, 2003. Intergovernmental Panel on Climate Change Good Practice Guidance for Land Use , Land-Use Change and Forestry. United Nation Framework Convention on Climate Change (IPCC).

Vega, E., Baldi, G., Jobbágy, E.G., Paruelo, J.M., 2009. Land use change patterns in the Río de la Plata grasslands: The influence of phytogeographic and political boundaries. Agric. Ecosyst. Environ. doi:10.1016/j.agee.2009.07.011

Verheijen, F.G. a, Jones, R.J. a, Rickson, R.J., Smith, C.J., 2009. Tolerable versus actual soil erosion rates in Europe. Earth-Science Rev. doi:10.1016/j.earscirev.2009.02.003

Vila, D.A., de Goncalves, L.G.G., Toll, D.L., Rozante, J.R., 2009. Statistical Evaluation of Combined Daily Gauge Observations and Rainfall Satellite Estimates over Continental South America. J. Hydrometeorol. 10, 533–543. doi:10.1175/2008JHM1048.1

Vitousek, P.M., Mooney, H.A., Lubchenco, J., Melillo, J.M., 1997. Human Domination of Earth' s Ecosystems. Science (80-.). 277, 494–499. doi:10.1126/science.277.5325.494

Wang, D.-D., Shi, X.-Z., YU, D.-S., Wang, H.-J., Weindorf, D.C., Yu, D.-S., Sun, W.-X., Ren, H.-Y., ZHAO, Y.-C., 2013. Regional Differences in the Effect of Climate and Soil Texture on Soil Organic Carbon. Pedosphere 23, 799–807. doi:10.1016/S1002-0160(13)60071-5

Wang, D.D., Shi, X.Z., Lu, X.X., Wang, H.J., Yu, D.S., Sun, W.X., Zhao, Y.C., 2010. Response of soil organic carbon spatial variability to the expansion of scale in the uplands of Northeast China. Geoderma. doi:10.1016/j.geoderma.2009.10.018

West, P.C., Gibbs, H.K., Monfreda, C., Wagner, J., Barford, C.C., Carpenter, S.R., Foley, J. a, 2010. Trading carbon for food: global comparison of carbon stocks vs. crop yields on agricultural land. Proc. Natl. Acad. Sci. U. S. A. doi:10.1073/pnas.1011078107

West, T.O., Bandaru, V., Brandt, C.C., Schuh, A.E., Ogle, S.M., 2011. Regional uptake and release of crop carbon in the United States. Biogeosciences 8, 2037–2046. doi:10.5194/bg-8-2037-2011

West, T.O., Wali, M.K., 2002. Modeling regional carbon dynamics and soil erosion in disturbed and rehabilitated ecosystems as affected by land use and climate. Water. Air. Soil Pollut. doi:10.1023/A:1015552330945

White, R., Murray, S., Rohweder, M., 2000. Pilot Analysis of Global Ecosystems: Grassland Ecosystems Technical Report. doi:10.1016/B978-0-12-384719-

5.00259-8

Williams, J.R., Arnold, J.G., Kiniry, J.R., Gassman, P.W., Green, C.H., 2008a. History of model development at Temple, Texas. Hydrol. Sci. J. - J. Des Sci. Hydrol. doi:10.1623/hysj.53.5.948

Williams, J.R., Izaurralde, R.C., Steglich, E.M., 2008b. APEX V0604 Theoretical Documentation. Temple, Texas.

Williams, J.R., Jones, C. a, Dyke, P.T., 1984. A modelling approach to determining the relationship between erosion and soil productivity. Trans. - Am. Soc. Agric. Eng. 27, 129–144.

Williams, J.R., Wang, E., Meinardus, A., Harman, W.L., Siemers, M., Atwood, J.D., 2006. EPIC user guide v.0509.

Wood, S., Sebastian, K., Scherr, S.J., 2000. Pilot analysis of global ecosystems: Agroecosystems, Food Policy Research Inst. and World Resources Intl. …. World Resource Institute, Washington, DC.

Zambrano-Bigiarini, M., Rojas, R., 2013. A model-independent Particle Swarm Optimisation software for model calibration. Environ. Model. Softw. 43, 5–25. doi:10.1016/j.envsoft.2013.01.004

Zhang, X., Friedl, M.A., Schaaf, C.B., Strahler, A.H., Hodges, J.C.F., Gao, F., Reed, B.C., Huete, A., 2003. Monitoring vegetation phenology using MODIS. Remote Sens. Environ. 84, 471–475. doi:10.1016/S0034-4257(02)00135-9

Zhang, X., Izaurralde, R.C., Manowitz, D., West, T.O., Post, W.M., Thomson, A.M., Bandaru, V.P., Nichols, J., Williams, J.R., 2010. An integrative modeling framework to evaluate the productivity and sustainability of biofuel crop production systems. GCB Bioenergy 2, 258–277. doi:10.1111/j.1757-1707.2010.01046.x

Zhang, X., Izaurralde, R.C., Manowitz, D.H.D., Sahajpal, R., West, T.T.O., Thomson, A.M.A., Xu, M., Zhao, K., LeDuc, S.S.D., Williams, J.R.J., 2015. Regional scale cropland carbon budgets: evaluating a geospatial agricultural modeling system using inventory data. Environ. Model. Softw. 63, 199–216. doi:10.1016/j.envsoft.2014.10.005

Zhang, X., Sahajpal, R., Manowitz, D.H., Zhao, K., LeDuc, S.D., Xu, M., Xiong, W., Zhang, A., Izaurralde, R.C., Thomson, A.M., West, T.O., Post, W.M., 2014. Multi-scale geospatial agroecosystem modeling: A case study on the influence of soil data resolution on carbon budget estimates. Sci. Total Environ. 479–480, 138–150. doi:10.1016/j.scitotenv.2014.01.099

Zhang, X., Srinivasan, R., 2009. GIS-Based Spatial Precipitation Estimation: A Comparison of Geostatistical Approaches. JAWRA J. Am. Water Resour. Assoc. 45, 894–906. doi:10.1111/j.1752-1688.2009.00335.x