Temporal stability and patterns of runoff and runoff with different cover crops in an olive orchard (SW Andalusia, Spain)

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Abstract

Conventional tillage (CT) and cover crops (CC) trigger different runoff (Q) and runoff (Q_{in}) magnitudes and patterns in woody crops. The spatial and temporal stability of these patterns is not well known yet. In this study, we run the uncalibrated *DR2-2013*[®] *SAGA v1.1* model (0.5 x 0.5 m of cell size) to simulate time to ponding (T_p), runoff duration (T_Q), initial runoff per raster cell (q_0), Q_{sim} and Q_{in} in six olive plots (480 m² per plot) during two years (108 rainfall events and 648 simulations). Two plots were managed with a mixture of plant species (CC-I), two with one single plant species (CC-II) and two with CT. Runoff yield from each plot was collected (Q_{obs}) in gauging-stations during 27 time-integrated samples and used for modelling validation (162 control points). On average, Q_{obs} was 9% higher under CT than under CC-I, and 8% higher than under CC-II. Topsoil saturation was simulated for the entire plots during 29 events (test-period), and Q_{sim} appeared in another 51 and 52 events in the plots with CC and CT. T_p with CT was 2.3 times higher (59 s) than the average duration with CC and the topsoil became saturated 3.3 times faster in the inter-rows than below the trees. Values of q_0 with CC were 2.3% lower than with CT and total Q_{sim} with CC was 2% higher than with CT. However, the differences of Q_{sim} between the different treatments were not statistically significant. The mean observed and simulated runoff coefficients were of 11 and 14%, with median values of 7 and 10%. Q_{sim} correlated well with Q_{obs} (Pearson ca. 0.861), and Q_{sim} was overestimated ca. 10%. The model performed better

when rainfall depth and intensity were high, and the range of variability of both Q_{sim} and Q_{obs} was similar. The average, best and worst Nash–Sutcliffe coefficients were 0.665, 0.791 (P6) and 0.512 (P3) and thus model simulations were satisfactory. The four plots with CC presented on average a worse performance (Kling–Gupta coefficient = 0.607) than the two plots with CT (KGE = 0.769). The lowest spatial variability of q_0 , Q_{obs} , Q_{sim} and actual available water (W_{aa} , the sum of Q_{in} and stored water in the soil surface) were found in the plots with CC. CT triggered higher spatial variability of runoff and higher temporal variability of runoff than CC.

Keywords: Runoff yield; runoff; olive orchard; cover crop; conventional tillage; DR2 model

1. Introduction

Cover crops (CC) in olive orchards and other woody crops (vineyards, almond groves and other fruit trees) provide an environmental-friendly alternative to conventional tillage (CT) for land management (Gómez et al., 2011). Indeed, CC reduce soil, nutrients and organic matter losses and pesticide delivery in comparison with CT and no-tillage systems (Gómez et al., 2009a; Gómez et al., 2011) and typically higher soil total organic carbon and total extractable carbon are usually found under this management (Gucci et al., 2012). Plant covers are also important for retaining and releasing nutrients under different tree demand rates (Gómez-Muñoz et al., 2014). On average, water infiltration improves in the inter-row area with CC compared to CT and thus runoff coefficients (Q_C , hereafter) decrease though these changes are highly dependent on soil permeability values (Gómez et al., 2009a; Taguas et al., 2010). In spite of these advantages, mechanical tillage and bare soil after using herbicides still represent the most common techniques of soil management in olive orchards within the Mediterranean Basin, mainly to avoid the development of a natural plant community in the inter-row area, leading to a competition with the olive trees for the scarce soil water.

Among the main environmental, economic and management limitations of much of the Mediterranean cultivated soils for fruit groves are the steep slopes and the shallow soil depth (Casalí et al., 2009). Under these conditions, the total volume of water that can be stored and used by the plants is limited. Soil erosion decreases the soil depth even further thus threatening long-term sustainable agriculture. To date, after requirements related to the Common Agricultural Policy (CAP) of the European Commission and decades of research and promotion, around 30% of the olive orchards in Spain are under CC management (MAGRAMA, 2015) aiming among other benefits the reduction of soil and water losses. Indeed, Durán-Zuazo et al. (2009) found in mountainous olive plots in Granada (SE Spain) a significant reduction in runoff (between 94 and 95% lower) and erosion rates (between 59 and 71% lower) with CC in comparison to plots without plant strips. Gómez et al. (2009a) also described a significant reduction of soil losses and Q_C (from 11.9 to 1.2%) with CC of barley near

Cordoba (S Spain). [Gómez et al. \(2009b\)](#) measured near Seville (SW Spain) an efficient reduction of runoff and sediment yield down to tolerable levels (QC ca. 5.7%) with CC in comparison with CT. The adoption of CC has also a positive economic impact such as that reported by [Taguas et al. \(2012\)](#), in terms of management operations, transformation of olives into olive oil, obtained yield income, and subsidies received by the farmer, in an olive micro-catchment in Cordoba. [Simoes et al. \(2014\)](#) found that olive production did not differ between CT and natural vegetation cover, although [Ferreira et al. \(2013\)](#) measured in a long-term experiment on a Portuguese rainfed orchard a decrease in yield for a CC treatment compared to bare soil management. [Gucci et al. \(2012\)](#) found lower fruit yield but similar oil content in irrigated orchards under permanent natural cover treatment than with CT.

To the best of our knowledge [Castro et al. \(2006\)](#) and [Pedrera-Parrilla et al. \(2014\)](#) are some of the few authors who reported on the spatial patterns of runoff (Q , hereafter) and runon (Q_{in} , hereafter) across an olive orchard. Although olive orchards have long been recognized as consisting of a mosaic pattern of infiltration and runoff ([Gómez et al., 2001a](#); [Romero et al., 2007](#)), there are almost no studies comparing these factors under CC and CT treatments. There is a limited number of studies that deal with the spatial patterns of Q and Q_{in} in olive groves and their temporal stability. Hence, further studies aiming at solving this issue are required. The lack of studies is surprising, as farmers and land managers consider Q and Q_{in} to be two critical attributes in fruit tree orchards regardless of their management (rain-fed, irrigated, with conventional, conservation or precision agriculture). CC are strongly recommended within the agricultural policy strategies of the European Union among other good agricultural practices ([Taguas and Gómez, 2015](#)). Results of this study will be of interest for agronomical and environmental studies and will offer valuable data for encouraging the implementation of CC by reducing the uncertainty in runoff-runon dynamics in olive groves.

The accurate description, quantification and modelling of Q and Q_{in} are complex tasks that can be achieved by the combination of different measurement, statistical and modelling techniques ([Cafarelli et al., 2015](#); [López-Vicente et al., 2015](#)). This goal appears as a non-solved question in olive orchards due to the significantly different effective diffusivity relationships that appear in the unsaturated zone in both the inter-row and under canopy areas ([Espejo et al., 2014](#)). [Palese et al. \(2014\)](#) found a higher storage of water from rainfall at different soil depths and an improved soil structure (macroporosity) in an olive orchard in Southern Italy under CC treatment than with CT.

Direct measurements of Q and Q_{in} are costly and relatively rare, so there is interest in methods to predict the hydrological response of the soil at ungauged sites. In spite of the current limitations of the hydrological models ([Semenova and Beven, 2015](#)), spatially distributed approaches provide the possibility for evaluating soil physical properties across fields and temporal scales and even to assess the impact of different land uses and management practices ([López-Vicente et al., 2014a](#); [Bussi et al., 2014](#)). [Taguas et al. \(2012\)](#) ran the AnnAGNPS model at event and monthly scales and analyzed the

results together with other data to assess the environmental and economic impacts of different soil management strategies in an olive crop microcatchment. Zema et al. (2016) also executed the AnnAGNPS model in a large watershed covered by olives, obtaining low accuracy by the default model, and better predictions after model calibration. Other models used in olive groves have been the ArcSWAT2009 (Napoli and Orlandini, 2015) and the WEPP (Licciardello et al., 2013) models. However, these two models only provided good predictions of runoff yield after model calibration and under specific temporal scales and humidity conditions. Additionally, there are specific models developed for olive orchards, such as the numerical approach proposed by Gómez et al. (2002) and used to simulate runoff and runoff in a virtual olive grove. More recently, Abazi et al. (2013) developed a water balance model (WABOL) to simulate the effect of different soil management alternatives on soil water balance using process-based methodologies. And López-Vicente and Navas (2012) developed the GIS-based distributed rainfall-runoff (DR2) model for Mediterranean agro-ecosystems.

In this study we hypothesize that the spatial patterns of time to ponding (T_p), Q and Q_{in} yields in an olive orchard are affected by the different inter-row cover strategies, and the temporal stability of these patterns also depend on the different treatments. To test this hypothesis, and during 2 hydrological years (2009/10 and 2010/11), we: i) ran the water-balance DR2-2013[®] SAGA v1.1 model at event scale and at high spatial resolution (0.5 x 0.5 m cell size) in six comparable olive orchard plots but under three different inter-row management practices (CT, CC with one and various plant species); ii) validated the simulated values of runoff (Q_{sim}) with those measured (Q_{obs}) in six gauging stations; and iii) analyzed the spatial patterns and the temporal stability of the observed runoff yield and simulated initial runoff per raster cell (q_0), Q_{sim} and Q_{in} in the six plots and three treatments. These results will be of interest to evaluate the effects of soil management in olive orchards on runoff and water balance, and thus for agricultural production and environmental services.

2. Material and methods

2.1. Study area and vegetation management scenarios

In 2002, a field experiment was established on the “Santa Marta” olive commercial farm (SW Spain; 37° 20' 36" N, 6° 13' 45" W) with an average elevation of 92 m above sea level (Figure 1). The olive plantation was established in 1985 with trees planted at 8 m x 6 m (more details in Gómez et al., 2009b). The climate is subtropical semi-humid Mediterranean with an average annual precipitation of 534 mm and a strong interannual oscillation (576 mm between 2003/04 and 2006/07, 976 mm in 2009/10 and 713 mm in 2010/11), concentrated mostly in late fall and winter, and an average annual air temperature of 18.6 °C. The soil belongs to the Petrocalcic Palexeralf series (García del Barrio et al., 1975), well drained, with an average organic matter content of 1.3%, 28% of CaCO₃, and a sandy loam texture class. There is no presence of rills below the

tree lines and small rills (< 2 cm of maximum depth) only appear along the inter-row land after the most intense rainfall events.

Six bounded runoff plots were established between 2003 and 2005. Each plot was 8 m wide (between 2 tree lines) and 60 m long (480 m²), laid out with the longest dimension parallel to the maximum slope and to the tree lines. The slope is uniform, oriented in the north-west direction with an average steepness of 12.5%. The olive variety, Gordal, used as a table olive, is very common in the area. Differential inter-row soil management started in the area the season before the delimitation of the runoff plots. Two plots (P2 and P4) were devoted to conventional tillage (hereafter CT) consisting of regular chisel plow passes (2–3 times a year at 10–15 cm depth) depending on weed growth. Another set of two plots (P1 and P5) consisted in a mixture of different selected plant species as cover crop (CC-I) of *Borago officinalis*, *Daucus carota*, *Echium plantagineum*, *Foeniculum vulgare*, *Hedysarum coronarium*, *Matricaria chamomilla*, *Melilotus officinalis*, *Moricandia moricandioides*, *Cichorium inthybus*, *Fagopyrum esculentum* and *Taraxacum officinalis*. These plants were manually sown during early fall at 15 kg of seed per ha in the area outside the vertical olive canopy projection. The third set of two plots (P3 and P6) was a uniform CC (CC-II) of *Lolium multiflorum* sown at 40–80 kg of seed per ha depending on the year. The maintenance of the CC includes two or three mowing passes during winter and spring, and a bare soil strip under the tree line maintained with herbicides. The intercrop strip was fertilized every year with nitrogen during the fall by direct application on the soil in the CC plots. In the two plots with CC-I plants were mowed in May. In the two plots with CC-II plants were chemically killed in late winter or early spring, depending on the previous total rainfall depth, to avoid competition for water with the olive trees. Olive trees were fertilized from April to October, during the irrigation season. The amount of water applied during the drip irrigation season was, on average, 240 mm, although it varied slightly from year to year depending on the rainfall conditions. In a previous study performed in the same plots, high values of soil erosion were recorded under CT treatment (19.4 Mg ha⁻¹ yr⁻¹ on average) whereas low values were obtained with CC (0.4 Mg ha⁻¹ yr⁻¹) (Gómez et al., 2009b).

2.2. The hydrologic DR2-2013[®] SAGA v1.1 model

2.2.1. Software development

In this study we ran the third version of the DR2 model (more details in López-Vicente et al., 2014b). It computes the depth of water stored and infiltrated in the soil and the runoff depth, considering spatial and temporal variations in rainfall intensity, soil saturation and upslope contributing factors. This model also provides the basis for the hydrological module of the Soil Erosion and Redistribution Tool (SERT) model (López-Vicente et al., 2013). A module for the open-source, free SAGA[®] 2.0.8 GIS software was developed, called DR2-2013[®] SAGA v1.0 (<http://digital.csic.es/handle/10261/84613>). Since January 2014 the executable file

(DR2.dll) of the version 1.1 is available for free downloading (<http://digital.csic.es/handle/10261/93543>). The module can simulate fifteen spatial patterns of runoff using four single flow (*D8*, *Rho8*, *KRA* and *DInf*) and four multiple flow (*MFD*, *BDR*, *DEMON* and *TMFD*) algorithms (FAA) with and without considering threshold values for the beginning of linear flow lines. Commercial GIS software (e.g., IDRISI, ArcGIS, GRASS, PCRaster) and tools (TauDEM v5.x, HydroTools v1.0, AccumPlus v1.0) and most downloaded hydrological and soil erosion models, such as SWAT (<http://swat.tamu.edu/software/arcswat/>) and WaTEM/SEDEM (<http://geo.kuleuven.be/geography/modelling/>) are commonly run with only two or three algorithms.

2.2.2. Runoff simulation

Effective cumulative runoff (Q_{sim} , mm) is calculated following a three-step procedure. In the first step, the time to ponding, Tp (s), and the unsaturated cells and cells saturated by direct rainfall (no runoff contribution) are differentiated:

$$\frac{1}{2} \frac{Sp_{ie}^2}{K_{fsT}} \ln \left(\frac{I_e}{I_e - K_{fsT}} \right) \leq Tp_{ie} \leq \frac{1}{2} \frac{Sp_{ie}^2}{I_e - K_{fsT}} \quad (1)$$

$$Sp_{ie} = \sqrt{2 \cdot (\Delta\theta_{ie}) \phi_i} \quad (2)$$

$$\Delta\theta_{ie} = \theta_{Si} - \theta_{0ie} \quad (3)$$

where Sp is the soil sorptivity ($\text{cm s}^{-0.5}$), K_{fsT} is the saturated hydraulic conductivity measured in the soil surface (cm s^{-1}), I (cm s^{-1}) is the rainfall intensity, ϕ is the matrix flux potential ($\text{cm}^2 \text{s}^{-1}$), and θ_s ($\text{m}^3 \text{m}^{-3}$) and θ_0 ($\text{m}^3 \text{m}^{-3}$) are the saturated and antecedent volumetric water content of the soil, respectively. The subscripts i and e correspond to each raster cell and to each rainfall event, respectively. Once topsoil is saturated the initial runoff per raster cell, q_{0ie} (mm), is estimated as a function of the depths of effective rainfall, ER_{ie} (mm), and rainfall to ponding, Rp_{ie} (mm):

$$q_{0ie} = ER_{ie} - Rp_{ie} = ER_{ie} - (Tp_{ie} I_e)10 \quad (4)$$

$$ER_{ie} = R_e (1 - A_{ie}) / \cos S_i \quad (5)$$

where A_{ie} (0–1) is the depth of precipitation intercepted by the canopy in relation to the total rainfall depth of each event, R_e (mm), and S_i (radians) is the slope angle. In the second step, q_{0ie} , is routed into the DEM using one of the selected FAA, FAA_{X-Type} in Eq. (6), and the potential cumulative runoff, Q_{0ie} (mm), is obtained:

$$Q_{0ie} = f(q_{0ie}, FAA_{X-Type}, DEM_{resol}) \quad (6)$$

$$Q_{0Bie} = \alpha \cdot Q_{0ie} = \frac{\sum_{i=1}^{i=k} q_{0ie}}{\sum_{i=1}^{i=k} Q_{0ie}} \cdot Q_{0ie} \quad (7)$$

where *resol* subscript is the spatial resolution of the DEM, given that the runoff depth also depends on this parameter, and α is the water balance correction factor so that volume of Q_{0B} equal to the initial volume of available water to be accumulated in the field. In the third step, the effective cumulative runoff, Q_{sim-ie} (mm), is calculated after considering the saturated hydraulic conductivity of the soil profile, K_{fs} (mm s⁻¹), and the total duration of the runoff event after the soil becomes saturated until all runoff volume is infiltrated or delivered throughout the outlet, T_{Qie} (s):

$$Q_{sim-ie} = (Q_{0Bie} - K_{fs} T_{Qie} - SS_{max-ie}) \sin S_i \quad (8)$$

$$T_{Qie} = T_{QR} + T_{Qafter} = (ER_i / 10 I - Tp_i) + (Ql / Qv) \quad (9)$$

and the maximum amount of water retained on the soil surface, SS_{max-ie} (mm):

$$SS_{max-ie} = 0.5 RG_{ie} \frac{\sin^2(SIG - S_i) \cot(SIG + S_i) + \cot(SIG - S_i)}{\sin(SIG) 2 \cos(SIG) \cos(S_i)} \quad (10)$$

where T_{QR} (s) and T_{Qafter} (s) are the duration of the runoff until and after stopping the rain, respectively, TR_e (s) is the duration of the rainfall event, Ql (m) is the flow length, Qv (m/s) is the flow velocity, RG_{ie} (mm) is the surface roughness, and SIG (radians) is the surface soil and surface furrow angle. Water demand by evapotranspiration is included in the DR2 model to estimate the soil moisture status (SMS) although it is not used in the quantification of Q_{sim} . The actual available water (Waa , mm) factor is defined as the total depth of water that is stored (SS_{max}) at the soil surface and infiltrated (Q_{in}) in the soil profile. Water inputs are assumed to be the sum of the direct rainfall depth and of the upslope contributing runoff. The depth of Waa at each pixel is computed with GIS techniques following a three-step-sequence (Figure 2).

2.3. Model parameterization, gauging stations and performance metrics

To achieve a sound parameterization of the model we measured all inputs in detail. The high resolution DEM of the farm (0.5 x 0.5 m of cell size) was generated by using derived contour lines every 0.1 m from the DEM-LIDAR (5 x 5 m) of the Spanish National Institute of Geography (IGN; free available files at <http://centrodedescargas.cnig.es/CentroDescargas/index.jsp>) and with field observations of the main overland flow pathways. Terrain below the olive lines is slightly elevated in comparison with the inter-row land within each plot. This small topographic difference (few centimeters) was not captured in the original DEM-LIDAR of the IGN and thus a correction was done in the generated DEM. An automatic weather station was installed at the experiment site and rainfall depth and intensity measured every 15 minutes. The

antecedent volumetric water content of the soil profile, θ_0 in Eq. (3), was measured every hour at 60 cm depth, and then average daily values calculated. We used the values of infiltration measured by Guzmán (2008) in four different areas in the same study site both in the inter-row and below the tree lines under CC and CT treatments and in two soil horizons (0-10 and 10-20 cm depth). We also used values of rainfall interception, A in Eq. (5), from previous studies: i) in the olive tree lines corresponded to those obtained by Gómez et al. (2001a) in two orchards at Cordoba (Spain) using average leaf area index (LAI) values; and ii) in the inter-rows were obtained from López-Vicente and Navas (2009) after distinguishing eleven periods for the two hydrological years, in order to account for the phenology of the CC, the sown and mown calendar (Oct/Nov09; Dec09; Jan10; Feb/Mar10; Apr/May10; Jun/Nov10; Dec10; Jan11; Feb/Mar11; Apr/May11; Jun/Sep11). Accounting sowing practices, we differentiated two periods, winter and summer, for the values of flow velocity, FIV in Eq. (9), and used the rates calculated by Haan et al. (1994). Four different areas were distinguished for the surface roughness factor, RG in Eq. (10), and values obtained from the study of Zobeck and Onstad (1987): below the trees (0.6 cm), bare soil strip under the tree line (0.7 cm), CC-inter-row (0.8 cm) and CT-inter-row (from 1.9 cm in October, December and April to 0.8 cm after the rainfall events). The range of input values is shown in Table 1. From the set of cumulative algorithms available in the module, we selected the Triangular Multiple Flow Direction (TMFD) approach without threshold value for linear flow as it appears suitable for overland flow redistribution in areas without presence of permanent streams (more details in López-Vicente et al., 2014b).

The runoff generated on each plot was directed to a system of three fiberglass collection tanks with flow splitters (ratio 1:15) allowing measurement of up to 110 m³ equivalent to 230 mm of runoff. Once carefully leveled, the splitters were kept free of leaves, small branches and other organic residues with a small protection net located upstream. On the first working day after a single large rain event, or after a weather front consisting of several rain pulses or events, the collection tanks were sampled. Runoff volume was measured in the tanks during 27 time-integrated surveys. The model was run at high spatial resolution (0.5 x 0.5 m of cell size) due to the small size of the plots. The DR2-2013[©] SAGA v1.1 software was not calibrated with observed data of runoff yield. This model does not include any mathematical operator to calibrate the simulation with subset data. We followed the criteria of Vogel and Sankarasubramanian (2003) who emphasized that calibration is a complementary task to the validation process, and thus model validation should be firstly done independent of calibration. After the model is well parameterized, results are directly validated with field-measured values of runoff yield (Q_{obs}) and using three metrics: i) the Pearson's linear correlation coefficient (r_p); ii) the Nash-Sutcliffe efficiency coefficient (NSE); and iii) the Kling-Gupta efficiency coefficient (KGE; Gupta et al., 2009):

$$r_p = \frac{\sum_{i=1}^n (CQ_{s-i} - \overline{CQ_{s-t}}) \cdot (CQ_{o-i} - \overline{CQ_{o-t}})}{\sqrt{\sum_{i=1}^n (CQ_{s-i} - \overline{CQ_{s-t}})^2} \cdot \sqrt{\sum_{i=1}^n (CQ_{o-i} - \overline{CQ_{o-t}})^2}} \quad (11)$$

$$NSE = 1 - \frac{\sum_{t=1}^T (CQ_o^t - CQ_s^t)^2}{\sum_{t=1}^T (CQ_o^t - \overline{CQ_o})^2} \quad (12)$$

$$KGE = 1 - \sqrt{(r-1)^2 + (\alpha-1)^2 + (\beta-1)^2} \quad (13)$$

$$\alpha = \sigma_s / \sigma_o \quad (14)$$

$$\beta = \mu_s / \mu_o \quad (15)$$

where r is the linear correlation, σ is the standard deviation and μ is the mean value (with subscript “s” for simulations and “o” for observations), α is the relative variability and β is the relative bias.

2.4. Spatial patterns and temporal stability of the hydrological response

The temporal stability of the spatial patterns of the q_0 , Q_{sim} and Waa factors were assessed. The relative difference, δ_{Px-t} , between the average value of the factor in the six plots at the simulated event “ t ” (q_{0-t1} , etc.) and the mean value ($q_{0-Px-t1}$) at each plot “ x ” was calculated:

$$\delta_{Px-t} = \frac{q_{0-Px-t} - \overline{q_{0-t}}}{\overline{q_{0-t}}} \quad (16)$$

$$MRD_{Px} = \frac{1}{N_T} \sum_{t=1}^{t=N_T} \delta_{Px-t} \quad (17)$$

where MRD_{Px} is the mean relative difference for the plot “ x ” and N_T is the number of the simulated events. And the temporal stability analysis of these differences was done calculating the standard deviation of the set $\delta_{Px-1}, \delta_{Px-2}, \dots, \delta_{Px-NT}$ of relative differences at the plot “ x ” over the events when runoff appeared in the six plots:

$$SDRD_{Px} = \sqrt{\frac{1}{N_T - 1} \sum_{t=1}^{t=N_T} (\delta_{Px-t} - MRD_{Px})^2} \quad (18)$$

The value of $SDRD_{Px}$ serves as one of the measures of the temporal stability (Vachaud et al., 1985; López-Vicente et al., 2015) by comparing its magnitude to the spatial variability of MRD_{Px} .

3. Results and discussion

3.1. Measured rainfall and observed runoff yield

A total of 108 rainfall events were recorded, 58 in the first hydrological year (2009/10) and 50 in the second (2010/11). Total rainfall depth reached 976 mm in the first year and 713 mm in the second year. Thus, both years were humid in comparison to the average (ca. 534 mm). Between October and May (rainy period) cumulative rainfall amounted to 93% of total rainfall depth (Figure 3a). For an average event, the rainfall depth (R) was of 15.6 mm with a maximum rainfall intensity (I_{30}) of 9.5 mm h⁻¹ and of 7.9 mm h⁻¹ without considering the two most intense events (106 and 77 mm h⁻¹). There were 29 rainfall events with R higher than 20 mm. Values of soil moisture, θ_0 , showed in most cases but not in all, a short time response associated with the main rainfall events (Figure 3a). The mean value of θ_0 during the rainy period was of 28.7 m³ m⁻³ for CT and 28.5 m³ m⁻³ for CC, whereas the mean values during the four drier months were of 22.8 and 19.9 m³ m⁻³. Therefore, the presence of cover crop did not have a significant effect on soil moisture.

Runoff yield (Q_{obs} , mm) was measured 14 times in the first year and 13 in the second year in the six gauging stations (Figure 3b). On average, Q_{obs} was 9% and 8% higher under CT than under CC-I and CC-II, respectively, although the lowest values of maximum Q_{obs} were obtained with CT (Table 2). The two plots devoted to CT showed similar values of mean, maximum and standard deviation Q_{obs} , whereas variability of Q_{obs} in the two plots with CC-I and with CC-II was much higher. Indeed, the highest (P1 and P6) and lowest (P3 and P5) values of mean, maximum and standard deviation Q_{obs} were obtained with CC treatment. This variability agree with the results obtained by Gómez et al. (2011) from six sites in France, Spain and Portugal, where significant reductions in mean annual runoff coefficients under CC were only obtained in two out of the six sites, whereas the other four sites presented similar values of QC for both treatments.

The median values of Q_{obs} in the plots number 1 (P1; CC-I) and 3 (CC-II) were lower than the values obtained in the two plots under CT, whereas P5 (CC-I) presented a similar value, and only P6 showed a higher value of the median Q_{obs} . As P6 has similar values of slope steepness, upslope contributing area, and extension of the inter-row and tree line areas, as those values in the other 5 plots, the observed variability may be explained due to not-described characteristics of the infiltration and percolation processes in the topsoil and deeper horizons. Specific overland flow pathways related to the unpredicted spatial and temporal heterogeneity of growth of the plants may also explain the higher variability under CC. This range of variability agrees with the relative differences reported in other studies of runoff volumes in field plots (e.g. Gómez et al., 2001b).

Q_{obs} of the six plots correlated well with the values of cumulative rainfall depth (R), especially in the first year (average r_p of 0.912; $P < 0.05$) and to a lesser extent during

the second year (average r_p of 0.507; $P < 0.05$) (Figure 3c and d). This result was not unexpected as annual rainfall was 37% higher in 2009/2010 compared to 2010/2011. Correlations were not significant ($r_p < 0.46$) with the values of mean rainfall intensity (I), but correlations improved with the mean and maximum values of maximum rainfall intensity in 30 minutes (I_{30}) and were significant in P3 (CC-II) (r_p ca. 0.72) and P4 (CT) (r_p ca. 0.51). Thus, R had a bigger influence on peak flows and runoff than I_{30} during the first year, but both factors played a similar role in the hydrological response of the soils during the second year. The different temporal response could be explained by the different magnitude of total rainfall depth recorded during each hydrological year and due to the different values of I_{30} during the first (10.2 mm h⁻¹ on average) and second year (16.5 mm h⁻¹).

3.2. Runoff simulation and water storage

3.2.1. Time to ponding (T_p) and initial runoff per raster cell (q_0)

The DR2-2013[®] SAGA v1.1 model was run for the 108 events. Topsoil (related to the upper horizon where K_{fsT} was measured) saturation ($T_p > 0$) was predicted in over the entire area in 29 events (test-period, hereafter), and for part of the area (mainly in the inter-rows and bare soil strips) in another 58 events. The remaining 21 events presented low values of I_{30} and thus topsoil was not water saturated. During the test-period, the average T_p in the plots with CT was 2.3 times higher (59.1 seconds) than the average duration with CC (25.2 s) (Table 3). These differences can be explained by the higher values of K_{fsT} in the plots under CT (25.6 mm h⁻¹, on average) than under CC (22.8 mm h⁻¹). Topsoil became water saturated sooner in the inter-row area (3.3 times faster), 20.7 and 18.4 s, than below the canopy, 97.4 and 31.9 s, both under the CT and CC, respectively. Minimum T_p was similar in CT (3.7 s) and CC (3.8 s) plots, but maximum T_p was almost four times higher under CT (446.1 s) than under CC (115.5 s).

The effective rainfall (ER) was calculated for the 87 rainfall events when topsoil was (at least partly) saturated. The spatial distribution of ER showed the effect of the different values of slope gradient and of the rainfall interception in the inter-row, the bare soil strips and under the tree canopy (Figure 4a). During three events, the long duration of T_p together with the low values of rainfall depth avoided the generation of runoff, and thus q_0 appeared in part of the soil surface in 54 events in the plots with CC and in 53 events for CT. There was an upper threshold value of T_p (58 minutes and 6 seconds on average) above which topsoil was only water saturated when rainfall intensity was very low (3 mm h⁻¹ on average) and rainfall depth was at least of 5 mm. This threshold value was 8% lower with CC than with CT. During the other 84 events, q_0 was higher than zero (Figure 4b). During one of these events q_0 was generated in the entire plot under CC but no runoff appeared with CT, and during only one event q_0 appeared in part of the plot under CC and no runoff appeared with CT. This pattern appeared conversely in other two events. During most of the test-period, q_0 was higher in the inter-row land than below the canopy in the six plots (11% higher on average)

due to the higher values of rainfall interception and of infiltration in the olive tree lines (Figure 4c). This pattern was more pronounced with CT (15% higher) than with CC (9% higher) and it appeared during the whole period.

The highest values of q_0 were obtained in the two plots with CT (31.3 mm on average) whereas the four plots with CC showed quite similar values of q_0 and on average was 2.3% lower than with CT (Table 3). The two plots with CC-I presented the lowest values of mean and maximum q_0 whereas values were intermediate in the two plots with CC-II. In the tree line and during most events, q_0 was higher with CC than with CT due to the lower duration of Tp whereas in the inter-row q_0 was higher in most events with CT than with CC (Figure 4d). The maximum variability of q_0 ($q_{0-max-var}$) varied markedly for the study period (Figure 4e). During the 29 events when runoff was generated throughout the plot, variability averaged 3.9%, whereas it was up to 45.3% during the 82 events with runoff production in the inter-row area. Regressions showed that q_0 was linearly related ($r^2=0.95$; $P<0.001$) with rainfall depth (R) and exponentially related ($r^2=0.53$; $P<0.05$) with maximum rainfall intensity (I_{30}). As we expected, q_0 was inverse and potentially related with time to ponding (Tp) ($r^2=0.65$; $P<0.05$), specially at the highest range of Tp values (Figure 4f). These relationships agree well with the linear correlations obtained with the measured values of runoff yield (Q_{obs} ; see previous section) and support the model predictions.

3.2.2. Simulated runoff (Q_{sim}) and model validation

The DR2-2013[®] SAGA v1.1 model predicted runoff in the four plots with CC during 80 events and in the two plots with CT during 81 events. During 81 events, the model predicted runoff in part of the 6 plots, and during 29 of these events throughout the total surface. The average simulated runoff (Q_{sim}) in the whole study area ranged from 0.01 (2 May 2011) to 21.99 mm event⁻¹ (20 Dec. 2009) (Figure 5a). The highest average values of Q_{sim} were obtained in P5 (CC-I) and P2 (CT) and the lowest in P1 (CC-I) and P4 (CT) (Table 4). However, the highest values of Q_{sim} were obtained in P3 (CC-II) in 42% of the total events and in P5 in 36% of the events. The lowest values were mainly found in P6 (59% of the events) (CC-II). Total Q_{sim} in the four plots with CC was 2% higher than total Q_{sim} with CT. However, the differences of Q_{sim} between the different plots and treatments were not statistically significant. Thus, no clear differences were predicted with the model between the three CC treatments after runoff was redistributed. During the two hydrological years, the average value of Q_{sim} with CC and CT were of 3.4 (sd = 4.4) and 3.3 (sd = 4.3) mm event⁻¹, respectively (Figure 5b). These results can be explained by the duration of runoff (T_Q) for CT plots, that was 2.1 and 2.2% longer than for the four plots with CC during the test-period and all events with runoff production, respectively (Figure 5d). In the inter-row, the total duration of runoff was 11 and 143% longer than below the trees during the test-period and all events with runoff production, respectively, and runoff continued longer after the rainfall had stopped (T_{Qafter}) in the inter-row (5 s) compared to the tree line (3 s) (Table 4). In the inter-rows, the magnitude of Q_{sim} was higher (5.7 and 2.4 mm event⁻¹ on average during

the test-period and all events) than below the trees (0.5 and 0.2 mm event⁻¹) in the six plots (Table 4). Ruiz-Colmenero et al. (2013) also found in Spanish vineyards greater steady-state infiltration in soils with cover treatments than that under tillage as Guzmán (2008) obtained in the olive groves. These contradictory results reinforce the need for further research focused on runoff velocity and delivery duration of generated runoff.

The average volume of water stored due to the soil roughness (SS_{max}) was only 3.1 mm yr⁻¹ and ranged during the year from 0.22 (Sep.) to 0.28 (Oct., Dec. and Apr.) mm month⁻¹. Below the tree-line SS_{max} was on average 26% lower (2.3 mm yr⁻¹) than in the inter-row with CC (3.1 mm yr⁻¹) and 62% lower than in the inter-row with CT (6.0 mm yr⁻¹) (Figure 5e). The runoff coefficients (QC_{sim}) were calculated considering the total effective rainfall (ER_T) (Figure 5c). The average QC_{sim} in the six plots and the 81 events was of 13.6% (sd = 8.2%), with a minimum of 0.01% and a maximum of 28.3%. The temporal pattern of the variability of QC_{sim} mirrored that of Q_{sim} ($r^2 = 0.73$) although the temporal differences in the values of QC_{sim} between the different plots were more marked than those of Q_{sim} . Similar values of QC_{sim} were obtained in the six plots and thus no clear differences were found between the different treatments in the inter-rows. Values of QC_{sim} (Table 4) were compared to those calculated after the 27 time-integrated runoff samples (QC_{obs} ; Table 2). The average integrated values of QC_{obs} and QC_{sim} were 10.9% and 17.0%, with median values of 7.3 and 20.4%.

With CT the average QC_{obs} was slightly higher than the value with CC, and conversely the average QC_{sim} under CT (16.5%) was slightly lower than the value with CC (17.2%). However, the differences of QC_{obs} and QC_{sim} between the six plots were not statistically significant. In a previous study in four plots (P2, P3, P4 and P6) of the same study area and during four hydrological years (2002-2007), Gómez et al. (2009b) obtained an average QC_{obs} of 5.7% in the two plots with CC and of 16.0% in the two plots with CT. These dissimilarities in the same study area can be explained due the differences in the total rainfall depth recorded in the different hydrological years, with humid conditions in this study and dry conditions in the study of Gómez et al. (2009b). Near Cordoba (S Spain), Gómez et al. (2009a) also found in a young olive grove lower QC with CC (1.4%) than with CT (4.5%) and non-tillage (13.6%). However, Francia et al. (2006) reported higher values of QC with CC (10.7%) than those with CT (3.0%) and NT (5.4%) in olive plots in Lanjarón (Granada, SE Spain). These opposite values between the different studies can be explained by the specific characteristics of each site and the complexity of the processes involved in runoff generation.

Validation of Q_{sim} was done by using the values of measured integrated runoff (Q_{obs}) (Table 5). On average, the simulated integrated-runoff (ΣQ_{sim}) was 10% higher than the observed runoff yield (Figure 6a) (underestimated in P1 and P6 and overestimated in the other four plots). The simulated rates were successfully correlated to the observed ones (Figure 6b). The mean Pearson's coefficient was of 0.86 and the best correlation ($r_p = 0.92$) appeared in P5 and the worst ($r_p = 0.79$) in P4. During the integrated-events with the highest rainfall depth (ΣR above percentile 50; 52.5 mm) and maximum intensity (I_{30max} above percentile 50; 7.8 mm h⁻¹) the mean Pearson's coefficients in the six plots

were of 0.826 and 0.864, respectively, whereas during the events with the lowest R and I_{30max} values were of 0.588 and 0.763. The average Nash–Sutcliffe model efficiency coefficient (NSE) (non-normal distribution of runoff) was of 0.665. The best NSE appeared in P6, P2 and P1 (NSE = 0.791, 0.729 and 0.714) and the worst in P3 (NSE = 0.512). Thus, model simulations can be judged as satisfactory. The variability of the NSE was similar in the four plots with CC (0.665 on average) and in the two plots with CT (0.663 on average). The Kling–Gupta efficiency coefficient (KGE) was on average 0.661. The goodness-of-fit was higher than 0.75 in P2, P4 and P6 and the worst in P5 (KGE = 0.443). The four plots with CC presented on average a little worse performance (KGE = 0.607) than the two plots with CT (KGE = 0.769).

The range of variability of ΣQ_{sim} was quite similar to the range of variability of Q_{obs} . The standard deviation (sd) and the coefficient of variation (CV or RSD) of the values of ΣQ_{sim} and Q_{obs} were of 10.5 and 12.4 mm and 106 and 137%, respectively. Taking into account that the DR2-2013[®] SAGA v1.1 model does not include calibration, and model predictions are directly made after parameterization, the model performance was better than that reported by Zema et al. (2016) with the AnnAGNPS model in olive groves before calibration. Moreover, we obtained a better mean correlation (r_p) than that obtained by Licciardello et al. (2013) after calibrating the WEPP model in La Conchuela farm (Cordoba, Southern Spain). Finally, the average model efficiency (NSE) in some plots was similar to that obtained by Abazi et al. (2013) (0.57 on average) with the calibrated water balance WABOL model in an olive orchard in Cordoba (Southern Spain).

3.2.3. Actual available water (Waa) and temporal stability

The actual available water (Waa), that is the sum between SS_{max} and Q_{in} , was calculated during the 81 events with runoff production and the average maps generated for the test-period and for the period when runoff appeared in the six plots (80 events) (Table 6). The mean values of Waa ranged from 6.3 (P5) and 7.0 (P4) mm event⁻¹ during the 81 events, and from 5.2 (P5) and 6.3 (P4) mm event⁻¹ during the test-period. Comparable spatial patterns of Waa were observed during the two test-periods but clear differences in the magnitude of stored water was shown. During the test-period the topographic control of the spatial pattern of Waa was predominant whereas during the whole period the spatial location of the inter-row and the tree-lines was also important. During the test-period, the mean and standard deviation values of Waa in the six plots were of 5.7 and 0.5 mm event⁻¹ (Figure 7a) whereas during all events were of 6.6 (15% higher) and 0.3 mm event⁻¹ (Figure 7b). For the whole period, the magnitude of Waa was 7% higher (mean value) with CT than with CC and these differences were even higher during the test-period, when Waa with CT was 9% higher than with CC. However, this pattern was not constant and during 38% of the events Waa was higher with CC than with CT. Indeed, the median value of Waa with CT was only 5% higher than with CC. Palese et al. (2014) found higher water storage (between 17 and 45%

higher) in olive groves in Southern Italy with spontaneous vegetation cover in comparison with groves with CT.

The mean relative differences (MRD, related to the spatial variability) in the values of Q_{obs} , q_0 , Q_{sim} and Waa in the six plots and the standard deviation of the relative differences (SDRD, metric of the temporal stability) were calculated for the events when runoff appeared in the six plots ($n=80$) (Table 6). The most stable spatial patterns appeared in the four plots with CC, with an average MRD of 0.056, -0.019, -0.015 and -0.025 mm event⁻¹ for the Q_{obs} , q_0 , Q_{sim} and Waa factors, whereas the average values of MRD in the two plots with CT were higher, related to the zero value, in all factors: -0.113, 0.038, 0.024 and 0.049 mm event⁻¹. Lightly higher temporal stability of runoff was found in the four plots with CC, with an average SDRD of 0.540, 0.095 and 0.204 mm event⁻¹ for the Q_{obs} , q_0 , and Q_{sim} factors, than in the two plots with CT, with SDRD values of 0.494, 0.184 and 0.196 mm event⁻¹, respectively. The temporal stability of Waa was higher in the four plots with CC than in the two plots with CT, with average SDRD values of 0.085 and 0.132 mm event⁻¹, respectively. Hence, the most stable spatial patterns of the observed and simulated hydrological factors appeared in the plots with CC, and also the highest temporal stability of runoff appeared with cover crops.

3.3. Further research

We think about the following research lines: I) to characterize the small topographic features that concentrate runoff, such as tractor tracks, or small rills developed in the CC system. II) To find differences in the depth and structure of the different soil horizons, hydrological gradients, presence of cracks and/or soil crusts, areas of preferential infiltration and/or higher humidity conditions, between the six plots for the purpose of understanding the different values of observed runoff in the gauging stations. III) To refine the parameterization of the model in those inputs with high uncertainty (e.g. water interception by the canopy related to the rainfall intensity, flow velocity with CC and CT, antecedent soil moisture) and high sensitivity of the model (runoff duration).

4. Conclusions

The uncalibrated DR2-2013[©] SAGA v1.1 model successfully simulated the spatial patterns and values of effective rainfall (ER), time (Tp) and rainfall (Rp) to ponding, duration of runoff (T_Q), duration of runoff after ending the rainfall (T_{Qafter}), runoff generation (q_0) and redistribution (Q_{sim}), surface storage of water by microtopography (SS_{max}) and runoff (Q_{in}) in the six olive field plots. Some of these parameters are difficult to measure in the field and thus the outputs of the model are of interest to understand the hydrological response of the soil during the rainfall and runoff events. The model identified those rainfall events without runoff production, those with runoff production throughout the plot and those with runoff generation in only part of the plots. The values of simulated runoff (Q_{sim}) correlated well with those observed (Q_{obs}) and model

simulation was satisfactory obtaining high values of the Nash–Sutcliffe and Kling–Gupta coefficients. As the model had high sensitivity to the values of runoff duration, field observations of this process is recommended to improve the accuracy of the model predictions in the study area and other agro-ecosystems with different soil types.

The model predicted clear differences in the values of T_p and q_0 between the plots with CC and those with CT, showing higher duration of T_p with CT (2.3 times) and a lower magnitude of q_0 (2.2%) with CC. Moreover, T_Q was lightly longer with CT than with CC. The model also distinguished the different duration of T_p and the magnitude of q_0 between the inter-row and below the tree areas, and T_Q and $T_{Q_{after}}$ were much longer in the inter-row than below the tree line. However, no clear differences were found in the values of Q_{sim} between the different treatments. The observed values of runoff (Q_{obs}) also presented an important variability although the rates were 9 and 8% higher under CT than those with the 2 types of CC.

On average, the magnitude of stored water ($Waa = SS_{max} + Q_{in}$) was higher with CT than with CC although during one third of the events Waa was higher with CC than with CT. The statistical analysis of Q_{obs} and the simulated hydrological parameters of q_0 , Q_{sim} and Waa allowed identifying the most stable spatial patterns in the four plots with CC, and the lowest temporal variability of runoff was also found with CC. The six plots presented a similar temporal variability of runoff yield. Thus, cover crops triggered higher spatial stability of runoff and lower temporal variability of runoff than conventional tillage.

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Table 1 Input parameters, tools and maps used by the *DR2-2013*[®] *SAGA v1.1* model and range of values (calculated for the whole study area and the test-period).

Type of data	Input	Description	Value			
			min	mean	max	sd [*]
Climate	<i>R</i>	Rainfall depth (mm) (n=108)	1.0	15.6	95.5	17.6
	<i>I</i> ₃₀	Maximum rainfall intensity (mm h ⁻¹) (n=108)	1.0	9.5	106.0	13.7
Soil	ϑ_s	Soil water content at saturation (% vol.)	46.0	47.5	49.0	1.1
	ϑ_0	Soil water content before rainfall (% vol.)	17.2	28.3	37.1	5.7
	<i>K</i> _{fsT}	Sat. hydr. conduct. (0-10 cm depth) (mm h ⁻¹)	11.8	23.7	38.7	11.4
	<i>K</i> _{fs}	Sat. hydr. conduct. (10-20 cm depth) (mm h ⁻¹)	27.3	35.6	39.6	4.2
	Φ	Matrix flux potential (cm ² s ⁻¹)	0.040	0.040	0.040	0
	<i>SIG</i>	Surface soil and surface furrow angle (radian)	0.52	0.52	0.52	0
	<i>RG</i> ^{**}	Soil surface roughness (mm)	0.60	0.82	1.53	0.32
Topography	<i>DEM</i>	Digital Elevation Model (m above sea level)	85.9	91.5	95.7	2.4
	<i>S</i>	Slope steepness (%)	5.0	13.4	27.2	2.5
	<i>FIL</i>	Flow length (m)	0.0	6.0	67.0	9.0
	<i>FAA</i>	Flow accumulation algorithm	<i>Potential cumulative runoff (Q₀)</i>			
Land use	<i>LULC</i>	Land use and land cover map	<i>Inter-row, tree-line and bare soil</i>			
Vegetation	<i>A</i> ^{**}	Rainfall interception by canopy (%)	0.0	8.6	14.0	5.6
	<i>FIV-w</i>	Flow velocity in winter period (m s ⁻¹)	0.76	1.57	4.91	1.10
	<i>FIV-s</i>	Flow velocity in summer period (m s ⁻¹)	0.76	1.75	4.91	1.13

^{*}: standard deviation; ^{**}: monthly scale.

Table 2 Values of measured runoff yield (Q_{obs}) and coefficients (QC_{obs}) during the 27 time-integrated field surveys in the gauging stations of the six plots and with the three vegetation treatments, and mean saturated hydraulic conductivity (K_{fs}) and slope (S) of the plots. Percentage of the inter-row (In) and below the canopy (Ca) land in each plot is also showed. med and sd stands for the median and standard deviation values.

Plot	Treatment	Q_{obs}					QC_{obs}	K_{fsT}	K_{fs}	S	Surface	
		(mm)					(%)	(mm/h)	(mm/h)	(%)	(%)	
		min	mean	max	sd	med	mean	mean	mean	mean	In	Ca
P1	CC-I	<0.1	10.4	80.7	17.1	3.3	11.4	22.6	38.2	12.2	53	47
P5	CC-I	<0.1	7.2	47.9	10.2	4.0	8.7	22.4	38.2	14.3	52	48
P1+P5	CC-I	<0.1	8.8	80.7	14.0	3.7	10.1	22.5	38.2	13.3	53	47
P3	CC-II	<0.1	7.6	31.3	9.6	3.2	10.3	22.8	38.2	14.0	55	45
P6	CC-II	<0.1	10.0	50.9	12.8	7.9	12.2	23.4	38.1	14.7	57	43
P3+P6	CC-II	<0.1	8.8	50.9	11.3	5.5	11.2	23.1	38.1	14.4	56	44
P2	CT	<0.1	9.8	42.3	13.3	3.8	11.5	25.5	30.3	12.2	51	49
P4	CT	<0.1	9.3	34.3	10.7	3.9	11.5	25.6	30.3	12.7	51	49
P2+P4	CT	<0.1	9.5	42.3	11.9	3.8	11.5	25.5	30.3	12.5	51	49

Table 3 Mean and standard deviation (sd) of time to ponding (T_p ; s) and initial runoff per raster cell (q_0 ; mm) under the 3 management scenarios in the soils below the canopy (Ca) and in the inter-rows (In) of the six plots and during the test-period.

Treatment	Plot	T_p (s)		q_0 (mm)			
		mean	sd	min	mean	max	sd
All	Canopy	53.8	89.5	5.53	29.32	85.39	19.23
	Inter-row	19.2	10.3	5.69	32.47	96.10	21.78
CC-I	P1			5.63	30.43	88.94	20.56
	P5			5.65	30.60	89.46	20.68
	P1&P5	25.2	21.3	5.63	30.52	89.46	20.44
	P1&P5_Ca	31.9	26.8	5.57	29.24	84.40	19.23
	P1&P5_In	18.4	10.7	5.69	31.95	95.04	21.86
CC-II	P3			5.69	30.73	89.76	20.74
	P6			5.65	30.49	88.97	20.56
	P3&P6	25.2	21.3	5.65	30.61	89.76	20.47
	P3&P6_Ca	31.9	26.8	5.61	29.52	85.39	19.41
	P3&P6_In	18.4	10.7	5.70	31.98	95.07	21.88
CT	P2			5.99	31.27	90.05	20.82
	P4			5.99	31.32	90.19	20.85
	P2&P4	59.1	107.4	5.99	31.29	90.19	20.65
	P2&P4_Ca	97.4	142.6	5.53	29.21	84.58	19.40
	P2&P4_In	20.7	9.8	6.46	33.48	96.10	21.96

Table 4 Mean duration of total runoff (T_Q) and runoff after ending the rainfall (T_{Qafter}). Simulated runoff (Q_{sim} , mm) during the test and the whole period (81 events), under the three management scenarios in the six plots. Simulated runoff coefficients (QC_{sim}) are also presented.

Plot	Treatment	T_Q^*	T_Q^{**}	T_{Qafter}^{***}	Q_{sim}^*				Q_{sim}^{**}				$QC_{sim}^{\$}$
		(s)	(s)	(s)	(mm)				(mm)				(%)
		mean	mean	mean	min	mean	max	sd	min	mean	max	sd	mean
All ^{\$\$}	Canopy	2751	5588	3.1	0	0.2	10.9	0.9	0	0.5	22.7	2.0	
	Inter-row	6674	6209	4.9	0	2.4	17.5	3.5	0	5.7	37.7	7.8	
P1	CC-I	4544	5813	4.6	<0.01 [#]	3.2 [#]	21.1 [#]	4.2 [#]	1.2 [#]	7.0 [#]	21.1 [#]	4.9 [#]	16.4 [#]
P5	CC-I	4502	5845	4.8	<0.01 [#]	3.7 [#]	24.4 [#]	4.9 [#]	1.5 [#]	8.1 [#]	24.4 [#]	5.7 [#]	18.9 [#]
P1+P5	CC-I	4522	5830	4.7	<0.01 [#]	3.5 [#]	24.4 [#]	4.6 [#]	1.2 [#]	7.6 [#]	24.4 [#]	5.3 [#]	17.6 [#]
P3	CC-II	4728	5870	4.0	0.02 [#]	3.4 [#]	21.5 [#]	4.3 [#]	0.3 [#]	7.2 [#]	21.5 [#]	5.0 [#]	16.9 [#]
P6	CC-II	4419	5821	3.6	<0.01 [#]	3.3 [#]	21.9 [#]	4.4 [#]	1.3 [#]	7.3 [#]	21.9 [#]	5.1 [#]	16.7 [#]
P3+P6	CC-II	4579	5846	3.8	<0.01 [#]	3.3 [#]	21.9 [#]	4.3 [#]	0.3 [#]	7.2 [#]	21.9 [#]	5.0 [#]	16.8 [#]
P2	CT	4691	5955	3.6	0.01 [#]	3.4 [#]	22.2 [#]	4.4 [#]	1.4 [#]	7.5 [#]	22.2 [#]	5.2 [#]	17.0 [#]
P4	CT	4613	5963	3.0	<0.01 [#]	3.2 [#]	20.9 [#]	4.2 [#]	1.3 [#]	7.1 [#]	20.9 [#]	4.8 [#]	16.1 [#]
P2+P4	CT	4650	5959	3.3	<0.01 [#]	3.3 [#]	22.2 [#]	4.3 [#]	1.3 [#]	7.3 [#]	22.2 [#]	5.0 [#]	16.5 [#]

*: All events with runoff production: 80 (CC) and 81 (CT) events; **: Test-period (29 events); ***: Average value per event; \$: during the 27 time-integrated field surveys; \$\$: from the average map for each period; #: from the simulated values at the outlet of the plots; sd: standard deviation.

Table 5 Integrated values of predicted runoff (ΣQ_{sim}) during the 27 field surveys in the six plots and the three land use treatments. The performance metrics of the simulated runoff values are also showed.

Plot	Treatment	ΣQ_{sim} (mm)				ratio*	r_p	NSE	KGE
		min	mean	max	sd	(%)			
P1	CC-I	0.2	9.5	44.8	10.2	-8.6	0.898	0.714	0.577
P5	CC-I	0.2	11.0	52.1	11.9	52.7	0.920	0.642	0.443
P1+P5	CC-I	0.2	10.2	52.1	11.0	22.0	0.909	0.679	0.510
P3	CC-II	0.2	10.0	46.6	10.6	32.6	0.813	0.512	0.612
P6	CC-II	0.1	9.7	46.5	10.6	-3.8	0.892	0.791	0.795
P3+P6	CC-II	0.1	9.8	46.6	10.5	14.4	0.852	0.651	0.703
P2	CT	0.2	10.2	47.5	10.7	3.8	0.855	0.729	0.757
P4	CT	0.2	9.5	44.7	10.1	2.5	0.790	0.598	0.781
P2+P4	CT	0.2	9.8	47.5	10.3	3.1	0.822	0.663	0.769

*: ratio between simulated (ΣQ_{sim}) and observed (Q_{obs}) runoff; r_p : Pearson's correlation coefficient; NSE: Nash–Sutcliffe efficiency; KGE: Kling–Gupta efficiency.

Table 6 Mean values of Waa and temporal stability of the changes in the values of q_0 , Q_{obs} , Q_{sim} and Waa during the 80 events when runoff appeared in the six plots. MRD: mean relative difference; SDRD: standard deviation of the relative differences.

Plot	Treatment	q_0 (mm)		Q_{obs} (mm)		Q_{sim} (mm)		Waa (mm)		
		MRD	SDRD	MRD	SDRD	MRD	SDRD	mean	MRD	SDRD
P1	CC-I	-0.020	0.095	0.280	0.590	-0.079	0.113	6.56	-0.012	0.072
P5	CC-I	-0.033	0.100	-0.112	0.487	0.046	0.133	6.28	-0.049	0.102
P1+P5	CC-I	-0.027	0.098	0.084	0.538	-0.017	0.123	6.42	-0.031	0.087
P3	CC-II	0.030	0.087	0.144	0.644	0.148	0.338	6.50	-0.014	0.069
P6	CC-II	-0.053	0.097	-0.087	0.439	-0.175	0.233	6.51	-0.023	0.096
P3+P6	CC-II	-0.012	0.092	0.029	0.542	-0.014	0.286	6.50	-0.019	0.082
P2	CT	0.049	0.188	-0.134	0.472	0.067	0.205	6.92	0.042	0.127
P4	CT	0.028	0.180	-0.092	0.516	-0.019	0.186	6.96	0.057	0.137
P2+P4	CT	0.038	0.184	-0.113	0.494	0.024	0.196	6.94	0.049	0.132

Figure 1 Location of the study area (Santa Marta farm) in SW Spain, near Seville city (source: <http://www.ign.es/iberpix2/visor/>). Pictures of the gauging stations and of the plots under the different cover crop treatments are shown together with a detailed map of inter-row and below the tree lands.

Figure 2 Step-by-step procedure to estimate the actual available water (W_{aa}) at pixel scale.

ER : Effective rainfall; T_p : Time to ponding; q_0 : initial runoff per raster cell; Q_0 : potential cumulative runoff; α : water balance factor; Q_{0B} : balanced potential cumulative runoff; Q_{sim} : simulated runoff; K_{fs}^* : infiltrated water during runoff event ($K_{fs} T_{Q_0}$, see Eq. (8)); SS_{max}^* : maximum surface storage capacity; R_p : rainfall to ponding.

Figure 3 Values of rainfall depth (R) and maximum intensity in 30 minutes (I_{30}), and of soil moisture with cover crops (Moist.CC) and conventional tillage (Moist.CT) during the two hydrological years (a). Measured runoff yield (Q_{obs}) in the six gauging-stations during the 27 time-integrated surveys (b). Pearson's correlation coefficients (dashed lines indicate significant correlation at $P < 0.05$) between the values of Q_{obs} and cumulative rainfall (ΣR), rainfall intensity (I) and I_{30} during the first (c) and second (d) year.

Figure 4 Spatial pattern of the mean effective rainfall (ER) (a) and initial runoff per raster cell (q_0) (b) during the test-period (29 events). Inter-row-to-canopy q_0 ratio for CC and CT plots (c), and CT-to-CC q_0 ratio (d). Maximum variability of q_0 during the test-period in the six plots (e) and regression between the mean q_0 (84 events) and the rainfall depth (R), maximum intensity (I_{30}) and mean time of ponding (T_p) (f).

Figure 5 Mean values of simulated runoff (Q_{sim}) in the six plots during the 84 events (a). Map of the mean Q_{sim} (mm event⁻¹) during the test-period (b). Simulated runoff coefficients (QC_{sim} , %) related to the effective rainfall during the 84 events (c). Average duration of runoff (T_Q) during the test-period (d), and average volume of water stored due to the soil roughness at each event (SS_{max}) (e).

Figure 6 Accumulated runoff from the model predictions and observed values during the two hydrological years (a). Pearson's correlation coefficients between the simulated and observed values of runoff in the six plots (dashed line indicate 1:1 relationship) (b).

Figure 7 Map of the average actual available water (W_{aa} ; mm event⁻¹) during the test-period (a) and all events with runoff production (b).