Supplementary Materials: Climate and Land Use Changes on Streamflow and Subsurface Recharge in the Fluvià Basin, Spain

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File S1: Historical and Downscaled Data

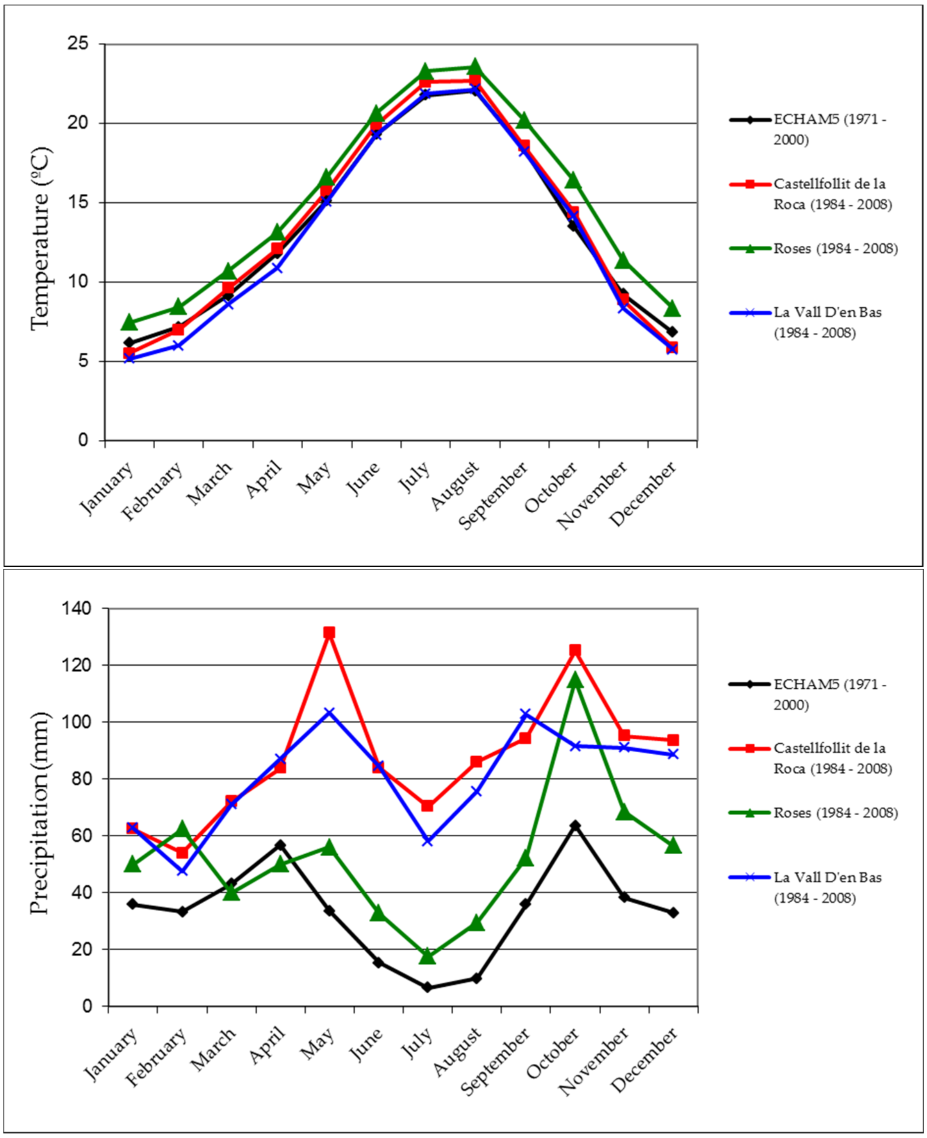
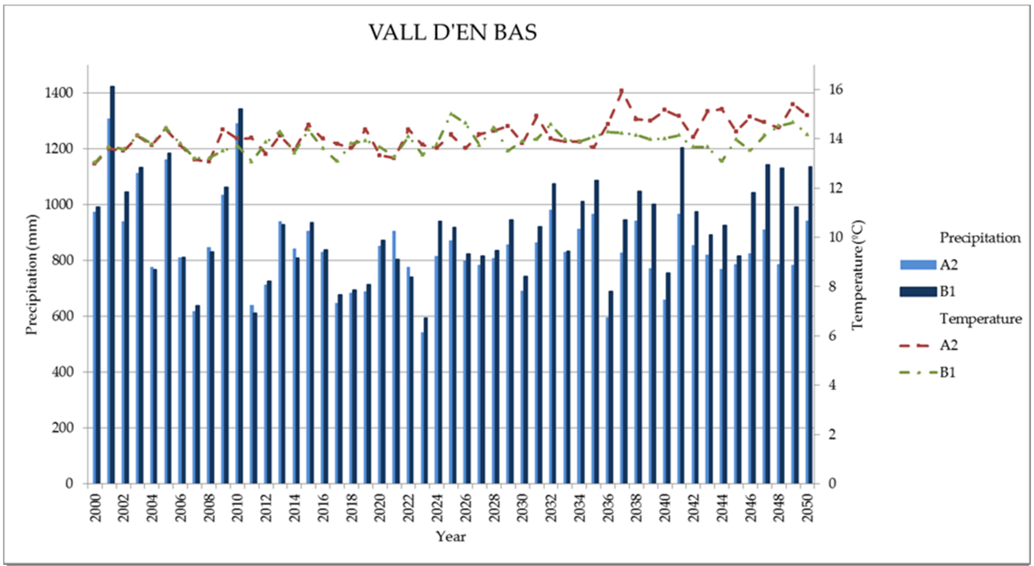
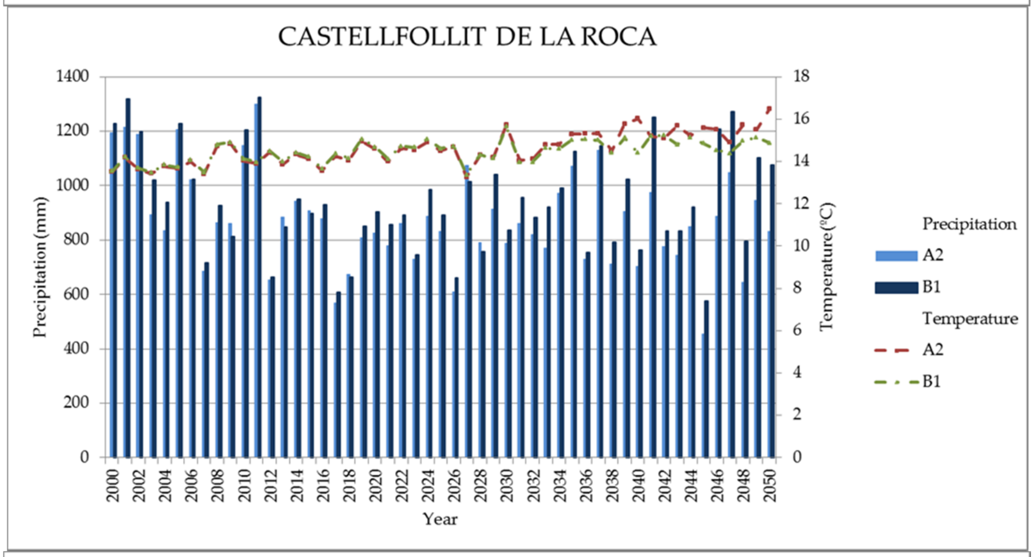
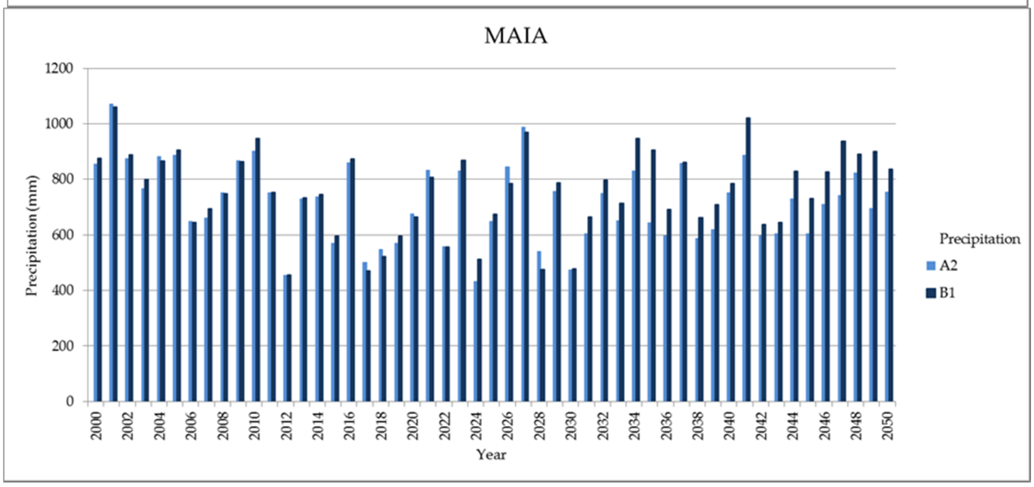


Figure 1. Monthly temperature (°C) and precipitation (mm) at the three meteorological stations in the Fluvià basin for the historical period (1984) and values simulated with ECHAM5 for the reference period (1971–2000).


VALL D'EN BAS
Precipitation (mm)
Temperature (°C)
Year
Precipitation
A2
B1
Temperature
A2
B1


CASTELLFOLLIT DE LA ROCA
Precipitation (mm)
Temperature (°C)
Year
Precipitation
A2
B1
Temperature
A2
B1


MAIA
Precipitation (mm)
Year
Precipitation
A2
B1

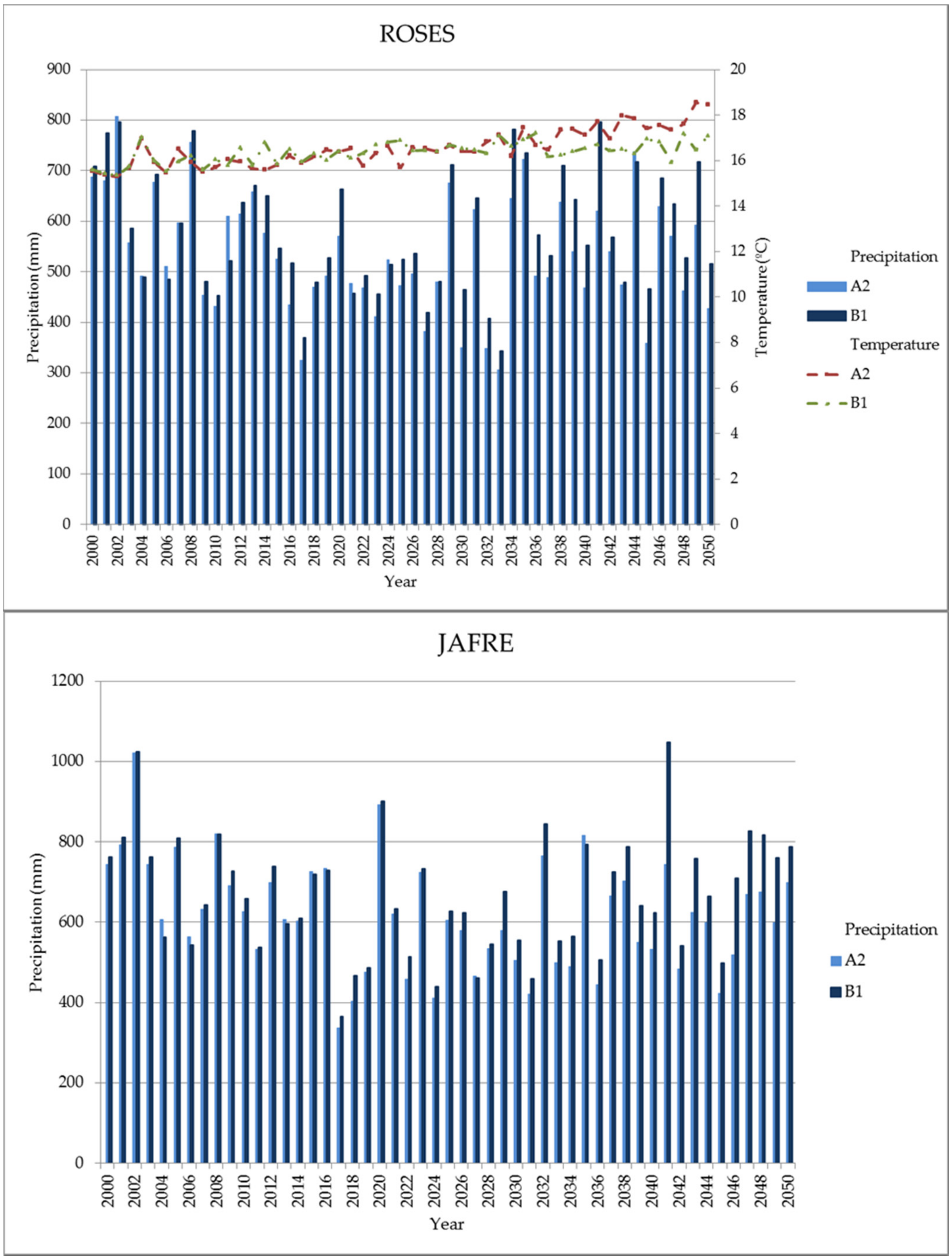


Figure 2. Downscaled P and T.

File S2: Statistical Downscaling

Statistical downscaling was carried out to translate the outputs from the global climate models into useful information on a regional scale. This process generates precipitation and temperature series from the statistical properties predicted by the global climatic model. Downscaling output for future climate change scenarios (temperature and precipitation) involves three steps [1,2]. Firstly, a stochastic weather generator is developed and parameter calibration is carried out to reproduce the statistics of the observed data (1984–2008). Secondly, changes in monthly rainfall (mean and standard deviation) between a control period (1971–2000) and the future scenarios predicted by the GCM are calculated. Thirdly, perturbation of the stochastic weather generator based on GCM predictions is developed.

For weather generation in the climate change scenario, a model suite was developed that comprised a stochastic daily rainfall generator and a stochastic mean daily temperature generator.

The rainfall generator is based on the well-known chain-dependent-process stochastic model for daily precipitation [3–5], which is a two-state model: a first-order non-stationary Markov chain for modelling rainfall occurrences, and a probabilistic sub-model for modelling amounts of rainfall [6]. This rainfall generator is capable of dealing with seasonal non-stationarity by simply evaluating the probability transition matrix and the parameters of the probabilistic sub-model on a monthly basis.

X_t represents the binary event of precipitation or no precipitation (precipitation refers to a rainfall event of more than 0.1 mm/day) occurring on day *t*:

$$X_t = \begin{cases} 0 \; if \;\; day \; t \; is \; dry \\ 1 \; if \;\; day \; t \; is \; wet \end{cases} \tag{1}$$

Then the time series of precipitation is:

$$Y_t = h_t \cdot X_t \tag{2}$$

where h_t represents non-zero precipitation.

The first-order Markov chain model for X_t follows from the assumption that the probability of a wet/dry day depends on whether there was a precipitation occurrence the previous day (t − 1).

$$\begin{aligned} Pr\{X_t = 1 | X_{t-1} = 0\} = p_{01} \\ Pr\{X_t = 1 | X_{t-1} = 1\} = p_{11} \end{aligned} \tag{3}$$

Equivalently, the complementary conditional probabilities are:

$$\begin{aligned} Pr\{X_t = 0 | X_{t-1} = 0\} = p_{00} \\ Pr\{X_t = 0 | X_{t-1} = 1\} = p_{10} \end{aligned} \quad \text{with} \quad \begin{aligned} p_{00} = 1 - p_{01} \\ p_{10} = 1 - p_{11} \end{aligned} \tag{4}$$

Parameters p_{01} and p_{11} are the conditional probabilities of a wet day following a dry day and of a wet day following a wet day. Both the definition of the parameters and Equation (3) are defined completely by the Markov model.

If precipitation occurs, then the amount of precipitation falling on a wet day is determined by using a predefined distribution frequency. In this case, the non-zero precipitation amount h_t (*i.e.*, rainfall over 0.1 mm) was simulated using the Weibull distribution [7].

$$F(h) = 1 - exp\left[- \left(\frac{h^{\beta}}{\alpha} \right) \right] \tag{5}$$

where α and β are the distribution parameters estimated using the maximum likelihood estimation procedure. To incorporate the seasonality of precipitation events, parameters were independently estimated for each month.

The stochastic simulation of series X_t under first-order Markov dependence is a straightforward process. Output u_t from a uniform [0,1] random number generator was compared with the appropriate transition probability from Equations (3) and (4). A wet day was simulated if the random number was lower than a "critical" probability p_c:

$$X_t = \begin{cases} 1 & if\ u_t \leq p_c \\ 0 & otherwise \end{cases} \text{ with } p_c = \begin{cases} p_{01} & if\ X_{t-1} = 0 \\ p_{11} & if\ X_{t-1} = 1 \end{cases} \tag{6}$$

The temperature daily series was obtained by multiplying the mean monthly temperature for the daily proportional coefficient, defined as the ratio between the mean k-daily temperature and the mean j-monthly temperature. The temperature generator is based on the classical Autoregressive Moving Average model (ARMA) [6], particularly of first-order in both the autoregressive and moving average parts (ARMA (1,1) model):

$$\begin{aligned} y_k &= \phi y_{k-1} + \varepsilon_k - \theta \varepsilon_{k-1} \\ y_k &= \frac{t_k - \mu(t)_j}{\sigma(t)_j} \end{aligned} \tag{7}$$

with:

$\mu(t)_j$ = monthly mean temp. for j_{th} month;

$\sigma(t)_j$ = monthly standard deviation temp. for j_{th} month;

ε_k = uncorrelated white noise process;

t_k = daily average temperature for k_{th} day.

The model was used in a normalised form to handle the seasonal non-stationarity in the original temperature series [8]. The parameters of the model were obtained by maximum likelihood estimation.

In climate change scenarios, meteorological series were built as follows: future rainfall scenarios were generated by the perturbation of the Weibull distribution parameters using the new values for monthly variance and the mean predicted by the GCM future scenarios; the rainfall generator is based on the hypothesis that only the precipitation amounts are affected by climate change and not the probability transition matrix. The new temperature series were obtained by multiplying the normalised series by climate scenario variances and then adding the corresponding mean.

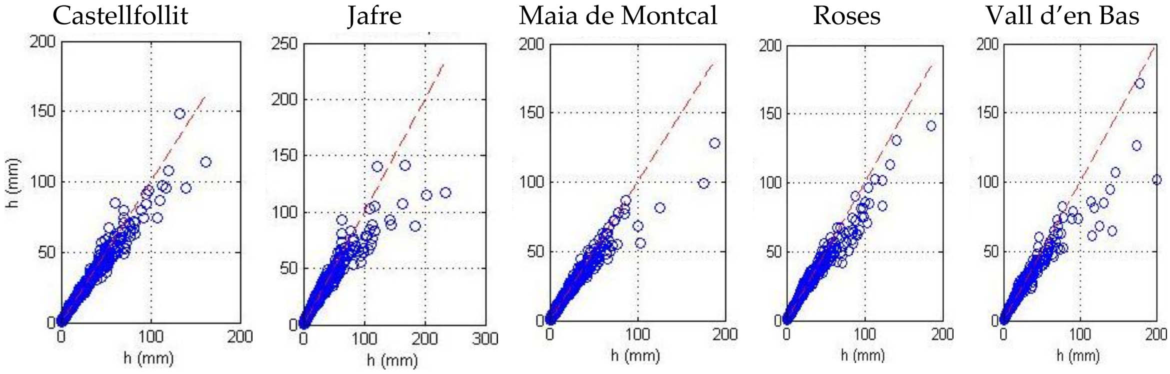


Figure 1. Results. Q-Q diagram of precipitation. Comparison of the historical period (meteorogical stations in the area) and the Weibull-simulated data.

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File S3: The Visual BALAN Numerical Model

Visual BALAN v. 2.0 [1], is a computer code suitable for long-term simulation of water balance in the soil, vadose zone and aquifer and similar to other existing codes, like INFIL [2] or SAHYSMOD [3] among others. The code comprises three sub-models for processes in (1) the upper part of the soil (root zone); (2) the vadose or unsaturated zone (lower soil) and (3) the saturated zone (aquifer). The approach assumes a cascade model for precipitation, interception, runoff, evapotranspiration and the recharge process. The state variable in each of the three zones is water volume, expressed as volume per surface unit (e.g., L/m^2) or equivalent height of water (e.g., mm).

For vegetated soil the water balance is represented by:

$$P + Ir - In - E_s - ET_a - P_e = \Delta\theta$$

where P is precipitation; Ir irrigation; In canopy interception; E_s runoff; ET_a actual evapotranspiration; P_e potential recharge to the vadose zone and $\Delta\theta$ variation of soil water storage.

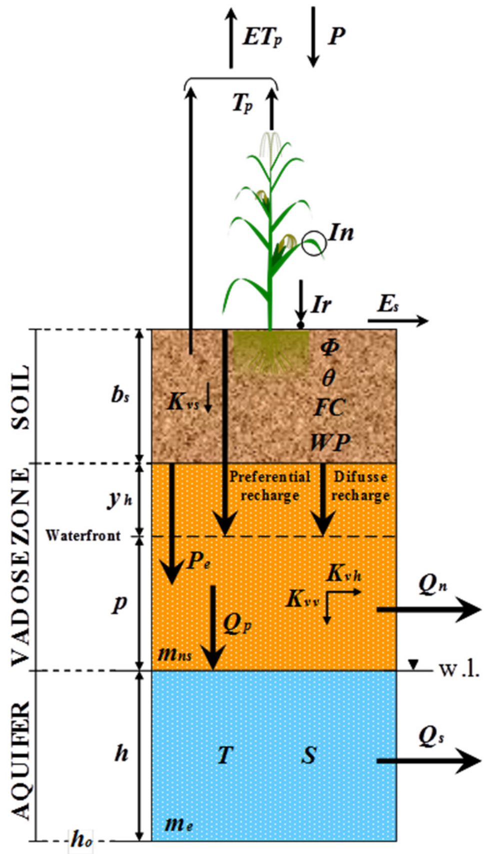

Figure 1. Balance components as defined in Visual Balan. The three soil components and hydrologic processes. (K) hydraulic conductivity; (Φ) drainable porosity; (θ) water content; (FC) field capacity; (WP) wilting point; (b_s)thickness; (y_h) thickness of the waterfront;(P_e) potential recharge; (Q_h) hypodermic flow; (Q_p) recharge; (m) porosity; (w.l) water level; (h) groundwater level; (T) transmissivity; S storage coefficient, (Q_s) groundwater flow.

In the vadose/unsaturated zone, potential recharge P_e, constitutes the entry of water, which can be hypodermic flow Q_h (constitutes baseflow) and vertical flow or percolation to the aquifer Q_p, which constitutes the deep recharge.

References

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File S4: Sub-Basins Characteristics

Table 1. Characteristics of sub-basins defined in Figure 1.

Sub-Basin	Area (km²)	Impervious Area (%)	Land_Use (%)		
			Forest	Crops	Bush
W270	202.2	0.5	93.6	1.5	4.4
W280	138.01	1.8	87.6	3.8	6.8
W300	71.9	2.7	85.5	1.5	10.3
W320	242.02	8.5	85.6	1.6	4.3
W410	127.9	4.2	75.8	19.9	0.1
W430	131.3	1.9	65.1	9.8	23.2