

1 **Supplementary material**

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3 **1. Generation of input maps for WATEM/SEDEM**

4 *1.1 Digital Elevation Model*

5 The DEM plays a central role in WATEM/SEDEM, since it is used to calculate
6 the slope gradient and the length–slope factor (LS_{2D}), and for routing the sediment
7 downstream. We used a DEM with a spatial resolution of 1 m elaborated by the Spanish
8 Ministry of Agriculture using photogrammetric restitution. The grid resolution of the
9 DTM was then reduced to 5×5 m grid by averaging the values on the original grid. A
10 pit-filling algorithm (Planchon and Darboux, 2001) was used to guarantee the
11 hydrological connectivity of the grid cells until the catchment outlet.

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13 *1.2 Stream network*

14 A map of the stream network was generated using the RUNOFF module in
15 IDRISI, with the assumption that an upstream catchment area greater than a fixed value
16 defined a channel. After testing different values, we concluded that a threshold area of 1
17 km^2 constituted a good approximation, since it showed good consistency with the stream
18 network as seen in the orthophoto map of the catchment. The 1 km^2 threshold represents
19 an upper limit beyond which sediment deposition is highly unlikely because of
20 concentrated overland flow (Verstraeten et al., 2007).

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22 *1.3 Parcel map*

23 The parcel map was a reclassification of the current land uses/land cover map
24 (Figure 2B), which was derived from aerial orthophotos (SIGPAC, 2003). The aerial
25 orthophotos were digitized and the LULC types were grouped into five major classes:
26 cultivated land, forest, grassland, infrastructure and built-up areas, and water bodies. The
27 original map was resampled to match the spatial resolution used in the study, using the
28 RESAMPLE algorithm implemented in IDRISI.

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30 **1.4 Soil erodibility (K-factor)**

31 The soil erodibility factor (K-factor of the RUSLE model) describes the
32 susceptibility of soil to erosion by rainfall. Because of the lack of detailed soil maps it
33 was necessary to analyze soil samples from the study area. A total of 77 bulk soil cores
34 were collected on a grid pattern at the intersections of a 200 m × 200 m grid (Figure 1B),
35 to assess the spatial distribution of physico-chemical soil properties relevant to soil
36 erosion. To provide a database for the automated land evaluation system several main soil
37 properties were analyzed in a previous study (Navas et al., 2005).

38 K-factor values were determined from soil texture data (Römken et al., 1987)
39 according to:

$$40 \quad K_{text} = 0.0034 + 0.0405 \exp \left[-0.5 \left(\frac{\log D_g + 1.659}{0.71} \right)^2 \right],$$

41 (1)

42 where K_{text} is a soil erodibility factor ($\text{Mg h MJ}^{-1} \text{ mm}^{-1}$) and D_g is the geometric mean
43 weight diameter of the primary soil particles (fraction < 2 mm). D_g was determined using
44 a Coulter laser diffraction particle size analyzer (Coulter LS 230) for the 2–2000 μm

45 fraction, following removal of organic matter (Buurman et al., 1997). K-factor values
46 were then corrected to reflect the effect of stones in the soil surface on soil erodibility
47 (Box, 1981):

$$48 \quad K = K_{text} \exp^{(-0.0278St)}, \quad (2)$$

49 where St is the weight of stones in the topsoil, expressed as a percentage of the total
50 weight of the topsoil. A K-factor map for the study area was obtained from the 77
51 selected sample points estimations by using a smoothing splines spatial interpolation
52 method (Figure 2C).

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54 ***1.5 Rainfall erosivity (R-factor)***

55 The rainfall erosivity factor (R-factor, MJ mm ha⁻¹ h⁻¹ y⁻¹) is used to represent the
56 impact of rain on soil erosion, and is based on the rainfall amount and intensity. The R-
57 factor value was calculated for the area using a database of rainfall series from the SAIH
58 system (automatic hydrological information network) of the Ebro basin water authority
59 (Confederación Hidrográfica del Ebro). We used all available data to calculate R-factor
60 values for the period October 1963 to September 2008. No high resolution (e.g. hourly)
61 data were available, so we used an approximation based on daily rainfall data (Angulo-
62 Martínez and Beguería, 2009). This way, an average R-factor of 1217 MJ mm ha⁻¹ h⁻¹ y⁻¹
63 was used.

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65 ***1.6 Crop management (C-factor)***

66 A crop management factor (C-factor) was used to define the susceptibility of
67 various LULC types to erosion by water. C-factor values were applied to each land use

68 category according to the values proposed by the Spanish Institute for Nature
 69 Conservation, ICONA (Almorox et al., 1994): 0 for water bodies and infrastructure built-
 70 up areas (i.e. no erosion); 0.003–0.030 for forest land cover; 0.030–0.250 for scrubland;
 71 0.045–0.150 for grassland; and 0.250–0.800 for bare soil categories (Table 2). A C-factor
 72 map was constructed by applying those values to the LULC map (Figure 2D).

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74 **1.7 Model efficiency statistics**

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The Nash-Sutcliffe statistic was computed as:

$$76 \quad NS = 1 - \frac{\sum_{i=1}^n (O_i - P_i)^2}{\sum_{i=1}^n (O_i - O_{mean})^2}, \quad (3)$$

77 where n is the number of observations, O_i is the observed value, O_{mean} is the mean
 78 observed value, and P_i is the predicted value. The value of NS can range from $-\infty$ to 1,
 79 and represents the proportion of the initial variance accounted for by the model. The
 80 closer the value of NS is to 1, the more efficient is the model in reproducing the observed
 81 values.

82 The relative root mean square error was computed as:

$$83 \quad RRMSE = 1 - \frac{\sqrt{\frac{1}{n} \sum_{i=1}^n (O_i - P_i)^2}}{\frac{1}{n} \sum_{i=1}^n O_i}. \quad (4)$$

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