UNIVERSIDAD DE EXTREMADURA

Departamento de Ingeniería Agronómica y Forestal
Material Vegetal y Tecnología de Cultivo Frutales de Hueso

TESIS DOCTORAL

"Aplicación y validación de metodologías de zonificación y modelos de simulación para la gestión de grandes superficies de cultivo de tomate para industria en las vegas bajas del Guadiana"

Memoria presentada por Rafael Fortes Gallego para optar al Grado de Doctor por la Universidad de Extremadura.

Badajoz, 2015

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Centro de Investigaciones Científicas y Tecnológicas de Extremadura

(CICYTEX)

Instituto de Investigación Agraria "Finca la Orden-Valdesequera"

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"Aplicación y validación de metodologías de zonificación y modelos de simulación para la gestión de grandes superficies de cultivo de tomate para industria en las vegas bajas del Guadiana"

Realizada por: Rafael Fortes Gallego

Dirigida por: Dr. Abelardo García Martín
Dr. Carlos Mario Campillo Torres

Badajoz, 2015

Abelardo García Martín, Doctor Ingeniero Agrónomo, profesor titular del Departamento de Ingeniería Agronómica y Forestal de la Escuela de Ingenierías Agrarias de Extremadura.

Carlos Mario Campillo Torres, Doctor Ingeniero Agrónomo, investigador del Centro de Investigaciones Científicas y Tecnológicas de Extremadura (CICYTEX), Finca la Orden-Valdesequera, perteneciente a la Consejería de Empleo, Empresa e Innovación del Gobierno de Extremadura.

INFORMAN:

Que la memoria titulada **"Aplicación y validación de metodologías de zonificación y modelos de simulación para la gestión de grandes superficies de cultivo de tomate para industria en las vegas bajas del Guadiana"**, que presenta el Ingeniero Agrónomo Rafael Fortes Gallego para optar al grado de Doctor, ha sido realizada bajo nuestra dirección en el Centro de Investigaciones Científicas y Tecnológicas de Extremadura (CICYTEX), Finca la Orden-Valdesequera del Gobierno de Extremadura y en el Departamento de Ingeniería Agronómica y Forestal de la Universidad de Extremadura.

Considerando que se trata de un trabajo original de investigación que reúne todos los requisitos establecidos en el RD 99/2011, de 28 de Enero, estimando que puede ser presentado para su defensa ante el tribunal nombrado al efecto.

Para que conste y preste los efectos oportunos lo firmamos, a petición del interesado en Badajoz a 9 de Febrero de 2015.

Fdo.: Dr Carlos Mario Campillo Torres

Fdo.: Dr. Abelardo García Martín

A mis padres Rafael y Virginia

INDICE GENERAL

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RESUMEN

La variabilidad en los cultivos es una de las principales dificultades cuando nos enfrentamos a la gestión de grandes superficies, la influencia de factores como el suelo, los nutrientes o el clima dificulta el conocimiento exhaustivo de las grandes superficies cultivadas, por tanto el uso de herramientas que permitan obtener una visión global de las superficies agrícolas se plantea como una de las soluciones necesarias para mejorar los rendimientos de una agricultura moderna, la cual tiende a la extensificación. En los últimos años han surgido herramientas como la agricultura de precisión o los modelos de simulación que se sitúan como herramientas claves en el manejo de las grandes superficies en la agricultura. En esta tesis se ha estudiado el uso de algunas de estas herramientas sobre grandes superficies comerciales de cultivo de tomate para industria. El objetivo general ha sido tratado en cuatro capítulos.

En el capítulo uno se expone la combinación de dos parámetros que se pueden muestrear de manera masiva y georreferenciada, dichos parámetros son la Conductividad Eléctrica Aparente, parámetro relacionado con las propiedades del suelo, y el Índice Normalizado de Vegetación (NDVI), parámetro relacionado con las propiedades de la planta. El estudio se llevó a cabo en una parcela comercial de tomate para industria, donde mapas predictivos de CEa y NDVI desarrollados mediante un análisis geoestadístico fueron comparados con la producción final obtenida en el cultivo. A pesar de ser obtenidos mejores resultados con el uso del NDVI, ambos parámetros resultaron buenos indicadores de la potencialidad productiva del suelo, y ofrecieron una importante información a la hora de zonificar y manejar el cultivo.

En el capítulo dos se utilizó la fuerte elación existente entre la textura del suelo y la CEa para evaluar una metodología encaminada a zonificar los terrenos agrícolas desde el punto de vista del manejo del riego. Se desarrollaron mapas de contenido de agua útil en tres parcelas comerciales de 40, 80 y 120 ha, mediante el uso de un análisis geoestadístico de regresión krigeado, donde las variables utilizadas fueron la conductividad eléctrica aparente del terreno y los datos analizados en laboratorio derivados de un muestreo de suelo guiado en función de la conductividad eléctrica aparente. El resultado obtenido fue evaluado obteniéndose resultados estadísticamente satisfactorios.

En el capítulo tres se desarrolló una metodología basada en la capacidad predictiva del índice de vegetación normalizado sobre la productividad del cultivo. El ensayo se desarrollo en dos fincas comerciales de tomate para industria. Se realizó un mapa de índice de vegetación normalizo del cultivo que fue utilizado para la posterior realización de un muestreo guiado de producción. Finalmente la técnica de regresión krigeado fue utilizada para la generación del mapa final, como variable principal se utilizaron los datos de producción obtenidos en campo, y como variable secundaria los valores de índice de vegetación normalizado desarrollados sobre el cultivo. El resultado obtenido fue evaluado obteniéndose resultados estadísticamente satisfactorios.

En el capítulo cuatro tiene por objetivo evaluar la utilidad del uso combinado de los modelos de simulación implementados con técnicas de agricultura de precisión. El trabajo se realizó sobre una parcela comercial de tomate para industria de 6.5 ha. En este capítulo se utilizó la metodología de zonificación de suelo desarrollada en el capítulo dos para establecer puntos de control, dichos puntos fueron utilizados para evaluar la capacidad del modelo de simulación AquaCrop para determinar la productividad del cultivo. El resultado obtenido fue evaluado obteniéndose resultados estadísticamente satisfactorios, tanto desde el punto de vista de la zonificación de la parcela como desde la evaluación del modelo AquaCrop para la estimación de la productividad del cultivo.

SUMMARY

The variability into crops is one of the main difficulties when faced large tracts of agricultural land are involved, the influence of factors such as soil, nutrients or weather hampers thorough knowledge of large cultivated areas. Therefore the use of tools which allow to obtain an overview of agricultural land is seen as one of the solutions needed to improve the performance of modern agriculture, which tends to extensification. In last years there have been tools such as precision agriculture or simulation models, that are positioned as key tools in managing large tracts of agricultural land. In this work we study the use of some of these tools on processing tomato crop. The overall objective has been treated in four chapters.

In chapter one the combination of two parameters that can be sampled on intensive way and georeferenced are expose, these parameters are the Apparent Electrical Conductivity, parameter related to soil properties, and the Normalized Difference Vegetation Index (NDVI), a parameter related to the properties of the plant. The study was conducted in a comercial processing tomato crop, where predictive maps of Apparent Electrical Conductivity and Normalized Difference Vegetation Index developed were used in a geostatistical analysis to compared with the final production of the crop. Despite being obtained better results with the use of Normalized Difference Vegetation Index, both parameters were good indicators of the potential productivity of surfaces, and offered an important information for zoning into the crop management.

In chapter two the strong relationship between soil texture and Apparent Electrical Conductivity was used to evaluate a methodology for improve irrigation zoning. Available water content maps were developed in three commercial plots, with

surfaces of 40, 80 and 120 ha. The regression Kriging methodology was used to combine data obtained on field and laboratory. The result obtained was evaluated statistically obtaining satisfactory results.

In chapter three a methodology based on the predictive ability of the normalized vegetation index for determine crop productivity was developed. The field test was developed in two commercial farms of processing tomato. The map of Normalized Difference Vegetation Index was used for a guided yield samples. Finally regression kriging technique was used to generate the final map, the main variable was the yield obtained on field, and we used as secondary variable the normalized vegetation index, for this process both variables were related statistically. The result obtained was evaluated statistically obtaining satisfactory results.

In chapter four was studied the utility of the combined use of simulation models implemented with precision agriculture techniques. The work was conducted on a commercial plot of processing tomato crop, with a surface of 6.5 ha. In this chapter the methodology developed in chapter two was used to locate the control points in field. These points were used to assess the ability of the FAO model AquaCrop for simulating processing tomato yield response. The result obtained was evaluated statistically, obtaining satisfactory results from the point of view of the zoning of the plot. From the point of view of AquaCrop model for estimating crop productivity, good results also were obtained.

INTRODUCCIÓN GENERAL

Según estimaciones realizadas por FAO (Food and Agriculture Organization) en el año 2050 más de 10 billones de personas necesitarán ser alimentadas, esta situación representará un reto que exigirá incrementar en un 70% la producción actual de alimentos. El regadío en la agricultura ocupa una extensión de 277 millones de hectáreas, produciendo unos rendimientos 3.6 veces superiores al de la agricultura no irrigada. Sin embargo es difícil incrementar las superficies de regadío debido al alto impacto y coste medioambiental que acarrean. El aporte de grandes cantidades de agua desviadas de los ríos con fines de riego cambia profundamente el balance de agua en las tierras regadas. En el regadío una aplicación de 10.000 m3 por ha por año no es excepcional, y para cultivos con un requerimiento alto de agua las dotaciones anuales en climas áridos pueden subir a 20.000 m3 por ha. Otro problema importante es la degradación del suelo por problemas de salinidad; Con el aporte de las grandes cantidades de agua para el riego también se aportan sales. Por ejemplo, asumiendo que el agua de riego tiene una baja concentración de 0,3 g/l (igual a 0,3 kg/m3 y una aplicación anual modesta de 10.000 m3 agua por ha (casi 3 mm/día), la irrigación introduce 3.000 kg sal/ha cada año. La importación continua de sales conduce a la salinización del suelo lo que seriamente disminuye la cosecha de los cultivos. Aproximadamente un tercio de las extensiones de regadío en los países más importantes en cuanto a agricultura regada experimenta serias problemas de suelos con sales, por ejemplo: Israel 13 %, Australia 20 %, Chile: 20 %, China 15 %, Egipto 30 %. Los problemas se manifiestan igualmente tanto en los grandes proyectos de riego como en los pequeños. A la vista de todos estos datos es difícil incrementar la superficie de riego, pero si es posible elevar la productividad de las superficies cultivadas, para ello las directrices de la PAC (Política Agraria Común) ponen énfasis en el uso de os recursos y la sostenibilidad. Suelo y agua son los recursos básicos naturales en los que hacer hincapié para elevar la productividad de las superficies agrícolas de una manera eficiente y sostenible.

A nivel mundial América del norte, Asía y Europa constituyen las principales superficies de producción agronómica. Dentro de Europa España tiene un papel predominante en la producción de alimentos, siendo uno de los principales exportadores de frutas y verduras de la unión Europea. Extremadura se enmarca dentro de España como una comunidad eminentemente, donde frutas, cereales y hortalizas son producidos y exportados hacia el mercado nacional e internacional. El cultivo de tomate para industria es uno de los cultivos más importantes de España y cultivo principal en Extremadura, lugar donde se desarrolla este estudio. El tomate de industria ocupa un puesto relevante en la producción total agrícola regional, con una producción equivalente al 80% de la producción total nacional y el 6% de la mundial. La superficie total de cultivo ronda las 25.000 ha, todas ellas de regadío, con un rendimiento medio de 80.000 kg/ha. En esta región el riego es imprescindible para el desarrollo comercial del cultivo y se convierte en uno de los principales factores de producción, determinante no solo sobre la productividad, sino también de la calidad de la cosecha. Así, la modernización de los regadíos Extremeños ha sido la principal responsable de que la producción media en la Vegas del Guadiana, que en año 1996 era de 50.000 Kg/ha haya pasado a los actuales 80.000 kg/ha, al pasar de un riego mayoritario por gravedad a riego localizado por goteo. En los últimos años el cultivo ha sufrido una gran intensificación debido a la introducción de nuevas prácticas de cultivo y el uso de nuevas tecnologías para la gestión del mismo, surgiendo empresas capaces de gestionar enormes superficies de cultivo, con las consecuentes dificultades que implica este tipo de gestión. El incremento del tamaño de las explotaciones supone una ventaja en cuanto a costes de cultivo, pero también conlleva nuevos restos desde el punto de vista técnico, relacionados con la variabilidad espacial de las parcelas. Dicha variabilidad provoca diferentes respuestas frente a las prácticas de cultivos tradicionales, aplicadas de manera uniforme. Las nuevas tendencias en la agricultura moderna conducen a un aumento muy significativo del tamaño de las explotaciones, debido a que las nuevas tecnologías en maquinaria facilitan la gestión de estas enormes superficies. Además, parámetros esenciales para cultivo como el riego pasan a ser muy difíciles de controlar cuando nos enfrentamos a la gestión de grandes superficies, dada la gran influencia de dicha variabilidad espacial. El cálculo de las necesidades de agua o fertilización es muy complicado en este tipo de gestión, además de aumentar considerablemente los costes económicos si no se realiza un uso eficiente de estos. Por lo tanto, el desarrollo de herramientas que permitan realizar una zonificación para tomar decisiones adecuadas en estas nuevas tendencias de gestión agronómica se convierte en fundamental para el futuro del sector. A la hora de plantear metodologías o analizar tecnologías útiles en este sentido debemos conocer los dos pilares fundamentales para el cultivo, estos son el suelo y la planta. En esta tesis se han estudiado ambos parámetros:

El primer factor a estudiar es el suelo que constituye un factor fundamental desde el punto de vista agronómico, la diversidad y complejidad del mismo constituye un factor fundamental a tener en cuenta a la hora de realizar un manejo adecuado de cualquier tipo de cultivo agronómico o forestal.

El desarrollo de las ciencias edáficas ha simplificado en gran medida el conocimiento del mismo, sin embargo, la variabilidad espacial en la distribución del suelo complica en gran medida la representatividad de las analíticas cuando nos enfrentamos a la caracterización de grandes superficies de terreno. Esta variabilidad suele estar provocada por diversos motivos, como son la orografía, la sectorización de los terrenos originales, nivelaciones en los mismos, el origen geológico de los suelos o incluso el uso antropológico de los mismos. Para disminuir este problema podemos ayudarnos de las tecnologías auxiliadas por información GPS que nos permiten realizar una caracterización del suelo de manera rápida y masiva con respecto a diferentes parámetros. Uno de ellos es la conductividad eléctrica aparente (CEa) que ha demostrado ser un indicador eficaz y rápido de la variabilidad y productividad del suelo (Kitchen et al., 1999), ésta variable mide la capacidad para conducir la corriente eléctrica a través del suelo, y aunque históricamente ha sido utilizada para evaluar la salinidad en el suelo (Rhoades et al., 1976), existen dispositivos comerciales que han desarrollado medidas rápidas y útiles en la toma de decisiones de gestión agrícola (Siri-Prieto et al., 2006). Estudios realizados por diferentes autores han demostrado la relación existente entre la CEa y la textura del suelo (arena, limo y arcilla) (Williams y Hoey., 1987). Las técnicas de análisis espacial han permitido obtener mapas muy precisos para todos los parámetros físicos- químicos a partir de unas pocas muestras tomadas en lugares estratégicos (López-Granados et al., 2005), otros estudios la han relacionado con la capacidad de intercambio catiónico (CIC) o la profundidad de la capa arable (Sudduth et al., 2001). Debido a que el rendimiento del suelo es extremadamente dependiente de las propiedades fisicoquímicas del suelo la CEa, puede relacionarse también con la productividad del mismo (Siri-Prieto et al., 2006). Esto datos también permiten ser utilizados para tomar decisiones a la hora de elegir cultivos o variedades más adaptadas a diferentes zonas de la parcela. La adecuación de elección de zonas representativas para la instalación de sensores de suelo puede ser de gran utilidad para obtener unos valores más adaptados a la parcela completa. Existen otras medidas de suelo que se pueden realizar de manera masiva como es el caso del pH, obteniéndose una información global y localizada de grandes superficies de terreno, permitiéndonos dirigir de manera efectiva las enmiendas con el consecuente ahorro económico que esto conlleva.

Otro pilar fundamental en la gestión agrícola es la planta, conocer el estado general del cultivo es fundamental a la hora de la gestión de grandes superficies agrícolas, detectar deficiencias sobre el cultivo de manera rápida permite establecer medidas correctoras mejorando los rendimientos y calidad del producto final. La monitorización de las superficies agrícolas mediante mapas de cultivo ofrece a los productores una información directa para analizar la variabilidad en la superficie de cultivo, ayudándoles a justificar sus actuaciones de cara a mejorar las prácticas productivas (Kitchen et al., 2003). Realizar mapas de estado nutricional de cultivo permite ajustar, adaptar y dirigir la fertilización, los mapas de estado hídrico en planta permiten adaptar el riego a las necesidades del cultivo en cada momento de sus ciclos, los mapas de predicción de cosecha permiten establecer el momento más adecuado para la recolección así como la organización de la misma y el análisis de las zonas más productivas. Esta tecnología permite no sólo caracterizar diferencias, si no también cuantificar de forma objetiva las unidades homogéneas que integran la parcela, lo que permite dirigir actuaciones a zonas específicas o adoptar la solución global más adecuada para el conjunto de la parcela. Toda esta información ofrece una visión global que nos permite localizar las diferentes superficies de actuación, con el consecuente ahorro económico y ambiental que ello conlleva. A este respecto el desarrollo de los índices de vegetación basados en la reflectancia ha permitido un avance en los métodos globales de medida de estado de la planta. La reflectancia se basa en el reflejo de la luz por parte de la plata con una intensidad y en una longitud de onda específica. Estudios sugieren que la reflectancia en el cultivo puede ser utilizada para monitorizar los condicionantes de la planta a varias escalas (Plant, 2001) así como sus variables biofísicas (Thenkabail et al., 2000; Goel et al., 2003). Existen mucho índices de vegetación que son utilizados para la monitorización de las condiciones de cultivo, el índice de vegetación de diferencia normalizado (NDVI) es un buen indicador de la vegetación, la biomasa y el estado sanitario del cultivo (Rouse et al., 1973; Tucker, 1979), pero también se suelen usar con frecuencia otro tipo de índices como el índice de vegetación de diferencia normalizado en verde (NDVI-G, Ma et al., 1996), el índice de vegetación ajustado a suelo (SAVI, Huete, 1988) o el índice de vegetación ajustado a suelo optimizado (OSAVI, Rondeaux et al., 1996). La ventaja del uso de estos índices de reflectancia sobre otros métodos de evaluación de planta se basa en la obtención de información de manera directa, masiva y georreferencia mediante el uso de tecnología GPS, permitiendo obtener una información global y localizada de la superficie del cultivo. El gran atractivo de la medida de la reflectancia reside en que al realizarse sobre cubiertas vegetales se convierte en una medida no destructiva, y que gracias a la configuración de los equipamientos de medición actuales, se pueden medir de manera rápida, integrando los resultados obtenidos en mapas de cultivo. Numerosos trabajos ponen de manifiesto el interés de estos índices para caracterizar aspectos de cultivo tan importante como su estado fenológico, fisiológico, nutricional o hídrico; Sin embargo, la aplicabilidad de esta información exige una puesta a punto las condiciones en las que se enmarcan los propios cultivos. Sin embargo las posibilidades de esta tecnología no han sido explotadas en todo su potencial, establecer los índices más adecuados para la detección de deficiencias en los distintos cultivos, o el desarrollo de nuevos índices dirigidos a darnos información sobre nuevos parámetros que resulten interesantes agronómicamente se encuentran actualmente en proceso de investigación.

Dichas investigaciones siguen generando estudios científicos que aportan información útil sobre los cultivos, dicha información permite adquirir un conocimiento preciso acerca del comportamiento de las plantas bajo determinadas condiciones, y de sus respuestas fisiológicas frente a determinados factores. La integración de todos estos conocimientos es la base de lo que se conoce como modelos de simulación de cultivos. La agricultura moderna está haciendo uso de modelos de cultivos / suelo / simulación agua básicamente como herramientas de investigación para analizar y organizar los conocimientos adquiridos en el campo de la experimentación. Sin embargo, hay una necesidad urgente de hacer uso de los modelos también como herramientas para la toma de decisiones y de transferencia de tecnología.

Modelos robustos y calibrados localmente, basados en datos y algoritmos físicos y fisiológicos, pueden ser utilizados para investigar un gran número de estrategias de gestión del agua en una explotación comercial, con la implementación de escenarios climáticos alternativos, ciclos de cultivo y nuevas zonas de cultivo. A pesar de algunas limitaciones y la incertidumbre, el enfoque del modelado de cultivos, permite la cuantificación de la variabilidad espacial y temporal que no sería posible utilizando metodologías tradicionales o que precisarían de muchos años de ensayo. Por lo tanto, el modelado representa una manera eficaz de asimilar diferentes componentes de un sistema de cultivo, análisis de datos, e integrar los datos obtenidos en diferentes experimentos científicos. Los modelos no son simples mecanismos para analizar la información sino instrumentos capaces de integrar las diferentes fuentes de investigación del manejo de cultivos, para ayudar al técnico a proyectar los futuros cultivos, gestionar las mejores zonas para cada tipo de cultivo, estudiar los a efectos de reducción de agua en determinados momentos del ciclo de cultivo y su efecto sobre la calidad y producción esperada, siendo una gran herramienta en la gestión y planificación de las parcela comerciales.

Los cultivos en el campo son afectados por las condiciones meteorológicas, por los factores fisicoquímicos del suelo, por los insectos, por las enfermedades, por las malas hierbas, y por las interacciones entre estos factores. En las décadas pasadas, mucho esfuerzo de investigación ha sido dedicado al desarrollo de modelos de producción de cultivos. Otro grupo de modelos de producción de cultivos ha sido diseñado para optimizar el uso y manejo del agua y del nitrógeno sobre un largo período con datos históricos. Los modelos usados para este propósito se basan en el hecho de que el agua y el nitrógeno estarán disponibles a la escala que recomienden. Estos esfuerzos de optimización pueden sugerir la mejor estrategia a largo plazo, para definir las aplicaciones de agua y nitrógeno (a menudo dependiente de etapa de crecimiento). Los modelos genéricos de cultivos pueden ser aplicados a varias especies mediante la utilización de parámetros específicos para cada cultivo. Algunos de estos modelos son DSSAT, DAISY, SOILN, EPIC, WOFOST, CROPSYST, APSIM, AQUACROP y STICS, otros modelos son específicos de cada cultivo como CERES (Maíz y Trigo). En el caso específico del cultivo del tomate, diferentes modelos de simulación de cultivos se han utilizado en condiciones de campo. Entre ello podemos destacar la Calculadora de Impacto Productividad (EPIC), (Cavero et al., 1998; 1999;. Rinaldi et al, 2001), TOMGRO (Jones et al., 1991; Bertin y Gary, 1993) y CROPGRO (Messina et al,. 2001; Koo., 2002; Ramírez et al., 2004; Rinaldi et al, 2007) son los modelos más citados en la literatura.

Uno de los más novedosos modelos es el modelo AquaCrop es un modelo de la productividad del agua para cultivos desarrollado por la FAO para proporcionar una herramienta de modelado y fácil de usar para una amplia gama de usuarios, desde los agricultores y asesores agrícolas a los gestores del agua y los responsables políticos (Steduto et al., 2009). La estructura del modelo se ha diseñado con el fin de que pueda aplicarse a través de localizaciones diversas, el clima y las estaciones. Para alcanzar esa meta AquaCrop diferencia parámetros (para casos específicos) conservadores (fijo) y no conservadoras. Parámetros conservadores no cambian con la ubicación geográfica, la variedad de cultivos, las prácticas de gestión o el tiempo, y están destinados a ser determinado con los datos de las condiciones limitantes no favorables y, pero siguen siendo aplicables a las condiciones de estrés a través de la modulación de sus funciones de respuesta al estrés. De hecho, se espera que esta estructura simple y un número reducido de parámetros podrían facilitar la calibración del modelo y la utilización para diferentes cultivos y bajo diferentes estrategias de gestión (Steduto et al, 2009; Raes et al, 2009).

El modelo se centra en la disponibilidad de agua de la planta como el factor más limitante del crecimiento de los cultivos, especialmente en las regiones áridas y semiáridas, donde la escasez de agua varía en intensidad, duración y momento de ocurrencia (Hsiao, 1973; Bradford y Hsiao, 1982).

El modelo AquaCrop ha sido evaluado para diferentes cultivos, como el maíz (Hsiao et al, 2009;. Heng et al, 2009;. Stricevic et al, 2011;. Abedinpour et al, 2012; Shrestha et al, 2013), el algodón (Farahani et al, 2009;. García-Vila et al, 2009; Hussein et al, 2011), girasol (Todorovic et al, 2009;. Stricevic et al, 2011), quinoa (Geerts et al. 2009), cebada (Araya et al, 2010; Abrha et al, 2012), la remolacha azucarera (Stricevic et al, 2011), trigo (Andarzian et al, 2011; Manasaḥ et al, 2012; Soddu et al, 2013; Shrestha et al, 2013; Xiangxiang et al, 2013) (Zeleke et al, 2011), tomate (Rinaldi et al., 2011; Katerji et al 2013), el repollo (Wellens et al., 2013), en diferentes lugares de todo el mundo. En muchos de estos estudios, existe la evidencia de que el modelo simula adecuadamente la productividad del agua para cultivos bajo condiciones riego según necesidades hídricas, mientras que tienden a desestimar que en condiciones de estrés hídrico: estas dificultades comprometen el uso del modelo para escenarios de riego deficitario o situaciones de déficit hídricos en momentos puntuales (Evett y Tolk, 2009). La utilidad de un modelo para orientar de forma eficaz las prácticas de cultivo requiere una necesaria fase previa de validación y calibración en caso necesario, para poder hacer uso del mismo con garantías.

OBJETIVOS

El objetivo general de esta tesis es la aplicación de nuevas metodologías para una gestión integral del cultivo de tomate de industria basadas en: modelos matemáticos de simulación , caracterización a gran escala de parcelas y desarrollo de cultivo; que permitan reducir los problemas generados en la heterogeneidad de las grandes parcelas agrícolas y establecer una metodología para la gestión del riego en grandes superficies de cultivo que permitan realizar recomendaciones al técnico para un uso más eficiente del riego en el cultivo del tomate de industria.

Para alcanzar este objetivo fundamental es preciso lograr una serie de objetivos secundarios, todos ellos complementarios entre sí, que son::

- Desarrollo y validación de nuevas metodologías de muestreo masivo para el estudio de la heterogeneidad del suelo, con el objetivo de desarrollar metodologías de zonificación que permitan el manejo de riego especifico de cada zona y adaptación del cultivo a las mismas. El cumplimiento de este objetivo se ha abordado en el siguiente artículo: “A methodology based on apparent electrical conductivity and guided soil samples to improve irrigation zoning". Precision agriculture 2015. DOI 10.1007/s11119-015-9388-7.

- Desarrollo y validación de nuevas metodologías de muestreo masivo para el estudio de la heterogeneidad del cultivo, que permitan desarrollar mapas de predicción de rendimiento para la identificación de las distintas zonas de producción en una parcela comercial. El cumplimiento de este objetivo se ha abordado en el siguiente artículo: "Using apparent electric conductivity and ndvi measurements for yield estimation of processing tomato crop". 2014. Transactions of the ASABE Vol. 57(3): 827-835. DOI 10.13031/trans.57.10456. y "Using NDVI and guided sampling to develop yield prediction maps of processing tomato crop". 2015. Spanish Journal of Agricultural Research, Volume 13, Issue 1. http://dx.doi.org/10.5424/sjar/2015131-6532

- Calibrar y validación del modelo de cultivos Aquacrop para las condiciones locales del cultivo de tomate en las vegas del Guadiana y ajuste de los parámetros en situaciones de estrés hídrico. El cumplimiento de este objetivo se ha abordado en el siguiente artículo: "Simulating processing tomato yield response with the FAO Aquacrop model and a geostatistical analyse based on electric conductivity sensor". Sumitt. Computers and Electronics in Agriculture.

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CAPÍTULO 1. “Using apparent electric conductivity and ndvi measurements for yield estimation of processing tomato crop”

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USING APPARENT ELECTRIC CONDUCTIVITY AND NDVI MEASUREMENTS FOR YIELD ESTIMATION OF PROCESSING TOMATO CROP

R. Fortes, M. H. Prieto, J. M. Terrón, J. Blanco, S. Millán, C. Campillo

ABSTRACT. *The use of predictive yield maps is an important tool for the delineation of within-field management zones. In particular, appropriate placement in the field of organically grown produce, as is the case for the processing tomato crop in this study, will ensure higher crop yield. Accurate estimation of yield can be used to plan the best time for harvesting and transport for industrial processing. Apparent electrical conductivity (EC_a) and vegetation indices based on crop reflectance are two tools that can be used to help attain these objectives. Developments in the use of sensors have enabled massive georeferenced data sampling of these parameters. The aim of this article is to assess the EC_a and normalized difference vegetation index (NDVI) using geostatistical techniques to optimize their use. Principal component analysis was used to evaluate the predictive yield maps developed. EC_a was a reasonably good indicator of crop production potential throughout the plot as a whole, but NDVI was the best indicator, offering a better resolution than EC_a and a reasonable estimation of yield distribution over the extensive tested crop surface area.*

Keywords. *Kriging, Predictive map, Principal component analysis, Yield monitoring.*

Yield monitoring and mapping have given producers a direct method for measuring spatial variability in crop yield. Yield maps have shown high-yielding areas to be as much as 150% higher than low-yielding areas (Kitchen et al., 1999). However, yield maps are confounded by the many potential causes of yield variability (Price et al., 1997), as well as by potential error sources from combined yield sensors (Lamb et al., 1995). When other georeferenced information is available, producers naturally want to access it and know how the various layers of data can be analyzed to help explain yield variability and gain insight into improving production practices (Kitchen et al., 2003). Along with yield mapping, producers have expressed increased interest in characterizing soil and topographic variability. The development of spectral reflectance indices has been extremely useful in this context, with studies suggesting that crop spectral reflectance can be used to assess plant nutrient and pigment status (Goel et al., 2003a; Osborne et al., 2002) as well as monitor plant conditions at various scales (Plant, 2001) and crop biophysical variables (Thenkabail et al., 2000; Goel et al., 2003b).

Numerous interrelated soil and plant parameters can be used to obtain yield maps. For soil characteristics, apparent electrical conductivity (EC_a) has recently been shown to be an effective and rapid indicator of soil variability and soil productivity (Kitchen et al., 1999). Soil EC_a measures the capacity to conduct electrical current through the soil profile. Historically, soil EC_a has been used to evaluate salinity (Rhoades et al., 1976), but recently commercial devices have been developed that rapidly measure soil EC_a for use in management decisions (Siri-Prieto et al., 2006). Studies have shown that soil EC_a reflects texture variability, as sand, silt, and clay content have a relatively low, medium, and high EC_a, respectively (Williams and Hoey, 1987). One of the most important factors influencing EC_a is the total volumetric water content of the soil (Rhoades et al., 1989), and this factor is strongly influenced by the soil texture and bulk density. Other factors that influence soil EC_a include salinity, cation exchange capacity (CEC), and topsoil depth (Sudduth et al., 2001). EC_a has the potential to indirectly estimate the variability of these properties, provided that the contributions of other soil properties affecting EC_a are known or can be estimated. Crop yield is extremely dependent on soil chemical and physical properties, and the effectiveness of EC_a mapping for predicting productivity is dependent on the degree to which these soil properties affect EC_a (Siri-Prieto et al., 2006).

Precision agriculture is an information-intensive agricultural production practice that depends on extensive soil, plant, and yield data on a site-specific basis (Koller and Upadhyaya, 2005). One potential way of acquiring useful soil, plant, and perhaps yield data for use in precision agriculture is through remote sensing (RS). A green plant canopy has spectral characteristics distinguishing it from other

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The authors are **Rafael Fortes**, Agricultural Engineer, **María Henar Prieto**, Agricultural Engineer, **José María Terrón**, Agricultural Engineer, **Jorge Blanco**, Agricultural Engineer, **Sandra Millán**, Agricultural Engineer, and **Carlos Campillo**, Agricultural Engineer, Scientific and Technological Research Center of Extremadura (CICYTEX), Guadajira, Spain. **Corresponding author:** Rafael Fortes, CICYTEX, 06187 Guadajira (Badajoz), Spain; phone: +34-9240-14092; e-mail: rafaelfortesgallego@outlook.com and carlos.campillo@gobex.es.

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materials, such as soil or dry plants (Koller and Upadhyaya, 2005). Numerous studies have investigated the correlation between vegetation characteristics and the remotely sensed reflectance of a canopy (Huete, 1988; Tucker, 1979). There are different types of vegetation indices based on crop reflectance, the most commonly used of which is the normalized difference vegetation index (NDVI), which is given by:

$$\mathrm{NDVI} = \frac{\rho_{\mathrm{NIR}} - \rho_{\mathrm{Red}}}{\rho_{\mathrm{NIR}} + \rho_{\mathrm{Red}}} \tag{1}$$

where ρ_{NIR} is reflectance in the near-infrared (NIR) band (700 to 2500 nm), and ρ_{Red} is reflectance in the red band (600 to 700 nm).

NDVI values are reported to have good correlation with several vegetation parameters. It has been shown that NDVI is a nearly linear indicator of photosynthetic capacity (Sellers, 1985), while other studies have revealed that it is a good indicator of vegetation, crop biomass, and crop health in agricultural applications (Rouse et al., 1973; Tucker, 1979). Gianquinto et al. (2011) studied yield prediction for tomato using different vegetation indices based on crop reflectance. The indices that used green and NIR wavelengths were the best indicators, with high precision in even small variations in yield. Koller and Upadhyaya (2005) used a vegetation index based on plant greenness, which appeared to be reliable for the evaluation of tomato yield.

While these soil and plant parameters are important separately, this study aims to find any possible relationship between them and apply that relationship to the development of predictive yield maps for a processing tomato crop. Predictive yield maps are of great importance to ensure that the crop is harvested at the right time and that production yields are maximized for industrial processing. Measurements from the field have traditionally been gathered as point data, as samples from individual plants, but newly developed devices allow massive data collection to give more weight to predictive yield maps. Spatial analysis methods can be used to interpolate measurements to create a continuous surface map or to describe its spatial pattern. Variograms (also referred to as semivariograms) are a powerful tool in geostatistics that characterize the spatial dependence of data and give the range of spatial correlation within which the values are correlated with each other and beyond which they become independent (Koller and Upadhyaya, 2005). The parameters of the best fitted model for a variogram can be used for kriging (Matheron, 1963; Stein and Corsten, 1991). For data analysis, kriging has been recommended as the best method to interpolate point data since it minimizes error variance using a weighted linear combination of the data (Panagopoulos et al., 2006).

Numerous studies have demonstrated the benefits of geostatistical analysis techniques for agricultural management. For example, kriging has been used to map the density of weeds in winter wheat (Heisel et al., 1996), and geostatistical methods have been used to interpolate data and produce maps of a field representing the spatial variability of all the soil and wheat properties (Stewart et al., 2002). Techniques such as regression-kriging, which involves various combinations of linear regressions and kriging, are useful tools to improve geostatistical analysis in prediction maps. The simplest model is based on a normal regression followed by ordinary kriging with the regression residuals (Odeh et al., 1995), hence the importance of analyzing the robustness of the predictive maps using tools such as principal component analysis (PCA), which is a multivariate technique commonly used for the analysis of several variables simultaneously (Balzarini et al., 2011). With the aid of these maps and empirical modeling techniques, the relationships between wheat and soil factors were determined with an investigation of the spatial variability of crop biomass and determination of whether site-specific management could be applied to a small field by using a variogram (Yamagishi et al., 2003). The objectives of the present study were to describe the possibility of merging different soil and plant parameters to produce reliable predictive yield maps for a processing tomato crop.

Materials and Methods

Study Area

The field research was conducted at the "Los Enviciados" farm (38.953482° N, -7.002723° W) near Badajoz in southwestern Spain. The area of the study site was 16 ha. Figure 1 shows a topographic map of the study field. The climate of this area is characterized by variation in both temperature and precipitation typical of a Mediterranean climate, with mean annual precipitation of less than 500 mm. One of the most important characteristics of the precipitation is its interannual variability. There is a dry season, from June to September, and a wet season, from October to May (80% of the precipitation falls between these months). Summers are hot, with temperatures on occasion higher than 40°C.

Crop Characteristics

The field was transplanted with processing tomato (*Solanum lycopersicum*, variety H9661) in April 2012 with a planting density of 33,333 plants ha^{-1} in single rows, with 30 cm between plants and 1.5 m between beds. Drip irrigation tape was used for the irrigation system with 1 L h^{-1} drippers spaced every 30 cm. The tested area only had an irrigation sector, where the same amount of water was applied in each irrigation event. Crop management involved organic practices with no inorganic nitrogen fertilizer input. Crop evapotranspiration (ET_c) was calculated on a daily basis using: $ET_c = ET_o \times K_c$, where ET_o is the reference crop evapotranspiration rate, which was calculated following the Penman-Monteith method, modified and adapted to local conditions (Baselga, 1996). Climate data were obtained from a weather station located near the experimental area. K_c is the crop coefficient for processing tomato (Allen et al., 1998). A flowmeter was installed at different inlet points to measure the real volume of water applied.

Sampling

EC_a measurements were made in March 2012, before crop transplanting, with a Veris 3100 soil electrical conduc-

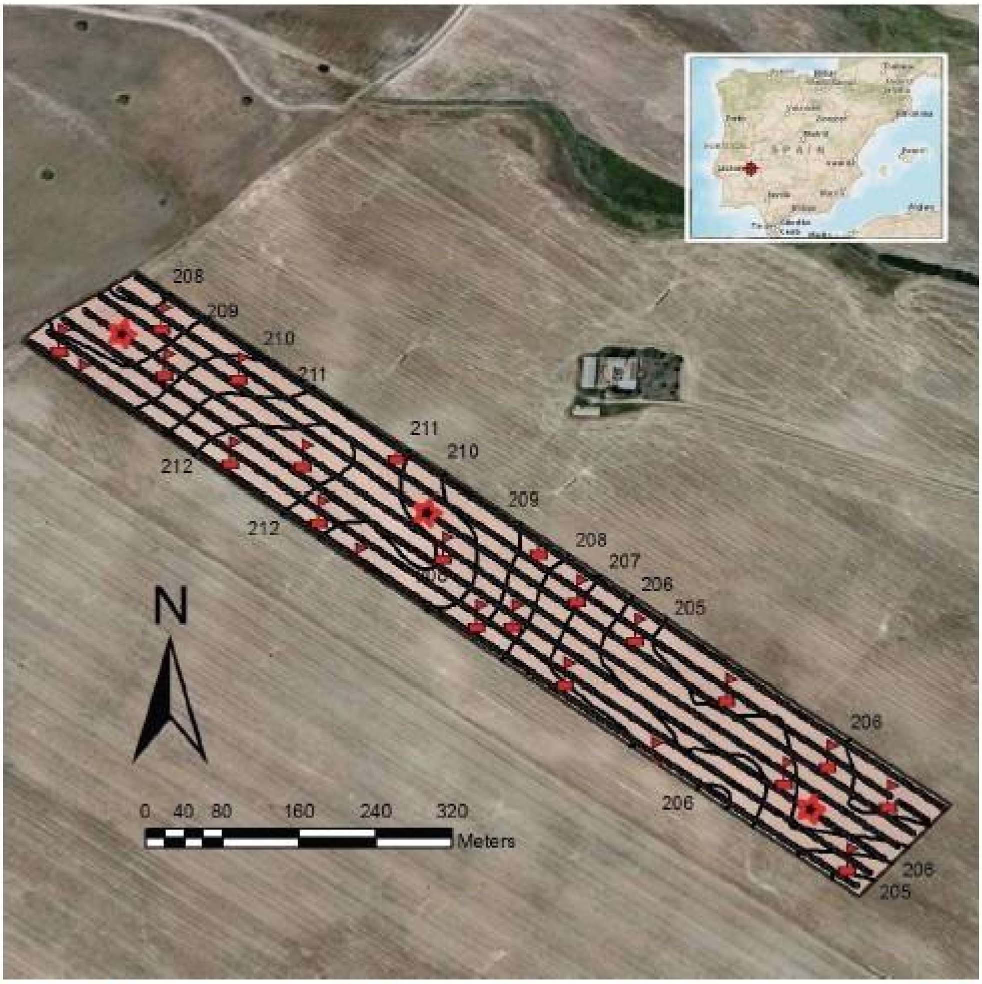

Figure 1. Aerial view of the study site showing soil sampling points (stars), transects of soil EC_a and NDVI measurements (individual points that form lines), and yield sampling points (flags). Topographic contour lines (in meters above soil level) are also shown.

tivity sensor (Veris Technologies, Inc., Salina, Kans.). As the Veris cart was pulled through the field with a tractor, one pair of coulter-electrodes (rotating discs) injected a current into the soil while the other coulter-electrodes measured the voltage drop using a Wenner array. The Veris 3100 generated two sets of data: topsoil data comprising shallow soil EC_a readings from 0 to 30 cm (EC_s) and deep soil EC_a readings from 0 to 90 cm (EC_d). The EC_s readings were used for this study since development of the processing tomato crop root does not extend below 50 cm depth, and the most important activity takes place in the first 30 cm. An ARVAtec monitor (ARVAtec, Milan, Italy) with a Topcon GB500 GPS (Topcon Positioning Systems, Livermore, Cal.) and Javad GDD base (Javad Navigation Systems, San Jose, Cal.) with sub-meter accuracy were used to georeference the EC_a measurements. Thus, latitude, longitude, and shallow and deep EC_a data at 1 s intervals were recorded on the Veris data logger in ASCII text format using Access 2007 (Microsoft Corp., Redmond, Wash.). Later, this raw ASCII file was transferred to other software for further analysis. EC_a measurements were made along different parallel transects, approximately 12 m apart, and the final database contained 2,536 values (individual points that form lines in fig. 1).

NDVI measurements were made in August 2012, ten days before crop harvest, with a Crop Circle ACS-470 reflectance sensor (Holland Scientific, Inc., Lincoln, Neb.) held by a tractor at a height of 80 cm over the canopy and covering an area of 65 cm diameter. The Crop Circle ACS-470 generated reflectance data in the 670 nm (red) and 760 nm (NIR) wavebands, which were combined to obtain the NDVI using equation 1. An ARVAtec monitor with a Topcon GB500 GPS and Javad GDD base with sub-meter accuracy were used to georeference the NDVI measurements. NDVI data at 10 s intervals were recorded on the ACS-470 data logger in ASCII text format using Microsoft Access 2007, taking a sample each 33 cm at 10 km h^{-1} tractor speed. Later, this raw ASCII file was transferred to other software for further analysis. NDVI measurements were made along different parallel transects, approximately 12 m

Table 1. Values of different soil parameters in test plot.

Location	EC_a Range ($mS\ m^{-1}$)	Sand (%)	Silt (%)	Clay (%)	Soil Texture	OM (%)	pH
South	0 to 4	55	22	23	Sandy clay loam	0.8	7.35
Middle	16 to 20	45	18	37	Clay	2.3	7.17
North	12 to 16	33	18	49	Clay loam	1.9	7.03

apart, and the final database contained 17,881 values that form lines in figure 1. These lines coincide with the lines of EC_a measurement, as the tractor covered exactly the same route for the two types of measurement.

Soil samples were taken in three zones (fig. 1), covering the three homogeneous zones described by the EC_a analysis. Soil samples were introduced into plastic bags, air-dried, and analyzed for particle size distribution by gravitational sedimentation using the Robinson pipette method (SCS, 1972), after passing the fine components through a 2 mm sieve. These fine components were also analyzed for pH in 1:2.5 (soil:water) suspension. Organic matter (OM) was determined by dichromate oxidation (Walkley and Black, 1934), and soil texture was determined by mechanical analysis with the hydrometer method (Bouyoucos, 1936). This information is shown in table 1.

Yield sampling was performed at the same time as the crop was harvested. This was done using a single-line mechanical harvester. Each time a sampling area was reached, the harvested tomato was poured into a Pegasus weighing hopper (Dinamica Generale, Poggio Rusco, Italy) to measure the weight of the crop in the sampling area. The harvested zones were measured and georeferenced, with the measurements made along different parallel transects, approximately 50 m long (flags in fig. 1). Calculation of production yield was made using the following equation:

$$\begin{aligned}\text{Production } (\text{T ha}^{-1}) &= \text{T fruit harvested} \\ &\div [\text{Measuring length of harvested sampling area} \\ &\times \text{Crop width of harvested sampling area}] \times 10{,}000\end{aligned} \qquad (2)$$

Table 2 gives a summary of all the data and statistics for the measured variables over the entire plot surface and in three zones where the maps show differences with respect to the parameters studied.

Statistical and Geostatistical Analysis

As stated above, the main objective of the present work was to study the possibility of using different soil and plant parameters to develop predictive yield maps for a processing tomato crop. With this in mind, we first studied the areas from which the yield samples were taken to determine the relationship between yield and plant (NDVI) and between yield and soil (EC_a). A comparison was carried out between the yield obtained in a given transect and the average EC_a and NDVI values measured in that transect. Pearson's correlation matrix and a coefficient of determination between yield and EC_a and NDVI were obtained using SPSS for Windows (version 13, SPSS, Chicago, Ill.). When the extent of the relationship between the parameters was known, a predictive map of yield, NDVI, and EC_a for the entire plot was developed using a simple kriging technique; see Isaaks and Srivastava (1989) and Goovaerts (1997) for a detailed presentation of the kriging algorithms. The predictive maps were developed by the geostatistical interpolation techniques described by Moral et al. (2010) in three phases:

1. An exploratory analysis of the data was performed without considering their geographical distribution. Statistics were applied to check data consistency, remove any existing outliers, and identify the statistical distribution of the data.
2. A structural analysis of the data was developed in which a spatial distribution was made using variograms of each variable (EC_a, NDVI, and yield). The equation of the mathematical model, nugget effect (micro-scale variation or measurement error), sill (variance of the random field), and range (distance at which data are no longer auto-correlated) were studied to develop these variograms.
3. Prediction maps were created using a data search by neighborhood copied from the variograms.

While this kind of map is extremely useful because it gives us information about the entire plot, the problem is to determine the accuracy of such maps. PCA can be an effective tool for this purpose. It is used to transform the data attributes in a multiband raster from the input multivariate attribute space to a new multivariate attribute space whose axes are rotated with respect to the original space. The axes in the new space are uncorrelated. The main reasons for transforming the data in PCA are to compress the data by eliminating redundancy, to emphasize the variance within the bands of a raster, and to make the data more interpretable. The result of a PCA is a multiband raster with the same number of bands as the original raster (one band per axis in the new multivariate space). The first principal component has the greatest variance, the second principal component

Table 2. Descriptive statistics of the sample data in the study areas (n = number of samples and SD = standard deviation).

Parameter		n	Minimum	Maximum	Mean	SD	Skewness	Kurtosis
Total plot	Yield ($t\ ha^{-1}$)	25	42.223	123.314	79.116	20.888	0.079	3.3
	EC_a ($mS\ m^{-1}$)	2,536	1.9	17.7	9.98	4.09	-0.15	1.9
	NDVI	17,881	0.48	0.72	0.61	0.07	-0.55	3.08
Yield ($t\ ha^{-1}$)	South area of plot	8	42.223	95.050	62.651	17.117	0.168	2.01
	Middle area of plot	10	79.021	123.314	93.129	18.831	1.52	3.7
	North area of plot	7	49.011	104.033	83.000	16.894	-0.68	2.75
EC_a ($mS\ m^{-1}$)	South area of plot	1,031	1.9	16.7	7.55	3.46	0.28	2.18
	Middle area of plot	994	2.1	17.3	12.023	3.49	0.6	2.34
	North area of plot	511	2.7	17.7	10.01	3.75	-0.47	2.17
NDVI	South area of plot	6,661	0.48	0.65	0.53	0.071	0.64	2.63
	Middle area of plot	5,617	0.5	0.72	0.62	0.05	0.18	2.25
	North area of plot	5,603	0.48	0.72	0.58	0.08	-0.39	2.56

has the second-greatest variance not described by the first, and so forth. The first three or four rasters of the resulting multiband raster often describe more than 95% of the variance, and the remaining individual raster bands can be dropped. Since the new multiband raster contains fewer bands, and more than 95% of the variance of the original multiband raster is intact, the computations will be faster and the accuracy will be maintained. PCA requires the input bands to be identified, the number of principal components into which to transform the data, the name of the statistics output file, and the name of the output raster. The output raster will contain the same number of bands as the specified number of components, and each band will depict a component. The shifting and rotating of the axes and transformation of the data for this methodology are described by Campbell (1987), Jensen (1986), Lillesand and Kiefer (1987), and Richards (1986). The geostatistical analyses were conducted using the Geostatistical and Spatial Analyst extensions of ArcGIS (version 10.0, ESRI, Inc., Redlands, Cal.). All maps were produced with the ArcMap module of ArcGIS.

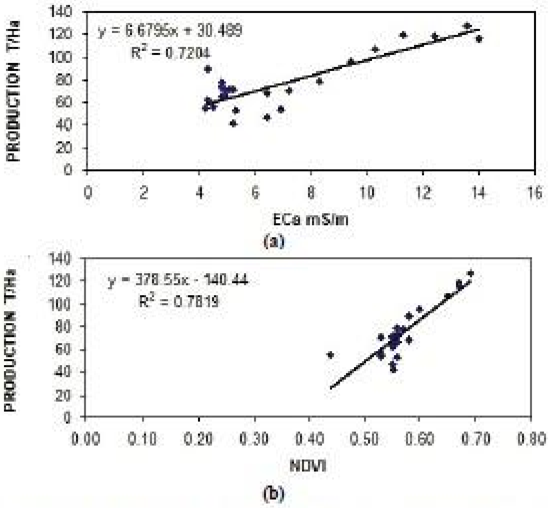

Figure 2. Relationships (a) between yield and apparent electrical conductivity (EC_a) and (b) between yield and NDVI for the selected sample areas. R^2 is the coefficient of determination between factors.

RESULTS AND DISCUSSION

Table 2 shows the summary statistics of the measured variables for the entire plot and for three homogenous areas within the plot. Due to differences in the numbers of measured samples for the different parameters, a general analysis of the entire plot was difficult to undertake. The maps developed using the different parameters showed three differentiable areas in the plot (north, middle, and south). These three areas were separated, and a new statistical analysis was carried out. The highest minimum, maximum, and mean yield values were found for the middle area, perhaps indicating higher variability in more productive areas. The standard deviations showed no apparent differences. The highest EC_a and NDVI values were also obtained in the middle area, and the skewness and kurtosis were also higher, confirming greater data variability. The lowest values of yield, EC_a, and NDVI were obtained in the south area of the plot. Table 3 and figure 2 show the respective relationships between EC_a and yield and between NDVI and yield for the selected sample areas. It can be seen that there is a better correlation between NDVI and yield (R^2 = 0.81 and R = 0.83, $p < 0.01$) than between EC_a and yield (R^2 = 0.72 and R = 0.74, $p < 0.01$).

NDVI measures real plant status, while EC_a is related to some soil properties that may help to explain potential plant status but that also depend on other parameters that are difficult to estimate. This might explain the better results obtained with the plant-based index than with the soil-based index. NDVI is an indicator that can be related with different physiological processes essential to achieve a good yield. For example, nitrogen concentration in green vegetation and chlorophyll content are strictly related (Vouillot et al., 1998), as they are crucial for one of the basic plant physiological processes and therefore promote a greater yield of the plant. Gianquinto et al. (2011) confirmed good correlations between many of the calculated reflectance indices (including NDVI), chlorophyll concentration, nitrogen status, and yield in a tomato crop. They found high coefficients of determination between NIR/R560 and predicted yield, and also obtained good results using NDVI and NDVI-G (NIR-560/NIR+560), which agreed with the results of Elwadie et al. (2005), who analyzed the ability to predict yield using NIR/R560, NDVI, and NDVI-G in corn. Similar results were obtained by Ma et al. (2001), with high performance of the NDVI index for yield prediction in corn. High values of NDVI suggested higher yield, and vice versa. This relationship between yield and NDVI was studied, with maximum NDVI values of 0.70 corresponding to maximum crop yield values. The samples were taken at the end of the crop cycle, when NDVI values fall as a result of crop senescence, with less canopy cover and an increase in fruit producing a decrease in reflectance. However, the influence of red tomatoes around the green plants was low, as the most productive plants also had the greatest canopy cover and highest chlorophyll concentration, which is reflected in higher NDVI values.

EC_a also seems to be a good indicator of potential crop yield, especially when used with organic practices with no inorganic nitrogen fertilizer input, where the soil plays an essential role, as in our case. In this work, the areas with the highest EC_a values were also the most productive. Figure 2a shows how yield decreased with EC_a. Soil samples (table 1 and fig. 1) were taken from the three homogeneous areas described by the EC_a map (fig. 3). Areas with higher EC_a values have higher organic matter (OM) values and correspond to clay soil, whereas soils with lower EC_a val-

Table 3. Pearson's correlation matrix between all measured variables. All values are significant at $p < 0.01$.

	Yield	NDVI	EC_a
Yield	1	-	-
NDVI	0.83	1	-
EC_a	0.74	0.61	1

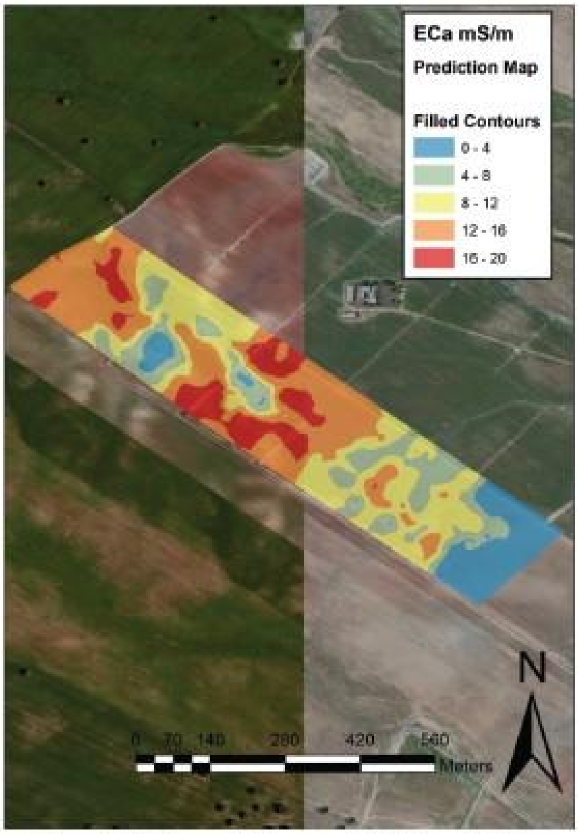

Figure 3. Kriged map of soil apparent electrical conductivity.

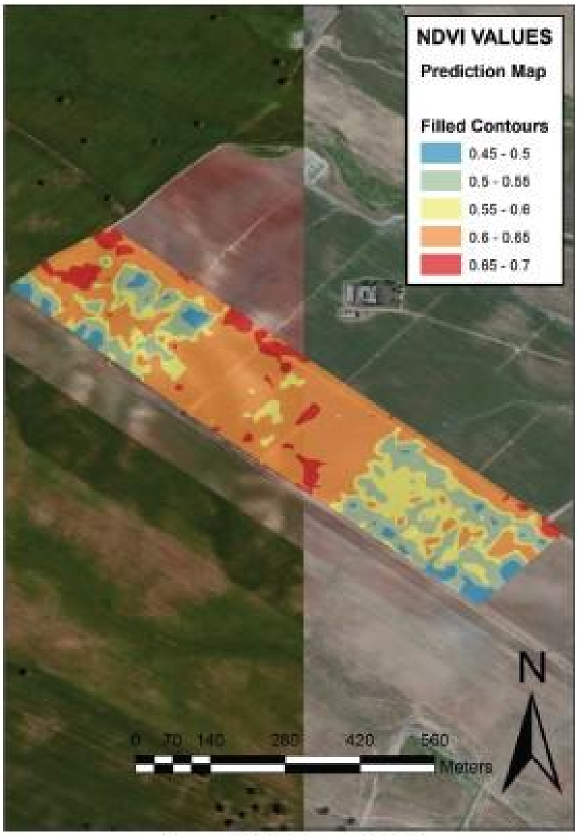

Figure 4. Kriged map of NDVI.

ues have lower OM values and are more sandy in nature. Moral et al. (2010) found no significant correlations between EC_a and OM, a close positive correlation between EC_a and clay content (which was expected since EC_a is mainly controlled by ions near soil constituents with a high surface area), and a close correlation between EC_a and sand content due to autocorrelation with clay content. Similar relationships between EC_a and these soil texture fractions have been reported elsewhere (Morari et al., 2009; Vitharana et al., 2008). In our case, clay soil can enhance water availability for the plants, maintaining better plant water status and improving the final yield. Kitchen et al. (2005) investigated whether productivity zones could be delineated using EC_a and elevation measurements. A comparison of ground truth and hypothetical productivity zones using an overall accuracy statistic and the kappa coefficient revealed a 60% to 70% agreement when combined EC_a and elevation data were used. Productivity zones were also addressed by Jaynes et al. (2005), who based the delineation of productivity zones on a series of profiling steps in conjunction with cluster analysis to determine the relationship between yield clusters and easily measured field properties of elevation, simple terrain attribute data, and EC_a. Kaffka et al. (2005) demonstrated the utility of EC_a measurements to establish the relationship between soil properties and sugar beet crop yield. In terms of the plot as a whole, geostatistical analysis is the key to obtaining the right information from prediction maps.

Figures 3, 4, and 5 show the EC_a, NDVI, and yield prediction maps, respectively. The maps show three different areas: a southern area where low yield values coincide with low NDVI and EC_a values, a central area with higher yield and higher EC_a and NDVI values, and finally an area in the north of the plot with intermediate values of the three parameters. The level of resolution differs between the three measured parameters, especially in the case of yield, where the number of data was lower than for the other parameters. The choice of the particular variogram model depends on the expected spatial variability. Variables like soil or plants can be distributed unevenly at reduced distances, and exponential or spherical models are the most suitable. Spherical mathematical models were used to develop the variograms in this work, as the mean and median values were very similar, which is indicative of data from a normal distribution.

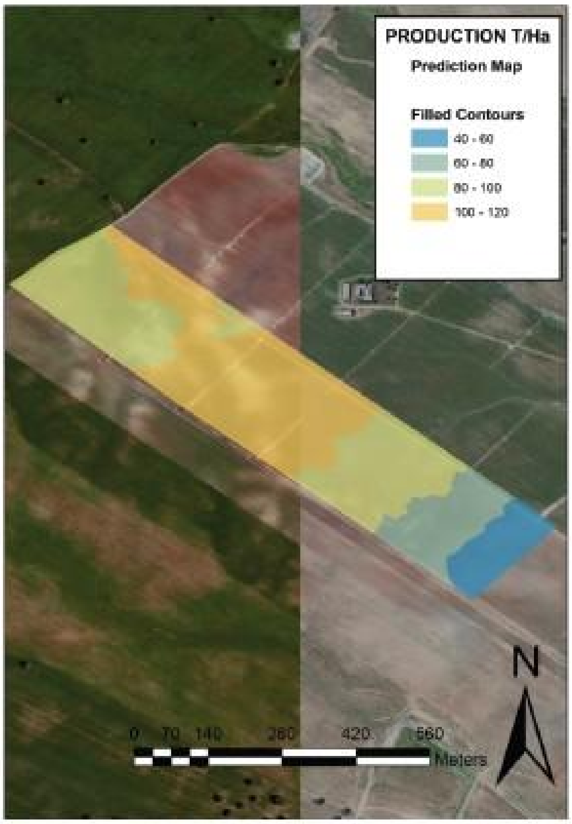

Figure 5. Kriged map of yield.

The variograms showed a considerable nugget effect (fig. 6); this is a normal situation because the variability of soil and plant properties can occur at a scale smaller than the minimum lag distance. Table 4 shows the theoretical spherical variograms fitted to the experimental variograms for the residuals. NDVI shows the highest nugget-sill ratio of 70.07%, which suggests a moderate spatial autocorrelation, while EC_a and yield show lower nugget-sill ratios of 13.67% and 2.05% respectively, indicating that spatial dependence was generally strong. According to Cambardella et al. (1994), the nugget-sill ratio can be used to denote the spatial dependence of attributes: a ratio of <25% indicates strong spatial dependence, a ratio between 25% and 75% indicates moderate spatial dependence, and a ratio of >75% indicates weak spatial dependence. Table 5 shows that NDVI was a better index for yield prediction (R = 0.72) than EC_a (R = 0.63). Similar results were obtained when applying geostatistical analysis like kriging to the entire plot. Although the level of resolution was lower than when analyzing the selected areas individually, the same tendency was observed in the three prediction maps, with the NDVI prediction map being most closely related to yield and the EC_a prediction map revealing a good but slightly lower relationship with yield.

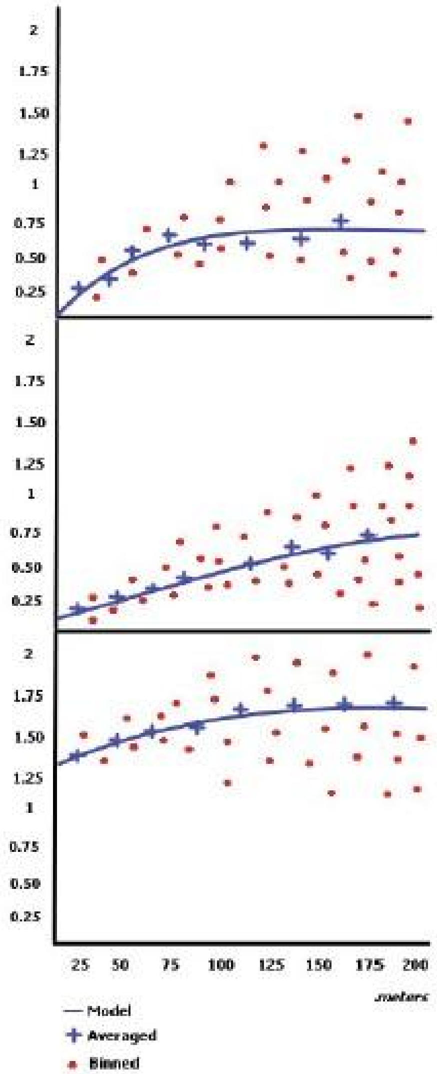

Figure 6. Experimental variograms (points), theoretical spherical variograms (lines), and average values (crosses) for (top to bottom) yield, EC_a, and NDVI.

Table 4. Theoretical spherical variograms fitted to experimental variograms for the residuals.

Variable	Nugget	Sill	Nugget-Sill Ratio (%)	Range (m)
EC_a	0.289	2.113	13.67	158
NDVI	1.245	1.759	70.07	113
Yield	0.013	0.632	2.05	101

Table 5. Correlation matrix between the ordinary kriging prediction maps for yield, NDVI, and EC_a.

	Prediction Map Yield	Prediction Map NDVI	Prediction Map EC_a
Prediction map yield	1	-	-
Prediction map NDVI	0.72	1	-
Prediction map EC_a	0.63	0.52	1

CONCLUSIONS

NDVI is a good estimator for predicting the yield of a processing tomato crop. This direct plant measurement is more accurate than other indirect measurements such as EC_a, a soil parameter that also gave good results. The advantage of these measurements is the possibility of taking mass georeferenced samples, which enables the development of prediction maps for large plots using geostatistical analysis with sufficient resolution to produce helpful information about crop management. It can therefore be concluded that this methodology is very useful for assessing potential crop yield and is a good estimator when planning crop harvesting.

This kind of study is very important for organically grown crops, as in the case for the processing tomato crop in this study, where the principal factor for high yield depends fundamentally on soil productivity, as opposed to other parameters, due to restrictions on the use of fertilizers and pesticides.

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CAPÍTULO 2. "A methodology based on apparent electrical conductivity and guided soil samples to improve irrigation zoning"

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A methodology based on apparent electrical conductivity and guided soil samples to improve irrigation zoning

R. Fortes · S. Millán · M. H. Prieto · C. Campillo

Abstract The spatial variability of soils is one of the main problems faced when planning irrigation management, especially when large tracts of agricultural land are involved. Parameters such as soil texture or soil water content are fundamental for understanding the determining factors of a soil with respect to water. Available water capacity (AWC) is a vital indicator when considering soil properties from the point of view of irrigation management. An analysis was made in this study of the relationship between the apparent electrical conductivity (ECa), a parameter which can be determined through intensive data sampling, and AWC. After demonstrating the relationship, a geostatistical methodology was used to develop efficient predictive maps for soil characterisation from the point of view of irrigation with the help of guided soil sampling based on the ECa. Ordinary and regression kriging models were used to generate predictive maps of AWC. When the maps
Abstract The spatial variability of soils is one of the main problems faced when planning irrigation management, especially when large tracts of agricultural land are involved. Parameters such as soil texture or soil water content are fundamental for understanding the determining factors of a soil with respect to water. Available water capacity (AWC) is a vital indicator when considering soil properties from the point of view of irrigation management. An analysis was made in this study of the relationship between the apparent electrical conductivity (ECa), a parameter which can be determined through intensive data sampling, and AWC. After demonstrating the relationship, a geostatistical methodology was used to develop efficient predictive maps for soil characterisation from the point of view of irrigation with the help of guided soil sampling based on the ECa. Ordinary and regression kriging models were used to generate predictive maps of AWC. When the maps
were statistically evaluated, those generated using a regression kriging approach were found to be more robust, though the resolution of the maps generated through ordinary kriging was acceptable. This information is of interest when considering the design of more efficient irrigation systems.

Keywords Predictive map · Ordinary kriging · Regression kriging · Available water capacity · Precision irrigation

Introduction

The spatial variability of soils is one of the most important problems that need to be dealt with when managing large tracts of agricultural land. This is particularly true for the

R. Fortes (✉) · S. Millán · M. H. Prieto · C. Campillo
Consejería de Empleo, Empresa e Innovación Gobierno de Extremadura, Centro de Investigaciones Científicas y Tecnológicas de Extremadura (CICYTEX), 06187 Guadajira, Badajoz, Spain
e-mail: rafaelfortesgallego@outlook.com

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question of irrigation management, where knowing the characteristics of the soil is the key to accurate calculation of the amount of water that the crop will need.

From the point of view of irrigation management, it is vital to know the soil texture as this is one of the key parameters that need to be taken into account when calculating crop water needs (Hedley 2008). The total amount of water a soil can supply to a crop is usually measured by the volume that it can hold between field capacity and wilting point, which can be assessed in the field (Hedley et al. 2005). Soil water status is the amount of this total available water that is available to a crop on any 1 day; and is commonly expressed as mm water per mm rooting depth in soil. However, the spatial variability of this status, as indeed is the case for many soil properties, will vary across the landscape, a fact largely ignored before the 1980s (Cook and Bramley 1998). When dealing with large tracts of agricultural land, it is common to find very different types of soil. This raises the question of whether the irrigation system being used has been adequately designed to adapt to differences that are often difficult to define. Unless the problem of the spatial variability of soils is taken into consideration, an irrigation design may not be efficient. Tools to solve this problem need to be developed and precision agriculture may be able to provide a possible solution. One of the aims of precision agriculture is to use in-field zoning in order to enable the establishment of different management strategies. Many authors have attempted to relate different types of soil with the spatial distribution of different soil attributes using digital elevation models (McBratney et al. 2003), while others have related apparent electrical conductivity (ECa) to different topographical variables (Kühn et al. 2009). The ECa parameter has been used in many studies as an important secondary variable when performing this type of in-field zoning (Moral et al. 2010; Fulton et al. 2011; Serrano et al. 2014). Geospatial measurement of ECa is an efficient ground-based sensing technology that is helping to bring site-specific crop management from a concept to a reality (Corwin and Lesch 2003). ECa can be intensively recorded in an easy and inexpensive way, and it is usually related to various soil physico-chemical properties across a wide range of soils (Sudduth et al. 2005). ECa can therefore be used to improve the estimation of soil variables, when they are spatially correlated (Moral et al. 2010). Moral et al. (2010) found a high positive correlation between ECa and clay content. This was expected since ECa is mainly controlled by ions near soil constituents with a high surface area. This fact allows ECa to be used as a guided soil sampling tool, and as a secondary variable to improve the principal variable. A spatial analysis method can be used to manage all this information. Spatial analysis methods can be used to interpolate measurements in order to create a continuous surface map or to describe the spatial pattern. Numerous studies have shown the benefits of spatial analysis techniques in agricultural management (Stewart et al. 2002). The present study is based on the work developed by Moral et al. (2010), in which a high positive correlation between ECa and textural typology was shown and successful results were obtained using ECa data as an auxiliary variable in the regression kriging technique to estimate soil texture in large tracts of agricultural land. The main parameter studied in this work was the available water capacity (AWC), which is directly related to soil texture in the first 300 mm of depth which is where the most important activity takes place with horticulture crops. AWC is the amount of water that can be stored in soil and be available for growing crops. The methodology described by Moral et al. (2010) was tested and developed in three commercial plots with large surface areas (40, 80 and 120 ha) used for horticultural crops.

Materials and methods

Study area

The field research was conducted in three farms with no salinity problems, "Los Enviciados" (38°.953482–7°.002723), "Alcazaba" (38°.962065–6°.707918) and "BuenaVista" (38°.937571–6°.719712)., with a study area of 120, 40 and 80 ha, respectively. All the farms are situated in the proximity of Badajoz (southwest Spain). The climate of this area is characterized by variation in both temperature and precipitation typical of a Mediterranean climate, with mean annual precipitation of less than 500 mm. One of the most important characteristics of the precipitation is its inter-annual variability. There is a dry season, from June to September and a wet season from October to May (80 % of the precipitation falls in these months). Summers are hot, with temperatures on occasions higher than 40 °C.

Sampling

The ECa survey was conducted in March 2011, with a 3100 Veris soil electrical conductivity sensor (Veris Technologies Inc., Salina, KS, USA). As the Veris cart is pulled through the field by a tractor, one pair of coulter-electrodes (rotating discs) injects a current into the soil while the other coulter-electrodes measure the voltage drop using a Wenner array. Veris 3100 generates two sets of data: topsoil data comprising shallow soil ECa from 0 to 0.30 m and deep soil ECa from 0 to 0.9 m. The first type were used for this study, since the root development of the horticultural crops that are typically grown in these areas does not extend beyond a depth of 0.5 m and the most important activity takes place in the first 0.3 m. An ARVATEC monitor with a Topcon HiPer Pro-GPS (Topcon Corporation, Tokyo, Japan) and Maxor-GGDT (Javad Navigation System, San José, CA, USA) base with sub-meter accuracy was used to georeference the ECa measurements. Latitude and longitude and shallow and deep ECa data were recorded at 1 s intervals on the Veris data logger in an ASCII text format. Later, this raw ASCII file was transferred to other software

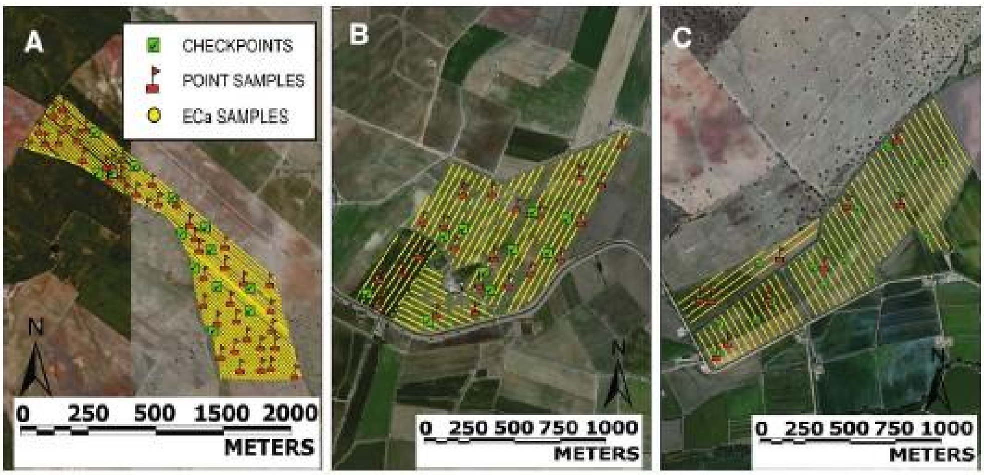

Fig. 1 Study sites at three locations, **a** Enviciados, **b** Buenavista and **c** Alcazaba. Soil sampling points (*red flag*), check points (*green flags*) and ECa samples (*yellow dots* that appear as *lines*) (Color figure online)

for further analysis. ECa measurements were made along different parallel transects which were spaced approximately 20 m apart and with 4 m between each measurement point. Different parallel transects and with different distances were tested in a representative area (10 ha). Variogram information emphasizing nugget effect, sill and range was studied and the correct densities to obtain a correct resolution were estimated. Resolution of the prediction map with the data obtained was evaluated from the spherical variograms. Ordinary kriging was used to develop an ECa map for the three plots. These maps were used for guided soil sampling of soil properties, taking into consideration a good sample distribution over the different plot areas and trying to cover the different ECa ranges. Soil samples were taken covering homogeneous zones described by the ECa prediction maps for use in the methodology (red flag in Fig. 1), other samples were taken manuallyover the field in a more or less even density to evaluate the methodology (green flag in Fig. 1). The soil samples were placed in plastic bags, air-dried and analysed for particle-size distribution by gravitational sedimentation using the Robinson pipette method (Soil Conservation Service 1972) after passing the fine components through a 0.02 m sieve. These fine components were also analysed for pH in 1:2.5 (soil:water) suspension, organic matter (OM) was determined by dichromate oxidation (Walkley and Black 1934), and soil texture was determined by mechanical analysis using the hydrometer method (Bouyoucos 1936). Calculation of AWC was made using the following equation:

$$\text{AWC} = \text{field capacity (FC)} - \text{permanent wilting point (PWP)} \quad (1)$$

The equations of Saxton et al. (1986) were used to calculate FC and the PWP values of each type of soil.

Statistical and geostatistical analysis

Firstly, a predictive ECa map for each entire plot was developed using the ordinary kriging technique (see Isaaks and Srivastava (1989) and Goovaerts (1997) for a detailed presentation of the kriging algorithms). The predictive maps were developed in three phases using the geostatistical interpolation techniques described by Moral et al. (2010): (i) An exploratory analysis of the data in which the data were studied without considering their

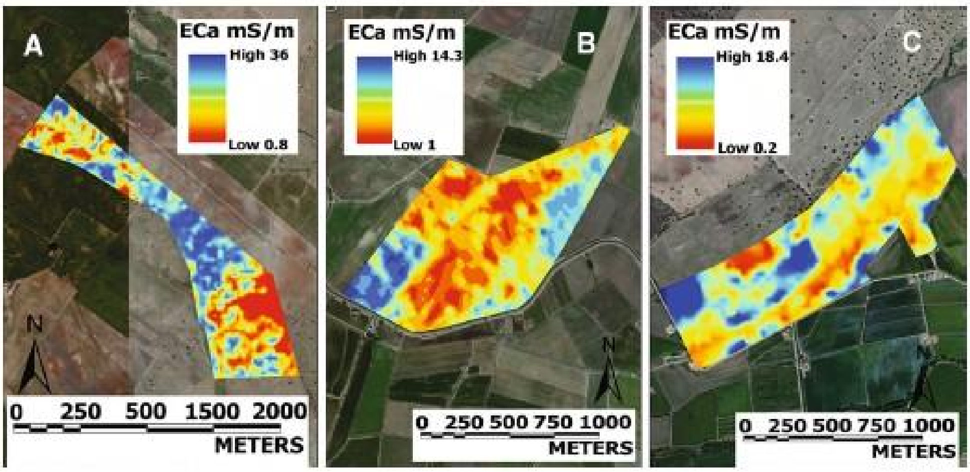

Fig. 2 ECa prediction map at three locations, **a** Enviciados, **b** Buenavista and **c** Alcazaba

geographical distribution and in which statistics were applied to check data consistency, removing any existing outliers and identifying the statistical distribution; (ii) development of a structural analysis of the data, in which a spatial distribution was analysed using variograms of the ECa variable: the equation of the mathematical model, the nugget effect (micro-scale variation or measurement error), sill (variance of the random field) and range (distance at which data are no longer auto-correlated) were studied to develop these variograms; (iii) the prediction maps were developed using a data search by neighbourhood copied from the variogram. The ECa prediction maps were used for guided soil sampling (Fig. 2). The areas were then studied from which the soil samples were taken in order to determine the relationship between ECa, AWC and other soil properties. A comparison was made between the ECa obtained at certain measured points and the AWC and soil properties values measured at the same points, and a Pearson's correlation matrix and coefficient of determination between AWC, soil properties and ECa were obtained using SPSS v.13 Windows Package (SPSS, Chicago, IL, USA). When the extent of the relationship between the parameters was known, a predictive map of AWC (Fig. 3) for each entire plot was developed using the simple kriging technique described above. Regression kriging technique was then used to develop a final AWC prediction map (Fig. 4). Predictions were made separately for the trend and residuals and then added back together. So, any parameter at a new unsampled point, x, could be estimated, Z*RK(x), using regression kriging as follows:

$$Z^*RK(x) = m(x) + r(x) \tag{2}$$

Where the trend, m(x), is fitted using linear regression analysis and the residuals, r(x), are estimated using the ordinary kriging algorithm. If cj are the coefficients of the estimated trend model, vj(x) is the jth predictor at location x, p is the number of predictors and wi(x) are the weights determined by solving the ordinary kriging system of the regression residuals, r(xi), for the n sample points, then the prediction is made by:

$$Z^*RK(x) = \Sigma pj = 0cj\ vj(x) + \Sigma ni = 1wi(x)\ r\ (xi) \tag{3}$$

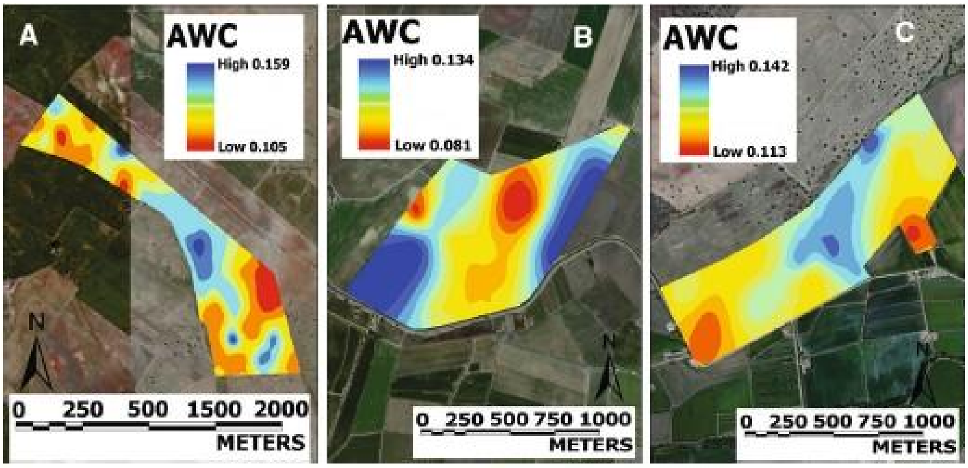

Fig. 3 AWC Ordinary Kriging at three locations, **a** Enviciados, **b** Buenavista and **c** Alcazaba

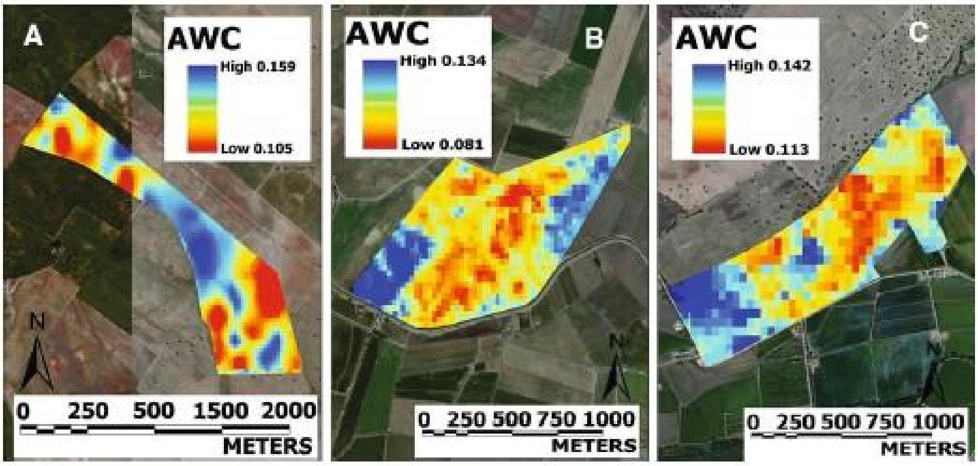

Fig. 4 AWC Regression Kriging at three locations, **a** Enviciados, **b** Buenavista and **c** Alcazaba

$$V(x) = 1$$

In this case study, only one predictor is used, ECa, so m(x) = a + b•(ECa(x)). In consequence:

$$Z^*RK(x) = a + b\ ECa(x) + \Sigma ni = 1wi(x)\ r\ (xi) \quad (4)$$

The residual at each sampling point, r (xi), is calculated as the difference between the value of the parameter and the estimate by the trend (r (xi) = Z (xi)− m (xi)).

Table 1 Descriptive statistics of the sample data in the study areas; n, number of samples, SD, standard deviation

Parameter	Location	n	Min	Max	Mean	Median	SD	Skewness	Kurtosis
ECa (mS/m)	Enviciados	16 596	0.8	36	12.3	11.8	8.4	0.46	2.3
ECa (mS/m)	Buenavista	10 292	1	14.3	6.3	5.8	3.4	0.4	2.14
ECa (mS/m)	Alcazaba	6 236	0.2	18.4	7.5	7	3.6	0.67	2.9
Sand (%)	Enviciados	44	29.5	72.5	53	52	11.2	−0.03	2.1
Sand (%)	Buenavista	21	29.6	83.4	60.8	69	17.18	−0.54	1.7
Sand (%)	Alcazaba	17	37.5	64.2	50.8	48	8	0.22	1.9
Clay (%)	Enviciados	44	13	43	28	27.4	8.7	0.16	1.9
Clay (%)	Buenavista	21	6	54	25	18	17	0.57	1.6
Clay (%)	Alcazaba	17	14.5	38	25	23	8	0.24	1.6
OM (%)	Enviciados	44	0.5	2.3	1.2	1.4	7.2	0.12	1.6
OM (%)	Buenavista	21	0.6	2.1	1.2	1.3	5.3	0.14	1.2
OM (%)	Alcazaba	17	0.6	2.4	1.3	1.4	4.2	0.16	1.4
AWC	Enviciados	44	0.105	0.159	0.136	0.143	1.5	−0.44	2
AWC	Buenavista	21	0.081	0.134	0.109	0.103	1.8	0.18	1.5
AWC	Alcazaba	17	0.113	0.142	0.131	0.133	0.9	−0.67	2.2

The geostatistical analyses were conducted using the geostatistical and spatial analyst extensions of the GIS software ArcGIS (version 10.0, ESRI Inc., Redlands, CA, USA). All maps were produced with the ArcMap module of ArcGIS.

Finally, a comparison was made between the AWC obtained at the measured validation points and the AWC values measured on the prediction maps (ordinary kriging and regression kriging). To assess the accuracy of the maps in predicting AWC, the statistical procedure proposed by Loague and Green (1991), consisting of the best fit of the predictions, was adopted. This procedure is based on the relative root mean square error (RRMSE), calculated from the following equation:

$$\mathrm{RRMSE} = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}} \cdot \frac{100}{\tilde{O}} \tag{5}$$

where n is the number of observations, Pi is the value predicted, Oi is the measured value, and Õ is the mean of the measured values. The validation is considered to be excellent when the RRMSE is <10 %, good if the RRMSE is between 10 and 20 %, acceptable if the RRMSE is between 20 and 30 %, and poor if it is >30 % (Jamieson et al. 1991).

Results and discussion

Table 1 shows an exploratory analysis of the data distribution described using classical descriptive statistics. From the point of view of the number of samples, there is a notable difference between the amount of ECa data compared to that of the other parameters. The mean and median values were very similar which was indicative of data coming from a normal distribution.

Although normality is not a prerequisite for kriging, it is a desirable property. Kriging will only generate the best absolute estimate if the random function fits a normal distribution (Goovaerts 1997). This was ratified by the fact that low skewness values were obtained. Furthermore, most of the coefficients of kurtosis were close to two. Similar results were obtained by Moral et al. (2010) for soil properties in the same parameters.

In this study, only the parameters directly related to soil water characteristics were studied. A correlation matrix between soil properties in the study areas was developed (Tables 2, 3, 4). It was necessary to study the three plots separately as the soil conditions when taking the ECa samples may have been different.

Though ECa showed a trend in different possible soil properties, the exact soil characteristics at a particular moment will have to be discovered by analysis of the soil itself; the ECa values will change over time influenced by weather conditions, but the trend will be the same. The coefficients of correlation between variables with respect to ECa were positively correlated with clay (0.71, 0.74 and 0.70) and AWC (0.70, 0.68 and 0.67) in the

Table 2 Correlation matrix between soil properties in Enviciados

Parameter	Eca	Sand	Clay	OM	AWC
ECa	1				
Sand	−0.68	1			
Clay	0.71	−0.79	1		
OM	0.06	−0.03	0.03	1	
AWC	0.7	−0.67	0.69	0.16	1

Table 3 Correlation matrix between soil properties in Buenavista

Parameter	Eca	Sand	Clay	OM	AWC
ECa	1				
Sand	−0.66	1			
Clay	0.74	−0.76	1		
OM	0.04	−0.02	0.04	1	
AWC	0.68	−0.69	0.71	0.17	1

Table 4 Correlation matrix between soil properties in Alcazaba

Parameter	Eca	Sand	Clay	OM	AWC
ECa	1				
Sand	−0.71	1			
Clay	0.7	−0.73	1		
OM	0.02	−0.02	0.05	1	
AWC	0.67	−0.73	0.74	0.21	1

three locations, and negatively with sand (−0.68, −0.66 and −0.71). Serrano et al. (2014) found a significant correlation between the ECa measured by the Veris sensor in clay, silt and sand (negative) on a pasture field. Similar results were obtained by Hedley and Yule (2009); they used ECa measurements using an ordinary kriging geostatistical analysis to relate AWC (0.76) and FC (0.77).

In this case, regression equations were available to predict the soil AWC and FC for each soil ECa value, due to the relationship of soil ECa to soil water holding properties, reflecting the major influence of soil texture and moisture on soil Eca (Hedley et al. 2004; Sudduth et al. 2005).

In another study (Hedley et al. 2004), significant differences were obtained in the soil waterholding characteristics of each ECa-defined zone that could therefore be used as an irrigation management zone on the basis of its soil water holding properties. In that study, the high, medium and low soil ECa management zones reflect decreasing or increasing AWC. In the study developed by Hezarjaribi and Sourell (2007), sensor-based measurements of ECa using VERIS 3100 at field capacity and in the non-saline conditions of fields in the current study could provide important information on within-field variation of the AWC in an upper shallow soil profile; There was a good correlation between ECa readings by VERIS 3100_sh and volume per cent of soil field capacity.

In this study, the regression equations were used in the geostatistical analyst to improve the predictive maps. Other relationships between ECa and these soil texture fractions have been reported elsewhere (Moral et al. 2010; Morari et al. 2009; Vitharana et al. 2008).

Table 8 shows these linear regression correlations in the study site. No significant correlations were found between ECa and OM, with the same result obtained by Moral et al. (2010). The correlation between AWC and OM was low, but higher with respect to ECa, since OM is used to calculate AWC. From the point of view of the total surface area of the plot, geostatistical analysis is the key to obtaining the right information from prediction maps. The choice of the particular variogram model is dependent upon the expected spatial variability. Variables, like soil, can be distributed unevenly in reduced distances and exponential or spherical models are the most suitable. Spherical mathematical models were used to develop the variograms in this work, as the mean and median values are very similar, which is indicative of data coming from a normal distribution.

In this work, the variograms showed a considerable nugget effect (Figs. 5, 6). This is a normal situation because the variability of soil properties can occur at a scale smaller than the minimum lag distance. Table 5 shows the theoretical spherical variograms (models that provided the best fit for all cases) fitted to experimental variograms for the residual data for different parameters and locations. AWC showed the highest sill-nugget ratio (around 70 % in the three locations), which suggests moderate spatial autocorrelation. ECa showed the lowest values for the sill-nugget ratio (24, 35 and 22 %), indicating that spatial dependence was generally strong. According to Cambardella et al. (1994), the nugget-to-sill ratio can be used to denote the spatial dependence of attributes (ratio <25 % indicates strong spatial dependence; between 25 and 75 % denotes moderate spatial dependence and greater than 75 % indicates weak spatial dependence). The range, the maximum distance of spatial dependence, varied from 122 to 174 m. It was very similar for the three soil variables.

The parameters of the best fitting model for a variogram can be used for kriging (Matheron 1963; Stein and Corsten 1991). From the point of view of data analysis, kriging has been recommended as the best method to interpolate point data since it minimizes error variance using a weighted linear combination of the data (Panagopoulos et al. 2006). The

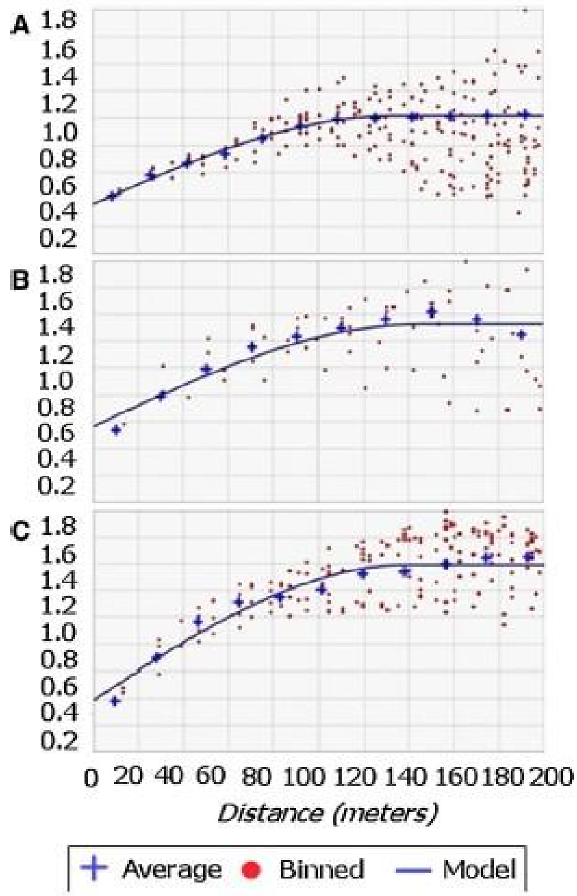

Fig. 5 Experimental variograms (*points*), theoretical spherical variograms (*lines*) and average (*cross*) for ECa at Enviciados (**a**), Buenavista (**b**) and Alcazaba (**c**)

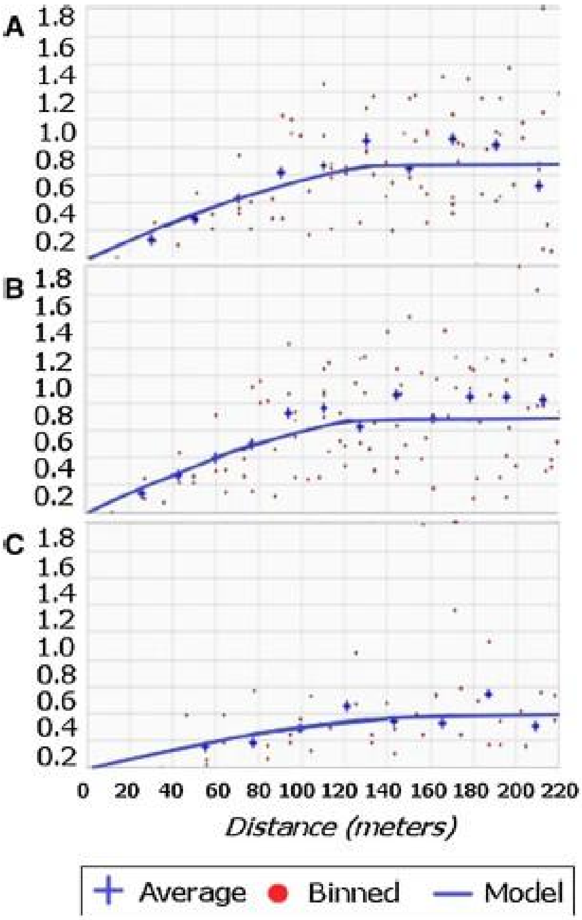

Fig. 6 Experimental variograms (*points*), theoretical spherical variograms (*lines*) and average (*cross*) for AWC at Enviciados (**a**), Buenavista (**b**) and Alcazaba (**c**)

Table 5 Theoretical spherical variograms fitted to experimental variograms for the residuals data

Variable	Location	Ratio nugget–sill (%)	Range (m)
ECa	Enviciados	24	122
ECa	Buenavista	35	146
ECa	Alcazaba	22	134
AWC	Enviciados	72	147
AWC	Buenavista	71	151
AWC	Alcazaba	74	174

Table 6 Linear relationships (Y = aX + b) between ECa (X) and WAC (Y)

Y	a	b	R^2
AWC Enviciados	0.0015	0.117	68
AWC Buenavista	0.0039	0.0864	58
AWC Alcazaba	0.0016	0.1183	67

methodology proposed by Moral et al. (2010) to develop regression kriging was followed. In that study, regression kriging was chosen as the optimum interpolation algorithm for the soil texture variables and ECa was used as the independent variable because it showed higher correlations with textural soil data. In the current case, the textural data was replaced with AWC, which also had a good correlation with ECa. This was expected since soil textural data are used for AWC calculation. To develop the proposed regression kriging methodology, the best linear relationship for each location had to be defined (Table 6; Fig. 7).

After developing the AWC prediction maps with both geostatistical analysis models (ordinary and regression kriging), RRMSE was used to measure the resolutions. Table 7 shows this analysis, with the best results obtained with the maps developed by regression kriging with values of 11, 13 and 15 % in the three locations (good between 10 and 20 % according to Jamieson et al. 1991). The values obtained by ordinary kriging were acceptable, 24, 29 and 33 % in the three locations (acceptable between 20 and 30 % according to Jamieson et al. 1991). These results show that the use of an intensive sampling parameter such as ECa is a good indicator of where different kinds of soil are located.

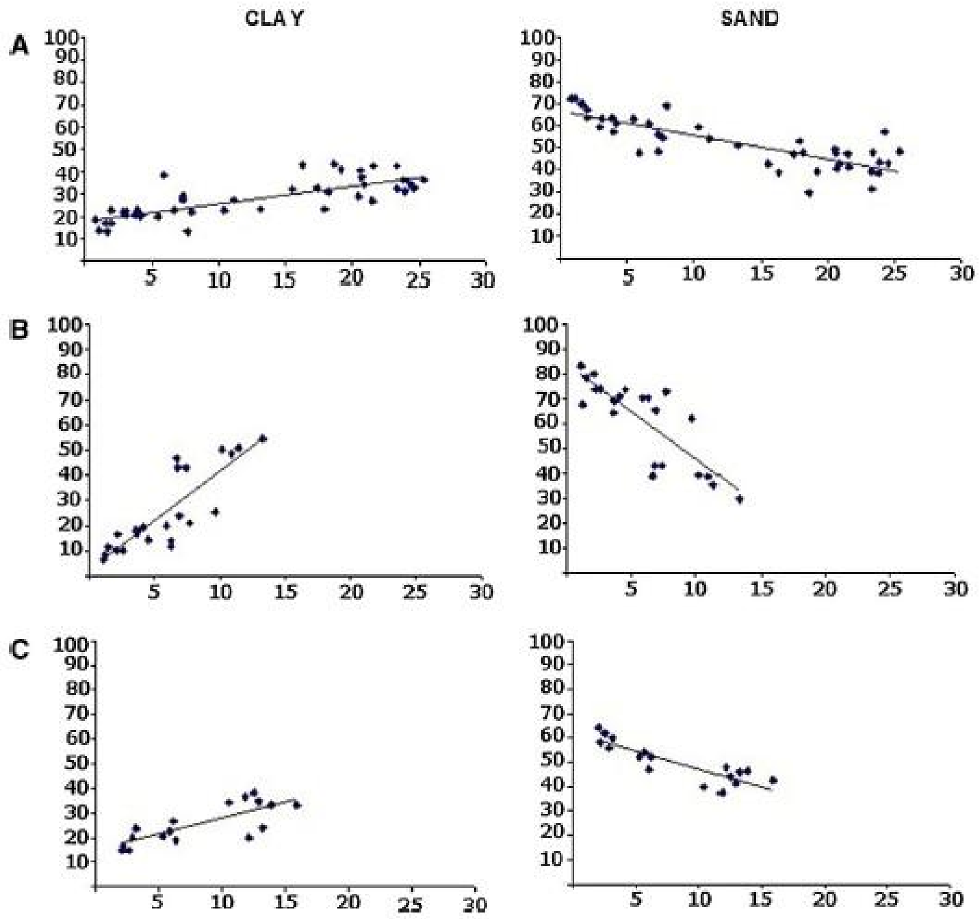

Fig. 7 Plots of percent clay and sand (independent variable %) in relation to ECa (dependent variable mS/m) measured at the Enviciados (a), Buenavista (b) and Alcazaba (c) sites

Table 7 Relative root mean square error (RRMSE in percentage) determined on different location with the two geostatistical estimation applied

AWC	Geostatistical Estimation	n	RRMSE (%)
Enviciados	Ordinary kriging	14	24
Buenavista	Ordinary kriging	10	29
Alcazaba	Ordinary kriging	17	33
Enviciados	Regression kriging	14	11
Buenavista	Regression kriging	10	13
Alcazaba	Regression kriging	17	15

Table 8 Linear regression correlations between ECa and the clay and sand soil content in the different sites

Location	Dependient variable (%)	Independient variable (mS/m)	Sample size (n)	Slope	Correlation coeficient (R^2)	P value
Enviciados	Clay	ECa	44	0.79	0.60	<0.01
Enviciados	Sand	ECa	44	−1.06	0.67	<0.01
Buenavista	Clay	ECa	21	0.91	0.71	<0.01
Buenavista	Sand	ECa	21	−0.93	0.66	<0.01
Alcazaba	Clay	ECa	17	1.29	0.60	<0.01
Alcazaba	Sand	ECa	17	−1.45	0.74	<0.01

It is also important to remember that a single recording of ECa over a field already provides a general pattern of soil properties and delivers insight into the spatial heterogeneity within a field (Benson et al. 1988). Mobile soil ECa measurements constitute one of the most efficient ways to quickly map soil spatial variability (Moral et al. 2010). In consequence, the use of ECa as a guided sampling tool could provide the best locations to take samples that would allow the development of prediction maps using geostatistical analysis techniques such as kriging or inverse distance weighting (IDW) with good results. However, due to the relationship of ECa with the soil parameters, it will be more effective to use ECa as a dependent variable in multi-variable analysis so that prediction maps can be developed that give information about homogeneous areas from the point of view of irrigation scheduling. This information would be useful in the design of the irrigation installation, the amount of water that the different surfaces needs or location of better places to install soil moisture probes Table 8.

Conclusions

The results of this study showed that using ECa to improve guided soil sampling offers an interesting tool for the agricultural management of soils. This information may be helpful for planning of more efficient irrigation management, through the adaptation of the design of the irrigation installation according to soil factors. It can indicate optimal locations for humidity probes to ensure that the information they give represents the entire plot, or the application of irrigation strategies which differ according to the water characteristics of the different soils.

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CAPÍTULO 3. Using NDVI and guided sampling to develop yield prediction maps of processing tomato crop

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Using NDVI and guided sampling to develop yield prediction maps of processing tomato crop

Rafael Fortes[1], María H. Prieto[1], Abelardo García-Martín[2], Anton Córdoba[3], Laura Martínez[4] and Carlos Campillo[1]

[1] *Centro de Investigaciones Científicas y Tecnológicas de Extremadura (CICYTEX), Ctra. A-V, km 372, 06187 Guadajira (Badajoz), Spain.*

[2] *Departamento de ingeniería del medio agrícola y forestal. Escuela de Ingenierías Agrárias. Universidad de Extremadura, Avda Adolfo Suarez s/n 06007 (Badajoz). Spain.*

[3] *Lola Fruits SL.* Plaza de España, 5, 06002 Badajoz, Spain.

[4] *Sociedad Gestora de Activos Productivos e Inmobiliarios (Roma SL). Ctra Villafranco balboa Km 1,5* Badajoz, Spain .

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Correspondence should be addressed to Rafael Fortes:
rafaelfortesgallego@outlook.com; Carlos Campillo: carlos.campillo@gobex.es

Abstract

The use of yield prediction maps is an important tool for the delineation of within-field management zones. Vegetation indices based on crop reflectance are of potential use in the attainment of this objective. There are different types of vegetation indices based on crop reflectance, the most commonly used of which is the NDVI (normalized difference vegetation index). NDVI values are reported to have good correlation with several vegetation parameters including the ability to predict yield. The field research was conducted in two commercial farms of processing tomato crop, Cantillana and Enviciados. An NDVI prediction map developed through ordinary kriging technique was used for guided sampling of processing tomato yield. Yield was studied and related with NDVI, and finally a prediction map of crop yield for the entire plot was generated using two geostatistical methodologies (ordinary and regression kriging). Finally, a comparison was made between the yield obtained at validation points and the yield values according to the prediction maps. The most precise yield maps were obtained with the regression kriging methodology with RRMSE values of 14% and 17% in Cantillana and Enviciados, respectively, using the NDVI as predictor. The coefficient of correlation between NDVI and yield was correlated in the point samples taken in the two locations, with values of 0.71 and 0.67 in Cantillana and Enviciados, respectively. The results suggest that the use of a massive sampling parameter such as NDVI is a good indicator of the distribution of within-field yield variation.

Additional key words: *Solanum lycopersicum* L.**;** ordinary kriging; regression kriging; vegetation index; precision agriculture.

Abbreviations used: ETc (Crop evapotranspiration); ETo (Reference crop evapotranspiration); Kc (Dual crop coefficient); Kcb (Basal crop coefficient); ke (Evaporation coefficient) NDVI (Normalized difference vegetation index); NIR (Near infrared); PCA (Principal components analysis); RRMSE (Relative root mean square error)

Introduction

The processing tomato is one of the most important crops in Spain, producing around 1.97 million tonnes. In recent years, the management regime of this crop has undergone a series of changes as a result of an increase in average field size. New tools are consequently required to enable a global view of these larger-sized fields and to determine the heterogeneous zones that often appear within them. The use of yield prediction maps is an important tool for the delineation of within-field management zones. In particular, appropriate placement in the field of organically grown produce, as is the case of the processing tomato crop in this study, will result in higher crop yield. Yield prediction maps are of great importance to ensure that the crop is harvested at the right time and that production yields are maximized for industrial processing (Gianquinto et al., 2011). Accurate estimation of yield can be used for zonal management of the most productive areas, to plan the best time for harvesting and its transport for industrial processing, and to locate any water and nutritional deficiencies in the crop. Yield monitoring and mapping have given producers a direct method for measuring spatial variability in crop yield. Yield maps have shown high-yielding areas to be as much as 150% higher than low-yielding areas (Kitchen et al., 1999). However, yield maps are confounded by many potential causes of yield variability (Price et al., 1997). When other geo-referenced information is available, producers naturally want to know how these various layers of data can be analysed to help explain yield variability and provide insight into improving production practices (Kitchen et al., 2003). Along with yield mapping, producers have expressed increased interest in characterizing soil and topographic variability. Vegetation indices based on crop reflectance are of potential use in the attainment of these objectives. Developments in the use of sensors have enabled massive geo-referenced data sampling of this parameter and numerous studies have investigated the correlation between vegetation characteristics and remotely sensed canopy reflectance (Xue *et al.*, 2004; Jongschaap, 2006; Gianquinto *et al.*, 2011). There are different types of vegetation indices based on crop reflectance, the most commonly used of which is the NDVI (normalized difference vegetation index).

NDVI values are reported to have good correlation with several vegetation parameters. It has been shown that NDVI is a near linear indicator of photosynthetic capacity (Sellers, 1985), while other studies have revealed that it is a good indicator of vegetation, crop biomass and health in agricultural applications (Koller & Upadhyaya., 2005). Gianquinto *et al.* (2011) studied the ability to predict tomato yield using different vegetation indices based on crop reflectance. The indices that used green and near infrared (NIR) wavelength were the best indicators, with high precision also obtained for small variations in yield. In a previous study, Koller & Upadhyaya (2005) used a vegetation index based on plant greenness which appeared to be reliable for evaluation of tomato yield. Field measurements have traditionally been gathered as point data, such as samples from an individual plant, but newly developed devices allow mass data collection to give more weight to yield prediction maps (Fortes *et al.*, 2014). Spatial analysis methods can be used to interpolate measurements to create a continuous surface map or to describe its spatial pattern. Variograms (also referred to as semivariograms) are a powerful tool in geostatistics which characterize the spatial dependence of data and give the range of spatial correlation within which the values are correlated with each other and beyond which they become independent (Koller & Upadhyaya, 2005). The parameters of the best-fitted model for a variogram can be used for kriging (Matheron, 1963; Stein & Corsten, 1991). From the point of view of data analysis, kriging has been recommended as the best method to interpolate point data since it minimizes error variance using a weighted linear combination of the data (Panagopoulos *et al.*, 2006). There are also numerous studies demonstrating the benefits of geostatistical analysis techniques for agricultural management. For example, kriging has been used to map the density of weeds in winter wheat (Heisel *et al.*, 1996) and geostatistical methods have been used to interpolate data and produce maps of a field representing the spatial variability of all the soil and wheat properties (Stewart et al., 2002). Techniques like regression kriging, which involves various combinations of linear regressions and kriging, are useful tools to improve geostatistical analysis in prediction maps. The simplest model is based on a normal regression followed by ordinary kriging with the regression residuals (Odeh *et al.*, 1995), hence the importance of analysing the robustness of the prediction maps using tools like principal components analysis (PCA), a multivariate technique commonly used for the analysis of several variables simultaneously (Balzarini et al., 2011). The aim of the present study is to describe the possibility of merging guided yield point sampling with massive sampling

(NDVI) to produce yield prediction maps for the processing tomato crop in a reliable way, using a multivariate analysis technique like regression-kriging.

Material and methods

Study area

The field research was conducted in two farms, "Los Enviciados" (-7.009427 38.950592 decimal degrees) and "Cantillana de Mesas" (-6.942781 38.946368 decimal degrees), with study areas of 6.50 ha and 7 ha, respectively. The farms are situated in the proximity of Badajoz (southwest Spain). The climate of this area is characterized by variation in both temperature and precipitation typical of a Mediterranean climate, with mean annual precipitation of less than 500 mm. One of the most important characteristics of the precipitation is its interannual variability. There is a dry season, from June to September, and a wet season, from October to May (80% of the precipitation falls between these months). Summers are hot, with temperatures sometimes rising above 40ºC.

Crop characteristics

The field was transplanted with processing tomato (*Solanum lycopersicum* L., cv. H9661) in April 2013, at a planting density of 33,333 plants/ha in single rows, with a distance between plants of 30 cm and width between beds of 1.5 m. The total water applied was 750 mm to all study surface. A drip irrigation tape was used with drippers of 1 L/h each 30 cm. The tested area comprised a single irrigation sector, where the same amount of water was applied in each irrigation. Crop management involved organic practices with no inorganic nitrogen fertilizer input. Organic nitrogen fertilizer units (280) were applied before transplanting. Crop evapotranspiration (ETc) was calculated on a daily basis using equation $ETc = ETo \cdot Kc$, where ETo is the reference crop evapotranspiration rate. It was calculated following the Penman-Monteith method, modified and adapted to local conditions (Baselga, 1996). Climate data were obtained from a weather station located near the experimental area. Kc is the dual crop coefficient for processing tomato (Allen et al., 1998), $Kc = Ke + Kcb$; considering the basal coefficients (Kcb), Kcb_ini (0.20); Kcb_mid (1.11); Kcb_end (0.60), and Ke being the evaporation coefficient. Although the tape was buried (not evaporation), we have considered an evaporation coefficient of 0.1, because surface water was observed during growth and we measured the width of the wet part. A flow meter was installed at different inlet points to measure the real volume of water applied.

Sampling

The NDVI survey was conducted in August 2013, 12 days before harvesting, with a Crop Circle ACS-470 reflectance sensor (Holland Scientific Inc., Lincoln, NE, USA) held by a tractor at a height of 80 cm above the canopy. The Crop Circle ACS-470 generated reflectance data in the wavebands 670 (red) and 760 (NIR) which were combined to obtain the NDVI following equation: NDVI= .

Where is a reflectance valor of the waveband (760nm) and is the waveband (670nm).

An ARVATEC monitor with Topcom GB500 GPS and JAVAD GDD base with sub-meter accuracy was used to geo-reference the NDVI measurements. NDVI data at 10 second intervals were recorded on an ACS-470 data logger in an ASCII text format. Later, this raw ASCII file was transferred to other software for further analysis. NDVI measurements were made along different parallel transects approximately 8 m apart (yellow dots with the appearance of lines in Fig. 1) and the final database contained 11,497 and 15,878 values for the Enviciados and Cantillana locations, respectively. Ordinary kriging was used to develop an NDVI prediction map for the two locations (Figs. 2A and 2B). These maps were then used to guide yield sampling to cover the different homogeneous zones described by the NDVI prediction maps for use in the methodology (red flags in Fig. 1), while other samples were randomly taken for validation of the methodology (green flags in Fig. 1). The harvested zones were measured and geo-referenced, with the measurements made along different parallel transects, approximately 8 m long. Calculation of production yield was made using the following equation:

Statistical and geostatistical analysis

Firstly, an NDVI prediction map for each entire plot was developed using ordinary kriging technique [see Isaaks and Srivastava, (1989) and Goovaerts, (1997) for a detailed presentation of the kriging algorithms]. The prediction maps were developed by the geostatistical interpolation techniques described by Moral *et al*. (2010) in three phases:

(i) an exploratory analysis in which the data were studied without considering their geographical distribution and statistics were applied to check data consistency, removing any outliers and identifying the statistical distribution of the data;

(ii) a structural data analysis was developed, in which spatial distribution was evaluated using variograms of the variable (NDVI); the equation of the mathematical model, nugget effect (micro-scale variation or measurement error), sill (variance of the random field) and range (distance at which data are no longer auto-correlated) were used to develop these variograms;

(iii) the prediction maps were developed using a data search by neighbourhood copied from the variogram; the NDVI prediction maps were used to guide yield sampling.

A study was then made of the areas from which the samples were taken to determine the relationship between NDVI and yield properties (Table 1). A comparison was made between the NDVI obtained at the sampled points and the yield values measured at those points. A Pearson's correlation matrix and a coefficient of determination between NDVI and yield were then obtained (Table 2) using SPSS v.13 Windows Package (SPSS, Chicago, IL, USA). When the extent of the relationship between the parameters was known a prediction yield map (Figs. 2C and 2D) for each entire plot was developed using ordinary kriging technique as described above. Regression kriging technique was then used to develop a final yield prediction map (Figs. 2E and 2F). With this technique, predictions are made separately for the trend and residuals and then added back together. Thus, any parameter at a new unsampled point, x, is estimated, Z*RK(x), using regression kriging as follows:

$$Z^*RK(x) = m(x) + r(x)$$

where the trend, m(x), is fitted using linear regression analysis and the residuals, r(x), are estimated using ordinary kriging algorithm. If cj are the coefficients of the estimated trend model, vj(x) is the jth predictor at location x, p is the number of predictors and wi(x) are the weights determined by solving the ordinary kriging system of the regression residuals, r(xi), for the n sample points, then the prediction is made by:

$$Z^*RK(x) = \Sigma pj=0cj\ vj(x) + \Sigma ni=1wi(x)\ r\ (xi)$$

$$V(x) = 1$$

In this case study, only one predictor is used, NDVI, so m(x) = a + b•(NDVI(x)). In consequence:

$$Z^*RK(x) = a + b\ NDVI(x) + \Sigma ni=1wi(x)\ r\ (xi)$$

The residual at each sampling point, r (xi), is calculated as the difference between the value of the parameter and the estimate by the trend (r (xi) = Z (xi) □ m (xi)).

The geostatistical analyses were conducted using the Geostatistical and Spatial Analyst extensions of the GIS software ArcGIS (v. 10.0, ESRI Inc., Redlands, CA, USA). All maps were produced with the ArcMap module of ArcGIS.

Finally, a comparison was made between the yield obtained at the validation points and the yield values according to the prediction maps (ordinary kriging and regression kriging). In order to assess the quality of the maps in terms of yield prediction we adopted the statistical procedure proposed by Loague & Green (1991), consisting of the best fit of the predictions. This procedure is based on the relative root mean square error (RRMSE), calculated from the following equation:

$$\mathrm{RRMSE} = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}} \cdot \frac{100}{\tilde{O}}$$

where n is the number of observations, Pi is the predicted value, Oi is the measured value, and Õ is the mean of the measured values. Validation is considered to be excellent when the RRMSE is <10%, good if it is between 10% and 20%, acceptable if the RRMSE is between 20% and 30%, and poor if it is >30% (Jamieson et al., 1991).

Results

Table 3 shows an exploratory analysis of the data distribution, described using classical descriptive statistics. Coefficient of variation (CV) values are similar for all parameters. Mean and median values were very similar, which could be initially indicative of data from a normal distribution. This was ratified by the fact that low skewness values were obtained. The skewness value is based on the size of the tails of a distribution and provides a measure of how likely the distribution will produce outliers. Thus, in this work, outliers should be scarce, and in fact there were not any, which is important to obtain accurate estimates. And, moreover, most of the coefficients of kurtosis were close to 3 (kurtosis of a normal distribution). Although normality is not a prerequisite for kriging, kriging will only generate the best absolute estimate if the random function fits a normal distribution (*e.g.,* Goovaerts, 1997). A correlation matrix between NDVI and yield in the study areas was also developed (Table 2). The coefficient of correlation between NDVI and yield was correlated in the point samples taken in the two locations, with values of 0.71 and 0.67 in Cantillana and Enviciados, respectively. Spherical mathematics models were used to develop the variograms. In this work, the variograms showed a considerable nugget effect (Fig. 3). This was not unexpected since the variability of crop properties can occur at a scale smaller than the minimum lag distance. Table 4 shows the results of theoretical spherical variograms (models that provided the best fit for all cases) fitted to experimental variograms for the residual data. Yield shows the highest nugget-to-sill ratio (~60% in the two locations), suggesting moderate spatial autocorrelation. NDVI had lower nugget-to-sill ratio values (19% in Cantillana and 23% in Enviciados), indicating that spatial dependence was generally strong. The range, that is the maximum distance of spatial dependence, varied from 57 to 163 m, with higher values being obtained for yield than for NDVI. To develop the proposed regression kriging methodology it was necessary to define the best linear relationship for each location (Table 1). After generating the yield prediction maps with both geostatistical analysis models (ordinary and regression kriging), RRMSE was used to measure their resolution. Table 5 shows this analysis, with the best results obtained using the maps developed by regression kriging, with respective values of 17% and 14% in Cantillana and Enviciados. The values obtained with ordinary kriging of 31% and 27% in Cantillana and Enviciados, respectively, can also be considered acceptable (Jamieson et al., 1991). Figs. 2 A and 2B show the NDVI prediction map for the two sites. Darker green colours correspond to higher NDVI values and their distribution, lighter green colours correspond to lower NDVI values. Figs. 2C and 2D show yield estimated by ordinary kriging at the two locations. A very similar trend can be observed to that of NDVI in Fig. 2, with higher yield values for those areas where NDVI also showed higher values (blue colours), though a larger transition area (green and yellow colours) can also be seen as a result of the fewer samples used in the geostatistical analysis. With this in mind, a third map was generated (Figs. 2E and 2F) in which yield was estimated for the two locations using regression kriging. With the higher yield values shown in blue and the lower values in red and orange, it can be seen that the transition surfaces are practically negligible as occurred in the NDVI prediction maps, because the smaller number of samples of the primary variable (yield) was associated with a broadly sampled secondary variable (NDVI). This was confirmed by the RRMSE geostatistical analysis comparing the regression and ordinary kriging prediction maps. Theoretical spherical models are represented on Fig. 3. Lower nugget effects were obtained for NDVI in both plots (Figs. 3A and B), consequence of the sampling density, the structural analysis was more accurate that for yield (Fig. 3C and D), also their sills were different because their variances were different as well. The ranges for both NDVI were similar, and lower than yield. Table 5 shows that better results were obtained with the maps developed with regression kriging, with RRMSE values of 14% and 17% in Cantillana and Enviciados, respectively, compared to 27% and 31 % when using ordinary kriging.

Discussion

The exploratory analysis of the data distribution in this work could indicate a normal distribution of the data, as it is indicated in the results chapter, corroborating the choice of kriging for this work. Kriging has been recommended as the best method to interpolate point data since it minimizes error variance using a weighted linear combination of the data (Panagopoulos et al. 2006). Given the large number of sampling points taken, and the spatial distribution of them in our work, a method as kriging was needed to minimize error variance. Panagopoulos et al., (2014) used kriging successfully to describe the spatial distribution pattern of variance in the spatial analysis of yield parameters in organic agriculture, which can only be roughly understood by descriptive statistics. In our study case, with an organic crop too, the influence of soil should be important, as occurred in the study of Panagopoulos *et al.* (2014), but we do not have these data. Variables like soil or plants can be distributed unevenly in reduced distances and exponential or spherical models are the most suitable (Isaaks & Srivastava, 1989). For this reason, spherical mathematical models were used to develop the variograms in this work. These variograms showed a considerable nugget effect (Fig. 5), with yield showing the highest nugget-to-sill ratio (~60% in the three locations), suggesting moderate spatial autocorrelation. NDVI had lower nugget-to-sill ratios (~20%), indicating that spatial dependence was generally strong. According to Cambardella *et al.* (1994), the nugget-to-sill ratio can be used to denote the spatial dependence of attributes (ratio < 25% indicates strong spatial dependence; between 25 and 75% moderate spatial dependence and greater than 75% weak spatial dependence). The NDVI index is an indicator that can be related with different physiological processes essential to achieve yield (Gianquinto *et al.*, 2011). Many parameters are crucial for the functionality of the basic plant physiological processes and affect crop yield, parameters as chlorophyll concentration has been studied for many authors using the vegetation index based on plant greenness with good results (Vouillot *et al.*, 1998; Koller & Upadhyaya, 2005, Gianquinto et al., 2011). In our study case, this parameter not was studied, but it is a parameter related with the health status of the plant, which is necessary to reach the suitable level of yield. Vegetation indices based on plant greenness also have been used to predict yield in differents crops (Ma *et al.*, 2001). In the specific case of processing tomato, Gianquinto *et al.* (2011) confirmed correlations between many of the calculated reflectance indices (including NDVI), with yield in processing tomato crop. We obtained similar results in our work for NDVI in processing tomato too, where areas with high NDVI values were also the most productive.

There are no studies showing the benefits of geostatistical analysis techniques to develop NDVI-based yield prediction maps for the processing tomato, though numerous studies have shown the benefits of geostatistical analysis techniques for agricultural management (Heisel *et al.*, 1996; Stewart *et al.*, 2002; Yamagishi *et al.*, 2003). This study shows that prediction maps based on the normalized difference vegetation index (NDVI) were suitable for describing crop yield. The NDVI data, analyzed by a geostatistical method, variogram, regression and ordinary kriging, gave a description of within-field spatial variation. And regression kriging was effective for predicting processing tomato crop yield. The study considered only one variety at two different locations subject to similar constraints, with samples taken at a specific phenological time. Different varieties, irrigation and fertilization management methods should be included in future studies.

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Table 1. Linear relationships (Y = aX + b) between NDVI (X) and Yield (Y).

Y	a	b	R^2
Yield Cantillana	63179	20318	0.82
Yield Enviciados	57828	25684	0.78

Table 2. Correlation matrix between yield and NDVI for the two locations.

Parameter	NDVI Cantillana	NDVI Enviciados
Yield Cantillana	0.71	
Yield Enviciados		0.67

Table 3. Descriptive statistics of the sample data in the study areas

Parameter	Location	n	Min	Max	Mean	Median	SD	CV	Skewness	Kurtosis
NDVI	Cantillana	15878	0.65	0.8	0.71	0.72	0.057	8.03	-0.93	4.07
	Enviciados	11497	0.66	0.78	0.73	0.74	0.065	8.90	-1.83	4.39
Yield (t/ha)	Cantillana	15	41	73	62	64	2.6	4.19	-0.51	1.99
	Enviciados	15	43	74	67	66	3.5	5.22	-0.54	2.24

n = number of samples, SD = standard deviation, CV = coefficient of variation.

Table 4. Theoretical spherical variograms fitted to experimental variograms for the residual data.

Variable	Location	Nugget/Sill ratio (%)	Range (m)
NDVI	Cantillana	19	61
	Enviciados	23	57
Yield (t/ha)	Cantillana	38	163
	Enviciados	42	159

Table 5. Relative root mean square error (RRMSE, in %) determined for the different locations with the two applied geostatistical estimation methods.

Yield	Geostatistical estimation	n	RRMSE (%)
Cantillana	Ordinary kriging	10	31
Enviciados	Ordinary kriging	12	27
Cantillana	Regression kriging	10	17
Enviciados	Regression kriging	12	14

Figure 1. *Study site of two locations Cantillana (A) and Enviciados (B). Yield sampling points (red flag), validation points (green flags) and NDVI samples (yellow dots).*

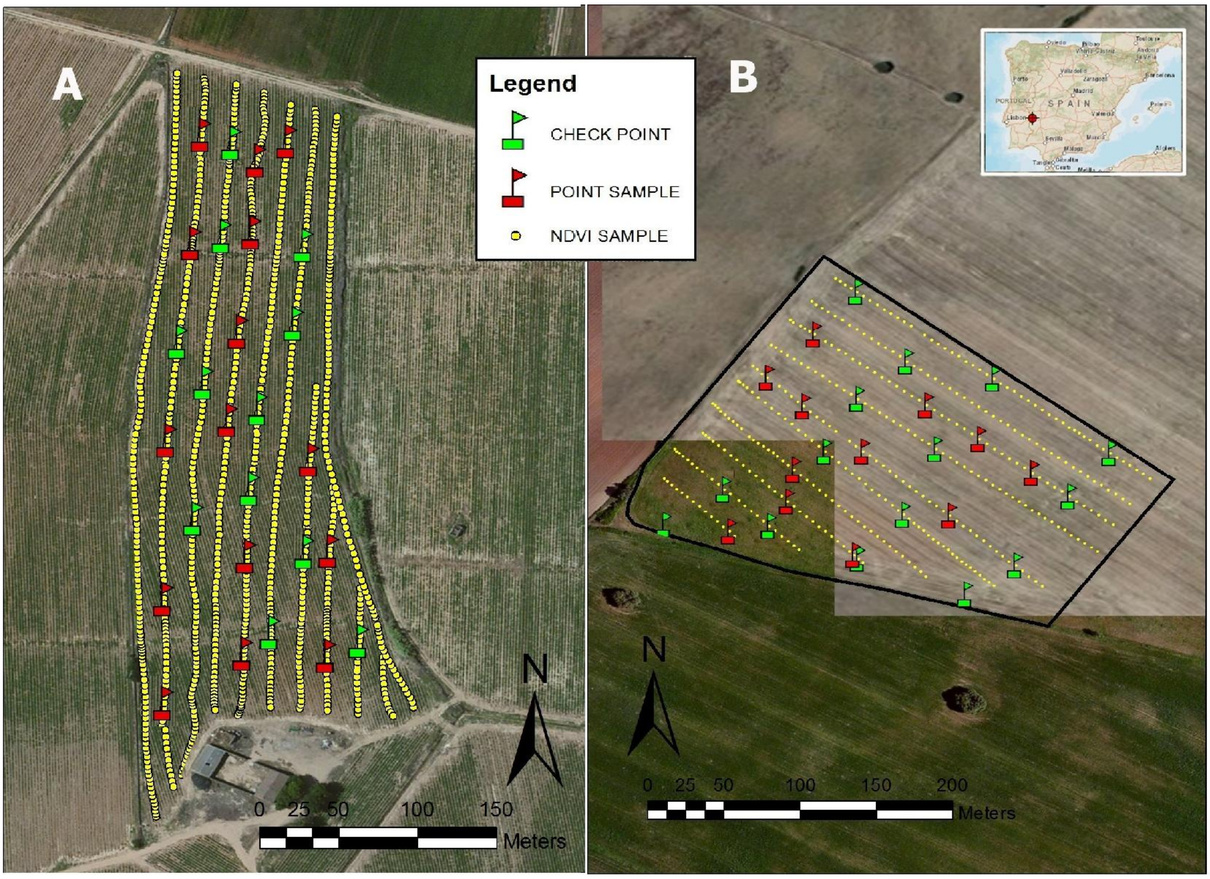


Figure 2. *NDVI prediction map for Cantillana (A) and Enviciados (B), ordinary kriging yield prediction map for Cantillana (C) and Enviciados (D), and regression kriging yield prediction map for Cantillana (E) and Enviciados (F).*

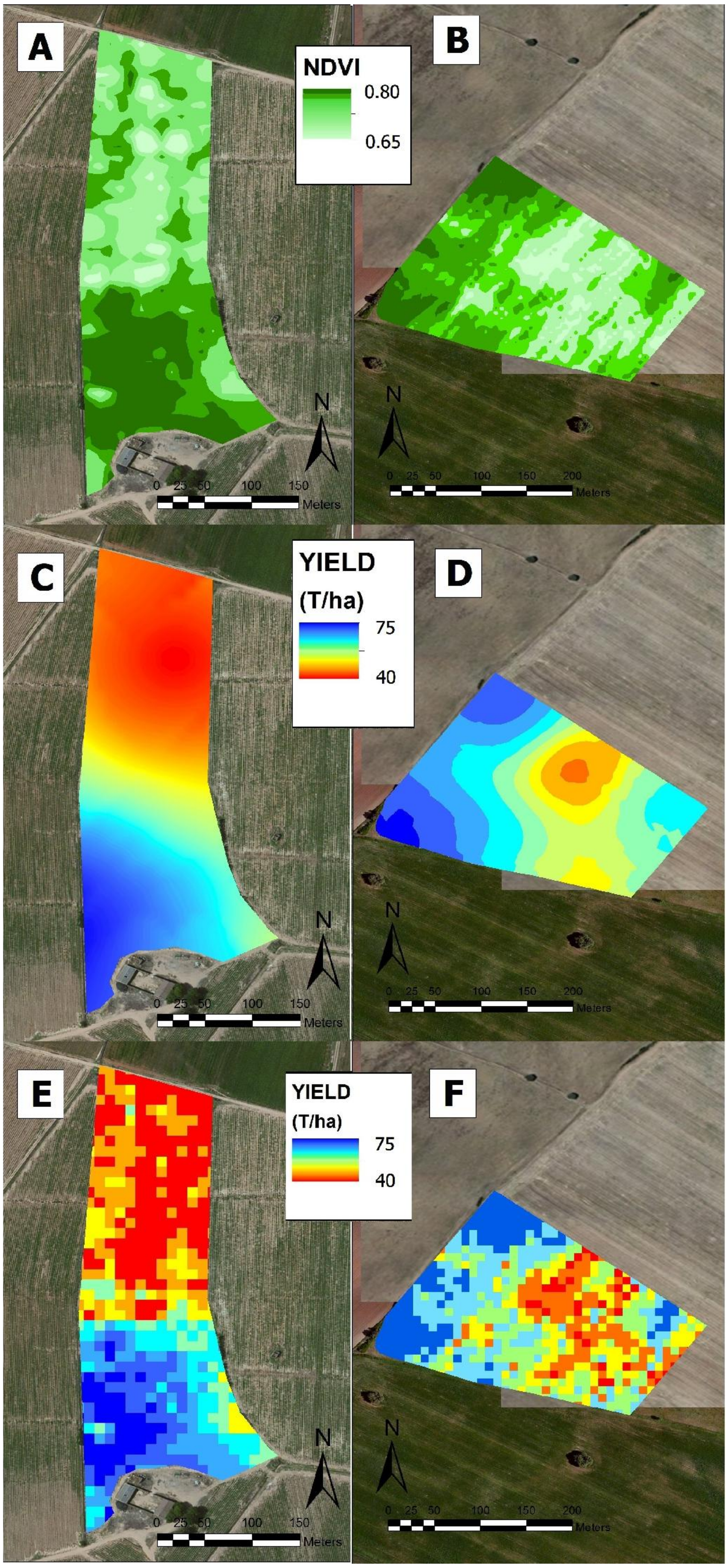
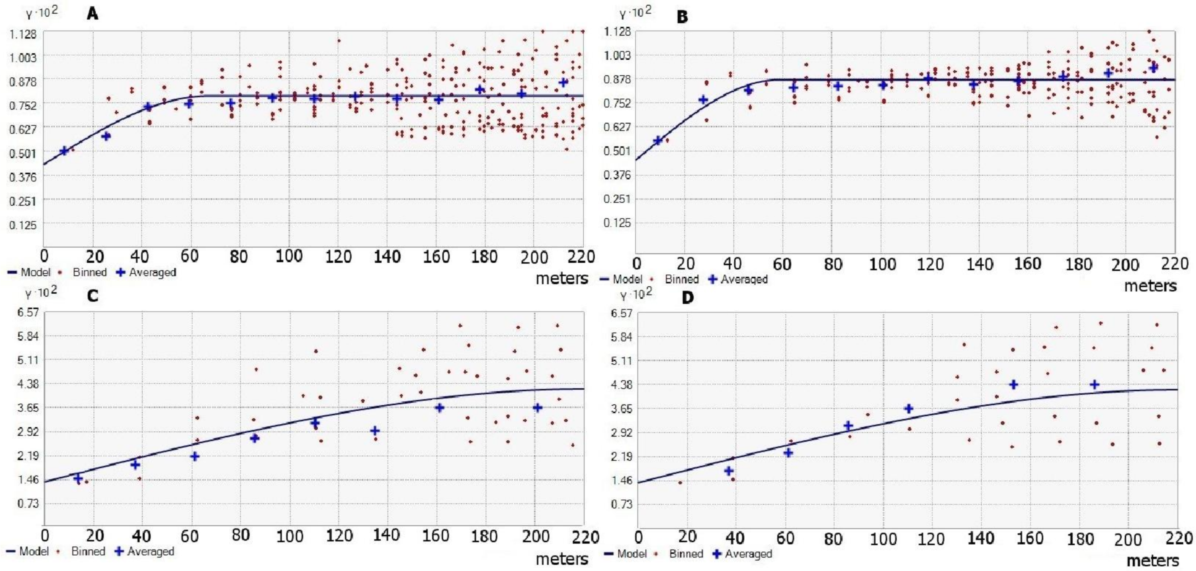


Figure 3. Experimental variograms (points), theoretical spherical variograms (lines) and average (cross) for NDVI at Cantillana (A) and Enviciados (B) and for yield at Cantillana (C) and Enviciados (D).



CAPÍTULO 4. Simulating processing tomato yield response with the fao aquacrop model and a geostatistical analyse based on electric conductivity sensor

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SIMULATING PROCESSING TOMATO YIELD RESPONSE WITH THE FAO AQUACROP MODEL AND A GEOSTATISTICAL ANALYSE BASED ON ELECTRIC CONDUCTIVITY SENSOR.

R. Fortes(1)*, M.H. Prieto(1), A. García-Martín(2), C. Campillo(1).**

(1) Scientific and Technological Research Centre of Extremadura, "La Orden" Research Centre, Extremadura Regional Ministry of Employment, Enterprise and Innovation, 06187 Guadajira, Badajoz (Spain).

(2) Department of Agroforestry Systems Engieering , School of Agricultural Engineering , University of Extremadura

Tel: +34924014092

Fax: +34924014001

*** rafaelfortesgallego@outlook.com**

**** carlos.campillo@gobex.es**

ABSTRACT:

The use of crop prediction maps is an important tool for the delineation of within-field management zones. Accurate estimation of yield can be used to locate the most productive areas, the amount of water that the crops needs in the different surfaces and to plan the best time for harvesting and transport for industrial processing. The spatial variability of soils is one of the main problems faced when planning crop management, especially when large tracts of agricultural land are involved. Parameters such as soil texture or soil water content are fundamental for understanding the determinant factors of a soil with respect to water or yield. The strong relationship between soil properties and the ECa was used to develop a prediction map of the differents soils surfaces in a processing tomato crop, using Available Water Capacity (AWC) as the main soil parameter, and the FAO AquaCrop model was used to estimate the virtual production of each area determined. Crop parameters were measured in the differents soil zones that were determined, to compare real values obtained on field with virtual values obtained using AquaCrop model. Crop physiological measurements and comparisons between simulated and observed final yield were compared to determine the suitability of the model to predict the crop parameters appropriately. The model simulated properly, however, the accuracy of the model was variable in function of the different type of soils studied, therefore, in future studies analyzing other parameters such as slope or aspect must be taken into account.

Key Words: Predictive Map, Ordinary Kriging, Regression Kriging, Available Water Capacity, Precision Agriculture and Precision Irrigation.

INTRODUCTION

The processing tomato is one of the most important crops in Spain, producing around 1.97 million tonnes. In recent years, the management regime of this crop has undergone a series of changes as a result of an increase in average field size. New tools are consequently required to enable a global view of these larger-sized fields and to determine the heterogeneous zones that often appear within them. The use of yield prediction maps is an important tool for the delineation of within-field management zones. Yield prediction maps are of great importance to ensure that the crop is harvested at the right time and that production yields are maximized for industrial processing. Accurate estimation of yield can be used for zonal management of the most productive areas, to plan the best time for harvesting and its transport for industrial processing, and to locate any water and nutritional deficiencies in the crop. Yield monitoring and mapping have given producers a direct method for measuring spatial variability in crop yield. Yield maps have shown high-yielding areas to be as much as 150% higher than low-yielding areas (Kitchen et al., 1999). However, yield maps are confounded by many potential causes of yield variability (Price et al., 1997), as well as by potential error sources from combine yield sensors (Lamb et al., 1995). When other geo-referenced information is available, producers naturally want to know how these various layers of data can be analysed to help explain yield variability and provide insight into improving production practices (Kitchen et al., 2003). Along with yield mapping, producers have expressed increased interest in characterizing soil and topographic variability. The spatial variability of soils is one of the most important problems that need to be dealt with when managing large tracts of agricultural land. This is particularly true for the question of irrigation management, where knowing the characteristics of the soil is the key to accurate calculation of the amount of water that the crop will need. From the point of view of irrigation management, it is vital to know the texture typology as this is one of the key parameters that need to be taken into account when calculating the crop water needs (Hedley, 2008). The total amount of water a soil can supply to a crop is usually measured by the volume it can hold between field capacity and wilting point, which can be assessed in the field (Hedley et al., 2005). Water status is the amount of this total available water that is available to a crop on any one day; and is commonly expressed as mm water per mm rooting depth in soil. However, the spatial variability of this status, as indeed is the case for many soil properties, will vary across the landscape, a fact largely ignored before the 1980s (Cook and Bramley, 1998). When dealing with large tracts of agricultural land it is easy to find very different types of soil. This raises the question of whether the irrigation system being used has been adequately designed to adapt to differences that are often difficult to define. Unless the problem of the spatial variability of soils is taken into consideration, an irrigation design cannot be efficient. Tools to solve this problem need to be developed and precision agriculture may be able to provide a possible solution. One of the aims of precision agriculture is to use in-field zoning in order to enable the establishment of different management strategies. Many authors have attempted to relate different types of soil with the spatial distribution of different soil attributes using digital elevation models (McBratney et al., 2003), while others have related apparent electrical conductivity (ECa) with different topographical variables (Kühn et al., 2009), but the predictive model values are very limited. The ECa parameter has been used in many works as an important secondary variable when performing this type of in-field zoning (Moral et al., 2009). Geospatial measurement of ECa is an efficient ground-based sensing technology that is helping to bring site-specific crop management from a concept to a reality (Corwin and Lesch, 2003). ECa can be intensively recorded, in an easy and inexpensive way, and it is usually related to various soil physico-chemical properties across a wide range of soils (Sudduth et al., 2005). ECa can therefore be used to improve the estimation of soil variables, when they are spatially correlated (Moral et al., 2009). Moral et al in 2009 found a close positive correlation between ECa and clay content. This was expected since ECa is mainly controlled by ions near soil constituents with a high surface area. This fact allows ECa to be used as a guided soil sampling tool, and as a secondary variable to improve the principal variable. A spatial analysis method can be used to manage all this information. Spatial analysis methods can be used to interpolate measurements to create a continuous surface map or to describe the spatial pattern. Numerous studies have shown the benefits of spatial analysis techniques in agricultural management (Heisel et al., 1996; Stewart et al., 2002). Examining the yield response to different water applications in field and/or controlled experiments is laborious and expensive (Andarzian et al., 2011). Crop models can be used to interpret experimental results and as agronomic research tools for research knowledge synthesis. In the specific case of tomatoes, different crop simulation models have been used in field conditions. Erosion Productivity Impact Calculator (EPIC) model, (Cavero et al., 1998; 1999; Rinaldi et al., 2001), TOMGRO (Jones et al., 1991; Bertin and Gary, 1993) and CROPGRO (Messina et al., 2001; Koo., 2002; Ramirez et al., 2004; Rinaldi et al., 2007) are the most cited models in literature. AQUACROP (Steduto et al., 2009; Raes et al., 2009a), is a new mathematical crop model, developed for environments, as Mediterranean area, in which the water is the limiting factor for the crop yield, focusing the core of simulation on component linked to water and water use efficiency (Rinaldi et al., 2011). Such models can be used as decision support tools for system management (Steduto et al., 2009) and to design and optimize deficit irrigation strategies (Pereira et al., 2009). In addition, they can be used in rural areas where daily weather data are not available (Andarzian., 2008). Model simulations could also be used to achieve a specific target yield as required by the Common Agricultural Policy, or to develop a deficit irrigation strategy when irrigation water is scarce (García-Vila et al., 2009). One important application of simulation models such as AquaCrop could be to compare attainable against actual yield in a field or region, and to identify constraints in crop production and water productivity (Salemi et al., 2011). AquaCrop has been developed by the Food and Agriculture Organization (FAO) of the United Nations. The model strikes a balance between accuracy, simplicity, robustness and ease of use, and is aimed at practical end users such as extension specialists, water managers, personnel of irrigation organizations, and economic and policy specialists who use simple models for planning and scenario analysis (Hsiao et al., 2009). The aim of this study was to evaluating the AquaCrop model response to different surfaces of management on processing tomato crop in the Spanish Southwest, combining the use of the model with a geostatistical analysis based on massive ECa measures of soil.

Materials and methods

2.1. Study area

The field research was conducted in the farm "Los Enviciados" (-7.009427 38.950592) decimal degrees with study area of 6.50 hectares. The farm is situated in the proximity of Badajoz (southwest Spain). The climate of this area is characterized by variation in both temperature and precipitation typical of a Mediterranean climate, with mean annual precipitation of less than 500 mm. One of the most important characteristics of the precipitation is its interannual variability. There is a dry season, from June to September, and a wet season, from October to May (80% of the precipitation falls between these months). Summers are hot, with temperatures sometimes rising above 40º C.

Crop characteristics

The field was transplanted with processing tomato (Solanum lycopersicum, variety H9661) in April 2013, at a planting density of 33,333 plants/ha in single rows, with a distance between plants of 30 cm and width between beds of 1.5 m. A drip irrigation tape was used with drippers of 1 L/h each 30 cm. The tested area comprised a single irrigation sector, where the same amount of water was applied in each irrigation. Crop management involved organic practices with no inorganic nitrogen fertilizer input. Different irrigation meters were located in the plot to determine the volume of water applied to the crop in the control points established.

2.3. Aquacrop Model

<u>A short description of aqua crop</u>

The AquaCrop crop model simulates attainable yields for herbaceous crops as a function of water consumption under different irrigation regimes (Steduto et al., 2012). AquaCrop directly links crop yields to water use and, estimates biomass production from actual crop transpiration through a normalized water productivity parameter, which is the core of the AquaCrop growth engine (Steduto et al., 2012). A full description of the conceptual basis and principles of AquaCrop are found in Steduto et al. (2012).

Relative to other crop simulation models, AquaCrop requires a low number of input data to simulate the yield response to water (Steduto et al., 2012). In AquaCrop, the input files can be grouped into projects. Each project contains up to 11 input files (text files with the appropriate extension for each file type) aggregated by topics. Thus, a single run requires up 12 files as listed in Table 1, which includes the project file. Those files marked with an asterisk are not mandatory for a simulation run of AquaCrop. Input files could be easily created or changed using the user-interface of Aqu- aCrop software (Raes et al., 2009).

When running a simulation, the user can track changes in the soil water content and the corresponding changes in the crop development, soil evaporation, transpiration, evapotranspiration rate, biomass production and yield. Simulation results are stored in output files and the data can be retrieved in spread sheet format for further processing and analysis.

2.3.1.Climate model data

For each day of the simulation period, AquaCrop requires a minimum (Tn) and maximum (Tx) of air temperature and a reference evapotranspiration (ETo) as a measure of the evaporative demand of the atmosphere and rain events. The other parameter required is the average annual concentration of CO_2. Temperature affects crop development (phenology) and biomass growth. Rainfall and ETo are crucial for the water balance of the root zone and the concentration of CO_2 in air affects the crop water productivity. Climate data were obtained from a meteorological station located a few meters from the test plot. The CO_2 concentration was obtained from the Mauna Loa Observatory, in Hawaii.

2.3.2. Soil Data

The ECa survey was conducted in March of 2013, with a 3100 Veris soil electrical conductivity sensor (Veris Technologies Inc., Salina, KS, USA). As the Veris cart is pulled through the field by a tractor, one pair of coulter-electrodes (rotating discs) injects a current into the soil while the other coulter-electrodes measure the voltage drop using a Wenner array. Veris 3100 generates two sets of data: topsoil data comprising shallow soil ECa readings from 0 to 30 cm and deep soil readings from 0 to 90 cm. The first type of readings were used for this study, since root development of the horticultural crops that are typically grown in these plots does not extend beyond 50 cm depth, and the most important activity takes place in the first 30 cm. An ARVATEC monitor with a Topcon HiPer Pro-GPS (Topcon Corporation, Tokyo, Japan) and Maxor-GGDT (Javad Navigation System, San José, CA, USA) base with sub-meter accuracy was used to georeference the ECa measurements. Latitude and longitude and shallow and deep ECa data were recorded at 1 s intervals on the Veris data logger in an ASCII text format. Later, this raw ASCII file was transferred to other software for further analysis. ECa measurements were made along different parallel transects, approximately 14 m apart and the final database contained 619 values (individual blue points in figure 1). Ordinary kriging was used to develop an ECa map for the plot (figure 2). This map was used for guided soil sampling of soil properties (Table 2), taking into consideration a good sample distribution over the different plot surfaces and covering the different ECa ranges. Soil samples were taken covering homogeneous zones described by the ECa prediction maps for use in the methodology (black flags in figure 1). Other samples were randomly taken to evaluate the methodology (soil check point flags in figure 1). The soil samples were analysed for particle-size distribution by gravitational sedimentation using the Robinson pipette method (Soil Conservation Service, 1972) after passing the fine components through a 2 mm sieve. These fine components were also analysed for organic matter (OM) that was determined by dichromate oxidation (Walkley and Black, 1934), and soil texture was determined by mechanical analysis using the hydrometer method (Boyoucos, 1936). The equations of Saxton et al. (1986) were used to calculate soil depth, saturated hydraulic conductivity, water content at the field saturation, water content at the field capacity, water content at the wilting point and Total available soil water the PWP values of each type of soil

(Table 2). A soil profile study was carried out to determine the number of horizons and the depth of each one in the surfaces studied.

2.3.3. Crop model data

The crop inputs on model must be separated on conservatives and non conservative parameters.

Conservative parameters

Conservative crop parameters do not change materially with time, management practices, or geographic location. For simulating productivity, evapotranspiration, and water use efficiency of processing tomato, they were assumed to be the same as those listed in the AquaCrop files (Raes et al., 2009a).

Non Conservative parameters

Yield sampling were taking to cover the different homogeneous zones of the plot (red flags in Figure 1 and numbers on figure 3). Three replicates were performed for each crop control point. The harvested zones were measured and geo-referenced. Calculation of production yield was made using the following equation:

$$\text{Production(T/ha)} = \frac{\text{T\_fruit\_harvested}}{(\text{Measuring\_length\_of harvested sampling area}) \times (\text{Crop\_width\_of harvested sampling area})} \times 10000$$

Another non-conservative parameters were also taked in the control zones. Table 3 shows non-conservative parameters used in this work. Crop development is one of the essential non-conservatives parameters, to assess it along the crop cycle as a non destructive mode the methodology proposed by Campillo et al., (2008, 2010) was used, this methodology was used to quantify the percentage of vegetation cover, employing the shade contour (SC) method as a measure of canopy cover (CC). The same methodology was also used to calculate the Canopy growth coefficient (CGC), Maximum canopy cover (CCx) and Canopy decline coefficient (CDC). This methodology is based on photograph taken weekly to process it and obtain values, but in the first two week of the trials photographs were taken daily to determinate the moment where the crop started the recovered phase. These photographs also were used to measure the amount of yellow (flowers) that presented the plants during the flowering phase, allowing to measure start and duration of flowering. Development of root is another of the main non-destructives parameter to take in count at time to input into the model, the method used perpendicular soil pits dug along the crop line to measure the maximum depth and width of roots. The pits were dug each 15 days a long the crop cycle. The Harvest Index (HI) values were determined (yield/total biomass) from samples collected at the end of the crop cycle. Biomass was calculated cutting five plants at ground level. The surface areas occupied by these plants were measured, with this area being the result of multiplying the length of the five plants by the width of the crop bed. Measurements were taken with a metric tape after harvesting. The five plants were weighed together, and a representative plant was selected. This plant was separated into its different organs (leaves, stems and fruits), which were weighed and, after passing through a forced air oven at 65 °C until a constant weight was reached, were also dry-weighed. Using these data, the total aerial biomass in g/m2 and its distribution in the different organs were calculated.

2.4. *Crop management data*

During the crop cycle 100% of the crop water needs was applied. The crop water need was obtained from the ETc by the expression:

$$ETc = ETo \times (Ke+Kcb)$$

ETo is the reference crop evapotranspiration, calculated using the formula of Penman and Monteith, as amended (Allen et al., 1998), and adapted to local conditions (Baselga,

1996) using data from a weather station near the test plot, Ke is the evaporative coeficient and Kcb the processing tomato crop coefficient (Allen et al., 1998).

The amount of water applied in each treatment was introduced as input into the model using the data reported by counter irrigation located into the different surfaces of the plots (crop control points). Water meters showed differences among them. There was not take in count the effect of soil fertility, since it was applied the same amount of fertilizer in all the surface, previously, a nutrients balance into the soil was made to adequately cover the needs of the crop.

2.5.*Statistical and geostatistical analysis*

Firstly, a predictive ECa map for each entire plot was developed using ordinary kriging technique (see Isaaks and Srivastava (1989) and Goovaerts (1997) for a detailed presentation of the kriging algorithms). The predictive maps were developed in three phases using the geostatistical interpolation techniques described by Moral et al., (2010). Sill and range) were studied to develop these variograms (table 4). The ECa prediction maps were used for guided soil sampling. The areas were then studied from which the soil samples were taken in order to determine the relationship between ECa, AWC and other soil properties. A comparison was made between the ECa obtained at certain measured points and the AWC and soil properties values measured at the same points, and a Pearson's correlation matrix and coefficient of determination between AWC, soil properties and ECa were obtained (Table 5) using SPSS v.13 Windows Package (SPSS, Chicago, IL). Regression kriging technique was then used to develop a final soil management prediction map based on WAC (figure 3). Predictions are made separately for the trend and residuals and then added back together. The methodology used was described by Fortes et al. (2015). Finally a prediction map comparing virtual and simulated yield obtained was developed (figure 4), for this, the ordinary kriging technique was used used as described previously. The geostatistical analyses were conducted using the geostatistical and spatial analyst extensions of the GIS software ArcGIS (version 10.0, ESRI Inc., Redlands, CA, USA). All maps were produced with the ArcMap module of ArcGIS.

Model validation:

A statistical measure of the performance of the model were calculated, comparing simulation results with measured data. This measure is based on the Relative Root Mean Square Error (RRMSE), calculated from the following equation:

$$\mathrm{RRMSE} = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}} \cdot \frac{100}{\tilde{O}}$$

Where n is the number of observations, P_i is the value predicted, O_i is the measured value, and $\tilde{O}$ is the mean of the measured values. The validation is considered to be excellent when the RRMSE is<10%, good if the RRMSE is between 10 and 20%, acceptable if the RRMSE is between 20 and 30%, and poor if >30% (Jamieson et al.,1991).

RESULTS AND DISCUSSION:

Table 7 shows an exploratory analysis of data distribution described using classical descriptive statistics. From the point of view of the number of samples, there is a notable difference between the amount of ECa data compared to that of the other parameters. The standard deviation reach the minimum values in the AWC values, but in all the other parameter shown relative low values too, shown the good distribution of the punctual samples taken. The mean and median values were very similar which was indicative of data coming from a normal distribution. Although normality is not a prerequisite for kriging, it is a desirable property. Kriging will only generate the best absolute estimate if the random function fits a normal distribution (Goovaerts, 1997). This was ratified by the fact that low skewness values were obtained. Furthermore, most of the coefficients of kurtosis were close to 2. Table 5 show that the coefficient of correlation between variables with respect to ECa were positively correlated with clay (0.65) and AWC (0.67), and negatively with sand (-0.66), in figure 5 it can see graphically the percent sand and clay in relation to ECa measured at the study site. Similar results were obtained for Hedley and Yule (2009), they used ECa measurements using a ordinary kriging geostatistical analysis to related with AWC (0.76) and FC (0.77), in this case the regression equations were available to predict soil AWC and FC for each soil ECa value, due to the relationship of soil ECa to soil water holding properties reflects the major influence of soil texture and moisture on soil ECa (Hedley et al., 2004; Sudduth et al., 2005). In our study the regression equations were used in the geostatistical analyst to improve the predictive maps. Another relationships between EC and these soil texture fractions have been reported elsewhere (Serrano et al., 2014, Moral et al., 2010, Morari et al., 2009 and Vitharana et al., 2008).

Variables like soil can be distributed unevenly in reduced distances and exponential or spherical models are the most suitable, soil can be distributed unevenly in reduced distances and exponential or spherical models are the most suitable. Spherical mathematical models were used to develop the variograms in this work. Table 4 shows the theoretical spherical variograms (models that provided the best fit for all cases) fitted to experimental variograms for the residual data in WAC and ECa. AWC showed the highest sill-nugget ratio (68%), which suggests moderate spatial autocorrelation. ECa showed the lowest values for the sill-nugget ratio (31 %), indicating that spatial dependence was generally strong according to Cambardella et al. (1994). The range, the maximum distance of spatial dependence, varied from 125 to 172 m in this study. Regression kriging was chosen as the optimum interpolation algorithm for the soil texture variables using WAC as main parameter (dependent variable), and ECa was used as the independent variable because it showed higher correlations with textural soil data. To develop the proposed regression kriging methodology the best linear relationship had to be defined (Table 6). RRMSE was used to measure the resolutions. In the table 7 shows it this analysis, with the result obtained for the regression kriging map with value of 21% (good between 10 and 20% and acceptable between 20 and 30% according to Jamieson et al., 1991). The resolution of the ECa map was also measured, obtained a value of 11% of RRMSE.

The use of a massive sampling parameter such as ECa is a good indicator of where different kinds of soil are located. It is also important to remember that a single recording of ECa over a field already provides a general pattern of soil properties and delivers insight into the spatial heterogeneity within a field (Benson et al., 1988). Mobile soil ECa measurements constitute one of the most efficient ways to quickly map soil spatial variability (Moral et al., 2010).

In consequence, the use of ECa as a guided sampling tool provide the best locations to take samples that allow the development of zoning maps of soil. Model yield simulator, in general terms, measured and simulated values followed very similar trend, the more productive surfaces obtained the higher simulated values and vice versa. Figure 6 shown the comparison between yield measured and simulated by AquaCrop model at the global study site, a good degree of calibration between measured and simulated data was observed with a value of R^2 of 0.9211. But in function of different surfaces studied, the degree of calibration was variable. Thereby, zones 8, 1,11 and 2 obtained the lowest values for *normalised differences (D) in %*, with values of -1.53, 2.51, 3.80 and 4.89

respectively. Medium values were obtained on surfaces 7, 9, 4 and 2, with values of 5.13, 6.39, 6.64 and 8.08 for D respectively. The higger values of D were reached for zones 3, 5 and 6, with values of 13.65, 11.69, and 11.44 for D respectively, all this results are showing on table 9. This results shown a good degree of calibration between measured and simulated data. If we analyse the difference between D values in the different surfaces studied the patterns are not related to soil characteristics observed. Different values of D are located on different kind of soils. There is not direct relationship between model accuracy and a determinate type of soil observed. The same amount water not was applied into the different surfaces by slope effect, and for this the different type of soil not influenced resolutely in the different levels of yield on the different surfaces. Also it can see two level of production yield, which is highly influenced by the existing soil and slope. It was a hard influence of the slope in the differents surfaces of the plot, so, the surfaces that occupied soils with high content in clay obtained a good degrees of yield when this zones were in the top of the slope, and the soil that were situated into soils with high sand content also obtained good yield when it was occupied the low of the slope. Therefore the slope was a big influence in the management of the water management. The AquaCrop accuracy in predicting canopy cover (CC) was acceptable (Figure 7), the accuracy to determine CC was variable in function of the differents crop checkpoints, anyway the tendency in the CC development maintained a similar trend, similar results were obtained for Rinaldi et al. (2011), Palumbo et al. (2012) and Katerji et al. (2013) in similar conditions and in the same crop. Finally a prediction map comparing virtual and simulated yield obtained was developed in figure 4; It is easy to observe a similar trend on plot surface, but the model simulated an amount of yield higher than the really measured. We did not find studies in which geostatistical analyses were combined with the model AquaCrop in processing tomato crop, however there are studies that have validated the model for this crop. Rinaldi et al. (2011), Palumbo et al. (2012) and Katerji et al. (2013) obtained similar results comparing simulated and measured data on processing tomato. Several authors have adopted the AquaCrop as a suitable research tool for studying the optimisation of irrigation water supply and for recommending the appropriate water management decisions (Andarzian et al., 2011; Rinaldi et al., 2011; Garcia-Vila, Fereres, 2012 and Katerji et al., 2013). Rinaldi et al, (2007) calibrated and validated CROPGRO model for growing tomato with the same experimental data comparing validation indices used by AquaCrop, however, AquaCrop showed a slight advantage over CROPGRO in terms of total dry matter of the plant, dry matter of fruit, development canopy and water content of the soil when the average values of the parameters calibrated for each year crop were compared.

CONCLUSION

The combined use of precision agriculture and crop simulation models could be an important tool for the delineation of within-field management zones. Both tools are starting to use, but there are not many studied about it. In this study we used a methodology based on apparent electrical conductivity and guided soil samples to determine the differents soils surfaces, since the soil could be the main parameter to find differences into the crop surfaces. The results obtained shown than soil is not the only parameter to take in count, and other parameters should be studied. This work also shown a good degree of calibration between measured and simulated data using the FAO AquaCrop model, therefore, studies combining soil properties, crop parameters and slopes must be developed to improve the combined use of simulation models and the geostatistical analysis.

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TABLES

Table 1. Filenames, extension, description and main inputs for each input file required for AquaCrop. Those filenames marked with an asterisk are not mandatory for a simulation run. Adapted from Lorite et al 2013.

Filename	Extension	Description	Main Inputs
Project	.PRO	Defines the specific inputs required by AquaCrop for each run	– Folder for inputs/outputs – Input file names – First/last day of simulation – First/last day of cropping – Crop parameters
Climate	.CLI	Defines the different climate input files	TMP, ET0 and PLU filenames – CO_2 filename
Temperature	.TMP	Defines temperatures	– Temporal variation - Minimum temperature – Maximum temperature
Reference ET	.ET0	Defines reference evapotranspiration	– Temporal variation – Reference ET
Rain	.PLU	Defines rainfall	– Temporal variation – Rainfall
Atmospheric CO_2	.CO2	Defines the default mean annual atmospheric [CO_2] from 1902 to 2099.	– CO_2 concentration
Crop	.CRO	Defines the complete set of required crop parameters)	– Base/upper temperatures - Soil water depletion factors – Root depth -Shape factor for stress -CGC, CCx, CDC coefficients – Length of stages
Irrigation*	.IRR	Defines information about the irrigation schedule	– Irrigation method – % Soil surface wet – Date/depth by irrigation event
Management *	.MAN	Defines the soil fertility level and soil conservation practices that affect the soil–water balance	– Soil fertility level Mulching/soil bunds – Reduction of runoff
Soil	.SOL	Defines the soil properties.	– Number of the soil horizons – Thickness of the soil horizons – Water content at FC/PWP – Curve Number – Saturated hydraulic conductivity – Depth of restrictive layer
Initial conditions	.SW0	Defines the soil profile layers at the start of the simulation period	– Water content of each layer – Thickness of each layer
Off Season*	.OFF	Defines the off-season (outside the growing season period) practices	-% Ground surface covered - Soil evaporation reduction – Irrigation (date and depth)

Table 2. The main soil characteristics observed in the differents soil surfaces at the study site.

SOIL SURFACE	% SAND	% CLAY	TEXTURE TYPE	**Depth (m)**	**Water content at the wilting point (vol.%)**	**Water content at the field capacity (vol.%)**	**Water content at the field saturation (vol.%)**	**Total available soil water (cm/cm)**	**Saturated hydraulic conductivity (mm/hr)**
1	67.21	16.75	Sandy Loam	0.7	10.70	18.90	40.00	0.08	22.91
2	60.92	20.08	Sandy Loam	0.68	12.50	21.80	40.20	0.09	15.36
3	67.19	21.80	Sandy Clay Loam	0.63	13.60	21.90	39.90	0.08	13.91
4	50.93	23.08	Sandy Clay Loam	0.53	14.30	25.40	41.00	0.11	9.60
5	47.28	26.82	Sandy Clay Loam	0.35	16.70	28.30	41.70	0.12	6.11
6	43.88	31.83	Clay Loam	0.42	19.60	31.50	42.60	0.12	3.51
7	47.30	32.71	Sandy Clay Loam	0.44	20.10	31.60	42.40	0.11	3.16
8	63.53	20.48	Sandy Loam	0.66	12.50	21.50	40.10	0.09	15.93
9	57.42	24.58	Sandy Clay Loam	0.36	14.90	24.90	40.60	0.10	9.61
10	63.29	20.72	Sandy Clay Loam	0.68	13.10	22.00	40.10	0.09	14.43
11	57.19	21.76	Sandy Clay Loam	0.67	13.70	23.70	40.50	0.10	11.75

Table 3. Comparison between the default values contained in the AquaCrop files (Raes et al., 2009) and the values calibrated at the study site.

Parameter Description	**Parameter Value**		**Unit**
	Default	**Calibr**	
Plant density	33333	33333	plants/ha
Maximun canopy cover (CCX)	75	80	%
GDD Recovered time of crop	43	25	ºC
GDD Reach max canopy	1009	800	ºC
GDD Reach senescence	1553	1144	ºC
GDD Reach maturity	1933	1456	ºC
GDD Reach flowering	525	430	ºC
GDD Duration of flowering	750	680	ºC
GDD Reach maximun rooting depth	891	806	ºC
Maximun effective rooting depth, Zx	1	0.5	m
Minimum effective rooting depth, Zn	0.3	0.15	m
Reference Harvest Index, HI_0	63	67	%
Building up of HI during yield formation	1050	988	ºC

Table 4. Theoretical spherical variograms fitted to experimental variograms for the residuals data.

VARIABLE	RATIO NUGGET-SILL (%)	RANGE (m)
ECa	31	125
WAC	68	172

Table 5. Correlation matrix between soil properties in the study site.

PARAMETER	Eca	Sand	Clay	OM	AWC
Eca	1				
Sand	-0.66	1			
Clay	0.65	-0.77	1		
OM	0.21	-0.19	0.11	1	
AWC	0.67	-0.86	0.66	0.15	1

Table 6. Linear relationships (Y = aX + b) between ECa (X) and WAC (Y).

Y	a	b	R^2
AWC	0.0016	0.0823	67

Table 7. Descriptive statistics of the sample data in the study areas; n, number of samples, SD, standard deviation.

PARAMETER	n	Min	Max	Mean	Median	SD	Skewness	Kurtosis
ECa (mS/m)	619	1.1	24.9	10.17	10.19	6.20	0.46	2.5
Sand (%)	11	43.8	67.21	56.92	56.44	11.2	-0.03	2.3
Clay (%)	11	16.75	32.71	23.69	23.73	8.7	0.14	1.9
OM (%)	11	0.6	1.35	1.3	1.4	4.2	0.17	1.6
AWC (cm/cm)	11	0.08	0.12	0.10	0.109	0.9	-0.67	2.1

Table 8. Relative root mean square error (RRMSE in %) determined in predictive maps (WAC and Eca) with the two geostatistical estimation applied.

PARAMETER STUDIED	Geostatistical Estimation	n	RRMSE (%)
WAC	Regression Kriging	7	21
ECa	Ordinary Kriging	7	11

Table 9. Yield measured (meas) and simulated (sim) by AquaCrop model for processing tomato in the differents soil surfaces at the study site. The normalised differences (D in %) between simulated and measured values are also reported.

Treatment	Yield (t ha $^{-1}$)		
	Meas	Sim	D (%)
zone 1	76.21	78.12	2.51
zone 2	73.11	79.02	8.08
zone 3	69.21	78.66	13.65
zone 4	54.80	58.44	6.64
zone 5	49.17	54.92	11.69
zone 6	71.44	79.61	11.44
zone 7	75.12	78.97	5.13
zone 8	59.34	58.43	-1.53
zone 9	74.13	78.87	6.39
zone 10	75.23	78.91	4.89
zone 11	76.41	79.31	3.80

FIGURES

Figure 1. Study site. Crop sampling points (green flags), soil check points (red flags), soil sampling (black flags) and ECa samples (blue dots). Topographic contour lines (in meters) are also depicted.

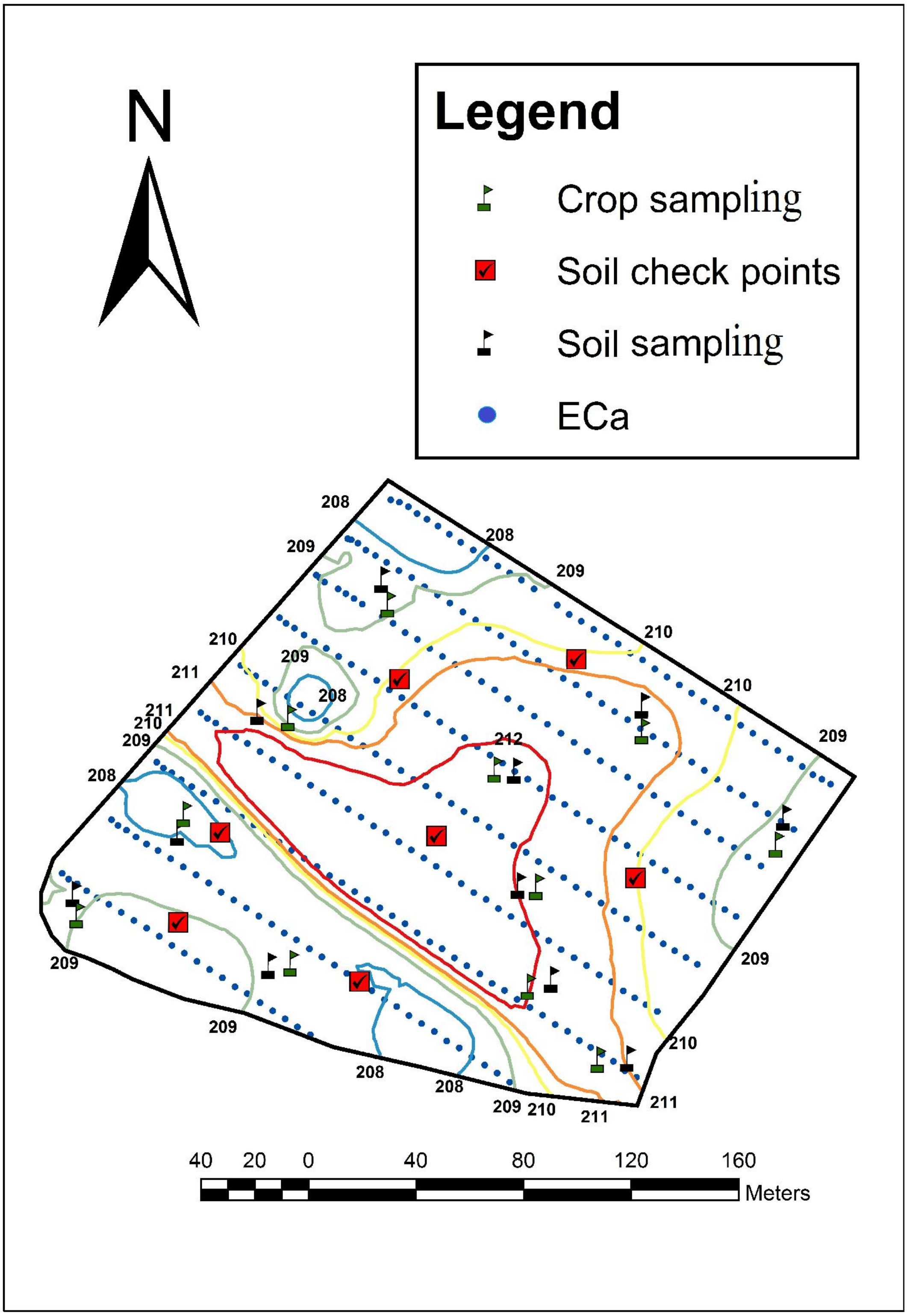


Figure 2. ECa prediction map of study site. Numbers are crop sampling points.

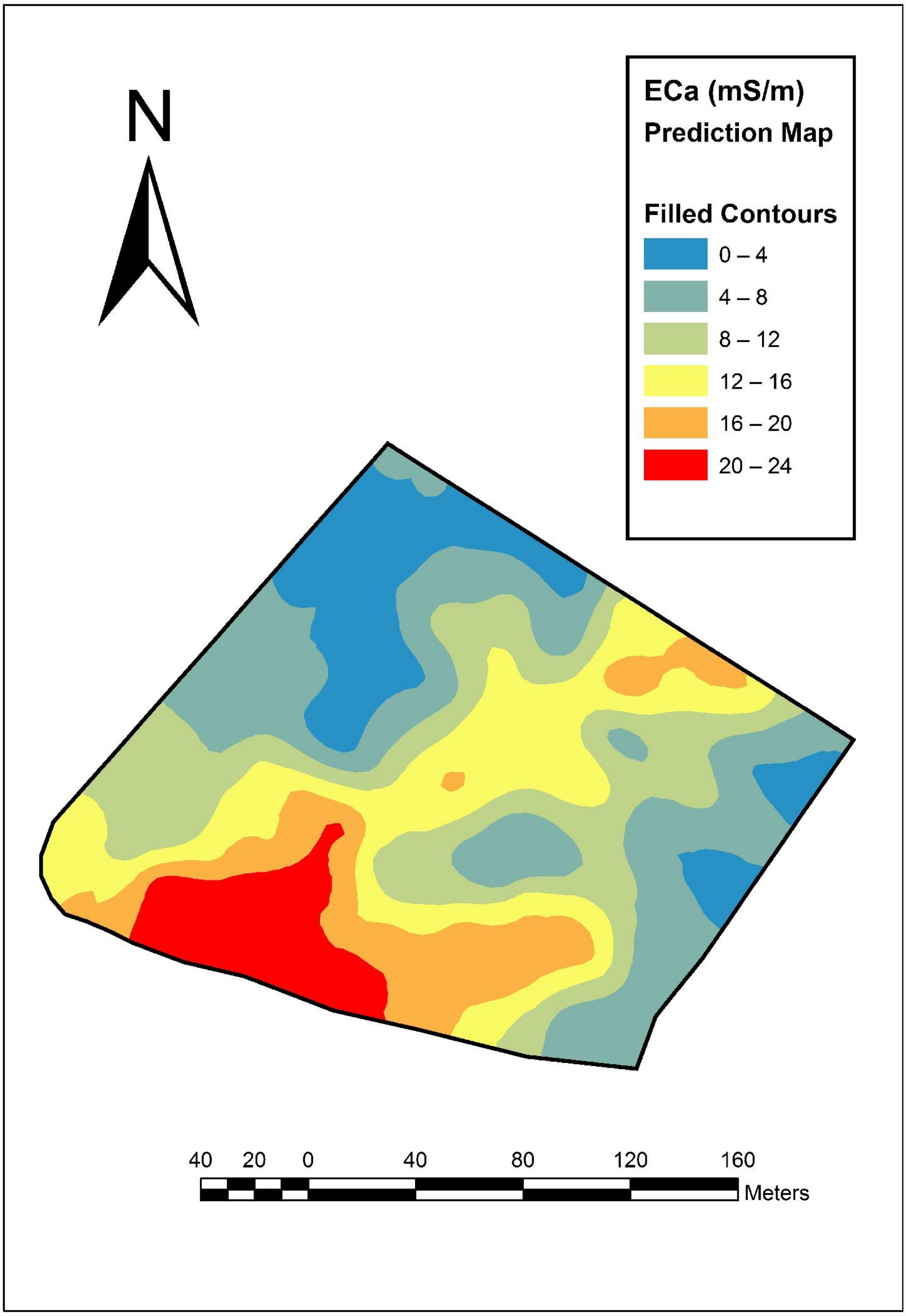


Figure 3. WAC Regression Kriging map on study site.

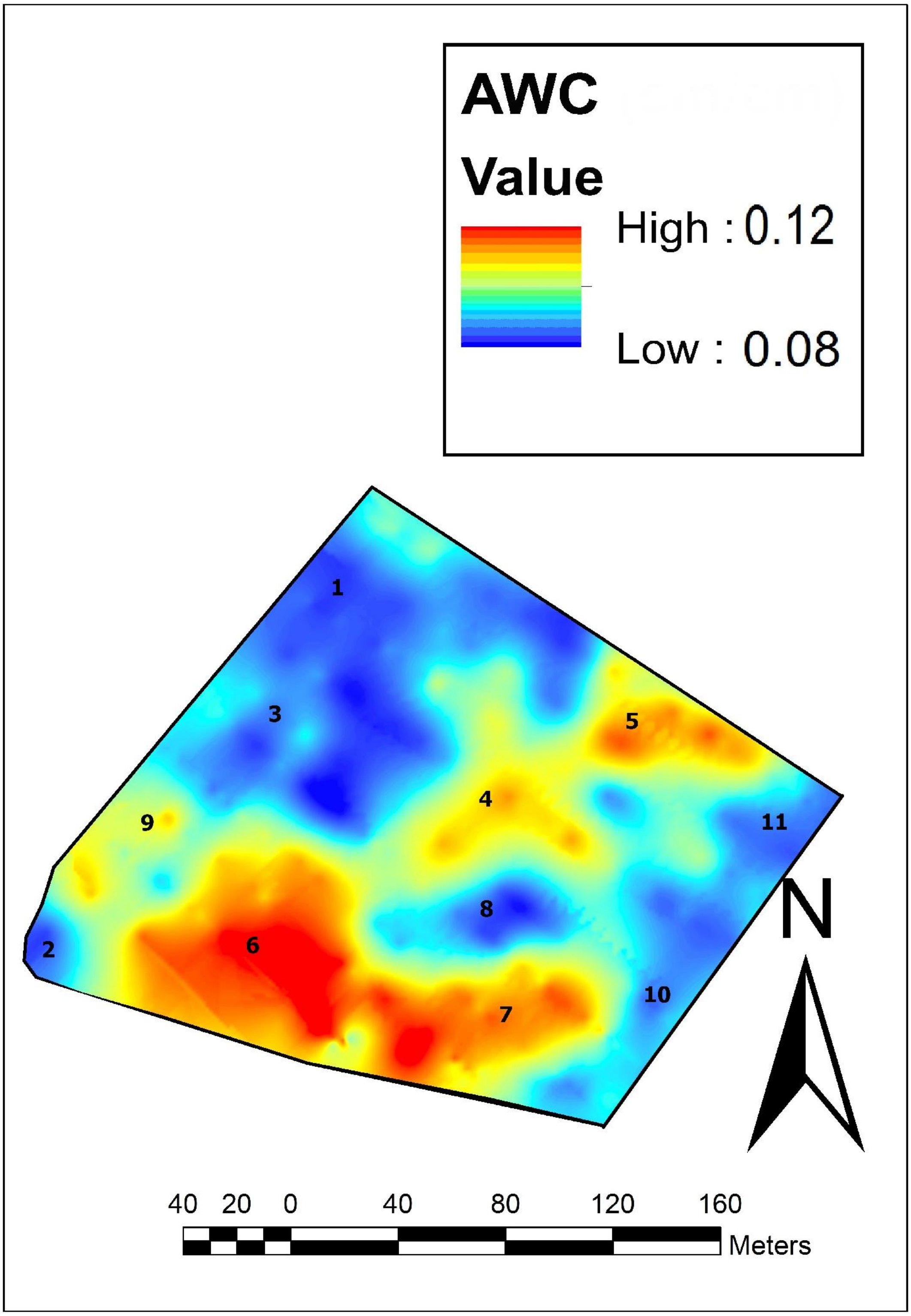


Figure 4. Prediction map of final yield measured and simulated by AquaCrop model for processing tomato crop.

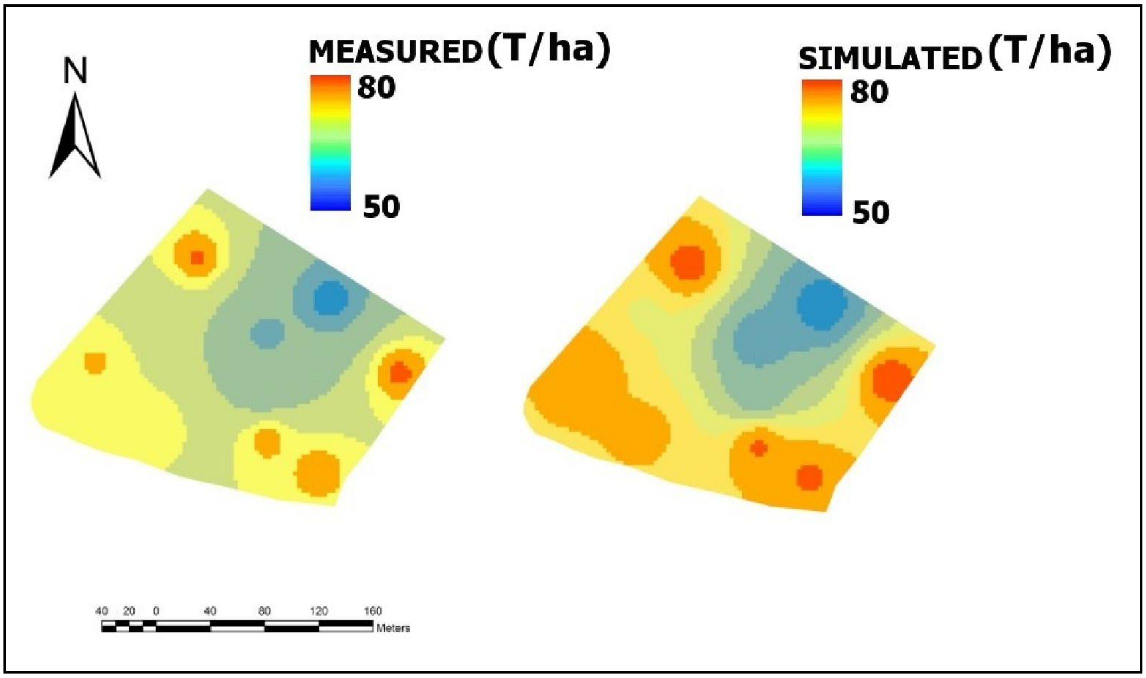


Figure 5. Plots of percent sand and clay (independent variable %) in relation to ECa (dependent variable mS/m) measured at the study site.

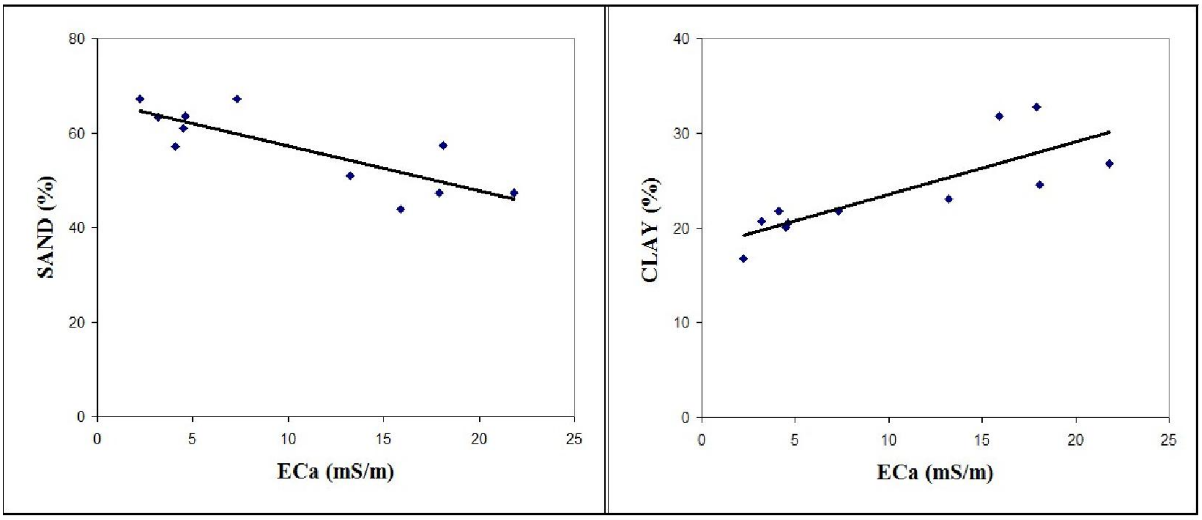


Fig 6. Comparation between Yield measured and simulated by AquaCrop model at the study site.

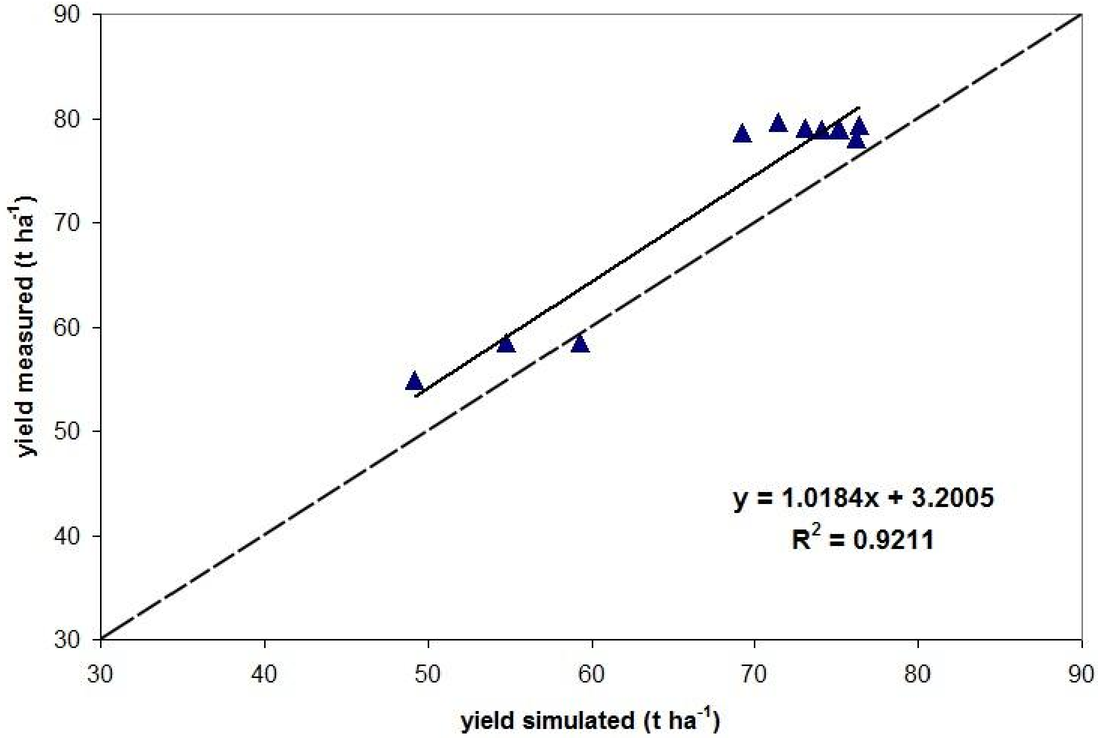
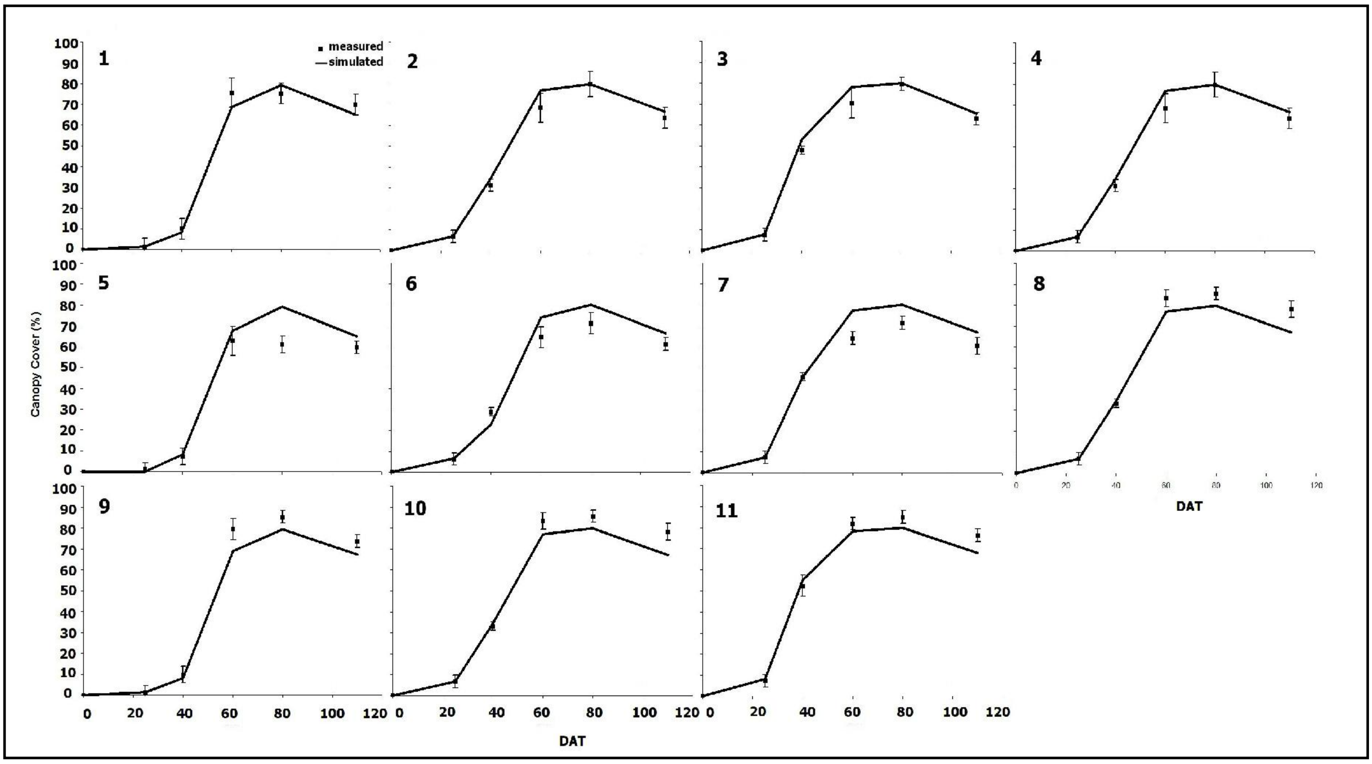


Fig 7. Canopy cover measured and simulated by AquaCrop model for crop check points. The bars represent SE of the mean of the measured data on field. DAT is days after transplanting.



CONSIDERACIONES FINALES

En la presente tesis se han evaluado diferentes herramientas para hacer frente al manejo de grande superficies de cultivo de tomate destinado a industria. Para ello se han evaluado parámetros de suelo y plantas medidos de manera masiva y georreferenciada, para poder apoyarlos en estudios estadísticos a través del uso de sistemas de información geográfica. Todo este trabajo se ha recopilado en cuatro capítulos que pretendían responder a una problemática específica en cada momento y circunstancia durante el periplo de tres años que ha llevado a la consecución de este trabajo.

En el capítulo uno se desarrolló un estudio combinado del uso de parámetros de zonificación basados en suelo y planta, así se evaluó la capacidad del índice de vegetación normalizado (NDVI) y la Conductividad Eléctrica Aparente (CEa), parámetros de suelo y planta respectivamente, sobre una parcela comercial destinada a tomate para industria. Ambos parámetros ofrecieron una información relevante a la hora de tomar decisiones en el manejo de los cultivos, identificándose durante dicho trabajo la capacidad del NDVI para estimar la productividad del cultivo, así como la influencia del suelo sobre la misma.

En el capítulo dos se desarrolló y evaluó una metodología para implementar el uso de la CEa, dada la gran capacidad de dicho parámetro para zonificar el suelo. La fuerte relación existente entre los valores medidos de CEa con la textura del suelo nos llevó a plantear una metodología que permitiera zonificar las parcelas agrícolas desde el punto de vista hídrico. Para ello se utilizó la conjunción de la CEa y medidas de textura en suelo obtenidas mediante un muestreo guiado en función de la distribución de la CEa sobre las superficies estudiadas. Esta conjunción de medidas de campo y medidas de laboratorio permitió desarrollar una metodología aplicable a grandes superficies y capaz de caracterizar grandes extensiones de terreno, ofreciendo una información útil a la hora de plantear diseños de instalaciones de riego más eficientes e implementar el uso de sondas de humedad para el control de riego.

En el capítulo tres utilizamos los buenos resultados obtenidos en el capítulo uno, y planteamos una metodología para estimar la productividad de las superficies agrícolas del cultivo de tomate para industria. Para ello se volvió a recurrir a la metodología basada en la regresión krigeado usada en el capítulo dos. Esta vez el parámetro utilizado para la zonificación de las superficies de cultivo fue el NDVI, un método de medición masiva y no destructivo. En base a las medidas de NDVI se realizó un muestro masivo de cosecha y mediante el uso combinado de la producción obtenida en campo y de su relación con el NDVI se desarrolló una metodología útil y aplicable para determinar y zonificar la producción final del cultivo de tomate para industria en grandes superficies.

Una vez determinada la potenciabilidad de la agricultura de precisión para obtener herramientas útiles en la zonificación para el manejo de los cultivos, la última tecnología que nos faltaba por evaluar era la implementación de los conocimientos adquiridos mediante el uso de modelos matemáticos de simulación de estados hídricos. Recurrimos al modelo desarrollado por FAO y denominado AquaCrop. Según la bibliografía consultada existía información alentadora acerca de su aplicabilidad sobre diversos cultivos, entre ellos el tomate para industria. Nuestro reto fue implementar el uso del modelo y extrapolar su aplicabilidad a una superficie de cultivo amplia. Recurrimos a la metodología desarrollada en el capítulo dos para zonificar la superficie de ensayo y establecer unos puntos de control donde aplicar el modelo y proceder a la toma de datos necesaria para su evaluación. El modelo simuló de manera adecuada las producciones finales del cultivo, y la metodología de zonificación permitió establecer los puntos adecuados para hacer representativo a la totalidad de la superficie los parámetros medidos sobre suelo y cultivo para nutrir al modelo. Sin embargo descubrimos la fuerte implicación de la pendiente del terreno a la hora de simular la potenciablidad productiva de los terrenos agrícolas irrigados, abriéndonos las puertas a futuros estudios para incluir dicho parámetro y mejorar así el uso combinado de sistemas de información geográfica y modelos de simulación en la obtención de información que implemente la gestión de las grandes superficies agrícolas.

CONCLUSIONES

Las conclusiones y consideraciones finales que puede extraerse de la presente tesis doctoral son las siguientes:

CAPÍTULO 1:

El índice de vegetación normalizado NDVI es un buen estimador para predecir la producción final en el cultivo de tomate para industria. Esta medida directa en planta es más precisa que otras medidas indirectas como la conductividad eléctrica aparente, un parámetro relacionado con las propiedades del suelo con el que también se obtuvieron buenos resultados. Las ventajas de este tipo de medidas radica en la posibilidad de tomar muestras georeferenciadas de manera masiva, lo que permite desarrollar mapas georreferenciados de grandes superficies para obtener información útil sobre el manejo del cultivo. Por lo tanto, se puede concluir que esta metodología es muy útil para evaluar el potencial productivo de los cultivos, además de ser un buen estimador a la hora de planificar la cosecha. Este tipo de estudio es especialmente relevante en el caso de cultivos ecológicos, como es el caso del cultivo objeto de estudio, en el que el factor principal para obtener un alto rendimiento depende fundamentalmente de la productividad del suelo en comparación con otros parámetros, debido a las restricciones al el uso de fertilizantes y fitosanitarios.

CAPÍTULO 2:

Los resultados de este estudio mostraron que el uso de conductividad eléctrica aparente combinada con un muestreo de suelos dirigidos para el análisis posterior de los mismos, ofrece una interesante herramienta para la gestión agrícola de los suelos. Esta información puede ser útil para la planificación de una gestión del riego más eficiente, a través de la adaptación del diseño de las instalaciones de acuerdo con los factores del suelo. Indicando los lugares óptimos para la ubicación de sondas de humedad, haciendo que la información obtenida a través de éstas de manera puntual sea extensible a mayores superficies, o a la aplicación de estrategias de riego diferenciadas según las características de las diferentes zonas de manejo.

CAPÍTULO 3:

Los mapas predictivos basados en el índice de vegetación normalizado (NDVI) fueron adecuados para describir una zonificación de la productividad del cultivo de tomate para industria. El análisis geoestadístico de la medida de NDVI ofreció una adecuada descripción de la variabilidad espacial de las superficies analizadas mediante el uso de la metodología basada en la regresión krigeado. El estudio sólo considera una variedad en dos lugares diferentes con limitaciones similares, y con muestras tomadas en un momento fenológico específico. Las diferentes variedades, riego y métodos de gestión de la fertilización deben ser incluidos en futuros estudios.

CAPÍTULO 4:

El uso combinado de la agricultura de precisión y los modelos de simulación de cultivos podría ser una herramienta importante para la delimitación de zonas de manejo en las superficies agrícolas. Ambas herramientas están comenzando a ser utilizadas, pero no hay muchos estudios al respecto. En este estudio se utilizó una metodología basada en la conductividad eléctrica aparente y muestreos guiados de suelo para clasificar las diferentes superficieses estudiadas, ya que el suelo podría ser el parámetro principal para encontrar una diferenciación en el rendimiento de los cultivos. Los resultados obtenidos muestran que el suelo no es el único parámetro a tener en cuenta, y que otros parámetros deben ser estudiados. Este trabajo mostró un buen grado de calibración entre los datos medidos y los simulados utilizando el modelo de FAO denominado AquaCrop, por lo tanto, estudios que combinen las propiedades del suelo, parámetros de cultivo y las pendientes en el terreno deben ser desarrollados para mejorar el uso combinado de modelos de simulación y análisis geoestadísticos sobre grandes superficies de cultivos agrícolas.