UNIVERSIDAD DE LA REPÚBLICA ORIENTAL DEL URUGUAY
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USO DE LOS ELEMENTOS DE AGRICULTURA DE PRECISIÓN Y MODELOS DE SIMULACIÓN PARA LA INCORPORACIÓN DE LA DIMENSIÓN ESPACIO-TEMPORAL EN LA INVESTIGACIÓN DE CULTIVOS AGRÍCOLAS:

A) Impacto de prácticas de manejo de suelos y atributos del terreno en la productividad de sorgo a escala de chacra

B) Simulación de la producción de arroz en Uruguay utilizando el modelo DSSATv4 CERES-Rice.

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RESUMEN

La aplicación de tecnologías de agricultura de precisión (GPS, sensores electrónicos y SIG) permite obtener información georeferenciada, estudiar su variabilidad espacial, incorporarla en el análisis estadístico de experimentos a escala de chacra, y predecir sus efectos en el rendimiento de los cultivos utilizando modelos de simulación. Se incorporaron estas herramientas en dos trabajos de investigación en el este de Uruguay. El primer trabajo consistió en un ensayo en fajas a escala de chacra, donde se estudió el efecto de la variabilidad espacial y temporal del rendimiento de sorgo en interacción con el efecto de prácticas de manejo en tres rotaciones cultivo-pasturas bajo siembra directa en Argiudoles oxiácuicos. La variación natural fue el principal factor determinante del rendimiento (r^2=0.14-0.69), mientras que los efectos de prácticas de manejo (rotación, laboreo sub-superficial y manejo de rastrojo) estuvieron supeditados a ocurrir dentro de un marco determinado por la variación temporal de las precipitaciones ocurridas y la variación espacial de atributos del suelo y del terreno. Por lo tanto, el estudio de estas variables resulta fundamental cuando se evalúan prácticas de manejo de suelos. En el segundo trabajo, se desarrollaron coeficientes genéticos en modelo DSSATv4 CERES-Rice para la variedad de arroz El Paso 144, que resultaron en una calibración y validación aceptable para la fenología (RCMEE para floración 5.9d y 4.5d) y rendimiento (RCMEE 1.1Mg.ha^{-1}, 13%) bajo condiciones no limitantes de fertilización nitrogenada, y zafras sin daño por frío. A partir de estos coeficientes, el modelo podría utilizarse en estudios de largo plazo sobre el efecto del cambio climático. No fue posible captar la variabilidad espacial a escala de chacra a partir del modelo; pero se identificaron posibles causas de esta restricción que podrían subsanarse mediante trabajos de investigación sobre la dinámica de nitrógeno en estos sistemas arroz-pasturas, e incluyendo una rutina que simule el daño por frío en etapas reproductivas del cultivo. La inclusión de estas herramientas en trabajos de investigación permitió estudiar interacciones de prácticas de manejo con la variabilidad temporal y espacial, e identificar necesidades concretas de investigación relevantes en el contexto de la producción agropecuaria del país, que llevarían a una mejor comprensión del sistema suelo-planta-atmósfera y podrían repercutir en prácticas de manejo para una producción de menor riesgo económico y ambiental. Por lo tanto, estas herramientas pueden realizar un aporte importante al incluirse en trabajos de investigación en Uruguay.

SUMMARY

Precision Agriculture (PA) Technologies (GPS, electronic sensors and GIS, etc.) allow to obtain georeferenced information, study its spatial variation, incorporate it in the statistical analysis of experiments at the landscape scale, and predict its effects on grain yield through development of crop simulation models. These technologies were used in two research works in eastern Uruguay. The first work consisted of a strip trial at the landscape scale, where the effect of temporal and spatial variability on sorghum grain yield was contrasted with management practices effects on Oxiaquic Argiudolls in three crop-pasture rotations under direct grazing. The natural variation was the first factor determining yield (r^2=0.14-0.69), while management practices effects (rotation, paraplowing and residues management) only affected yield within a range determined by rain temporal variation and soil an terrain spatial variation. Therefore, studying these variables is essential when evaluating soil management practices. In the second research work, genetic coefficients for DSSATv4 CERES-Rice model were developed for El Paso 144 rice cultivar, that resulted in satisfactory calibration and validation for phenology (RMSE for anthesis 5.9d y 4.5d, respectively) and grain yield (RMSE 1.1Mg.ha^{-1}, 13%) under no nitrogen fertilization restriction or chilling injury effects. This model could be useful for long-term studies of global warming using the developed coefficients. Field spatial variation could not be captured with the model. However, possible causes explaining this restriction were identified, and should be overtaken by more research information on nitrogen dynamics in Uruguayan rice-pasture systems, and by including a routine to simulate floret sterility due to chilling injury in reproductive stages. Including PA technologies in these research works made possible to study interactions between management practices effects and spatial and temporal variation, also identifying relevant research needs in Uruguayan production systems; that could allow a better understanding of the soil-plant-atmosphere system and could determine management practices for agriculture production under less economic and environmental risk. Therefore, PA technologies adoption could be an important improvement in Uruguayan research.

INTRODUCCIÓN

Variación espacial en la agricultura: desafíos para la investigación con diseños experimentales tradicionales

La productividad de los cultivos está definida por factores del suelo y clima que varían en el espacio y el tiempo. Cuando las causas de esta variabilidad pueden ser identificadas y medidas, esta información puede usarse para modificar las prácticas de manejo del cultivo con el objetivo de mejorar la rentabilidad de la producción o disminuir su impacto ambiental (Plant, 2001).

La variación en las propiedades del suelo dentro de una misma serie de clasificación generalmente se debe a pequeños cambios en la topografía que afectan el transporte y almacenaje de agua a través y dentro del perfil del suelo (Mulla y McBratney, 2002). Esto se debe a que la formación del suelo es el resultado de la influencia del clima, la vegetación y el tiempo actuando sobre el material geológico parental en diferentes posiciones del terreno (Jenny, 1941). A esta variación natural, se suman errores debidos a la escala de mapeo, que llevan a incluir suelos con diferentes características dentro de una misma unidad donde no son dominantes, e imprecisiones en la definición de límites entre unidades. A nivel de chacra, existen efectos locales de la actividad humana como la aplicación de fertilizantes y pesticidas, laboreo y drenaje de los campos, rotaciones de cultivos, implementación de riego, etc (Mulla y McBratney, 2002).

Propiedades del suelo como el contenido de materia orgánica y nutrientes (P, K, Ca, Mg), la textura, pH y conductividad eléctrica han sido estudiadas desde el punto de vista de su variación espacial, y han sido relacionadas con el rendimiento de los cultivos (Kravchenko et al., 2003, Cox et al., 2003; Terra et al., 2006; Parent et al., 2008, Marquez da Silva y Silva, 2008). Propiedades del terreno asociadas a la capacidad de almacenaje de agua en el perfil del suelo también se encuentran frecuentemente relacionadas con el rendimiento de de cultivos en secano y su variabilidad espacial (Kravchenko y Bullock, 2000; Fraisse et al., 2001, Kaspar et al., 2003, Terra et al., 2006, Parent et al., 2008, Marquez da Silva y Silva, 2008).

A pesar de que la variabilidad espacial de las propiedades del suelo y del terreno asociadas al rendimiento es ampliamente reconocida, la interacción entre prácticas de manejo del suelo y rotaciones cultivo-pasturas con los atributos del suelo y del terreno han sido raramente abordadas en investigación en forma simultánea (Bermudez y Mallarino, 2004; Terra et al., 2006).

La investigación tradicional utiliza diseños estadísticos para la experimentación que se basan en los propuestos por Fisher en 1935, donde la variación es evitada o controlada mediante la implementación de bloques homogéneos y repeticiones (Steel y Torrie, 1981). En experimentos agronómicos y estudios de suelos esta variación está dada principalmente por la variación del suelo (Bishop y Lark, 2006). Los bloques se distribuyen de manera que la variación dentro del bloque sea minimizada, mientras que la variación entre bloques es maximizada. Una parte de la variación ambiental es expresada entonces como diferencias entre bloques.

La extensión de los experimentos clásicos parcelarios y de sus resultados a escala de chacras muchas veces no resulta factible, ya que al pasar a una escala mayor es difícil encontrar sitios homogéneos como los bloques experimentales. Las observaciones cercanas en el espacio tienden a ser más parecidas que aquellas que se encuentran más apartadas, por lo tanto la distribución espacial de los atributos observados no es al azar (Goovaerts, 1997). Cuando se detectan patrones espaciales una de las suposiciones claves de los métodos estadísticos clásicos deja de ser válida: los errores no son independientes ni se encuentran idénticamente distribuidos (Bhatti et al. 1991). Si la variabilidad espacial no es controlada el error experimental es sobreestimado, reduciendo la precisión de las estimaciones del efecto de los tratamientos (Wu et al., 1998, Bishop y Lark, 2006). Para evitar que esto suceda, la variabilidad espacial debería ser estudiada, y los patrones espaciales removidos del error experimental en el análisis estadístico de los tratamientos (Bhatti et al. 1991).

La variabilidad espacial puede ser estimada utilizando métodos de muestreos continuos o discretos (Mulla y McBratney, 2002). En los métodos de medición continuos, medidas de la variable en observación son obtenidas en todas las localidades de campo experimental. Este tipo de información se obtiene mediante técnicas de sensoramiento remoto, como las imágenes satelitales y monitores de rendimiento. En los métodos de muestreo discretos, se colectan muestras en sitios predeterminados utilizando métodos destructivos. En este caso solamente una parte de la población de muestreo es observada.

Colectando un número de muestras suficientes, es posible inferir características de la población muestreada utilizando métodos estadísticos.

En estadística clásica, una población de muestreo se caracteriza por su distribución de frecuencias utilizando los parámetros de la media y desvío estándar (Mulla y McBratney, 2002). La dispersión de los valores alrededor de la media que se representa mediante el desvío estándar (S), es una medida de la variabilidad de una población muestreada, al igual que el coeficiente de variación (CV) y el rango. Sin embargo, la distribución de frecuencias no provee ninguna información sobre la correlación espacial entre las muestras. La estructura espacial de una población puede ser estimada utilizando una rama de la estadística aplicada denominada Geoestadística (Webster y Oliver, 2007).

Esta especialidad cuantifica la dependencia y la estructura espacial de una variable de muestreo, y luego la utiliza para predecir los valores que se obtendrían para esa variable en sitios que no fueron muestreados. La dependencia entre los valores encontrados en función de la distancia que separa las muestras se determina a través de la construcción de un semivariograma (Goovaerts, 1999). El semivariograma mide la disimilaridad promedio entre pares datos separados por vector de distancia, y se calcula como la mitad del cuadrado de la diferencia entre los componentes de pares de datos. El ajuste de un modelo para el semivariograma observado permite predecir el valor de la variable en estudio para los sitios no muestreados utilizando información recabada en sitios vecinos (Wollwenhaupt et al., 1997). Utilizando métodos geoestadísticos, la distribución espacial de los errores puede ser descripta, modelada y luego removida de los datos de campo o integrada en modelos complejos de análisis espacial para mejorar la precisión de las estimaciones del efecto de los tratamientos (Bhatti et al. 1991, Hernández y Mulla 2002).

En los últimos años, se han desarrollado herramientas que permiten obtener y procesar cantidades importantes de información georeferenciada con costos y en tiempos razonables. La aplicación de este tipo de información a la producción agrícola es lo que se denomina agricultura de precisión (Mulla y Schepers, 1997, Plant, 2001). Los monitores de rendimiento, sistemas de posicionamiento global (GPS), sistemas de información geográfica (SIG), nuevos programas de computación y diversos tipos de sensores equipados con GPS se encuentran entre las herramientas identificadas como tecnologías de agricultura de precisión. Estas herramientas permiten identificar y estudiar la variación espacial de la productividad de los cultivos y las propiedades del suelo a través del terreno (Plant, 2001).

En base a este tipo de información y de herramientas informáticas, el análisis geoestadístico puede ser utilizado para detectar efectos de tratamientos teniendo en cuenta la presencia de variación sustancial intrínseca del campo (Bhatti et al. 1991, Hernández y Mulla 2002, Bishop y Lark, 2006). De esta manera es posible trasladar los trabajos experimentales a escalas similares a las comerciales obteniendo información precisa a través de todo el terreno.

Agricultura de precisión

Cook y Bramley (1998) describen a la agricultura de precisión como un proceso cíclico, que comienza con la adquisición de información detallada sobre la performance de un potrero, continúa con la interpretación y evaluación de la información, utilizándola luego para controlar más precisamente las entradas al sistema. En este círculo de flujo de información, la mayor disponibilidad de la misma no produce ningún beneficio por si sola, sino que las probabilidades de obtener mejores resultados pueden aumentar dependiendo de la interpretación que se realice sobre dicha información.

Las tecnologías de agricultura de precisión han sido introducidas a nivel comercial a través de ensayos a escala de chacra y demostraciones a nivel productivo. La posibilidad de medir el rendimiento de los cultivos y las causas que lo afectan de forma precisa posibilita que los productores y técnicos privados realicen sus propias pruebas de campo (Plant 2001). La separación de zonas dentro de las chacras según el ambiente productivo para realizar un manejo de insumos sitio-específico es la meta actual de los productores innovadores que buscan producir más eficientemente (Bongiovanni, 2007). Esto a llevado a que muchos productores y empresas agropecuarias a nivel mundial a incorporar herramientas de agricultura de precisión en los últimos años. El primer lugar en cuanto a la adopción de estas tecnologías lo ocupa Estados Unidos, con el mayor número de monitores de rendimiento seguido por Argentina, Australia y Dinamarca (Bongiovanni y Lowenberg-DeBoer, 2006).

A nivel regional, Argentina ha liderado la investigación, comenzando su proyecto de investigación en agricultura de precisión en 1996 en INTA Manfredi (Córdoba)

(Bongiovanni y Lowenberg-DeBoer, 2006). En Uruguay, esto sucedió más tardíamente, consolidándose un proyecto de investigación en INIA a partir de 2003; a la vez que se instalaba el interés a nivel comercial con un proyecto de monitoreo de chacras arroceras financiado por el Ministerio de Ganadería, Agricultura y Pesca (Roel y Firpo, 2006). Este desarrollo paralelo simplificó la extensión del uso de estas tecnologías a nivel comercial, valorándose la retroalimentación entre la producción y la investigación.

Tecnologías de información aplicadas a la agricultura

La inferencia adecuada sobre las posibilidades de ocurrencia de eventos futuros en base a la interpretación de la información es fundamental en el proceso de toma de decisiones, ya que permite disminuir el riesgo de error (Cook y Bramley, 1998).

La variabilidad temporal de los indicadores de producción a escala de charca frecuentemente resulta de mayor magnitud que la variabilidad espacial. Esto aumenta el riesgo de realizar acciones económicamente y ambientalmente inapropiadas cuando el manejo diferencial toma en cuenta únicamente la variabilidad espacial. Por lo tanto, es necesario contar con análisis científico de tratamientos que consideren ambos tipos de variación (Whelan y McBratney, 2000).

Los modelos de simulación de cultivos pueden utilizarse para integrar conocimientos de procesos biofísicos determinantes del sistema suelo-planta-atmósfera, prediciendo el desarrollo y rendimiento de los cultivos bajo diferentes escenarios. De esta forma, permiten evaluar la incertidumbre asociada a varias opciones de manejo, y extrapolar los resultados a diferentes localidades y climas (Monteith, 1996, Timsina y Humphrey, 2006), y han sido adaptados como sistemas de soporte para la toma de decisiones sobre el manejo sitio-especifico de las chacras (Thorp et al., 2008).

A partir de información sitio-especifica, modelos de simulación en combinación con SIG pueden ser utilizados para identificar causas de la variabilidad del rendimiento y zonas de comportamiento estable a través del tiempo dentro de las chacras (Basso et al., 2001 y 2007). Además, el desarrollo de modelos puede aportar a la investigación brindando atención a brechas en el entendimiento y por lo tanto estimular nuevos trabajos experimentales o teóricos a la vez que pueden proveer de un marco a la interpretación de los resultados de experimentos de campo bajo diferentes ambientes (Monteith, 1996).

La aplicación de tecnologías de la información a la agricultura brinda nuevas posibilidades en la búsqueda de mayores potenciales productivos y acerca la investigación a la producción. El futuro direccionamiento de la agricultura depende de la habilidad de la comunidad científica para conducir este nuevo tipo de estudios, con la confianza de productores y ambientalistas en que los cambios beneficiarán al ambiente y aumentarán la eficiencia de la producción agrícola (Hatfield, 2000).

Objetivos

El objetivo general de la presente investigación fue caracterizar la variación espacial y temporal del rendimiento de cultivos a escala de chacra en condiciones de Uruguay, de los factores ambientales que la determinan y su interacción con prácticas de manejo a través de la incorporación de herramientas de agricultura de precisión en la investigación. Se utilizaron dos enfoques, y para cada uno se estableció un trabajo de investigación:

1) la evaluación del efecto de prácticas de manejo de suelos sobre el rendimiento de sorgo en interacción con las propiedades del suelo y del terreno utilizando ensayos en fajas a escala de chacra;

2) la calibración y validación de modelos de simulación para el cultivo de arroz, evaluando la captación de la variabilidad espacial y temporal del modelo para las condiciones de producción de Uruguay.

Los trabajos de investigación fueron escritos en formato de artículo científico, según las instrucciones para los autores de las publicaciones de American Society of Agronomy (ASA), Crop Science Society of America (CSSA) y Soil Science Society of America (SSSA).

SOIL MANAGEMENT AND LANDSCAPE ATTRIBUTE IMPACTS ON FIELD-SCALE SORGHUM PRODUCTIVITY UNDER THREE NO-TILL CROP-PASTURE ROTATION SYSTEMS.

ABSTRACT

Soil management practices can interact with field spatial and temporal variability in their effects on crop productivity. We evaluated at a field-scale the effects of soil management practices on sorghum (*Sorghum bicolor* L.) grain yield during three years in Uruguay (soil: Oxyaquic Argiudoll). Treatments were established in randomized complete block design in strips traversing the landscape in a sorghum-soybean (*Glycine max*) sequence integrated in three no-till crop-pasture rotation systems: 1) continuous cropping (CC) with a winter cover crop for grazing; 2) short rotation (SR): two years of a grass-legume pasture and two years like CC; 3) long rotation (LR): four years pasture and two years like CC. Treatments consisted of a factorial arrangement of two levels of cover crop residues generated by winter direct grazing with or without paraplow subsoiling. Yield monitor data were analyzed with mixed models accounting for spatial correlation. Field variation was assessed with intensive grid sampling for soil analysis, terrain attributes and soil electrical conductivity (EC). Temporal variation was the first factor determining yield (8.15, 4.61, and 6.05 $Mg.ha^{-1}$, in 2005-06, 2006-07 and 2007-08, respectively) followed by terrain attributes, rotation and its interactions. Terrain attributes and EC associated with soil units explained 77% of the site variation and determined 14-64% of yield variability within fields. Systems including perennial pastures had greater soil C(0-15cm), but did not guarantee higher yields than CC. Subsoiling reduced soil penetration resistance, but only improved yield in 2007-08 in LR. Grazing intensity did not affect yield

IMPACTO DE PRÁCTICAS DE MANEJO DE SUELOS Y ATRIBUTOS DEL TERRENO EN LA PRODUCTIVIDAD DE SORGO A ESCALA DE CHACRA EN TRES SISTEMAS DE ROTACIONES CULTIVO-PASTURAS EN SIEMBRA DIRECTA.

RESUMEN

Los efectos de prácticas de manejo de suelos en la productividad de los cultivos pueden interactuar con la variabilidad temporal y espacial de las chacras. Se evaluó el efecto de prácticas de manejo de suelos en el rendimiento de sorgo (*Sorghum bicolor* L.) a escala de chacra durante tres años (Argiudoles oxiácuicos). Los tratamientos se ubicaron en fajas a través del terreno en un diseño de bloques completos al azar, en la secuencia sorgo-soja (*Glycine max*) integrada en tres sistemas de rotaciones cultivo-pasturas en siembra directa: 1) Cultivo continuo (CC) con cobertura invernal para pastoreo, 2) Rotación corta (RC): dos años de pasturas de gramíneas y leguminosas y dos años ídem CC, 3) Rotación larga (RL): cuatro años de pasturas y dos años ídem CC. Los tratamientos consistieron en un arreglo factorial de dos niveles de residuos generados por pastoreo invernal, con y sin subsolado con paraplow. Los datos de rendimiento tomados con monitor y GPS, fueron analizados con modelos mixtos, considerando la variación espacial. La variación del suelo y del terreno se midió en un intenso muestreo en grilla, el cálculo de atributos topográficos y la medición de conductividad eléctrica (CE). El primer factor determinante del rendimiento fue la variación temporal (8.15, 4.61, y 6.05 $Mg.ha^{-1}$, en 2005-06, 2006-07 y 2007-08, respectivamente), seguido por los atributos del terreno, la rotación y sus interacciones. Los atributos del terreno y la CE explicaron 77% de la variación, y determinaron 14-69% del rendimiento dentro de las chacras. Los sistemas que incluyeron pasturas de larga duración tuvieron mayores valores de C orgánico en el suelo, pero no garantizaron mayores rendimientos que CC. El subsolado redujo la resistencia a la penetración del suelo, pero solamente mejoró el rendimiento en RL en 2007-08. El pastoreo animal no afectó el rendimiento.

INTRODUCTION

Crop area has grown in Uruguay since 2000 following the rise of international grain prices (DIEA, 2008). This has determined the expansion of agriculture, mostly soybean, to marginal soils of lower use capacity. Sorghum is one of the best options to rotate with soybeans, particularly in conservation systems where high production of residues is critical.

Abruptic and Oxyaquic Argiudolls in eastern Uruguay have some limitations for grain production. Their mollic epipedon is weak in structure and is prone to erosion when it is not covered by residues. The argillic horizon is compact and has little porosity, which results in low water holding capacity, strongly retained water, and limited drainage. Rational management of these soils should emphasize erosion control and amelioration of soil physical properties, as well as maintaining organic matter level and increasing soil fertility (Durán, 1991).

Animal production based on direct grazing has traditionally been the main farming activity of the study area. However, it has been displaced in the last years by more intensive rotations where cash crops are also sown in these soils. Degradation of soil chemical and physical properties has been reported under direct grazing. Animal grazing can also increase soil nutrient losses in overland flow. Kurz et al., (2006) reported an increase of particulate nitrogen, organic phosphorous and potassium concentrations in overland flow after grazing. Moreover, removing residue cover under no-till systems can result in soil degradation and grain yield reduction (Huang et al., 2008). Residue cover affects soil water dynamics, enhancing infiltration rate (Martino, 2001; Singh and Malhi, 2006), while reducing water losses as runoff and evaporation (Martino, 2001, Singh and Malhi, 2006, Huang et al., 2008).

Animal trampling under direct grazing compacts topsoil, affecting pore size distribution, and reducing macroporosity at high stocking rates, altering soil hydraulic conductivity (Singleton and Addison, 1999; Kurz et al., 2006). Animal treading also increases soil bulk density and penetration resistance (Kurz et al., 2006). Soil compaction limits root proliferation and leads to poor soil water utilization in deep soil layers (Martino, 2001).

Results from a long term experiment installed in 1962 at INIA La Estanzuela (Uruguay) using conventional tillage demonstrated that integrating crop-pasture rotation systems reduces erosion, preserves soil quality, reduces chemical inputs and improves crop yield and economic stability compared with continuous cropping (García-Prechac et al., 2004). However, there is still soil organic carbon loss due to tillage during the crop's rotation phase that can be reduced by integrating no-till to rotation systems. Conservation systems including no-till and crop-pasture rotations can sustain soil organic C in the long term, even compared with undisturbed soil under pristine vegetation (Terra et al., 2006a).

Deep tillage has been reported as a useful tool to overcome soil physical constraints, reducing soil bulk density and penetration resistance (Varsa et al., 1997, Díaz-Zorita, 2000, Baumhardt and Jones, 2002a, Siri-Prieto et al., 2007). Infiltration and evaporation rate are also increased by paraplowing, and its balance determines soil water content (Martino, 2001). Deep tillage with paraplow can improve roots proliferation (Martino, 1998) and was shown to increase corn, sunflower, wheat and barley grain yield in Uruguayan Mollisols (Martino, 1998; Martino, 2001; Ernst and Bentancur, 2004).

Soil properties and terrain attributes linked with water holding capacity and field-scale water regime are usually related to crop yield spatial variability (Kravchenko and Bullock, 2000; Fraisse et al., 2001). However, the interactions between soil management practices and crop-pasture rotations with soil and terrain attributes have been rarely assessed (Bermudez and Mallarino, 2004; Terra et al., 2006b).

Traditional field experiments use designs based on statistical methods as pioneered by Fisher in 1935, where spatial variation is avoided or controlled by homogeneous blocks and replication (Steel and Torrie, 1981). In agronomic trials and soil research this variation is mainly due to the spatial variability of soil (Bishop and Lark, 2006). Blocks are distributed so that variation within blocks is minimized, and maximized between blocks. A part of the environmental variation is then expressed as differences between blocks.

Extension of classical plot experiments and their results to field scales is often not plausible, because it is hard to find uniform conditions such as experimental blocks at such large-scale. Observations close to each other on the ground tend to be more alike than those further apart; so spatial distribution of observed attribute values is not random (Goovaerts, 1997). When spatial patterns are detected one of the key assumptions of classical statistics methods is not valid: errors are not independent, nor do they have uniform distribution (Bhatti et al. 1991). If spatial variability is not controlled, the estimated experimental error is inflated; reducing the precision of treatment effects estimates (Wu et al., 1998, Bishop and Lark, 2006). To avoid this, spatial variability should be studied, and patterns removed from the experimental error in statistical analysis of treatments (Bhatti et al. 1991).

New technologies such as yield monitors, GPS, and new software have been developed in the last years, making possible to obtain and process great amounts of georeferenced information at reasonable cost and time. Yield monitors allow identifying and studying spatial variability through the field (Plant, 2001). Based on this type of information, geostatistical analysis can be useful to detect treatment effects taking in account the presence of substantial inherent variation of the field (Bhatti et al. 1991, Hernández and Mulla 2002, Bishop and Lark, 2006). Spatial distribution of errors can be described, modeled and removed from the dataset to improve treatment estimates accuracy (Bhatti et al. 1991, Hernández and Mulla 2002).

The hypotheses of this experiment were:

1) Implementing management practices which maximize soil water storage and minimize soil compaction will improve sorghum grain yield in crop-pasture rotation systems of Uruguayan Oxiaquic Argiudolls and Argiaquolls;

2) Management practices interaction with factors explaining yield spatial and temporal variation through the fields can be detected using precision agriculture technology and geostatistics in strip trials.

The objective of this research was to determine the impact of four soil management practices and three crop-pasture rotation systems with soil landscape variability on sorghum field scale yield on Argiudolls and Argiaquolls of eastern Uruguay, focusing on three aspects:

1) Integrating crops in rotation with pastures.

2) Using soil management practices that increase soil water conservation and mitigate surface soil compaction caused by animal trampling.

3) Identifying soil properties and terrain attributes associated with yield spatial and temporal variation.

MATERIALS AND METHODS

Site description and management practices

The field-scale study was conducted during 2005-06, 2006-07 and 2007-08 growing seasons at the ‘Palo a Pique’ experimental unit of the National Agricultural Research Institute (INIA) in Treinta y Tres, Uruguay (33°:15'36"S, 54°:29'26"W, 60-m elevation). Historical (1973-2008) mean annual rainfall and temperature at the site are 1375-mm and 16.6° C, respectively. According to the USDA-NRCS soil Taxonomy (Durán et al., 2005), soils were classified as Abruptic Argiaquolls and Oxyaquic Vertic Argiudolls (fine, smectitic and thermic) with an argillic horizon at 27-99 cm depth. The field had been under three contrasting no-till rotation systems since 1995 following regenerated native pasture vegetation.

The experiment evaluated the field-scale impact of four soil management practices in three soil use intensities (rotations) on sorghum grain yield during three seasons. These rotations were part of a long-term experiment that had been implemented for 10 years when the management practices experiment started.

Soil use intensity treatments (rotations) were based on a sorghum- soybean (*Sorghum bicolor-Glycine max*) sequence crop stage rotating with a pasture stage for grazing of different length: 1) Continuous annual cropping (CC) with a winter cover of *Lolium multiflorum* Lam. for grazing; 2) Short rotation (SR): two years of pasture (mixture of *Trifolium pratense* L. and *Lolium multiflorum*) and two years like CC and; 3) Long rotation (LR): four years of pasture (mixture of *Dactylis glomerata, Trifolium repens* L. and *Lotus corniculatus* L) and two years like CC. After the perennial pasture stage, a winter cover of *Lolium multiflorum* planted for grazing was the first annual species of the cropping phase before sorghum. All rotation entry points were present each year, except for CC, which had only one field. The CC field was planted either by sorghum or soybean in alternated years according to the cropping sequence.

Soil management practices were the result of a factorial arrangement. The first factor, with two levels, was the amount of crop residue of not grazed biomass left by grazing animals. The second factor was with or without paraplowing. Levels of residue biomass were generated in each season by different winter grazing ryegrass intensity preceding sorghum. In one treatment grazing was suppressed one month before herbicide application and in the other treatment one week prior to spraying. Ryegrass was grazed by steers (180 kg body weight) at a stocking rate of 6.3 head.ha^{-1} and sprayed in the last week of Sept. with 2.4 l glyphosate a.i.ha^{-1}. Subsoiling was performed at 40-cm depth using a paraplow immediately before planting in each season.

Soil management treatments were evaluated in replicated strip experiments located in each rotation system during the 2005-06, 2006-07 and 2007-08 growing seasons. Treatments were established each season in 7-10-m wide (depending on the width size of the paddock) and 100-m long strips across the landscape in a randomized complete block design (RCB). Each experiment had three blocks arranged according to the topographic position and two replications per block (Fig.1).

Sorghum (DK39) was planted using a 6 line-Semeato Personale Drill direct planter at 250,000 viable seeds ha^{-1} in 0.40m rows on 17 Nov 2005, 15 Nov 2006 and 7 Nov 2007. The seed was treated with imidacloprid (500cc/100kg seed). Fertilization at planting was done with 22.5 kg N. ha^{-1}, 45 kg P_2O_5.ha^{-1} and 22.5 kg K_2O.ha^{-1} in 2005-06, and 22.5 kg N. ha^{-1}, 57.5 kg P_2O_5.ha^{-1} in 2006-07 and 2007-08 seasons. Starter fertilizer was applied 50% in the row and 50% broadcast on the surface. Urea was broadcast at growing point differentiation stage on each season at a rate of 46 kg N.ha^{-1} spread on the soil surface. Insecticides were necessary to control armyworms and grasshoppers in the last two seasons. Sorghum grain was harvested between March 15th and April 15th in all seasons.

Data collection and measurements

Field strips were divided in 20m x 7m cells, in a grid of 40 cells per block (Fig.1). This grid was used for point sampling of soil properties and residue cover at the beginning of fallow, and crop variables during the growing seasons.

Soil samples (0.15-m depth) were taken each year before planting and analyzed for soil organic carbon (dry combustion and infrared detection), phosphorous (citric acid), and potassium (NH_4OAc extraction and atomic absorption), according to the laboratory methods described by Burt (1996). Sampling sites were evenly distributed through cells one to five in a stratified systematic unaligned sampling design (Woolenhaupt et al., 1997) allowing one sample at each strip of the block (Fig. 1).

Soil electrical conductivity surfaces of all sites at 0-30 cm (EC30) and 0-91-cm (EC91) depths were obtained on 19 Oct 2007 with a Veris® Tech 3100 soil sensor (Veris Tech. Salina, KS) equipped with a DGPS. Topographic position and sampling points were georeferenced with a DGPS (Trimble AgGPS® 132).

Soil water content was measured weekly (0-90cm depth) in one cell of each strip in every block. A neutron probe (Troxler Electronic laboratories- model 4300) calibrated for gravimetric water on the experimental field was used in the first two seasons. Data was collected only in the SR field during 2005-06 season, while in 2006-07 measurements were taken in both SR and LR.

Height of rye grass residues covering the soil surface was measured at the beginning of fallow at five random positions of each cell of the grid. Three height values were taken from a sampling rectangle of 20cm x 50 cm. A regression between residues height and dry matter was calculated on a five height scale basis for each rotation, and used to estimate biomass residues at each cell. Two samples were taken for each scale value, where residue height was measured and biomass covering the soil surface was cut and oven-dried for 48 h at 105°C for dry matter calculation (R^2=0.88). Crop stand was measured 3 to 4 weeks after planting on cells 2 and 4 of each block and replication for every field on each season.

Soil penetration resistance was determined before harvesting on March 11, 2008, when soil water content was at field capacity, using a Rimik CP10a cone penetrometer equipped with a 30° cone of 113 mm^2 basal area (Agridry Rimik Pty Ltd., ELE International Ltd., Hemel Hempstead, Hertfordshire, England). Measurements were taken (0-78 cm depth) in every centroid of cells 2 and 4 of each strip for SR, LR and CC fields. Three insertions were done and averaged at each position. Chlorophyll meter readings were taken using a Minolta SPAD 502 instrument (Spectrum Technologies, Inc.; Plainfield, Illinois, USA) every two weeks between the 6 leaf growth stage and maturity. Readings were taken on the last totally expanded leaf, on five randomly selected plants around the centroid of the cells 2 and 4 of each block and replication.

Sorghum grain yield was recorded and geo-referenced across the fields using a combine equipped with a DGPS (Trimble AgGPS® 132) and an Ag Leader PF3000 yield monitor (Ag. Leader Tech. Inc., Ames, IA).An elevation map with one meter interval contour from a traditional topographic survey of the area was georeferenced with a DGPS

(Trimble AgGPS® 124/132) using ArcView 3.2 software (ESRI, Redlands, CA). Elevation data was interpolated using punctual ordinary kriging to generate a digital elevation model (DEM) using GS+, v. 5.1 (Gamma Design Software, Plainwell, MI, USA). The DEM was converted to a 5-m grid using Spatial Analyst 2.0a (ESRI, Redlands, CA).

Topographic wetness index (TWI), Stream Power Index (SPI) and Length-Slope Factor (L-S factor) were secondary compound attributes calculated with ArcView. These attributes are important to assess potential soil moisture and potential erosion. Scripts used for these calculations were developed by Schmidt (2003), based on equations by Moore and Wilson (1992) and Moore et al. (1993). The script is based on the D8 flow algorithm, and calculates a mean filtered grid for TWI and SPI using a 3 cells radius neighborhood in order to bur the static unrealistic pattern caused by the algorithm (Schmidt, 2003). The TWI is calculated from the specific catchment area of a point and the local slope gradient. It is based on the assumption that topography controls the movement of water in a sloped terrain, and thus the spatial pattern of soil moisture. High values are found in converging, flat terrain. Low values are typical for steep, diverging areas (Schmidt, 2003).

$TWI = \ln (A_s/\tan\beta)$

Where:

A_s= specific catchment area

β=Slope

The SPI is proportional to stream power, and it is a measure of the erosive power of overland flow (Moore et al., 1993).

$SPI = \ln (A_s * \tan\beta)$

Where:

A_s= specific catchment area

β=Slope

L-S Factor is a sediment transport capacity index, derived as a function of specific catchment area and slope by Moore and Wilson (1992). It gives a value for the water erosion potential relative to a slope of 22.13 m length and a slope angle of 5º; and for a two dimensional hillslope it is equivalent to the combined L-S factor in the Revised Universal Soil Loss Equation (RUSLE, Moore and Wilson, 1992).

$LS\ Factor = (m+1)(A_s/22.13)^m (\sin\beta/0.0896)^n$

With m=0.4 and n=1.3 for a slope length <100 and a slope angle <14º

Where:

A_s= specific catchment area

β=Slope

m=slope-length exponent in the LS factor in the USLE

n=slope-angle exponent in the LS factor in the USLE

Data analysis

Spatial autocorrelation

Soil properties, terrain attributes and yield data were analyzed for spatial correlation and interpolated using GS+, v. 5.1. Spatial structure was characterized constructing sample semivariograms $\gamma(h)$ with experimental data. The sample semivariogram describes spatial dependence among samples as a function of separation distance h. It is computed as half the average squared difference between the components of data pairs (Goovaerts, 1997), according to the equation 1 (Wollenhaulpt et al., 1997):

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} (z_i - z_{i+h})^2 \qquad (1)$$

where $N(h)$ is the number of data pairs at a separation distance h, and z_i and z_{i+h} are the sample property values at two locations separated by a distance h. Semivariograms often increase in value as separation distances increases and level off to nearly constant value at large separation distances (Wollenhaupt et al., 1997). In this study, sample semivariograms were fitted with spherical variogram models defined by equation 2.

$$\gamma(h)= C_0 + C_1 [1.5(h/a) - 0.5(h/a)^3], \quad \text{if } h \le a \qquad (2)$$

$$\gamma(h)= C_0 + C_1, \quad \text{if } h > a$$

where:

h= lag class interval,

C_0 = nugget variance,

C_1= structural variance

a = range parameter.

Samples separated by distances closer than the range are spatially dependent, while those separated by greater distances are spatially independent. With a spherical model, spatial correlation exists if the range *a* is grater than zero (Bhatti et al., 1991). The value of the semivariogram at the range is called the sill and usually corresponds to the sample variance (C_1). The nugget represents the variance due to variability of samples at separation distances smaller than the closest sample spacing (Wollenhaupt et al., 1997). A property exhibiting no spatial correlation will be best modeled by a linear model in which the slope is zero. This is known as pure-nugget model (nugget/sill=1), indicating that variability is completely random (Bhatti et al., 1991).

Semivariance models were first selected by visual fit and the regression coefficient of determination. Adequacy of the chosen model was tested using the cross-validation technique, were each data-point is deleted one at a time and estimated by kriging based on the remaining data (Myers, 1991). Estimation of coefficients of determination between estimated and measured values, sum of square errors, and mean error are calculated in cross-validation, and represent criteria of model fit (Myers, 1991). After modeling spatial variation, spatial dependence was classified as strong, moderate of weak, based on nugget/sill ratio. Classification criteria was based on Cambardella et al. (1994), who suggested that a nugget/sill ratio <25% indicated strong dependence, between 25 and 75% indicated moderate dependence, and >75% indicated weak spatial dependence.

Yield data manipulation

Yield monitor data were cleaned of erroneous data such as field and block borders or combine stops. Data were analyzed for spatial correlation by field. When residuals were spatially correlated yield was adjusted by the method proposed by Hernández and Mulla (2002) as a variant to the method Papadakis first proposed in 1937. A residual for each cell was calculated substracting the treatment mean from the cell yield.

$$^{m}r_{ij} = \frac{(Y_{ij} - \bar{Y}_{t(ij)})}{\bar{Y}_{t(ij)}} \qquad (3)$$

Where:

$^{m}r_{ij} =$ Normalized residual at each *ij* location

$Y_{ij} =$ Observed yield values at the location *ij*

$\bar{Y}_{t} =$ Yield mean for the treatment t

Spatial structure of the residuals ${}^{m}r_{ij}$ was determined and kriging was performed to estimate a new residual for each cell by cross-validation of nearest neighbor observations (equation (4)).

$$ {}^{m+1}\hat{r}_o = \sum_{h=1}^{n} \lambda_h \, {}^{m}r_{ij} \qquad (4) $$

where:

${}^{m+1}\hat{r}_o =$ Estimated residual for the *m+1* iteration

$\lambda_h =$ Vector of ordinary krigging weights based on semivariance modeling

${}^{m}r_{ij} =$ Residual from Equation (3)

This new residuals ${}^{m+1}\hat{r}_o$ were used to recalculate yield with the equation (5). The constant *b* was set to 0.5, so that the adjustment removed partially the trend, avoiding oscillations in treatment means (Bhatti et al., 1991).

$$ {}^{m+1}Y_{ij} = {}^{m}Y_{ij}(1 - b \times {}^{m+1}\hat{r}_o) \qquad (5) $$

where:

${}^{m+1}Y_{ij} =$ Updated yield value for the m+1 iteration

${}^{m}Y_{ij} =$ Original yield at the locations *i* and *j*

$b =$ Constant (0.5)

${}^{m+1}\hat{r}_o =$ Estimated residual form equation (4) for the m+1 iteration

This procedure was iterated with updated yields until the sill of the semivariogram of the r_{ij} indicated no remaining structure, and then year, rotation, and management practices effects on yield could be analyzed with linear models with random errors.

Rotation and management practices effects

Mixed models (Littell et al., 1996) performed with SAS software PROC MIXED (SAS Inst., Cary, NC) were used to analyze treatment effects. For the overall mixed model, rotation systems and management practices were considered as fixed effects, while year was considered as a random effect. An F statistic was used to determine the significance ($p \leq 0.05$) of the fixed effects for all analysis. Management practice effects on soil water content were analyzed as a repeated measures experiment by depth (every 15cm). An analysis by date was also performed, considering that water content interaction with crop development stages was better interpreted by date. Management practice effects on soil penetration resistance were analyzed by soil depth, every 2cm, up to a depth of 78cm.

Relationship between variables

Factor analysis was used to reduce the dimensionality of soil properties and terrain attributes data, identifying internal relationships between these variables. SAS FACTOR procedure was performed using the Principal Component method based on the correlation matrix, and Varimax orthogonal rotation (Khattree and Naik, 2000). As a result from this analysis, variables are grouped so that correlation is large between variables within the same group, but it is small between variables from different groups. Each group is represented by a new variable created from the variables in the group, defined by a common factor that makes them vary together within a field. These new variables are called latent variables or factors, as they attempt to represent underlying directly unobservable factors such as an intrinsic property of the field or a management practice (Mallarino et al., 1999). Their interpretation is based on agronomic knowledge of potential reasons for the observed co-variation and subjective judgment is involved (Mallarino et al., 1999, Khattree and Naik, 2000). In this experiment, new variables with eigenvalues greater than 1 were interpreted as latent factors.

Scores were calculated for these latent factors in each of the 192 cells containing complete soil data. Then, latent factors were used as independent variables in a multiple regression equation, where yield variation respect to the treatment mean was the dependent variable. Regression statistical analysis was performed for each year*rotation combination using stepwise regression in SAS ($p < 0.05$) (Freund and Littell, 2000).

Finally, an integrative approach was taken. Classification and regression trees (CART) was used to put a perspective on the relationships between yield and season, rotation, management practices, soil analysis, and terrain attributes. CART is a non parametric statistical method developed by Breiman et al. (1984) that uses a tree-structured approach to classification and regression problems. Rather than trying to identify and model a general relationship between responsive and predictor variables, it partitions the multidimensional space defined by the predictor variables into zones that are as homogeneous as possible in terms of response. This method has been used in different research fields, including the identification of factors underling grain yield spatial variability (Roel et al., 2007). This analysis was preformed using the software R version 2.8.1 (R Development Core Team, 2005) with rpart package (Therneau et al., 2005).

RESULTS AND DISCUSSION

Rainfall

Precipitation amount and distribution differed considerably during the three seasons (Table 1). Rains occurred in all seasons during the 4 weeks after spraying fallow (110, 53, 221mm in 2005-06, 2006-07 and 2007-8), allowing the soil profile to store water. However, rainfall during the sorghum growth season was different for the three years. In 2005-06 no rains were registered from planting until the growing point differentiation stage, but well distributed rains during the growing point differentiation-soft dough stages (310 mm) determined high grain yields. In 2006-07 rainfall between planting-soft dough stages was only 185 mm, 40% lower than the previous season, leading to poor grain yields. In 2007-08 events of rain and low temperature that followed planting delayed crop emergence in all treatments. Although the first stages of development were completed with scarce water, rains occurred at the stage of 6-8 leaves (160mm). Water was low during bloom and grain filling stages (92mm), although the situation was not as extreme as in 2006-07.

Soil properties

Cropping systems that included perennial pastures had a significantly greater soil organic carbon content than CC ($p < 0.05$) in 2005-06 (14.2 vs 15.9 and 17.8 g. kg^{-1} average values for CC vs SR and LR, respectively) (Table 2). Rotations with perennial pastures phase of four years had a significantly greater organic carbon content than rotations including shorter perennial pastures (18.7 vs 16.3 g. kg^{-1} in 2005-06, 18.3 vs 16.5 g. kg^{-1} in 2006-07 and 16.4 vs 14.9 g. kg^{-1} in 2007-08 for LR vs SR, respectively). This was in agreement with results from a long term experiment in Uruguay, where crop rotations including pastures recovered most soil organic carbon lost by plowing during the cropping phase (García-Préchac et al. 2004). In another study, in the same site of our experiment, Terra et al. (2006a) reported that crop-pasture rotations coupled with no-tillage were able to maintain similar soil organic carbon to adjacent uncultivated natural grasslands. These results suggest that for Uruguayan Arguidolls, perennial pastures rotating with crops are necessary to preserve soil organic C even under no-tillage.

Ryegrass residues left on the soil surface before sorghum planting were affected by year, rotation, and treatment (Table 3). Residue biomass at fallow was 71% and 53% lower in 2005-06 than in 2006-07 and 2007-08 (812 vs. 2804 and 2311 $kg.ha^{-1}$, respectively). Residue biomass in CC was 72% and 54% lower than residues biomass in rotations including perennial pastures in 2005-06 and 2007-08 seasons, respectively. Differences in residue cover amount due to grazing strategy were observed in all seasons and every rotation. Strips grazed until the previous week to fallow had an average of 56% (range: 36-72%) less residues biomass than strips that had not been grazed for the last month.

There were no significant management practice effects on soil water content during 2005-06 season (data not shown). However, in the drier season of 2006-07 management practice effects on soil water storage were evident. In 2006-07 restricted grazing strips accumulated more water than treatments more intensively grazed. Differences were significant only in the top 15 cm soil layer, where restricted grazing strips had an average of 1.5% more gravimetric water (3 mm available water) than intensively grazed strips (Fig.2). Higher residue cover on restricted grazing strips allowed more water stored from rains that occurred before planting in the 2006-07 growing season (Fig.2a). Residue biomass on the soil surface acts as runoff barrier, preventing soil superficial crusting, and reducing soil erodability (Martino, 2001; Durán and García-Préchac, 2007); as well as regulating soil water storage at fallow, improving water infiltration and avoiding evaporation (Singh and Malhi, 2006). Nevertheless, differences were only significant until sorghum growing point differentiation stage (28 DAP).

Paraplowed treatments had an average of 1.8% less gravimetric water (10 mm) in soil layers at 0-45 cm depth than no-paraplowed treatments from 56 DAP until the end of the growing season (Fig. 3). This suggests that there was more root exploration and water extraction in paraplowed treatments compared with no-paraplowed ones. However, these differences were observed close to wilting point, and therefore, few or no advantages of paraplowing were expected in sorghum productivity. Differences in soil penetration resistance were observed between subsoiled and not subsoiled treatments, but no differences due to grazing strategy or its interaction with subsoiling were detected (Fig.4).

Paraplowing reduced penetration resistance respect to no-paralowed treatments at 0-56 cm depth, with the greatest differences (0.405 MPa) detected at 12 cm depth (Fig.4). These results agreed with those of other authors (Varsa et al., 1997; Pikul and Aase, 1999, Martino, 2001, Siri-Prieto et al., 2007) who found that deep-tillage with no surface disturbance can improve soil quality by reducing cone index, increasing infiltration and improving root proliferation.

On the other hand, the peak of cone index measured did not reach the value of 2-2,5 MPa at any treatment (Fig. 4). This value is reported in the literature as the critical value that completely suppress root growth (Hamza and Anderson, 2005). This suggests that root growth might not have been limited by soil mechanic impedance.

Although negative effects of animal treading on soil physical properties (macroporosity, bulk density and resistance to penetration) have been reported, the intensity of these negative effects depend on animal stocking rate (Singleton and Addison, 1999; Drewry and Paton, 2000; Kurz et al, 2006). Soil penetration resistance was not affected by animal treading at a stocking rate of 6.3 steers.ha^{-1} (180 kg body weight) 4 weeks before planting (Fig 4).

Grain yield

Rotation systems and management practices effects on yield

Grain yield observed for the different seasons was highly related to accumulated precipitation during the most water demanding crop development stages. The highest yield (8.15 Mg-ha^{-1}) was observed in 2005-06, when 310 mm of rain were accumulated from growing point differentiation until soft dough stages (Table 1). In 2006-07 yield was 43% lower than in 2005-06, and rainfall during critical stages of growing point differentiation to soft dough was 121 mm. In 2007-08 crop productivity was 26% lower than in 2005-06 and 252 mm of rainfall occurred in the same period (Table 4). These results emphasize the concept that water availability is the most important factor influencing grain yield in rainfed summer crops in conditions such as those found in Uruguay.

No consistent effect of soil use intensity was observed on grain yield over seasons (Table 4). Under favorable rainfall regime (in 2005-06); the highest yield was observed in CC and the lowest in LR (8.6 vs 7.74 Mg.ha^{-1}). Meanwhile, a slight tendency to higher yield was observed in SR respect to LR (8.12 vs y 7.74 $Mg.ha^{-1}$). In 2006-07, no differences in yield were observed between SR and LR. Finally, in 2007-08 no differences between rotations were detected at $p<0.05$, however, a strong trend to higher yield was observed in SR ($p<0.1$) compared with LR and CC (15 and 23%, respectively).

Although CC had lower soil organic carbon than SR and LR; rotations including long term pastures did not result in higher grain yields. Infestation with Bermuda grass (*Cynodon dactylon*) is usually a problem in Uruguayan long-term perennial pastures (Rios, 2001). We speculated that high incidence of this weed in LR residues reduced organic matter mineralization rate and affected crop plant stand and initial growth. Litter mineralization occurs when C/N ratio is less than 20-30, while immobilization of nitrogen to microbial tissue is expected for higher ratios. The C:N ratio of Bermuda grass residues has been estimated to be 37 (Morón, 2001). In the 2007-08 growing season, when the LR plots were heavily invaded with Bermuda grass, sorghum plant stand was 16% and 25% lower than CC and RC, respectively (Table 5). Moreover, in the last two seasons the crop in SR had a higher SPAD index (Table 6) than in LR.

More residues were incorporated before sorghum planting in SR and LR than CC every year (Table 3). Pasture residues in SR probably had lower C/N ratio than in LR because of lower incidence of Bermuda grass. Therefore, SR was the rotation with the best fallow in terms of residues incorporated; which in theory would have increased water and nitrogen availability at planting. This could explain the higher plant stand and nutritional status (SPAD) of the crop during boot stage that ended up in higher yield in SR compared with CC and LR in 2007-08.

Ryegrass grazing strategy did not affect sorghum grain yield in any of the three seasons evaluated, despite the differences in water storage (Fig.2) and residue biomass (Table 7). Residue biomass affected soil water storage in the first stages of sorghum development (Fig.2). Once the crop covered the soil surface, residues had no influence on water storage, and crop performance.

Suppressing direct grazing one month before fallow herbicide application did not affect grain yield when it was compared with direct grazing until one week before spraying (Table 7). Nevertheless, trampling effects on soil physical properties have been reported to increase with stocking rate and soil moisture at the moment of grazing (Warren et al., 1986;

Hamza and Anderson 2005, Savadogo et al., 2007). As long as direct grazing is performed taking in account these limitations, it seems not to be a problem for the following crop's productivity.

Deep tillage effect of paraplow on yield showed an interaction with year and rotation. In most of the year*rotation combinations no effect of paraplowing was detected on yield, in spite of the reduction detected in soil strength and higher water extraction from the soil profile (Table 7). These results agree with different authors who reported no effect of subsoiling on corn, wheat and sorghum yield but also reported a reduction in soil penetration resistance and bulk density when subsoiling (Varsa et al., 1997; Pikul and Aase, 1999; Díaz-Zorita, 2000; Baumhardt and Jones, 2002b).

The only significant effect of subsoiling on grain yield was observed in LR in 2007-08 (1.45 $Ton.ha^{-1}$), which was infested with bermudagrass. Under these circumstances, subsoiling contributed to mechanically control the weed, and also improved physical soil conditions for planting and emergence. Paraplowed strips had 45% more plants than no-paraplowed strips in 2007-08 LR (Table 5), which could explain higher yields. In contrast, only a tendency to higher stands on paraplowed treatments was detected in other rotations and seasons with no effects on yield.

Yield spatial structure

Yield spatial structure was affected by season and rotation. In 2005-06, spatial autocorrelation was not detected, while in 2006-7 and 2007-08 strong spatial dependence was detected in all rotations (Fig.5, 6 and7). Constructed semivariograms showed pure nugget effect for all rotations in 2005-06 (Fig.5). Therefore, errors were assumed to be homogeneous and identically distributed through the experimental units. A statistical approach with mixed models was performed, with no further application of geostatistics. In 2006-07 season, yield data from LR and SR had a nugget/sill=1.3% and 21.4%, respectively (Fig 6). Among rotations, LR showed smaller spatial correlation range (72 vs 165m in SR). In 2007-08, yield spatial correlation was stronger than in 2006-07 in all rotations; with grater nugget/sill ratios (0.1, 0.5 and 0.4% for LR, RC and CC, respectively) and larger spatial correlation ranges (Fig 7). Autocorrelation range was similar in SR and CC, but larger than in LR (510m vs 125m, respectively).

Temporal variation between seasons was associated to differences in accumulated rainfall (Table 1). Temporal variation in water availability affected yield spatial variability. While in 2005-06 rainfall favorable conditions did not restrict yield potential and masked spatial patterns; drought and intermediate rainfall in the second and third growing seasons let the crop performance show dependence on field attributes. Spatial structure was removed from 2006-07 and 2007-08 data. Semivariance sill was reduced with the removal of spatial patterns in every field, indicating that experimental variance was reduced (Fig.6 and 7).

Spatial variability of soil properties, terrain attributes and relation with yield

Soil chemical properties showed no significant spatial autocorrelation at the site for any rotation*year combination. Semivariance was not successfully modeled as a function of distance for organic carbon, phosphorous or potassium soil content. Then, no homogeneous zones for N, P or K could be outlined based on the soil sampling grid used. Spatial variability of soil properties has been extensively reported for different cropping systems around the world (Kerry and Oliver, 2004, Kravchenko et al., 2006, Parent et al., 2008). However, few reports were found in pasture systems (Su et. al., 2006, Zhao et al., 2007), and no reports were found that consider crop-pasture rotation systems under direct grazing, which are common systems in Uruguay.

Nutrient redistribution dynamics through animal feces and urine is widely known in pasture systems. The stock camping activities of grazing animals result in an increase of fertility and biological activity in soils from camp areas at the expense of these properties on the main grazing areas (Haynes and Williams, 1999; Iyyemperumal et al., 2007; Jewell et al., 2007). The interaction between these nutrient redistribution effects of grazing animals with soil chemical nutrients spatial patterns occurring in crop-pasture rotation systems has not been assessed. In this context, the fact that no spatial structure was detected in soil chemical properties in our experiment using an intense sampling grid suggests that such interactions should be further investigated.

Soil apparent electrical conductivity measurements identified a zone of high values in the CC rotation field. Considering the known relation between EC values and soil salinity (Corwin and Lesch, 2005a and b), this may identify a patch of saline soil in the field. This patch was not mapped at the site in a soil pedogenic survey performed in 1991 (Fig. 8a and b). Elevation at the experimental site ranged from 47.8 to 61.6 m. Fields were situated transversing the topography gradient, thus every terrain condition was present in each year-rotation combination (Fig.8c). The TWI maps indicated zones of high potential of soil moisture (high TWI) and zones that dry up first (lower TWI) (Fig.8d). Experimental fields had similar TWI, ranging between 7.6-10.2, with the higher values at the summit.

The SPI and LS-Factor maps showed areas of essentially no risk of erosion (SPI and LS-factor =0.0-0.2) representing a minor area in the experimental fields, dominated by zones with higher erosion potential (SPI > 0.44 and LS-Factor >0.50) (Fig.8e and 8f). High elevation areas consisted of flat summits with high TWI and low SPI and LS-Factor scores, corresponding with poorly drained patches in the fields. Middle and toeslope topographic positions had moderate slope, and consequently better drainage that corresponds to moderate TWI, and higher SPI and LS-Factor, but also determining higher risk of erosion (Fig.8 d, e and f). These two areas with contrasting terrain attributes agree with soil classification mapping positions of Argiaquolls at the summit and Argiudolls at the toeslope positions of the field (Fig.8c).

Integrating soil properties and terrain attributes in the factor analysis resulted in four latent factors with eigenvalues grater than 1, which explained 77% of the experimental site variation (Table 8). The first factor revealed that variation was grouped in the first place by terrain attributes associated to field drainage and risk of erosion. It was named “Drainage”, and it explained 25% of total variation (Table 8). Shallow and deep soil EC and pH were the major components of the second factor, which explained 23% of the variation. Considering the EC map (Fig.8a), and given the known relationship between these variables and soil salinity (Corwin and Lesch, 2005a and b), this factor was named “Salinity”. The third factor was associated to clay levels, and was named “texture”. The forth latent factor was associated to deep/shallow EC ratio, probably indicating the degree of clay concentration of the argillic horizon respect to the soil superficial horizon, and was named “textural differentiation”.

Latent factors explaining most of the field variation were determined by variables showing similar mapping to soil classification. Variables with greatest influence on the first latent factor had contrasting mapping areas at the summit, and middle and toe slope areas, consistent with soil classification mapping units of Argiaquolls and Argiudolls (Fig.8). These results agree with Thompson et al. (1997). They related topographic terrain attributes to patterns of color index associated with the occurrence of hydric soils, and concluded that soil landscape modeling could assist soil mapping.

The fact that none of the latent factors explaining most of the field variation was determined by soil nutrients may indicate that soil variation is not determined by the effect of a few variables but by complex interactions between them. These interactions were better identified by the assessment of terrain topographic attributes than by nutrient chemical analysis alone, and appeared to be related to soil genetic processes.

Latent factors relation with yield was affected by season and rotation. Results varied from no significant association detected, to a maximum Pearson correlation coefficient of 0.79 (Table 9). In the 2005-06 season, no consistent association was found between any of the latent factors and yield. Rainfall conditions in that season determined high yield with random spatial distribution (Fig.5) that was not significantly affected by field properties (Table 9). Drought in 2006-07 increased crop dependence on soil attributes, and yield spatial autocorrelation was detected (Fig.6), while latent factors were significantly associated with yield (Table 9). “Drainage” latent factor was positively correlated with yield in both SR and LR (r^2=0.58 and 0.45, respectively). Argiudoll mapped areas were located on medium and toe-slope areas with low TWI and high SPI and LS-factor values (Fig.8), which were major components of “Drainage” latent factor. This suggests Argiudolls were associated to higher yields than Argiaquolls. Observed results were consistent with those reported on Illinois Arigudolls, where Kravchenko and Bullock (2000) found that terrain attributes as slope and flow accumulation affected yield particularly under extreme topographic locations combined with low precipitation conditions.

In 2007-08, most of yield variation in SR was explained by “Textural differentiation” (r=0.79 and partial R^2=0.63). “Salinity” was negatively correlated with CC yield (r=-0.77) and “Texture” was correlated with LR yield (r=0.52). Latent factors in 2007-08 season explained 69%, 59% and 27% of yield variation in SR, CC and LR, respectively. These relations were stronger than the ones found in the 2006-07 season, where 34 and 21% of the yield variability was explained for SR and LR, respectively.

Average rainfall conditions in 2007-08 season determined greater crop yield than in 2006-07, stronger yield spatial variability detected (Fig.7), and also stronger association between yield and latent factors than in 2005-06 and 2006-07 (Table 9). When soil water availability was not as limiting as in 2006-07, crop productivity probably depended on other soil properties as well, and expressed these differences in soil properties in grain yield. These results agree with Kravchenko et al. (2003), who reported that the range of significant spatial correlations between yield and soil EC and topographic attributes was related to precipitation data.

Latent factors relation with yield was stronger in SR than in LR in both seasons (R^2= 0.46 vs 0.21 and 0.69 vs 0.27 for SR vs LR in 2006-07 and 2007-08, respectively), agreeing with larger spatial autocorrelation range of yields on SR relative to LR in those seasons (165 vs 72m and 510 vs 125m, respectively) (Fig 6 and 7). These results suggest that pasture phase length in the rotation may have affected yield spatial dependence and its relation with soil and terrain attributes. Therefore nutrient spatial distribution through grazing animals on the pasture phase should be studied.

Overall, yield was associated with latent factors that represented differences in soil forming factors leading to different classification soil profiles. Soil pedogenic classification as Argiduolls, Argiaquolls and saline soils assessed by DEM could be useful to delineate zones of different yield potential. Such zones could be used for site-specific management based on expected yield. These results agree with those of Kaspar et al. (2003), who studied the relationship between terrain attributes and six years of corn yield on a 16 ha field in central Iowa, and concluded that this relationship could provide opportunities for implementing site-specific management. However, sorghum yield and its association with soil and terrain attribute latent factors were affected by season. Therefore, long term information is necessary to determine the convenience of site-specific management under these conditions. Quantification of spatial and temporal variability of crop and soil parameters is crucial to test the “null hypothesis” of site-specific management as stated by Whelan and Mc Bratney (2000): “Given the large temporal variation evident in crop yield relative to the scale of a single field, then optimal risk aversion strategy is uniform management”.

Classification and regression tree analysis for yield considering all available data for all cells (season, rotation, treatments, soil analysis, and terrain attributes), showed that temporal variation was the most relevant variable determining yield. The first split separated 2005-06 season from 2006-07 and 2007-08 seasons. This group was spit again due to season, separating 2006-07 from 2007-08 data (Fig.9). Within 2007-08 season, soil textural differentiation measured as EC and terrain attributes from DEM were the first variables determining yield. After these variables, rotation was the next split, separating CC from SR and LR. Only after these branches were separated in 2007-08 season data, 2005-06 and 2006-07 data were split. This suggests that there was more variability within 2007-08 data than within 2006-07 and 2007-08, which is consistent with semivariance analysis of yield spatial variability (Fig 5, 6 and 7). The next split that decreased average error within groups was rotation within 2005-06 data, separating CC. In 2006-07 data the first split was due to terrain attributes, and then rotation. Overall, these results suggest that temporal variability was the first factor determining yield followed by terrain attributes, leaving management practices in a second place. Temporal variation associated to differences in rainfall not only affected yield levels (Table 4) and its spatial variation (Fig.5-7) but also its relation with terrain latent factors (Table 9).

CONCLUSIONS

Cropping systems including no-tillage and long term pastures preserved soil organic carbon under undegraded soils in a temperate climate, but did not result in consistently higher sorghum yield than continuous cropping systems.

Suppressing direct grazing one month before fallow herbicide application did not affect grain yield during the three years of research when it was compared with direct grazing until one week before spraying. This gave a new perspective to direct grazing effects of residue cover removal and animal trampling on grain yield. Specifically it indicates that soil compaction produced by animal trampling during the studied period appeared not to be an important factor affecting crop grain yield, while residues biomass only affected water dynamics during the first crop stages.

Subsoiling reduced soil penetration resistance, but only improved sorghum grain yield in one out of eight evaluated fields. That situation was a field under crop-pasture rotation with long lasting pastures that had been invaded by Bermudagrass (*Cynodon dactylon*), where subsoiling probably resulted in mechanic weed control and better crop implantation. More research in situations like this would be useful in order to determine if the use of paraplow could be an alternative in such cases.

Temporal variation associated with differences in seasonal rainfall was the first factor determining yield, its spatial variation, and its relation with soil and terrain attributes. Soil water availability and its distribution through landscape are major determinants of sorghum grain yield in rainfed crop-pasture systems of Uruguay. Management practices effects on grain yield can only take place within a range determined by these natural conditions.

Even under high temporal variation, sorghum proved to be a rustic crop and an alternative to integrate crop-pasture rotation systems with no-till in Uruguayan Argiudolls after three contrasting climatic seasons. Grain production was high under favorable weather (8.15 $Mg.ha^{-1}$ in 2005-06), but was also acceptable in a dry season (4.6 $Mg.ha^{-1}$ in 2006-07).

Soil nutrients showed no spatial autocorrelation for crop-pasture rotations and sampling scale studied, implying that no homogeneous zones could be delimited in terms of soil nutrient availability. Moreover, relations between soil analysis of organic C, P and K with grain yield were not detected. New questions arise about nutrient dynamics and management with precision agriculture techniques in crop-pasture rotations in the presence of animal direct grazing nutrient redistribution. The reasons determining higher yield in more intensive systems, their sustainability and constraints should also be further studied.

Terrain attributes derived from DEM and EC showed similar mapping to soil classification, and were associated to grain yield within fields. If supported by long term information, site-specific management based on yield expectation for different soil classes could be an option to consider.

Overall, these results suggest that temporal variability was the first factor determining yield, its spatial variation and its relation with terrain attributes, which were the other major yield determinant factors, leaving management practices in a second place. Yield spatial variability and terrain attributes relation with yield also interacted with rotation. Therefore, long-term quantification of both temporal and spatial variability of crop and soil attributes is crucial when studying management practice effects on grain yield.

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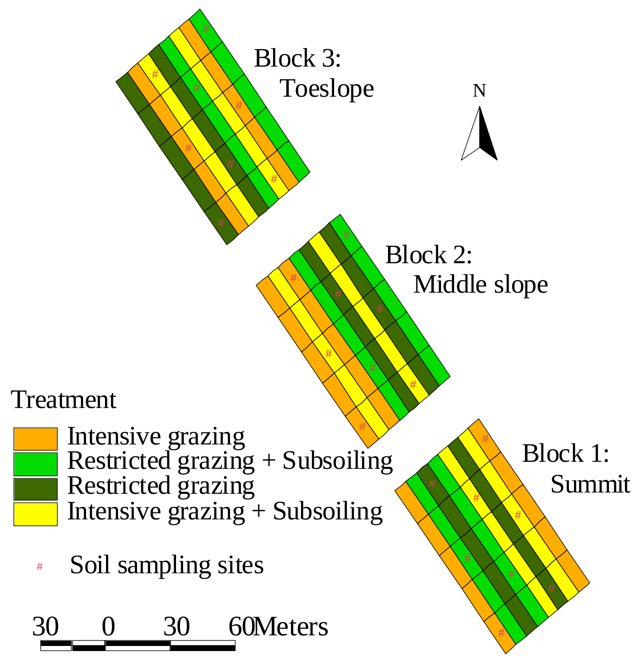
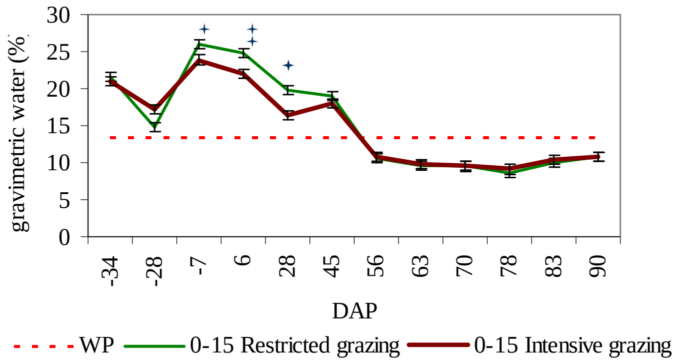
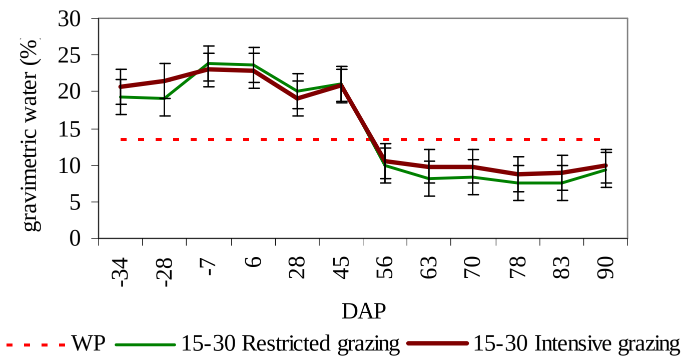


Fig.1. Blocks and strip treatments arrangement in one of the fields, and soil sampling site.



a



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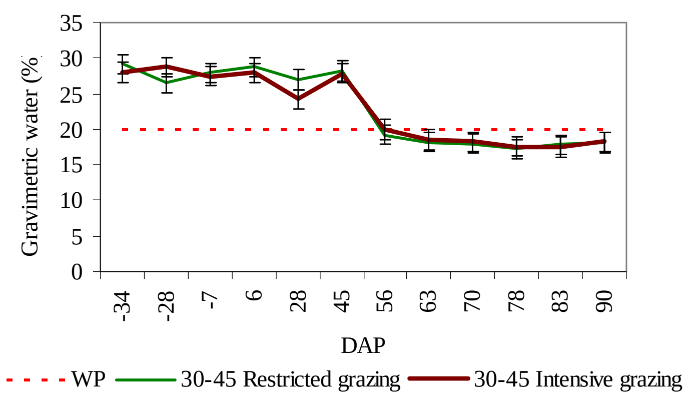
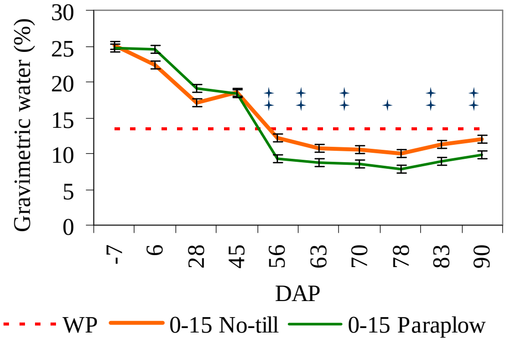


c

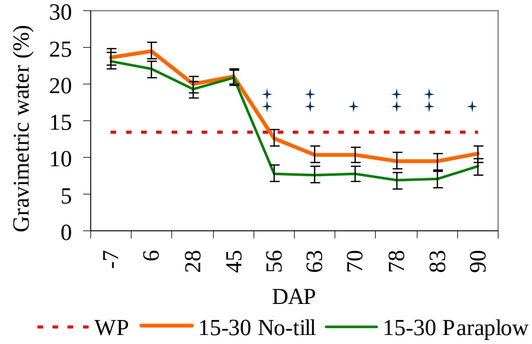
Fig.2. Average soil gravimetric water in 2006-7 season. Restricted grazing is the average for the treatments grazed until 4 weeks before fallow beginning, and Intensive grazing are the treatments grazed until the week previous to fallow beginning, compared with the soil water at the wilting point (WP). a. Soil water at 0-15 cm soil depth. b. Soil water at 15-30 cm soil depth. c. Soil gravimetric water at 30-45 cm soil depth.

+ Soil gravimetric water are different due to grazing strategy with p= 0.1.

‡ Soil gravimetric water are different due to grazing strategy with p= 0.05.



a



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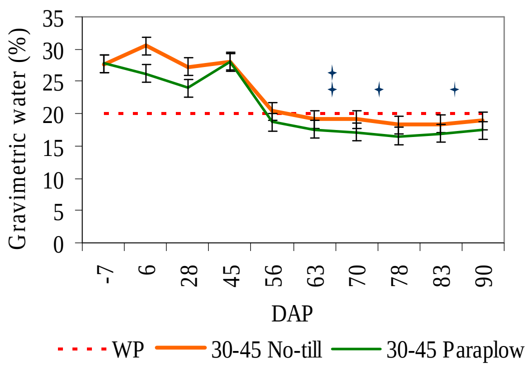

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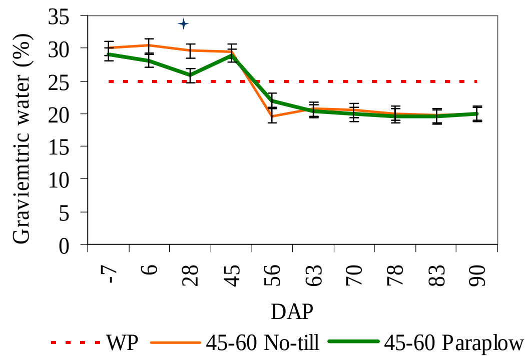


d

Fig.3. Average soil gravimetric water during 2006-7 season. Days After Planting (DAP). Paraplow is the average for the treatments paraplowed the week before sowing at 40 cm soil depth, and No till is the average soil gravimetric water for the treatments that were not paralowed, compared with the laboratory wilting point (WP).

a. Soil gravimetric water at 0-15 cm soil depth. b. Soil gravimetric water at 15-30 cm soil depth. c. Soil gravimetric water at 30-45 cm soil depth. d. Soil gravimetric water at 45-60 cm soil depth.

† Soil gravimetric water are different due to grazing strategy with p= 0.1.

‡ Soil gravimetric water are different due to grazing strategy with p= 0.05.

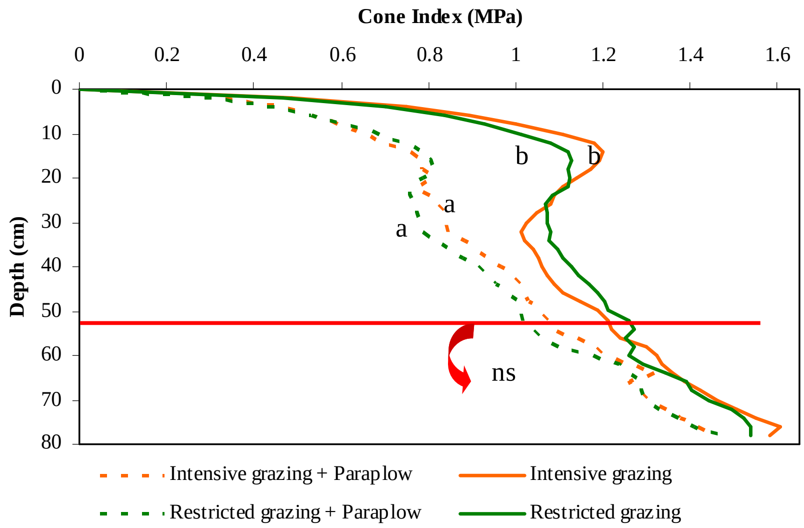
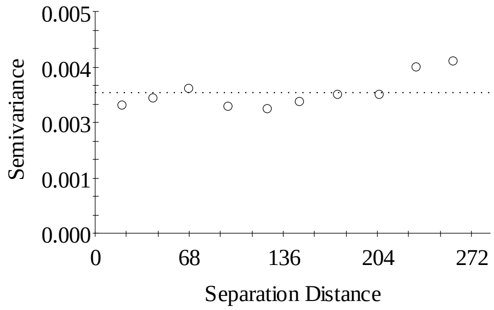


Fig.4. Soil penetration resistances (Cone Index) plotted by depth for each management practice treatment (restricted or intensive grazing, with or without paraplowing). Lines followed by the same letter are not significantly different at P ≤ 0.05 level, with statistical analysis performed for data every 2 cm depth. No differences in soil penetration resistance were found between treatments at soil depth below the red line (54cm).



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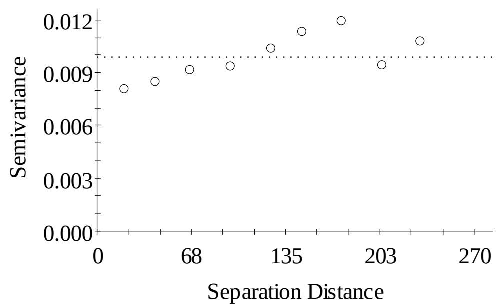

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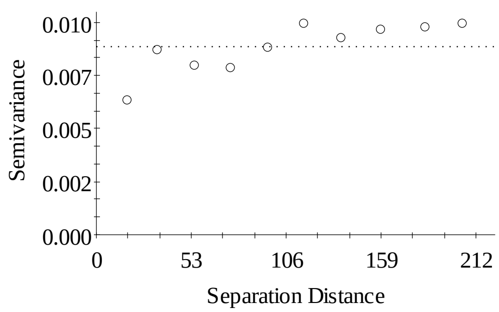


c

Fig.5. Isotropic semivariograms for 2005-06 growing season residuals for each rotation system. a- Long Rotation. b- Short Rotation. c- Continuous cropping.

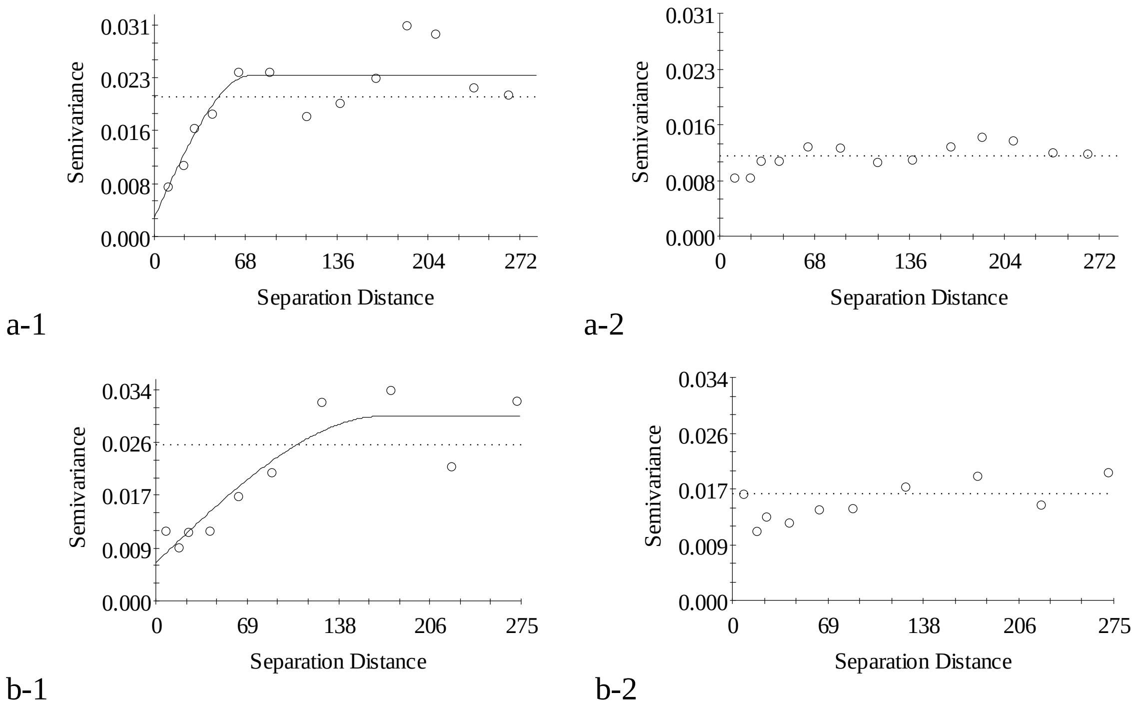
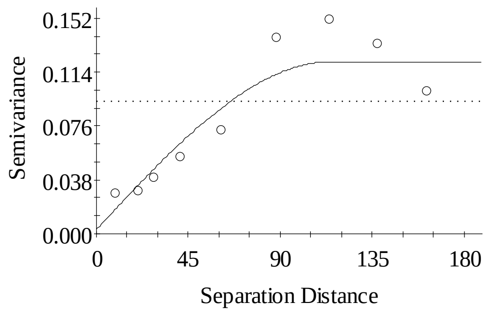
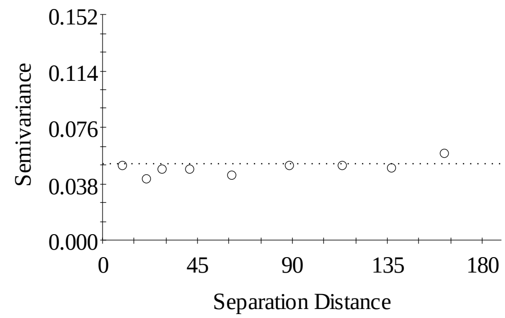


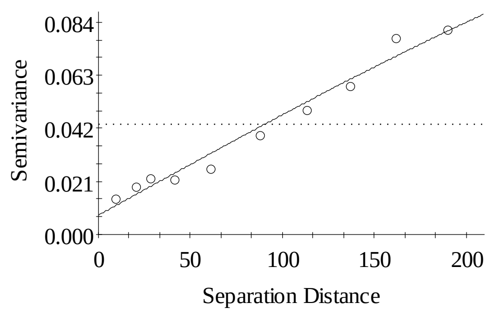
Fig.6. Isotropic semivariograms for 2006-07 growing season sorghum grain yield: a. After long term pasture. b. After short term pasture. 1- Sorghum yield normalized residuals before adjustment. 2- Sorghum yield normalized residuals after adjustment.



a-1



a-2



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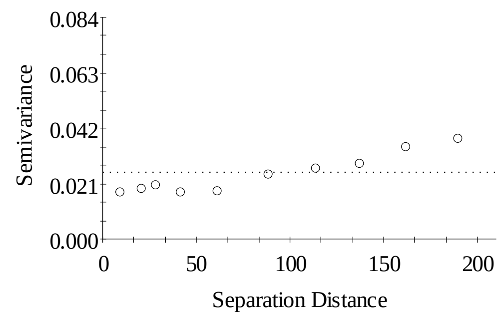

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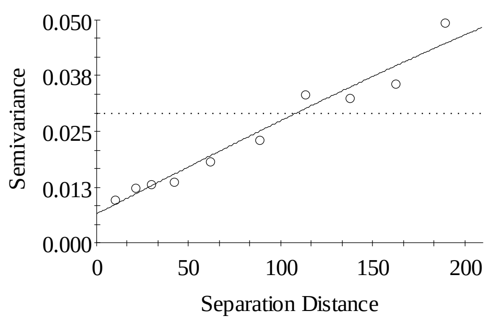
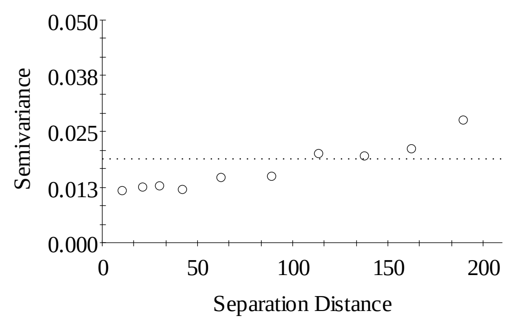


c-1



c-2

Fig.7. Isotropic semivariograms for 2007-08 growing season sorghum grain yield: a. After long term pasture. b. After short term pasture. c. In continuous cropping system. 1- Normalized residuals before adjustment. 2- Normalized residuals after adjustment.

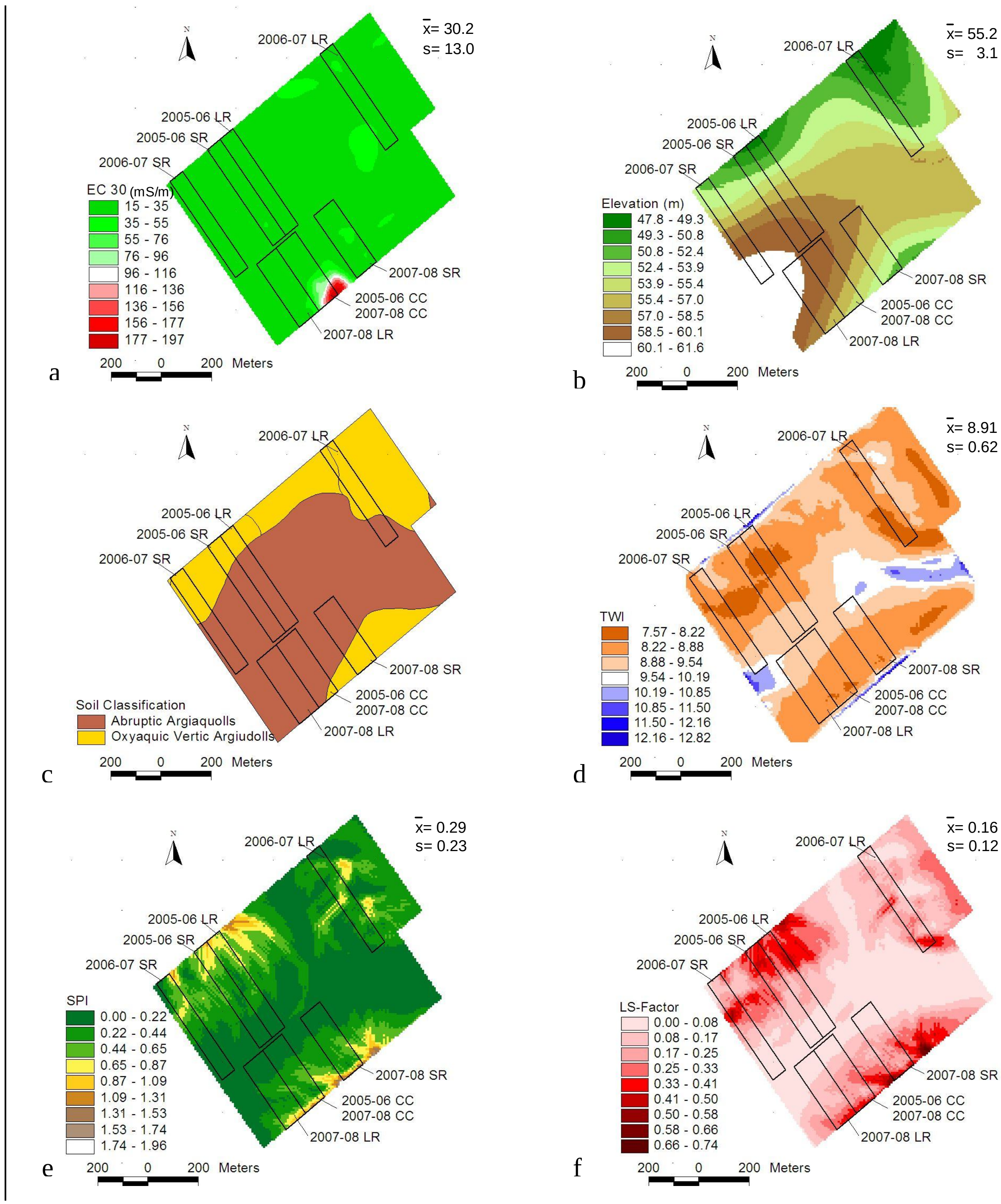


Fig.8. Terrain attributes and soil classification at the experimental site for eight year*rotation combination. (a) Electrical Conductivity at 30cm depth (EC 30), (b) Soil classification, (c) Elevation, (d) Topographic Wetness index (TWI), (e) Stream Power index (SPI), and (f) Length-Slope Factor (SL-Factor).

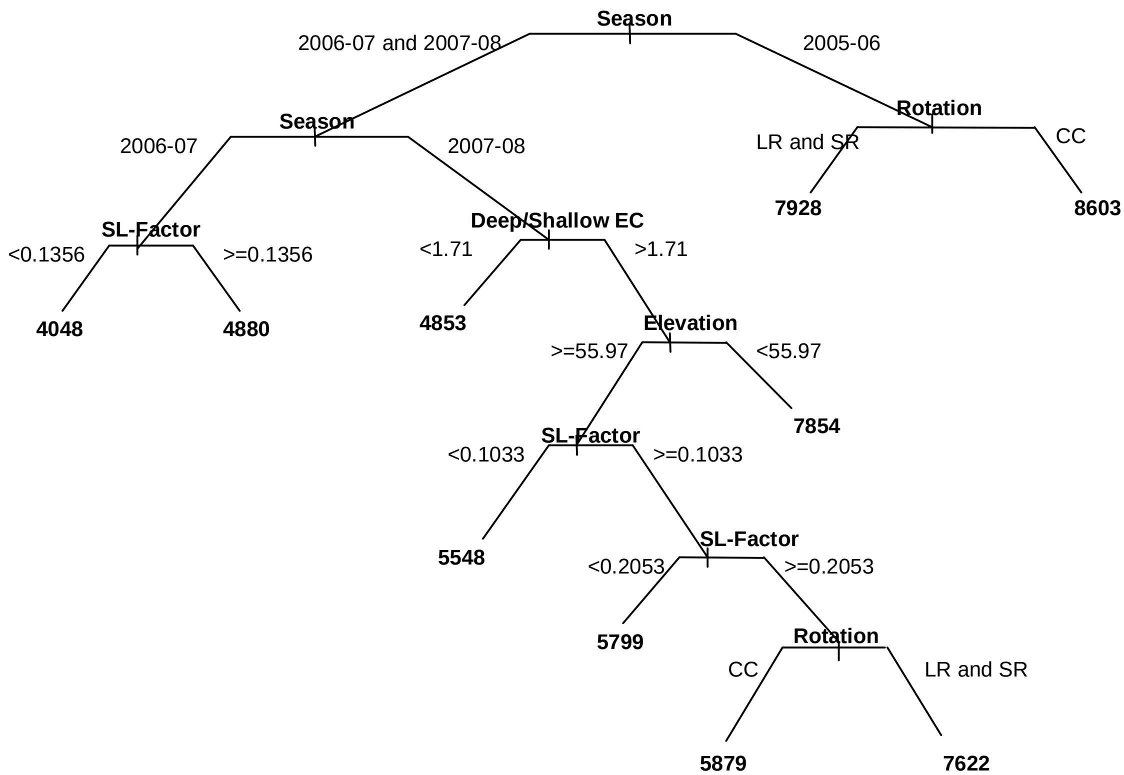


Fig.9. Regression tree of yield against predictor variables of season, soil properties, terrain attributes and management practices.

Table 1. Accumulated rain (mm) during each sorghum development stage since fallow until harvesting for the three seasons evaluated.

Stage of sorghum development	Season 2005-06	2006-07	2007-08
	--------------Rainfall (mm) ----------		
Fallow- Planting	110	53	221
Planting-Growing point differentiation	0	64	81
Growing point differentiation-Boot stage	141	54	160
Boot stage-Half bloom	79	23	62
Half bloom-Soft dough	90	44	30
Hard dough-Maturity	50	92	148
Maturity-Harvest	36	132	46

Table 2. Effect of 12 years of three crop-pasture rotation systems with different pastures duration on soil chemical properties (0.15 cm) in a no-till experiment in Uruguay.

	Org. C -g.kg^{-1}-			P(citric) -µg P/g-			K -meq/100g-		
	Year‡			Year‡			Year‡		
Rotation†	2006	2007	2008	2006	2007	2008	2006	2007	2008
LR	18.7a	18.3a	16.4a	10.8c	10.9b	14.8b	0.24a	0.22b	0.25a
SR	16.3b	16.5b	14.9b	13.8b	12.4a	16.0b	0.22b	0.24a	0.20b
CC	13.6c	--	14.8b	21.3a	--	25.1a	0.18c	--	0.24a

† Continuous cropping (CC): ryegrass-sorghum-ryegrass-soybeans; Short Rotation: two years idem CC and two years perennial pasture; Long Rotation (LR): two years idem CC and four years perennial pasture;

‡ Least square means followed by the same letter within a column are not significantly different at P ≤ 0.05 level.

Table 3. Three soil use intensity (rotation) and two grazing strategies effect on dry matter of residues cover at fallow beginning on three evaluated years (2006, 2007, and 2008).

	Year							
	2006			2007		2008		
	---------- Rotation† ----------							
Treatment	CC‡	SR‡	LR‡	SR‡	LR‡	CC‡	SR‡	LR‡
	---------- DM (kg/ha) ----------							
Restricted grazing	361a	1477a	1517a	2808a	4769 a	1832a	3913a	4074a
Intensive grazing	231b	862b	425b	1481b	1838 b	730b	1629b	1154b
Mean§	**296B**	**1169A**	**971A**	**2279B**	**3328A**	**1289B**	**2814A**	**2831A**

† Continuous cropping (CC): ryegrass-sorghum-ryegrass-soybeans; Short Rotation (SR): two years idem CC and two years perennial pasture; Long Rotation (LR): two years idem CC and four years perennial pasture;

‡ Least square means followed by the same lower case letter within a column are not significantly different at $P \leq 0.05$ level .

§ Least square means followed by the same capital letter within a row are not significantly different at $P \leq 0.05$ level

Table 4. Rotation systems and year effects on sorghum yield in a field-scale experiment in Uruguay.

Rotation	Growing season 2005-6†	2006-7†	2007-8†
	----------------------Mg.ha^{-1}------------------		
Continuous Cropping	8.60 b	--	5.49 a
Short Rotation	8.12 ab	4.76 a	6.77 a
Long Rotation	7.74 a	4.52 a	5.88 a
Mean‡	8.15 C	4.64 A	6.05 B

†Least square means values followed by the same letter within a column are not significantly different at $P \leq 0.05$ level

‡Least square means values followed by the same captial letter within a row are not significantly different at $P \leq 0.05$ level

Table 5. Three soil use intensity (rotation) and four grazing and soil management practices effect on sorghum plant stand on three evaluated years (2006, 2007, and 2008).

	Year							
	2006			2007		2008		
	Rotation†							
Treatment	CC‡	SR‡	LR‡	SR‡	LR‡	CC‡	SR‡	LR‡
	Plants/m²							
Restricted grazing + Paraplow	18.1a	17.1a	19.1a	21.0a	23.7a	16.7a	19.4a	17.6 a
Intensive grazing +Paraplow	19.1a	18.6a	19.5a	20.0a	23.8a	17.0a	18.5a	15.6 a
Restricted grazing	17.5a	17.6a	18.6a	19.7a	21.3a	16.8a	18.6a	11.3 b
Intensive grazing	18.7a	17.8a	18.8a	19.3a	21.3a	16.9a	18.5a	11.6 b

† Continuous cropping (CC): ryegrass-sorghum-ryegrass-soybeans; Short Rotation (SR): two years idem CC and two years perennial pasture; Long Rotation (LR): two years idem CC and four years perennial pasture;

‡ Least square means followed by the same letter within a column are not significantly different at P ≤ 0.05 level

Table 6. SPAD readings at boot stage, for each soil use intensity (rotation) at three seasons of evaluation.

Rotation	Growing season		
	2005-06†	2006-07†	2007-08†
	------------ SPAD Index ---------		
Continuous Cropping	52.3b	--	42.25 b
Short Rotation	53.3ab	45.1 a	46.23 a
Long Rotation	53.6a	42.4 b	43.32 b

†Least square means values followed by the same letter within a column are not significantly different at $P \leq 0.05$ level

Table 7. Soil use intensity (rotation), previous ryegrass grazing strategy and soil management practices impact on sorghum grain yield in Uruguay during three growing seasons evaluated.

Growing season	Grazing strategy – Soil management	Rotation			Mean
		Continuous cropping	Short Rotation	Long Rotation	
		kg/ha			
2006	Restricted Grazing	8508 a	8441 a	7737 a	8238 a
	Restricted Grazing + Paraplow	8523 a	8276 ab	7778 a	8193 a
	Intensive Grazing	8705 a	7723 b	7679 a	8031 a
	Intensive Grazing + Paraplow	8677 a	8018 ab	7771 a	8174 a
2007	Restricted Grazing		4724 a	4420 a	4572 a
	Restricted Grazing + Paraplow		4954 a	4423 a	4689 a
	Intensive Grazing		4597 a	4671 a	4634 a
	Intensive Grazing + Paraplow		4771 a	4566 a	4669 a
2008	Restricted Grazing	5370 a	6616 a	5011 b	5814 a
	Restricted Grazing + Paraplow	5385 a	6952 a	6700 a	6826 a
	Intensive Grazing	5578 a	7098 a	5298 b	6198 a
	Intensive Grazing + Paraplow	5635 a	6392 a	6500 a	6446 a

Values followed by the same letter within a column are not statistically different with $P \leq 0.05$.

Table 8. Rotated latent factors names, loadings and variance explained for measured soil properties and terrain attributes in a field scale experiment in Uruguay.

Latent factor number and name	Factor 1- Drainage	Factor 2- Salinity	Factor 3- Texture	Factor 4- Textural differentiation	Total
	--------------------Coefficients--------------------				
Elevation	-0.74	0.17	-0.04	0.30	
TWI	**-0.86**	-0.13	-0.03	-0.10	
SPI	**0.84**	0.09	-0.02	-0.14	
L-S	**0.95**	0.09	0.00	-0.02	
EC 30	0.20	**0.87**	-0.06	-0.38	
EC 30-91	0.15	**0.88**	-0.15	0.30	
EC0-91 /EC30	-0.12	-0.17	0.01	**0.92**	
pH	0.21	**0.82**	-0.04	-0.33	
OrgC.	0.29	-0.52	0.61	-0.19	
P	-0.39	0.63	-0.09	0.00	
K	0.07	-0.06	**0.63**	-0.34	
Sand	0.20	-0.04	**-0.81**	-0.21	
Clay	0.06	-0.15	**0.89**	0.08	
Eigenvalue	3.29	2.97	2.25	1.51	10.02
Variance explained	0.25	0.23	0.17	0.12	0.77

Table 9. Regression statistics form stepwise procedure estimating yield as a function of latent factors, for each year - rotation combination evaluated.

				Regression estimates		Model		
Year	Rotation†	Latent Factor	Pearson r	Parameter	Partial R^2	Intercept	R^2	P
2005-06	CC	2-Salinity	-0.39	-252	0.16	8808	0.16	0.0574
	SR	2-Salinity	-0.37	-697	0.14	7927	0.14	0.0732
	LR		Ns					
2006-07	SR	1-Drainage	0.58	479	0.34	4686	0.46	0.0016
		3-Texture	-0.28	-583	0.12			
	LR	1- Drainage	0.45	737	0.21	4137	0.21	0.0343
2007-08	CC	2-Salinity	-0.77	-569	0.59	5995	0.59	0.0001
	SR	4-Textural differentiation	0.79	1087	0.63	6783	0.69	<.0001
		3-Texture	-0.48	-455	0.06			
	LR	3-Texture	0.52	933	0.27	6361	0.27	0.0093

† Continuous cropping (CC): ryegrass-sorghum-ryegrass-soybeans; Short Rotation (SR): two years idem CC and two years perennial pasture; Long Rotation (LR): two years idem CC and four years perennial pasture.

MODELING IRRIGATED RICE PHENOLOGY, BIOMASS, N UPTAKE AND YIELD USING DSSATv4 IN URUGUAY

ABSTRACT

The DSSATv4 CERES-rice simulation model was calibrated and validated for the genotype El Paso 144 in Uruguayan Argiaquolls. Genetic coefficients for DSSATv4 CSM CERES-rice were satisfactorily calibrated under no N fertilizer restrictions (ANR). Phenology prediction was reasonable for both calibration and validation datasets. Under ANR simulated grain yield achieved reasonable agreement with observed values in seasons without chilling injury (RMSE 1.1Mg.ha^{-1} and 13%; R^2=0.52). For seasons with cold damage grain yield was greatly overestimated (RMSE 4.7Mg.ha^{-1}, 69%). Using real applied nitrogen fertilizer as inputs (RAN), biomass, plant nitrogen, nitrogen use efficiency (NUE) and yield were underestimated. The greatest underestimation in yield were found under no nitrogen application, ranging between 0.36-0.91, respect to observed values. Observed NUE defined as plant biomass produced in relation to accumulated nitrogen was grater than simulated for all datasets At maturity the average of NUE of observed vs simulated values were of 82 vs 61 kg.DM. kgN^{-1} indicating that under Uruguayan conditions high values of yield and plant biomass can be achieved with lower plant nitrogen than assumed by the model. The model was not able to capture yield spatial variability at the rice fields suggesting that at the scale of these studies differences in soil data sets were no sufficient to affect modeled yield. However, the inability of the model to correctly simulate biomass production under RAN eliminates all possibilities of the use of this tool to study yield spatial variability at the scale of this studies.

SIMULACION DE FENOLOGIA, BIOMASA, ABSORCIÓN DE NITRÓGENO Y RENDIMIENTO DE ARROZ IRRIGADO UTILIZANDO EL MODELO DSSATv4 EN URUGUAY

RESUMEN

El modelo DSSATv4 CSM CERES-rice fue calibrado y validado para la variedad de arroz El Paso 144 en Uruguay (Argiaquols). Se ajustaron coeficientes genéticos con un resultado satisfactorio sin restricciones de fertilización nitrogenada (SRN). Las predicciones en fenología fueron razonables tanto para la base de datos de calibración, como para la de validación. El rendimiento simulado bajo SRN se ajustó razonablemente con los valores observados para las zafras sin daño por frío (RCMEE 1.1Mg.ha^{-1} y 13%; R^2=0.52). en las zafras con daño por frío, el rendimiento en grano fue ampliamente sobreestimado (RCMEE 4.7Mg.ha^{-1}, 69%). Utilizando valores reales de aplicación de fertilizante nitrogenado (RAN), la biomasa, el contenido de nitrógeno en planta, la eficiencia de uso de nitrógeno (EUN) y el rendimiento fueron subestimados. La mayor subestimación del rendimiento ocurrió sin fertilización nitrogenada, oscilando entre 0.36-0.91, respecto de los valores observados. La EUN observada, definida como biomasa producida en relación al nitrógeno acumulado, fue mayor que la simulada para todas las bases de datos. Al momento de madurez fisiológica, los valores promedio de EUN observados vs simulados fueron de 82 vs 61 kg.DM. kgN^{-1}, indicando que bajo las condiciones de producción de Uruguay, es posible obtener altos valores de rendimiento y biomasa producida con menor cantidad de nitrógeno que la asumida en el modelo. El modelo no fue capaz de capturar la variabilidad espacial del rendimiento a escala de chacra, lo que siguiere que a la escala de muestreo utilizada la variabilidad en las bases de datos de suelos no era suficiente para afectar el rendimiento simulado. Sin embargo, la incapacidad del modelo para predecir correctamente la biomasa producida bajo RAN elimina toda posibilidad de utilizar esta herramienta para estudiar la variabilidad espacial del rendimiento a la escala estudiada.

INTRODUCTION

Rice-pasture rotation systems cover up to 600,000 hectares in Uruguay. Typical rotation consists of one or two years of rice where only one crop per year is grown, followed by 3 to 4 years of pastures. Most of the rice area (65%) is cultivated with one genotype, “El Paso 144” (DIEA, 2008a). Rice planted area in 2007-08 season reached 168,337 hectares, 14% of the total cropping area planted in the country, with an estimated production of 1.33 million tons of dry and clean rice (DIEA, 2008b). Rice producers in Uruguay are a very dynamic group of farmers, open to incorporate new technology, and highly integrated with agronomists, researchers and industry.

Crop models are powerful tools for technology transfer, in the sense that the effect of using new technologies can be predicted for different farm situations. They can potentially be used to integrate knowledge of the biophysical processes governing the plant-soil-atmosphere system to evaluate the production uncertainties associated with various management options, and to extrapolate results to other sites and climates (Timsina and Humphrey, 2006). The estimation of technology effects in advance of using any resources may facilitate the adoption by farmers who do not want to take high risks of their profit.

Spatial and temporal yield variability has been assessed using crop models (Basso et al., 2001 and 2007; Xiong et al., 2008), that have also been adapted as precision agriculture decision support systems for site-specific management (Thorp et al., 2008).

When site specific inputs are used, models simulating yield across the fields in combination with GIS tools can be used to identify temporary stable zones and causes for yield variability (Basso et al., 2001 and 2007). When this information can be used to modify management practices to increase profit or decrease environmental impact, site-specific management is justified (Plant, 2001).

Studies at the regional scale have been used to capture differences between rice planting areas with crop models (Xiong et al., 2008), and can be useful for climate change assessment and adaptation (Roel and Baethgen, 2007; Xiong et al., 2008).

Crop models are useful tools to integrate knowledge of the bio-physical processes governing the plant-soil-atmosphere system, and to extrapolate research results to other locations or sites (Timsina and Humphrey, 2003). The decision support system for agrotechnology transfer (DSSAT) was originally developed by an international network of scientists (International Benchmark Sites Network for Agrotechnology Transfer- IBSNAT) to facilitate the application of crop models in a system approach to agronomic research. Crop models developed under the IBSNAT project are process oriented computer models (Hoogenboom et al., 1994). The DSSATv4 is a collection of independent programs that work together, centered on a crop simulation models module (CSM) integrated with soil, climate, and management (Jones et al., 2003).

The DSSAT-CSM has a main driver program, a land unit module, and modules for the primary components. The primary modules are for weather, soil, plant, soil-plant-atmosphere interface, and management components. Collectively, these components describe the time changes in the soil and plants that occur on a single land unit in response to weather and management (Jones et al., 2003).

The weather module reads or generates daily weather data from the daily weather file (minimum and maximum air temperatures, solar radiation and precipitation, relative humidity and wind speed when available). It also can modify daily weather variables for studying climate change or simulating experiments in which these variables are set at constant values of increased/decreased relative to their read in values (Jones et al., 2003).

The soil module integrates information from four submodules: soil water, soil temperature, soil carbon and nitrogen, and soil dynamics (Jones et al., 2003). Soil carbon and nitrogen submodules include two options to simulate soil organic matter (SOM) and nitrogen balance. In addition to the original version based on CERES, a SOM module developed by Gijsman et al. (2002) based on the CENTURY model (Parton et al., 1987) is included. This module separates organic residues as either surface or soil litter. Both types of litter are also divided into easy decomposable (metabolic materials) and recalcitrant (structural materials). After decomposition, these materials become part of different SOM pools, active, intermediate and passive SOM. Each of these SOM pools has different C/N ratio and N mineralization/immobilization rates. Decomposition and mineralization/ immobilization processes are affected by soil temperature and texture. After the incorporation of the CENTURY based SOM module, DSSAT-CSM has become more suitable for simulating low input systems, where almost all nutrients are derived from SOM-residue decomposition (Gijsman et al., 2002).

Models of 16 crops are available in the CSM derived form CROPGRO and CERES models (maize, wheat, soybean, peanut, rice, tomato, drybean, sorghum, millet, pasture, chickpea, cowpea, velvetbean, brachiaria grass, and faba bean), allowing the simulation of crop production systems in crop rotations for single or multiple seasons (Jones et al., 2003).

The DSSAT-CSM CERES-Rice predicts daily photosynthesis using the radiation-use efficiency approach as a function of daily irradiance for full canopy, which is then multiplied by factors ranging form 0 to 1 for light interception, temperature, leaf N status, and water deficit. Growth of new tissue depends on daily available carbohydrates and partitioning to different tissues as a function of phonological stage, which is modified by water deficit and N deficiency stress indices (Timsina and Humphreys, 2003).

The CERES models describe the process through the crop life cycle using degree day-accumulation (heat sum). Crop growth stages are simulated in response to temperature and photoperiod as described by Ritchie and NeSmith (1991). Genetic coefficients are used as model inputs to describe differences between species and cultivars in phenology components (Table 1).

Although DSSAT-CSM simulates crop production at any location where minimum inputs are provided (Jones et al., 2003), all crop models should be evaluated in the environment of interest if the results of applications are to be credible (Timsina and Humphrey, 2006). However, most of the reports provide very little detail on determination of genetic coefficients, and the values used. Therefore genetic coefficients for commonly grown varieties of rice are not readily available (Timsina and Humphreys, 2003).

Timsina and Humphrey (2006) review several data sets form Asia and Australia and found that CERES-Rice predicted well anthesis and maturity dates, but grain and biomass yield predictions were more variable (RMSE=23%). Model performance was poorer under conditions of low N, water deficit and low temperatures during reproductive stages.

DSSAT v3.5 CERES-Rice model has been reported to be able to capture satisfactorily well rice spatial and temporal variability for one field in Uruguay, but underestimate grain yield (Roel and Baethgen, 2007).

The objectives of this work were: 1) to calibrate DSSAT v4 CERES-Rice for the genotype “El Paso 144” in Uruguay using local soil and climate data; 2) to validate the model, and 3) to evaluate the model's performance in capturing temporal and spatial field variability.

MATERIALS AND METHODS

Calibration

Nine seasons of bioclimatic experimental data were used for model calibration. Experiments were carried out between 1995 and 2004 in Uruguay, as part of a rice phonological characterization project, at Paso de la Laguna Experimental Unit (PLEU) (33°16' S 54° 10' W) from the National Institute of Agricultural Research (INIA-Uruguay) (Table 2). A randomized block design with four replications was used in two planting dates per season. Phenologic data and grain filling were registered for El Paso 144 that was one among several rice genotypes included in the project. Dates of planting, emergence, tillering, panicle initiation, 50% anthesis and maturity were registered. Grain weight was measured every five days until it reached constant weight. As yield was only registered in 2001-02 through 2002-03 experiments; data from one field planted in 2006 at the same experimental site was also used for yield calibration. Biomass at panicle initiation, number of tillers and grains/panicle and grain weight data was measured at 40 points in the 12 ha field in 2006-07 season.

Predominant soil at the site was classified as Argiaquoll according to the USDA-NRCS soil Taxonomy (Durán et al., 2005), and Brunosol Subéutrico Lúvico L Fase Hidromórfica according to the local classification system. Typical soil superficial analysis values are pH 5.3, 16.7 g-kg^{-1} organic carbon, 4.7 ppm P Bray I, 20 meq.100gr^{-1} K (Table 3).

Daily meteorological data was available from the weather station located at PLEU since 1973. Maximum and minimum temperature, radiation, relative moisture, precipitation, evaporation and wind speed were incorporated into the model weather data. Data included 1973 to 2008 daily information, and were used for model calibration and validation. Monthly averages generated by the Weatherman module are presented in Table 4.

Heat sum with a base temperature of 9ºC was calculated for the phenology dates described at each experiment, and was used to estimate preliminary genetic coefficients. These preliminary coefficients were used in the first iteration of the model adjustment runs.

Coefficients were modified to minimize differences between simulated and observed values. Iterations ended when final genetic coefficients gave a close match between simulated and observed values of phenology, growth and yield. These final coefficients were used in the subsequent validation.

Validation

Data from 13 experiments carried out with El Paso 144 cultivar in different seasons at the same experimental site were used for model validation (Table 5). Anthesis dates had been registered in 12 of them, and all had registered grain yield, and were used for model validation in phenology and yield performance. Simulated crop biomass was validated with 5 datasets at panicle initiation, but only two experiments (Porto and Castro, 1994 and Baez and Toledo, 1998) were used to evaluate biomass at maturity.

Plant nitrogen was evaluated using two experimental datasets. Castera et al. (2000) determined plant nitrogen and growth with 4 different fertilizer applications (0, 40, 80 and 120 kg $N.ha^{-1}$) and two flooding irrigation dates. Biomass and plant nitrogen were estimated at 51, 70, 91, 125 and 167 days after planting (dap), when the crop was at tillering, before and after panicle initiation, 100% anthesis, and maturity stages, respectively. De Los Santos and Jaques (1999) evaluated plant nitrogen under different fertilizing dates using the same nitrogen dose. Starter fertilizer was 15.4 kg $N.ha^{-1}$ and 66.6 kg $P.ha^{-1}$, while 23 kg N ha^{-1} were applied as urea at tillering and at panicle initiation. Treatments differed on date of fertilizing during tillering or panicle initiation. However, treatment effects were not detected and only average data is presented here.

Spatial variation was assessed using measured data from a 12 hectares field at PLEU (Roel et al., 2004). Planting date, timing and rate of fertilization (46 kg $P.ha^{-1}$, and 64 $kgN.ha^{-1}$) were reported. Soil sampling data (organic carbon, pH, clay, sand and silt) at two depths (0-10 and 10-20) were available from 36 georeferenced locations. Crop biomass and yield data were also available for each location.

Model fit

Model evaluation involves comparison of model outputs with real data and determination of suitability for an intended purpose (Jones et al. 2003). Statistical criteria used for goodness of fit for model evaluation and validation were root mean square error (RMSE) and regression analysis (Boote, 1999) performed with SAS software (SAS Inst., Cary, NC), and p<0.05. Emphasis was put in RMSE, as recommended by Willmott et al. (1985), who compared different statistical approaches for crop model evaluation. RMSE is expressed in absolute and relative terms, according to the following equations:

$$RMSE = \left[N^{-1} \sum_{i=1}^{n} (P_i - O_i)^2 \right]^{0.5}$$

$$Normalized\,(relative)\,RMSE(\%) = 100 \times \frac{RMSE}{\overline{O}}$$

Where P_i and O_i are predicted and observed values, and $\overline{O}$ is the mean observed value over several replicates.

RESULTS AND DISCUSSION

Calibration

The first required genetic coefficient (P1) is the time period expressed as degree days from seedling emergence during which the rice plant is not responsive to changes in photoperiod. The period from emergence to panicle initiation was reported for a base temperature of 10ºC, with an average value of 674 GDD for the different seasons and planting dates of data sources in Table 2. This period was longer than the physiological phase required in the model, and also the base temperature was one degree higher. Aware of these differences, this value was used as the first approximation to the actual P1 value, in an iteratively process. A final value of 600 GDD was estimated for P1.

Photoperiod was calculated for the anthesis date at each experiment for 33º16' latitude. Heat sum from seedling emergence to anthesis was recalculated for a base temperature of 9ºC. The relationship between these two variables was plotted to estimate critical photoperiod and photoperidical sensibility (Fig 1). Photoperiod at the minimum heat sum for emergence-anthesis was estimated in 13.2 $h.d^{-1}$. However, a final value of 13.5 $h.d^{-1}$ was adjusted after procedure iteration. The change in the heat sum due to changes in photoperiod was low, so a minimum value of 5.0 was adjusted for P2R.

Grain filling stage was reported from 50% anthesis to maturity, with an average of 492 GDD and a base temperature of 10ºC for calibration experiments. Genetic coefficient G2 is the time since the beginning of grain filling to maturity on a base temperature of 9ºC. Reported value of 492 GDD was used as the first value in the adjustment procedure, and a value of 380 GDD was estimated as final value for P5. Single grain weight was available for all calibration experiments, and was estimated to a maximum value of 0.027 g.

Default values for potential spikelet number coefficient (G1), tillering coefficient (G3) and growth temperature tolerance coefficient (G4) were used in the first run. Iteration adjustment ended with a value of 65 for G1, while G3 and G4 remained as default (1.00). More specific experimental information is needed in order to calibrate these coefficients. Overall final genetic coefficients adjusted iteratively are summarized in Table 6.

Using final genetic coefficients, measured and predicted anthesis dates ranged from 88 to 117 days after planting (dap), and 94 to120 dap respectively, with RMSE of 5.9 d. Maturity observed dates were 130 to 165 dap, while simulated values were 138-166 dap, with a RMSE of 11.1d (Table 7). Considering the large dataset involved, the RMSE value indicated a good association between predicted and observed values.

Simulated yield was considerably underestimated for all datasets (1.95 vs 8.67 $Mg.ha^{-1}$ average values for simulated and measured) when the simulation was run using real applied nitrogen fertilizer as inputs (RAN) (Fig. 2).

Running the model with the option of no nitrogen restrictions (NNR), yield was accurately predicted for the experiments planted in seasons 2001-02, 2002-03 and 2006-07 (RMSE=0.33 $Mg.ha^{-1}$, 4% and r^2=0.85). However, in 2000-01 season there were large discrepancies between observed and predicted values (Fig.2). Predicted yields were 1.2 and 4.0 $Mg.ha^{-1}$ lower than observed for October and November planting dates, respectively. Hours of bright sunshine in late February and March of that season were lower than normal (4.4-5.2 vs 7.2 $h.d^{-1}$, respectively). Low sunshine hours could have affected rice yield particularly for the crops with latter planted dates (Deambrosi et al. 1997, Méndez et al, 2001). This effect was captured by the model. Nevertheless, observed yield was similar to other seasons.

Validation

Observed and predicted anthesis date for 12 datasets from 8 different seasons and planting dates presented a RMSE of 4.5d, and r^2=0.88 (Fig.3). Observed and predicted anthesis dates ranged from 91 to 125dap, and 97 to 123dap respectively.

Biomass accumulation was underpredicted when model runs included Nitrogen simulation based on soil analysis and real fertilizing amounts (Table 8). The greatest differences between observed and simulated plant biomass were found for the no nitrogen fertilized treatment (25-92% lower than observed for 51-125 dap). This was consistent with calibration results.

Simulated biomass was similar to observed when the model was run using the option of applying Nitrogen fertilizer each time the crop requires it (ANR). Therefore the results suggest that the model is not simulating N dynamics accurately.

Simulated yield was underestimated when the model run under RAN. Moreover, best adjustment between observed and predicted values were found comparing the no fertilized treatment with the simulation fertilized as required.

Plant nitrogen showed similar results to biomass accumulation (Table 9). In the treatment without fertilization, simulated values were underestimated from early development stages, with increasing differences as the crop developed. Simulated values for plant nitrogen were 36 and 91% lower than observed for 51 and 125 dap, respectively. In fertilized treatments differences between observed and predicted values were detected later in the crop cycle (70 dap for 40 and 80 kg N.ha^{-1}, and 91 dap in 120 kg N.ha^{-1}). With grater fertilizer doses, not only plant nitrogen underprediction was delayed, but also was lower. Predicted plant nitrogen values along the crop cycle ranged between 36-91%, 29-66%, 13-45% and 20-26% less than observed values for 0, 40, 80 and 120 kg N.ha^{-1} fertilization doses, respectively.

When simulating under ANR, simulated plant nitrogen values were grater than any of the observed values. Differences decreased with increasing dap and fertilization amount. The greatest differences in plant N were found for the treatment without fertilization, 215% and 17% at 51 dap and 167 dap, respectively. The smallest differences were found for 120kg N.ha^{-1}, with differences of 173%-2% for the same dates (Table 9).

Similar results in biomass accumulation and plant nitrogen were obtained when running the model for other datasets (Table 10). Biomass accumulation was underestimated when using the actual fertilization rates as inputs (52% and 28% at anthesis and maturity, respectively). Close matches between observed and simulated biomass were also observed when the model was run under ANR (RMSE 16% and 9% at anthesis and maturity, respectively). Moreover, plant nitrogen was underestimated under RAN, and simulated plant required nitrogen were grater than observed (73% and 42% grater N at panicle initiation and anthesis, respectively).

These results suggest that plant nitrogen uptake from the soil and other sources of nitrogen than fertilization, as well as nitrogen use efficiency were underpredicted by the model.

Overall, when the model run under ANR, simulated N fertilizing doses were 180-240 kg $N.ha^{-1}$, and yield and biomass closely matched observed values under real fertilization amounts (0-120 kg $N.ha^{-1}$). However, plant N was clearly overestimated (279 vs 326 kg $N.ha^{-1}$); indicating that under Uruguayan conditions high values of yield and plant biomass can be achieved with lower plant nitrogen than assumed by the model.

Deambrosi and Méndez (2007) studied N fertilization of two cultivars (El Paso 144 and Olimar) in 9 situations in Uruguay, and only detected a positive effect of N fertilization on rice yield on 56% of the cases. Interaction of N fertilization with radiation incidence and temperature at reproductive stages and indigenous N were mentioned by the authors as some of the possible causes of these results. Experiments carried out with three rice genotypes in Uruguay showed that 68-92% plant N at panicle initiation origins form other sources than fertilizer (Méndez, R., pers. com.). In other lowland regions, soil N supply has been estimated to be half to two third of total N taken up by rice crops even in N fertilized rice paddies (Sahrawat, 1983).

Rice production systems in Uruguay rotate with 3 to 4 years of pastures before one or two years of rice. Most frequent pasture species planted in rotation with rice are Lotus (*Lotus corniculatus* L.), white clover (*Trifolium repens* L.) and ryegrass (*Lolium multiflorum*) (DIEA, 2008b). Nitrogen fixation is expected to occur during the pasture period, and incorporated to the soil as part of the fresh SOM pool. Nitrogen availability, the size of soil microbiological communities and other biochemical indicators (enzyme activity) have been reported to be higher under pasture-rice rotations compared with continuous rice and other rice rotations with cash crops (Benintende et al., 2008).

Other source of nitrogen uptake in rice crops are symbiotic relationships with nitrogen-fixing microorganisms. Although nitrogen-fixing bacteria have been isolated in Uruguayan genotypes and soils (Labandera et al., 2004, Irisarri et al., 2008, Fernández, 2009), their contribution to rice nitrogen uptake has not been determined.

The inclusion of CENTURY based soil submodule into DSSAT improved SOM dynamics simulation, showing better suitability for long-term simulations and low-input systems than the CERES-based module when it was validated on a long-term bare fallow experiment in the UK (Gijsman et al., 2002). However, DSSAT v4 (including CENTURY based soil module) was not able to satisfactorily simulate rice N uptake in Uruguayan rice systems; particularly when the crop was not fertilized (Tables 9 and 10).

For cultivated and grassland soils, the initial SOM ratio active/intermediate/passive used by the CENTURY based soil module is 0.02:0.64:0.34, with C/N ratios of 10, 17, and 7, respectively (Gijsman et al., 2002). The active soil fraction includes the live soil microbes and microbial products, and has a turnover of months to a few years, depending in the environment and soil texture. It can be estimated by doubling the estimated microbial biomass to account by the microbial components (Metherell et al., 1993). Microbial biomass organic carbon in rice-pastures rotations has been estimated in 2.99% of the total organic carbon of dry soil (Benintende et al., 2008). Therefore, active biomass can be estimated as at least 5.98% of the total SOM, almost three times the ratio assumed in the model soil module. Moreover, Benintende et al. (2008) estimated C/N ratio for the microbial biomass in 7.6, lower than the ratio of 10 used by the model. These reports indicate that actual active SOM and its degradation rate for rice-pasture rotations could be grater than assumed in the model, and therefore soil nutrients released by SOM decomposition could be underestimated.

In Uruguayan production systems, rice fields are flooded about 50 dap, and remain in such conditions until water is drained before harvesting. Under flooding conditions, absence of oxygen as an electron acceptor affects soil organic matter and nitrogen dynamics (Bohn et al., 1985). CENTURY based soil module does not include a section for the simulation under anaerobic conditions (Gijsman et al., 2002).

More research is needed to understand and quantify nitrogen dynamics in Uruguayan pasture-rice systems before such process can be incorporated in simulation models.

Plant nitrogen use efficiency (NUE) as kg of biomass produced per kg of plant nitrogen (kg DM. kg N^{-1}) can be estimated integrating tables 8, and 9. Observed NUE was grater than simulated for all datasets particularly at the last stages of crop development; reaching average observed vs simulated values of 82 vs 61 kg DM. kg N^{-1} at maturity (Table11).

Variability in NUE between different rice genotypes has been reported (Singh et al., 1998, Inhapanya et al., 2000, Haefele et al., 2008). Some genotypes have been reported to only be able to produce 5 $Mg.ha^{-1}$ grain yield with nitrogen uptake of 160 $kg.ha^{-1}$, while others can achieve grain yields of 9 $Mg.ha^{-1}$ with nitrogen uptake values of 164-180 kg at maturity (Singh et al., 1998, Lin et al., 2006). These nitrogen uptake values reported are much lower than simulated here when the model was run under ANR (Tables 9 and 10). Besides, there are few reports of CERES-rice evaluation under N limiting conditions, and this suggests that the model does not perform well under such conditions (Timsina and Humphreys, 2003). Our results suggest that model NUE should be revised to improve crop N dynamics and biomass simulation.

Field spatial variability could not be captured under these conditions when soil analyses were the main site-specific inputs at one field (Fig.4). Moreover, capturing actual yield spatial variability in modeled yield with site-specific soil analysis as inputs could not be expected when actual yield variability did not respond to such factors (Fig.5).

Crop relationships with field variability determining yield spatial patterns are more complex than direct responses to isolated soil properties. Besides, irrigated rice yield can be greatly affected by management factors such as adequate irrigation and weed control (Roel et al., 2007). Site-specific simulation can not directly incorporate such factors.

When the complete dataset was used (Table 5), grain yield under ANR was poorly estimated (RMSE 3.3 $Mg.ha^{-1}$, 43%). These results agree with those reported in Australia, where large discrepancies between simulated and observed yield was due to inability of the model to simulate chilling injury (Meyer et al., 1994, Godwin et al., 1994). According to historical data, 20% of the seasons are likely to have cold damage in the southern rice region of Uruguay (Deambrosi et al. 1997).

Datasets were separated in two groups according to minimum temperatures registered during each season. The first group included seasons were minimum temperatures during reproductive stages had been lower than 15ºC for several days, were chilling injury had probably occurred. The second group included all the other seasons where such temperature condition was not held. The groups are referred to as “chilling seasons” and “normal seasons”, respectively.

Grain yield was reasonably well estimated for “normal seasons” when simulation did not include nitrogen limitations for experiments planted in 1992, 1995, 1999, 2005 and 2006 (RMSE 1.1 $Mg.ha^{-1}$, 13%). Xiong et al. (2008) reported similar results for the performance of CERES-rice in China, were RMSE was estimated in 0.99 $Mg.ha^{-1}$ and 14.9%.

However, grain yield of experiments planted in 1997, 2003 and 2004 (“chilling seasons”) were highly overestimated (RMSE 4.7 $Mg.ha^{-1}$, 69%) (Fig.6). Minimum temperatures lower than 15 °C were registered in those seasons during rice reproductive stages, which led to high sterility of florets (Roel, 1998, Méndez and Roel, 2004, Roel and Méndez, 2005).

A routine to simulate this effect was developed by Godwin et al., (1994) which greatly improved the accuracy of simulated yields when it was included in the model. However, these modifications of the model code need to be refined and further tested, and are not provided with the official versions of DSSAT (Timsina and Humphreys, 2003). Inclusion of such code modifications in official versions of the model would be valuable for modeling in Uruguayan conditions.

Regression analysis on these separated datasets showed that prediction within each group was good, with a determination coefficient between observed and simulated values of 0.52 for “Normal seasons” and 0.77 for “Chilling seasons” (Fig.7).

CONCLUSIONS

Genetic coefficients for DSSATv4 CSM CERES-rice were satisfactorily calibrated under no limiting conditions. Phenology was well simulated for calibration and validation datasets.

Simulation under RAN underestimated N uptake, biomass and yield. Fertilization nitrogen inputs required to simulate observed production values were twice as much as averagely applied for Uruguayan conditions. Plant biomass produced per unit of accumulated nitrogen was underestimated, particularly at the last stages of crop development. Rice nitrogen use efficiency needs to be revised in DSSATv4 to improve biomass and grain production simulation. Further research on nitrogen dynamics is needed to understand and quantify basic soil-plant system processes under the particular environment of rice-pasture systems in Uruguay.

Grain yield under ANR was reasonably well estimated for seasons without chilling injury.

DSSAT Ceres rice model can be used to evaluate long term climatic scenarios. Grain yield under no limited N fertilization was reasonably well estimated for seasons without chilling injury. For years with low temperatures during reproductive stages, code modifications are necessary to simulate rice florets sterility.

Field spatial variability was not captured by the model at the field scale of this study. Improvement of Nitrogen dynamics and incorporation of more site-specific information than soil chemical analysis may be useful for capturing this variability.

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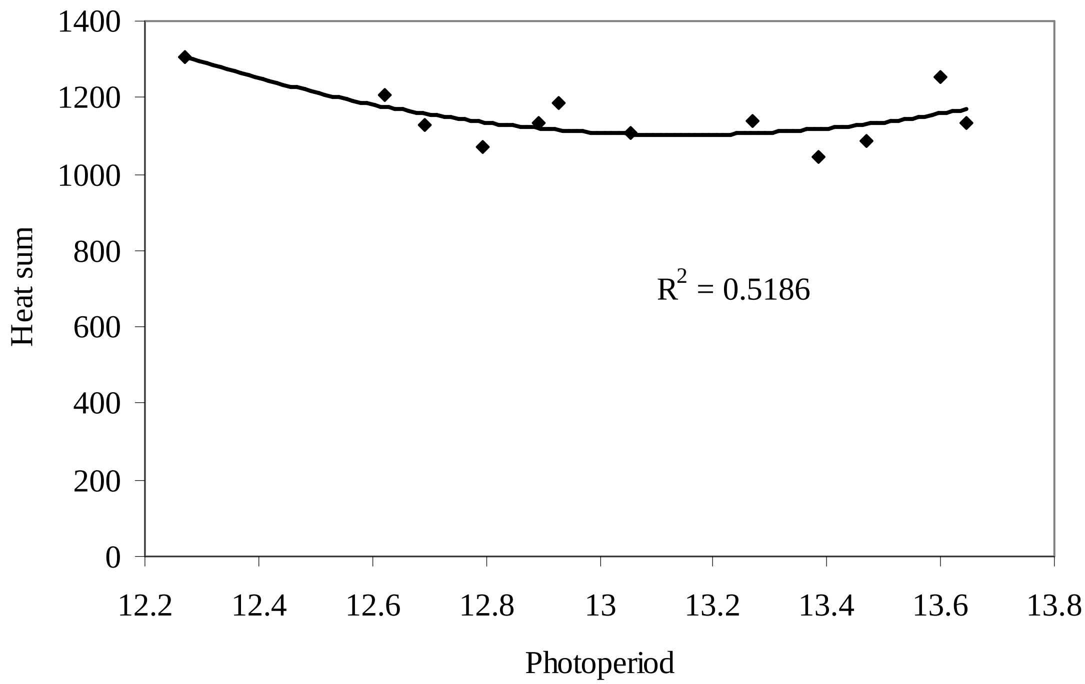

Fig.1. Rice observed heat sum to anthesis as a function of photoperiod. Critical photoperiod was estimated in 13.2 light h.d^{-1}.

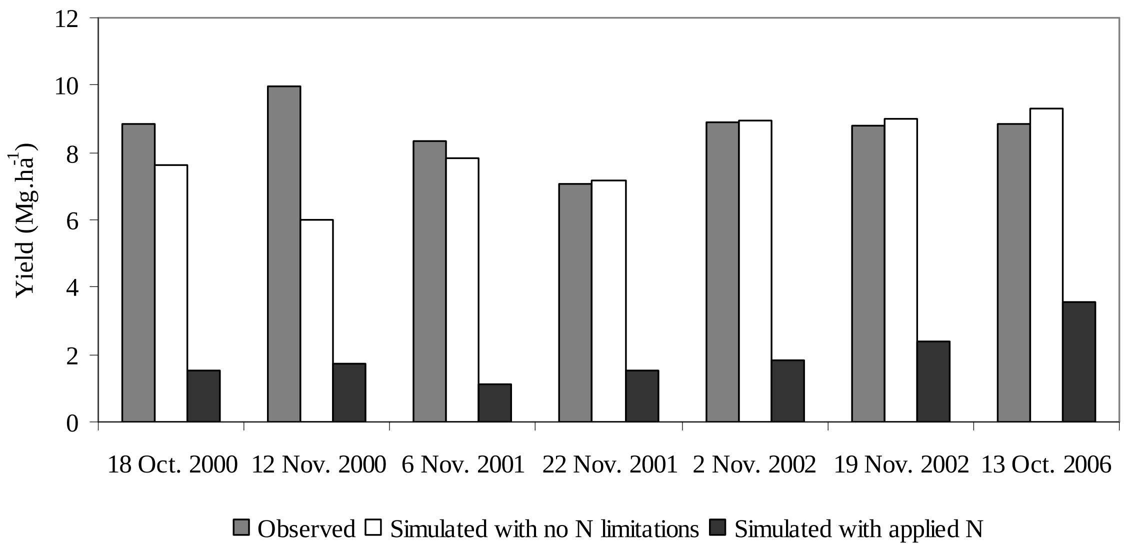

Fig.2. Rice grain yield observed and simulated with DSSATv4 (CERES-rice) for seven datasets from Uruguay used in model calibration. Each dataset is followed by its planting date. Datasets from 2000, 2001 and 2002 were taken from Méndez and Roel (2001, 2002 and 2003), and 2006 data is an average on 36 sampled points in one field at the same experimental site (unpublished). Shaded bars represent observed values. Open bars represent simulated values with the option of no nitrogen limitations. Solid bars represent simulated values with real nitrogen applications.

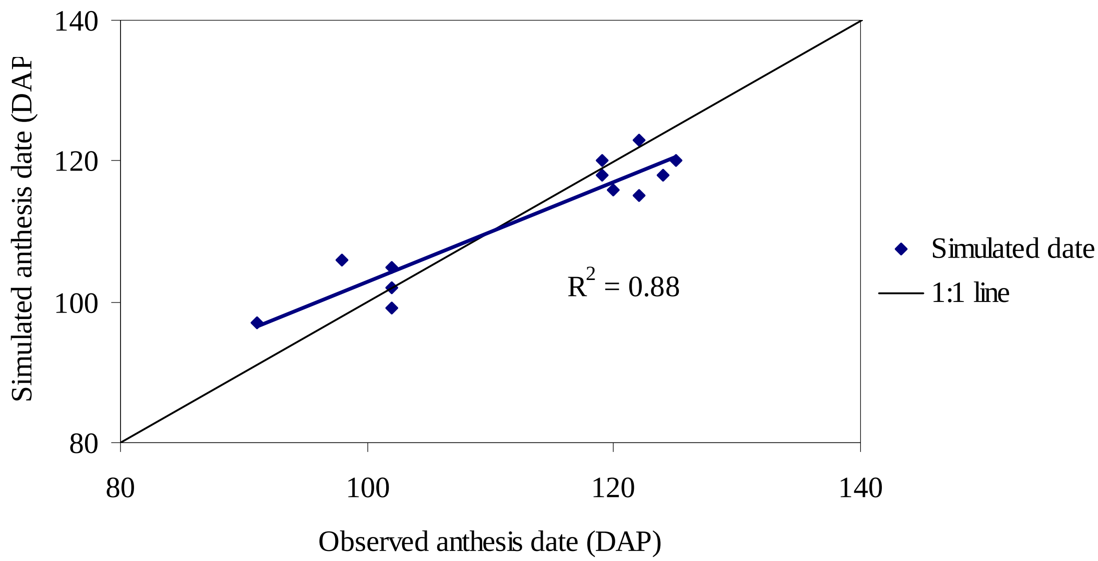

Fig.3. Linear regression analysis of anthesis date simulated with DSSATv4 (CERES-rice) and observed for twelve datasets from Uruguay used in model validation. DAP: days after planting.

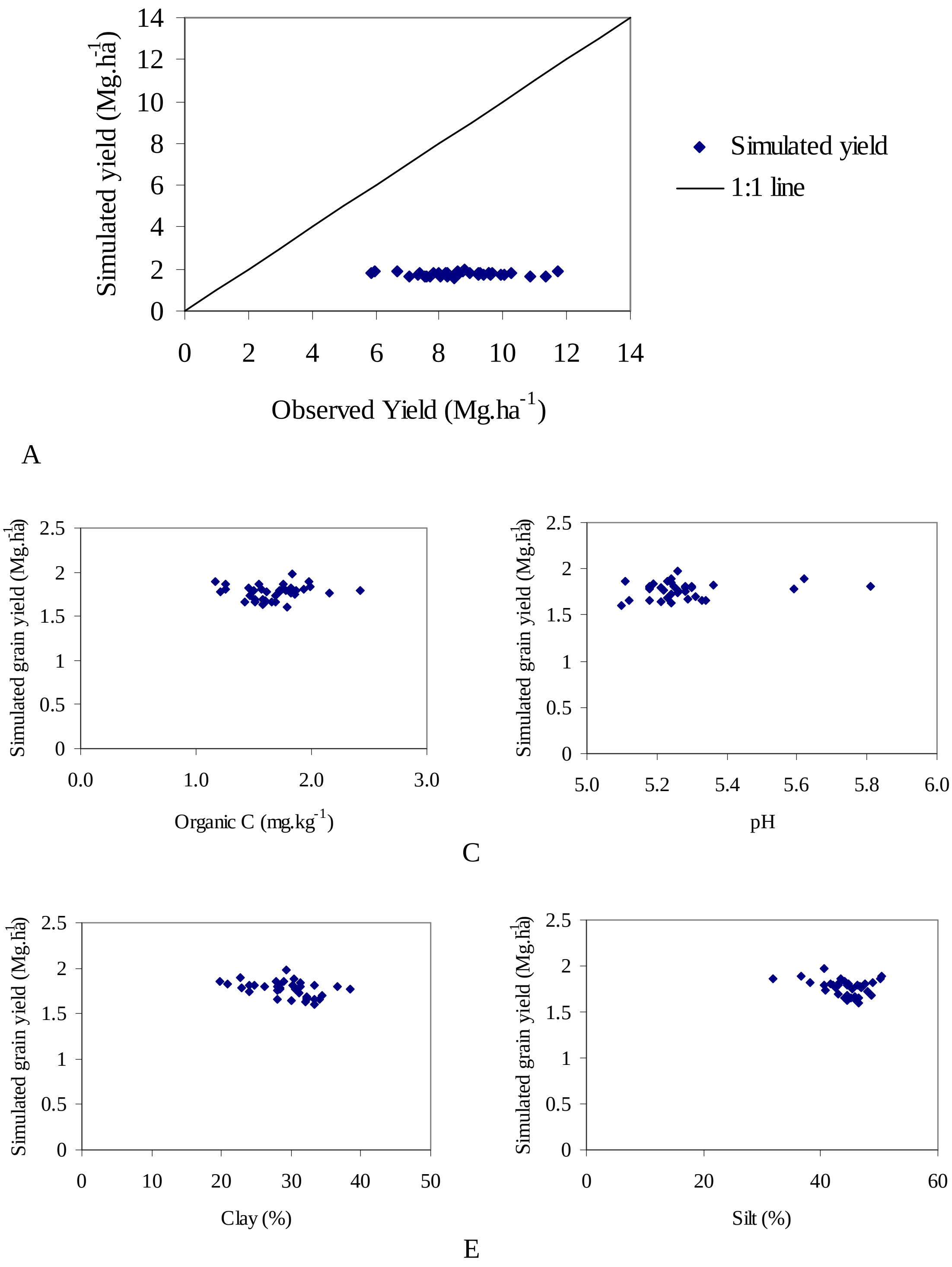

Fig.4. Simulated rice grain yield as a function of observed variables at 36 locations of a 12 hectares field in Uruguay: observed rice grain yield (A), and soil analysis parameters at 10 cm depth samples: organic carbon (B), pH (C), Clay (D), Silt (E).

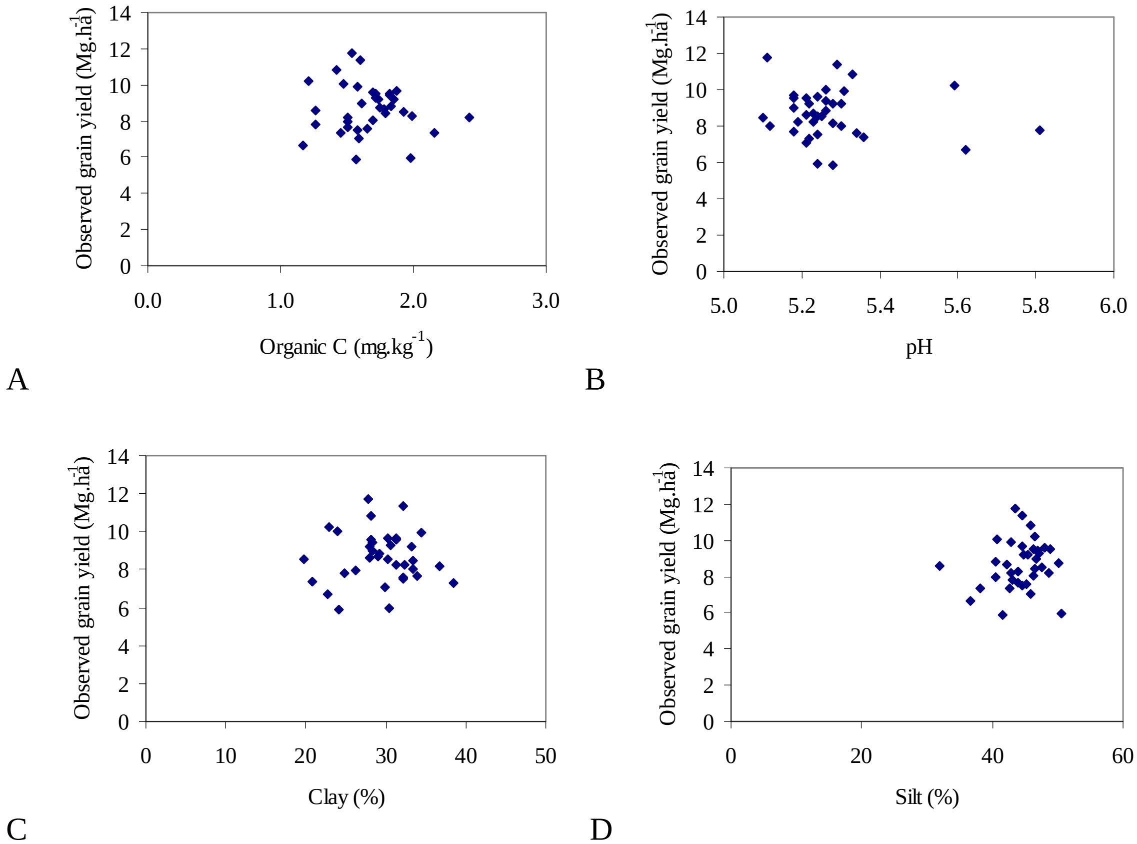

Fig.5. Observed rice grain yield as a function of observed soil analysis variables at 36 locations of a 12 hectares field in Uruguay: organic carbon (A), pH (B), Clay (C), Silt (D).

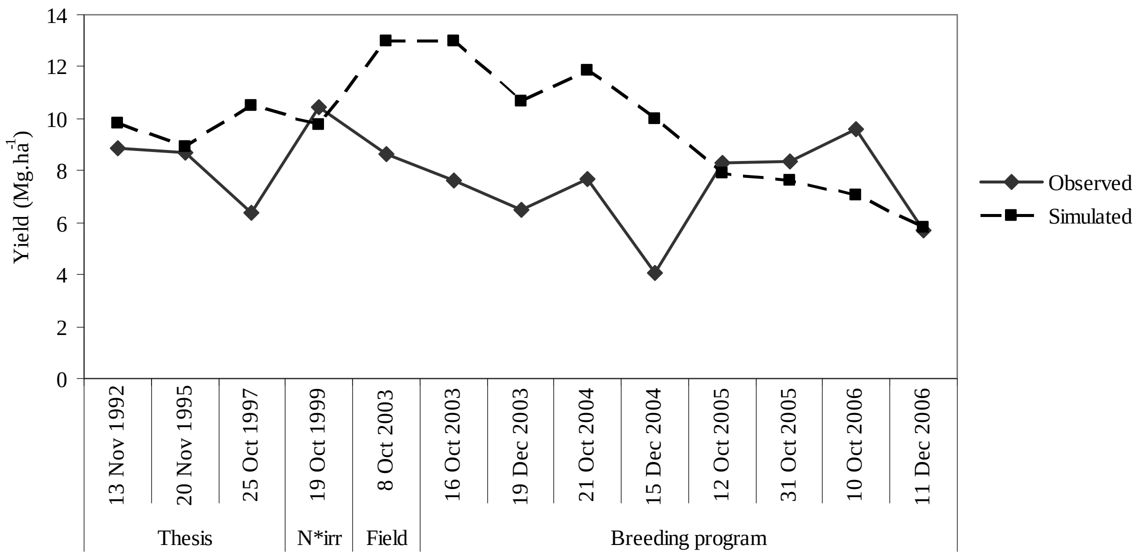

Fig.6. Rice grain yield observed in different experiments from Uruguay, and simulated with DSSATv4 CERES-rice for validation. Each dataset is followed by its planting date and experiment name, corresponding with sources from Table 3.

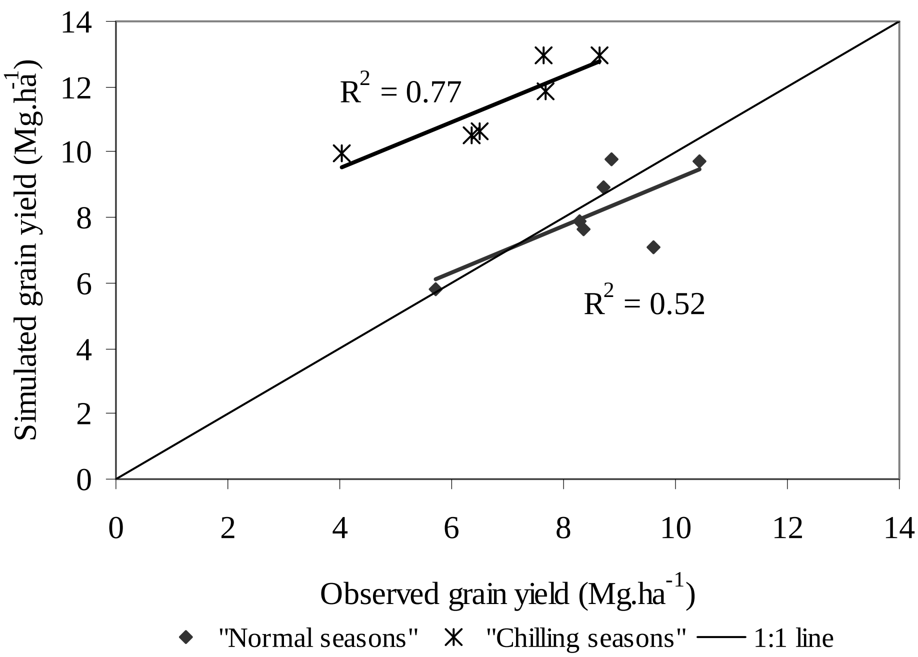

Fig.7. Regression analysis of rice grain yield observed in different experiments from Uruguay, and simulated with DSSATv4 CERES-rice for validation. Dataset was separated in two (normal season or season with chilling injury), according to chilling damage reports for each planting season.

Table 1. Rice genetic coefficients used in DSSATv4 CERES-rice

Genetic coefficient	Definition
P1	Time period (expressed as growing degree days [GDD] in ºC above a base temperature of 9ºC) from seedling emergence during which the rice plant is not responsive to changes in photoperiod. This period is also referred to as the basic vegetative phase of the plant.
P20	Critical photoperiod or the longest day length (in hours) at which the development occurs at a maximum rate. At values higher than P20 developmental rate is slowed, hence there is delay due to longer day lengths.
P2R	Extent to which phasic development leading to panicle initiation is delayed (expressed as GDD in ºC) for each hour increase in photoperiod above P20.
P5	Time period in GDD (ºC) from beginning of grain filling (3 to 4 days after flowering) to physiological maturity with a base temperature of 9ºC.
G1	Potential spikelet number coefficient as estimated from the number of spikelets per g of main culm dry weight (less lead blades and sheaths plus spikes) at anthesis. A typical value is 55.
G2	Single grain weight (g) under ideal growing conditions, i.e. nonlimiting light, water, nutrients, and absence of pests and diseases.
G3	Tillering coefficient (scaler value) relative to IR64 cultivar under ideal conditions. A higher tillering cultivar would have coefficient greater than 1.0.
G4	Temperature tolerance coefficient. Usually 1.0 for varieties grown in normal environments. G4 for japonica type rice growing in a warmer environment would be 1.0 or greater. Likewise, the G4 value for indica type rice in very cool environments or season would be less than 1.0.

Table 2. Sources of data from experiments carried out in Paso de la Laguna Experimental Unit (Uruguay) used for calibration of DSSATv4 CERES-rice model.

Experiment name	Source	Planning date
Bioclimático 95-96 Ep1	Méndez, 1996.	10/23/95
Bioclimático 95-96 Ep2	Méndez, 1996.	12/01/95
Bioclimático 96-97 Ep1	Méndez and Roel, 1997.	10/23/96
Bioclimático 96-97 Ep2	Méndez and Roel, 1997.	12/02/96
Bioclimático 97-98 Ep1	Méndez and Roel, 1998.	10/27/97
Bioclimático 97-98 Ep2	Méndez and Roel, 1998.	11/24/97
Bioclimático 98-99 Ep1	Casterá et al., 1999.	10/21/98
Bioclimático 98-99 Ep2	Casterá et al., 1999.	11/27/98
Bioclimático 99-00 Ep1	Casterá et al. 2000.	10/18/99
Bioclimático 99-00 Ep2	Casterá et al. 2000.	11/12/99
Bioclimático 00-01 Ep1	Méndez and Roel, 2001.	10/18/00
Bioclimático 00-01 Ep2	Méndez and Roel, 2001.	11/13/00
Bioclimático 01-02 Ep1	Méndez and Roel, 2002.	11/06/01
Bioclimático 01-02 Ep2	Méndez and Roel, 2002.	11/22/01
Bioclimático 02-03 Ep1	Méndez and Roel, 2003.	11/02/02
Bioclimático 02-03 Ep2	Méndez and Roel, 2003.	11/19/02
Bioclimático 03-04 Ep1	Méndez and Roel, 2004.	10/17/03
Bioclimático 03-04 Ep2	Méndez and Roel, 2004.	12/02/03
Field 2006-07	Unpublished	12/17/06

Table 3. Chemical analysis for average soils in Paso de la Laguna Experimental Unit (Uruguay).

Depth (cm)	pH	Org C	P -Bray I	K	Sand	Silt	Clay
		($g.kg^{-1}$)	(µg P/g)	(meq/100g)	------------%------------		
0-10	5.27	16.7	4.67	24	26.3	44.3	29.4
10-20	5.60	12.1	2.19	18	24.8	45.4	29.7

Table 4. Weather station monthly averages from the weather station located at Paso de la Laguna Experimental Unit (Uruguay).

Month	SRad ($MJ.m^{-2}.d^{-1}$)	TMax (ºC)	TMin (ºC)	Rain (mm)	NWet	SunH	Amth	Bmth
Jan	20.1	29.4	16.6	115.3	8.5	36	0.186	0.602
Feb	17.5	28.4	16.6	147.6	9.6	31.5	0.176	0.634
Mar	15.3	27.0	15.2	108.0	9.5	29.3	0.170	0.653
Apr	11.7	23.4	11.7	114.0	9.3	25.6	0.161	0.693
May	9.2	19.7	8.1	126.9	9.2	22.8	0.155	0.731
Jun	7.7	16.7	5.9	121.7	10.7	19.1	0.146	0.798
Jul	8.0	16.3	5.6	125.2	10.0	19.5	0.147	0.790
Aug	9.9	17.8	6.7	104.3	9.6	22.1	0.153	0.743
Sep	12.8	19.3	7.9	112.4	9.9	24.4	0.159	0.708
Oct	16.0	22.5	10.6	100.4	10.3	28.4	0.168	0.662
Nov	19.1	25.0	12.2	98.7	8.1	33.9	0.181	0.616
Dec	20.3	27.8	14.7	98.9	8.5	35.7	0.186	0.604

SRad Mean daily solar radiation for month, $MJ.m^{-2}.d^{-1}$

TMax Mean daily maximum temperature for month, ºC

TMin Mean daily minimum temperature for month, ºC

Rain Mean Total rainfall for month, mm

NWet Mean number of days with rainfall for month

SunH Mean daily hours of bright sunshine for month, percent of day length

Amth Intercept A in Angstrom equation for month

Bmth Multipier B in Angstrom equation for month

Table 5. Sources of data from experiments carried out in Paso de la Laguna Experimental Unit (Uruguay) used for Validation of DSSATv4 CERES-rice model, and parameters evaluated.

Experiment name	Planning date	Phenology	Biomass	Yield	Plant N	Source
Thesis	11/13/1992	X	X	X		Porto and Castro, 1994
Thesis	11/20/1995	X	X	X		Baez and Toledo, 1998
Thesis	10/25/1997	X	X	X	X	De Los Santos and Jaques, 1999.
N*irrigation time	10/19/1999	X	X	X	X	Castera et al., 2000
Field	10/10/2003	X	X	X		Roel et al., 2004.
Breed. program evaluation	10/16/2003	X		X		Blanco et al. 2004.
Breed. program evaluation	12/19/2003	X		X		Blanco et al. 2004.
Breed. program evaluation	10/21/2004	X		X		Blanco et al. 2005.
Breed. program evaluation	12/15/2004	X		X		Blanco et al. 2005.
Breed. program evaluation	10/12/2005	X		X		Molina et al., 2006
Breed. program evaluation	10/31/2005			X		Molina et al., 2006
Breed. program evaluation	10/10/2006	X		X		Pérez de Vida and Blanco, 2007.
Breed. program evaluation	12/11/2006	X		X		Pérez de Vida and Blanco, 2007.

Table 6. Rice genetic coefficients estimated for “El Paso 144” in Uruguay in DSSATv4 CERES-rice.

Genetic coefficient†	Estimated value
P1	600.0
P20	5.0
P2R	380.0
P5	13.5
G1	65
G2	0.027
G3	1.00
G4	1.00

†Coefficients as defined in Table 1

Table 7. Observed and simulated anthesis and maturity dates for experimental data used in DSSATv4 CERES-rice model calibration from experiments planted in different dates at Paso de la Laguna Experimental Unit (Uruguay).

Experiment name	Source	Planning Date	Anthesis date (dap†) Measured	Anthesis date (dap†) Simulated	Anthesis date (dap†) Diff.	Maturity date (dap†) Measured	Maturity date (dap†) Simulated	Maturity date (dap†) Diff.
Bioclimático 95-96 Ep1	Méndez, 1996	10/23/95	117	110	-7	165	146	-19
Bioclimático 95-96 Ep2	Méndez, 1996	12/01/95	104	99	-5	155	140	-15
Bioclimático 96-97 Ep1	Méndez and Roel, 1997	10/23/96	108	103	-5	146	140	-6
Bioclimático 96-97 Ep2	Méndez and Roel, 1997	12/02/96	88	**94**	6	130	138	8
Bioclimático 97-98 Ep1	Méndez and Roel, 1998	10/27/97	109	117	8	149	162	13
Bioclimático 97-98 Ep2	Méndez and Roel, 1998	11/24/97	**100**	**112**	**12**	142	166	24
Bioclimático 98-99 Ep1	Casterá et al., 1999	10/21/98	114	120	6	156	151	-5
Bioclimático 98-99 Ep2	Casterá et al., 1999	11/27/98	102	105	3	142	158	16
Bioclimático 99-00 Ep1	Casterá et al. 2000	10/18/99	114	110	-4	143	146	3
Bioclimático 99-00 Ep2	Casterá et al. 2000	11/12/99	106	102	-4	149	146	-3
Bioclimático 00-01 Ep1	Méndez and Roel, 2001	10/18/00	109	111	2	147	143	-4
Bioclimático 00-01 Ep2	Méndez and Roel, 2001	11/13/00	105	102	-3	133	135	2
Bioclimático 01-02 Ep1	Méndez and Roel, 2002	11/06/01	**100**	**113**	**13**	132	149	17
Bioclimático 01-02 Ep2	Méndez and Roel, 2002	11/22/01	106	108	2	141	149	8
Bioclimático 02-03 Ep1	Méndez and Roel, 2003	11/02/02	101	**105**	4	138	144	6
Bioclimático 02-03 Ep2	Méndez and Roel, 2003	11/19/02	102	103	1	142	150	8
Bioclimático 03-04 Ep1	Méndez and Roel, 2004	10/17/03	118	116	-2	155	157	2
Bioclimático 03-04 Ep2	Méndez and Roel, 2004	12/02/03	107	106	-1	145	147	2
RMSE					5.9d			11.1d

dap†: days after planting

Table 8. Total observed and simulated biomass and yield for different Nitrogen fertilization rates.

	Applied Nitrogen								
	------------------------kg.ha^{-1}-----------------------								
	0		40		80		120		ANR†
dap††	Obs§	Sim‡	Obs§	Sim‡	Obs§	Sim‡	Obs§	Sim‡	Sim†
	----------------------------Biomass (Mg.ha-1)---------------------------------								
51	0.4	0.3	0.4	0.6	0.5	0.6	0.5	0.6	1.0
70	1.8	0.7	2.0	1.7	2.4	2.3	2.5	2.6	3.8
91	5.1	1.0	6.5	2.9	6.6	4.5	7.7	5.5	8.7
125	15.9	1.3	15.0	5.2	17.0	9.2	15.7	11.9	16.1
167	22.9	1.4	21.5	6.1	25.7	11.1	28.3	13.8	18.2
	-------------------------------Grain Yield (Mg.ha-1)-------------------------------								
Yield	9.3	0.1	10.7	1.5	10.8	2.9	10.9	5.5	9.7

ANR†: Model run under the option of applying Nitrogen fertilizer each time the crop requires it

dap††: days after planting

Obs§: Observed data from Castera et al, 2000.

Sim‡: Simulated data with DSSATv4 CERES-rice for each fertilization rate

Table 9. Observed and simulated accumulated plant Nitrogen for different Nitrogen fertilization rates.

	Applied Nitrogen								
	------------------------kg.ha^{-1}-----------------------								
	0		40		80		120		ANR†
dap††	Obs§	Sim‡	Obs§	Sim‡	Obs§	Sim‡	Obs§	Sim‡	Sim†
	---------------------------Plant Nitrogen (kg.ha^{-1})-----------------------------								
51	13	8	13	15	15	15	15	15	41
70	36	11	45	32	57	49	61	65	114
91	84	14	103	51	115	92	149	120	181
125	194	19	175	63	211	116	201	158	227
167	279	23	283	96	320	179	319	235	326

ANR†: Model run under the option of applying Nitrogen fertilizer each time the crop requires it

dap††: days after planting

Obs§: Observed data from Castera et al, 2000.

Sim‡: Simulated data with DSSATv4 CERES-rice for each fertilization rate

Table 10. Biomass and plant Nitrogen observed (De Los Santos and Jaques, 1999) and simulated with different nitrogen option simulation.

Observed data source		Observed	Simulated‡	ANR§
		----------Plant Biomass ($Mg.ha^{-1}$)---------		
Porto and Castro, 1994	Panicle initiation	4.80	3.23	3.77
	Anthesis	14.40	8.48	12.69
	Maturity	16.80	12.48	18.39
Baez and Toledo, 1998	Panicle initiation	3.67	3.42	3.96
	Anthesis	15.90	7.85	12.36
	Maturity	16.55	11.52	17.89
De Los Santos and Jaques, 1999	Panicle initiation	4.16	1.92	4.48
	Anthesis	13.29	4.62	13.98
	Maturity	n/a†	6.35	19.32
		----------Plant Nitrogen ($kg.ha^{-1}$)---------		
De Los Santos and Jaques, 1999	Panicle initiation	67.2	32.5	116
	Anthesis	146.2	59.3	208
	Maturity	n/a†	115	352

†n/a: not available

‡ Simulated data with DSSATv4 CERES-rice with real fertilization inputs

ANR§: DSSATv4 CERES-rice model run under the option of applying Nitrogen fertilizer each time the crop requires.

Table 11. Observed and simulated accumulated Nitrogen use efficiency (NUE) for different Nitrogen fertilization rates.

	Applied Nitrogen								
	------------------------kg.ha^{-1}-----------------------								
	0		40		80		120		ANR†
dap††	Obs§	Sim‡	Obs§	Sim‡	Obs§	Sim‡	Obs§	Sim‡	Sim†
	--------------------------------NUE (kgDM. kgN^{-1})-----------------------------------								
51	31	38	31	40	33	40	33	40	24
70	50	64	44	53	42	47	41	40	33
91	61	71	63	57	57	49	52	46	48
125	82	68	86	83	81	79	78	75	71
167	82	61	76	64	80	62	89	59	56

ANR†: Model run under the option of applying Nitrogen fertilizer each time the crop requires it

dap††: days after planting

Obs§: Observed data from Castera et al, 2000.

Sim‡: Simulated data with DSSATv4 CERES-rice for each fertilization rate

DISCUSION GENERAL Y CONCLUSIONES GLOBALES

La implementación de una nueva modalidad de ensayos a campo permitió estudiar la variación espacial y temporal del rendimiento de sorgo sobre Argiudoles y Argiaquoles (Argisoles y Planosoles) del este de Uruguay, sus interacciones y relaciones con los atributos del suelo y del terreno. La intensidad de uso del suelo evaluada a través de diferentes rotaciones cultivo-pasturas interaccionó con esta variación.

La variación temporal asociada a diferencias en las precipitaciones anuales fue el primer factor determinante del rendimiento de sorgo (Fig. 9). En la zafra 2005-06, se registraron 310 mm de precipitaciones acumuladas durante las etapas críticas del cultivo, con un rendimiento de 8.15 $Mg.ha^{-1}$, mientras que en 2005-06, solo se registraron 121mm, en el mismo periodo y el rendimiento fue 43% inferior (4.61 $Mg.ha^{-1}$). La zafra 2007-08 se comportó de forma intermedia, con un registro de 252mm en las etapas crìtica del cultivo, y una producción promedio de 6.05 $Mg.ha^{-1}$, 26% inferior que en la primera zafra.

Dentro de cada zafra, el rendimiento estuvo determinado en primer lugar por las propiedades del terreno, y luego por la rotación (Fig.9). Esto sugiere que la disponibilidad de agua y su distribución a través de la topografía del terreno son los determinantes principales del rendimiento de sorgo en sistemas producción de siembra directa en rotaciones cultivo-pasturas en Uruguay.

Los sistemas de cultivos y pasturas de larga duración bajo siembra directa preservaron el carbono orgánico del suelo, pero no garantizaron mayor rendimiento en grano de sorgo que sistemas de cultivo continuo bajo siembra directa. Bajo un régimen pluviométrico favorable (en 2005-06), el mayor rendimiento fue observado en CC, y el menor en RL (8.6 vs 7.74 $Mg.ha^{-1}$), mientras que se detectó una tendencia a mayor rendimiento en RC respecto de LR. En 2006-07 no se observaron diferencias entre RC y RL. Finalmente, en 2007-08 se observó una tendencia ($p<0.1$) a mayor rendimiento en RC respecto de RL y CC (15 y 23%, respectivamente).

Se detectó interacción entre los efectos año, rotación y tratamiento, ya que solamente en una de las rotaciones*año (RL 2007-08) hubo un efecto positivo del subsolado sobre el rendimiento de sorgo. Para las demás combinaciones de año y rotación no se detectaron efectos de las prácticas de manejo de suelos implementadas en el rendimiento de sorgo.

La variación temporal, además de afectar el nivel de rendimiento e interaccionar con el efecto de rotación, también afectó su variación espacial y su asociación con los atributos del suelo y del terreno. La variabilidad espacial del rendimiento fue mínima en la zafra con mayores precipitaciones y sin autocorrelación espacial detectable; se encontró en la zafra seca como una fuerte autocorrelación, y fue máxima en la zafra con precipitaciones intermedias, presentando un mayor alcance (range) (72-165m en 2006-07 vs. 125-510m en 2007-08) y menor relación pepita/meseta (nugget/sill) en los semivariogramas (1.3-21.4% en 2006-07 vs 0.1-0.5% en 2007-08).

La variabilidad espacial interaccionó con el efecto de rotación. Rotaciones con menor intensidad de uso del suelo, con una fase de pasturas más larga y consecuentemente mayor tiempo de pastoreo directo mostraron menor dependencia espacial en los semivariogramas que rotaciones con una fase de pasturas más corta. Los atributos del terreno derivados de modelo digital de elevación y la conductividad eléctrica se asociaron con el rendimiento del cultivo en las chacras, siendo esta asociación más fuerte en rotaciones más intensivas; mientras que no se encontró relación entre el rendimiento y los nutrientes del suelo analizados, que no mostraron autocorrelación espacial a la escala de muestreo utilizada.

Surgieron nuevas interrogantes sobre la dinámica de nutrientes y las posibilidades del manejo sitio-específico en rotaciones cultivo-pasturas bajo el efecto pastoreo directo, basadas en: 1) la menor estructura espacial del rendimiento bajo rotaciones con pasturas de larga duración, 2) su menor asociación con los atributos del terreno, 3) la ausencia de detección de autocorrelación espacial de nutrientes del suelo muestreadas en una grilla intensiva, y 4) la ausencia de relación detectable de la disponibilidad de nutrientes con el rendimiento. La redistribución espacial de nutrientes que realizan los animales, y las razones determinantes de los mayores rendimientos obtenidos en sistemas más intensivos y sus sustentabilidad deberían ser estudiadas.

Los resultados del primer trabajo sugieren que los efectos de prácticas de manejo como la rotación implementada, el laboreo sub-superficial y el manejo de rastrojo en el rendimiento del cultivo estuvieron supeditados a ocurrir dentro de un marco determinado por la variación temporal de las condiciones climáticas y la variación espacial de lo atributos del suelo y del terreno. Las rotaciones de cultivo-pasturas ocuparon el tercer lugar como variable determinante del rendimiento, luego efecto del año y de los atributos topográficos del terreno y de conductividad eléctrica del suelo (Fig.9). Por lo tanto, el estudio de estas variables es fundamental en la evaluación del efecto de prácticas de manejo sobre el rendimiento de los cultivos. Es necesario incorporar tecnologías como las de agricultura de precisión y realizar ensayos a mediano y largo plazo que permitan incorporar estas variables cuando se evalúan prácticas de manejo en ensayos a campo.

En el segundo trabajo, se calibró y validó el modelo DSSATv4 CERES-Rice. Se obtuvieron coeficientes genéticos que resultaron en una calibración y validación aceptable para la fenología de la variedad El Paso 144 (RCMEE para floración: 5.9d y 4.5d). En cuanto a los caracteres cuantitativos de producción, se logró un ajuste razonable del rendimiento de arroz y biomasa para condiciones no limitantes de fertilización nitrogenada, y para los años sin daño por frío en las etapas reproductivas (RCMEE 1.1Mg.ha^{-1}, 13%). A partir de estos coeficientes genéticos, el modelo podría utilizarse para estudios de largo plazo sobre el efecto del cambio climático.

En cuanto a la simulación del efecto del frío en las etapas reproductivas, es necesario incluir una rutina que restrinja el rendimiento en función de la exposición del ápice reproductivo a bajas temperaturas. Dicha rutina ha sido desarrollada en Australia (Godwin et al., 1994), pero por el momento no está disponible en DSSATv4.

Se encontraron restricciones en la predicción del modelo al utilizar los valores reales de fertilización nitrogenada, referentes a la dinámica de nitrógeno en rotaciones arroz-pasturas en Argiaquoles de la zona este de Uruguay. La mayor subestimación del rendimiento correspondió a simulaciones sin fertilización nitrogenada, donde las diferencias con los valores observados oscilaron entre 0.36-0.91 en proporción a estos últimos. Se identificó falta de información sobre la actividad biológica de los suelos en estos sistemas, asociadas al aporte de nitrógeno endógeno al cultivo, y la necesidad de revisar la eficiencia de uso del nitrógeno en planta asumida por el modelo. Contar con una mejor comprensión de estos aspectos es fundamental para determinar las necesidades de uso de fertilizantes en estos sistemas, lo que tiene implicancias ambientales y económicas.

Si bien no se logró captar la variabilidad espacial a escala de chacra a partir del modelo calibrado y validado, se identificaron posibles causas de este comportamiento, que podrían subsanarse mediante trabajos de investigación.

La suma de los resultados obtenidos con ambos trabajos indica que las herramientas de agricultura de precisión pueden realizar un aporte importante al incluirse en trabajos de investigación. Permitieron estudiar interacciones de prácticas de manejo con la variabilidad temporal y espacial intrínseca de las chacras, e identificar necesidades concretas de investigación relevantes en el contexto de la producción agropecuaria del país, que llevarían a una mejor comprensión del sistema suelo-planta-atmósfera. Este tipo de estudios podrían repercutir en acciones de manejo que tiendan a una producción más eficiente y de menores riesgos ambientales y económicos.

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