

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

2 ***1.1 Digital Elevation Model***

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

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11 ***1.2 Stream network***

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

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20 ***1.3 Parcel map***

21 The parcel map was a reclassification of the current land uses/land cover map
22 (Figure 2B), which was derived from aerial orthophotos (SIGPAC, 2003). The aerial
23 orthophotos were digitized and the LULC types were grouped into five major classes:
24 cultivated land, forest, grassland, infrastructure and built-up areas, and water bodies.

25 The original map was resampled to match the spatial resolution used in the study,
26 using the RESAMPLE algorithm implemented in IDRISI.

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28 **1.4 Soil erodibility (K-factor)**

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

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

$$39 \quad K_{text} = 0.0034 + 0.0405 \exp \left[-0.5 \left(\frac{\log D_g + 1.659}{0.71} \right)^2 \right],$$

40 (1)

41 where K_{text} is a soil erodibility factor ($\text{Mg h MJ}^{-1} \text{ mm}^{-1}$) and D_g is the geometric mean
42 weight diameter of the primary soil particles (fraction < 2 mm). D_g was determined
43 using a Coulter laser diffraction particle size analyzer (Coulter LS 230) for the
44 2–2000 μm fraction, following removal of organic matter (Buurman et al., 1997). K-
45 factor values were then corrected to reflect the effect of stones in the soil surface on
46 soil erodibility (Box, 1981):

$$47 \quad K = K_{text} \exp^{(-0.0278St)}, \quad (2)$$

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

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53 **1.5 Rainfall erosivity (R-factor)**

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

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64 **1.6 Crop management (C-factor)**

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

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74 **1.7 Model efficiency statistics**

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The Nash-Sutcliffe statistic was computed as:

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

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
79 1, and represents the proportion of the initial variance accounted for by the model.
80 The closer the value of NS is to 1, the more efficient is the model in reproducing the
81 observed values.

82 The relative root mean square error was computed as:

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

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