



Natural uncertainty of spatial average aquifer recharge through atmospheric chloride mass balance in continental Spain



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SUMMARY

In a previous paper, the atmospheric chloride mass balance (CMB) method for spatial average diffuse aquifer recharge by rainfall (\bar{R}) in large and varied territories was evaluated. Continental Spain was chosen to show the reliability of this application. Two main sources of uncertainty (measured by the coefficient of variation, CV) affecting \bar{R} , induced by the inherent natural variability of the variables (CV_R) and from mapping (CV_R^K), were separated. While CV_R^K may be decreased with better data coverage, the part of CV_R inferred by the variable length of yearly data series can be corrected by comparing them to existing long series. With the same data sets and methods as in a previous paper, a data-correction procedure to improve \bar{R} and CV_R is presented. The critical balance period (N) to reach comparable steady (long-term) CMB averages and CV values (CVs) was defined. The correction considered the timing of short series to incorporate the yearly data oscillating trend from longer series, additional trends deduced from longer series having incomplete N -year cycles, and changing stationary parameters over space from several long series. In continental Spain, $N = 10$ years. This period coincides with the decadal global climatic cycles acting on the Iberian Peninsula. Corrected CMB averages and CVs were regionalized by ordinary kriging using the same $10 \text{ km} \times 10 \text{ km}$ 4976-nodes grid used for mapping the original CMB components. Nodal \bar{R} values varied from 17 to 715 mm year^{-1} , 90% ranging from 35 to 300 mm year^{-1} . Data correction did not significantly change averages; corrected average \bar{R} was 2% higher. However, the CVs changed conspicuously. The average CV_R was 0.29, more than twice the original 0.13. This more realistic estimation of CVs avoids the illusory precision obtained when the short series correspond to small change periods. The average CV_R^K was 0.09, similar to the original 0.07. The improvement is shown by the CV of CV_R and CV_R^K , which notably decreased below 0.1, even when their absolute values increased.

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1. Introduction

The calculation of aquifer recharge is essential for the quantitative evaluation and modelling of groundwater resources (De Vries and Simmers, 2002). As is the case for most natural hydrological variables, aquifer recharge is intrinsically uncertain because weather and physical variables as well as parameters used for its calculation are also uncertain (Milly and Eagleson, 1987; Scanlon, 2000). In addition, spatial evaluations may increase recharge uncertainty through the mapping procedure (Bogena et al., 2005; Mair et al., 2013) when the variables mapped include data sets of suboptimal quality and uneven spatial coverage. For management

purposes, recharge calculations should be accompanied by the evaluation of their uncertainty.

This paper examines steady (long-term) average recharge, i.e., that produced under stable conditions over many years from available data series. This means that the addition of adjacent time periods does not significantly change the average value.

In a previous paper, Alcalá and Custodio (2014) evaluated the reliability of the atmospheric chloride mass balance (CMB) method (Claassen et al., 1986; Dettinger, 1989; Wood and Sanford, 1995; Coes et al., 2007; Guan et al., 2010; Bresciani et al., 2014; and references therein) for the spatial evaluation of average diffuse aquifer recharge by rainfall in large and varied territories, when steady conditions can be assumed (Custodio, 2010). Continental Spain was chosen as a typical large territory with varied climate, geology, relief, soil-vegetation conditions, and land use, where data are available but of variable quality (often short series) and irregular spatial coverage. The spatial interpolation of the CMB averages

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by ordinary kriging allowed the evaluation of spatial average aquifer recharge from non-spatially coincident data series reasonably well distributed throughout the territory.

The temporal and spatial variability of the CMB variables were identified as two main sources of uncertainty affecting the spatial average aquifer recharge evaluation. Because long records of CMB variables are rare, steady averages had to be estimated from the available, variable-length series, which are often 1–5 years long, especially for atmospheric chloride deposition and chloride export by runoff, thus making the average recharge evaluation uncertain. The selection of interpolation techniques was based on the rather poor spatial coverage of data sets and the possibility of providing the mapping variance. The CMB variables were considered poorly correlated (Wood and Sanford, 1995; Alcalá and Custodio, 2008a) and were mapped separately by ordinary kriging (Kitanidis, 1997). Ordinary kriging is an exact and unbiased estimator that provides the variance of the interpolated values. This mapping variance was required in order to evaluate how the spatial distribution of data sets affects recharge uncertainty. The inherent natural (background) uncertainty of the variables was separated from the mapping uncertainty.

The natural uncertainty of average recharge can be improved when the short yearly data series can be confidently corrected to better represent the long-term condition, by comparing them to long series (Bence, 1995), and taking their oscillating trends into account. However, the degree to which the mapping uncertainty can be reduced is limited, although reduction is possible when the uneven spatial distribution of data sets can be offset.

The CMB variables show temporal oscillating trends induced by the global dynamics of atmospheric chloride deposition components (Erickson and Duce, 1998; Yokouchi et al., 2000), as well as by the short-scale influence of soil-vegetation dynamics, land attributes, and geology on the other balance variables (Alcalá and Custodio, 2014). Long-term oscillating trends are reasonably predictable, as pointed by Alcalá and Custodio (2008a), and thus allow corrections in short yearly data series when the measurement periods are inside or overlap a long period of reference series that behave similarly.

This paper develops a procedure to correct the CMB averages and their natural uncertainties deduced from variable-length, short series, focussed on improving the stationary evaluation of average aquifer recharge and its natural uncertainty. For this, the critical balance period (N) for stationary evaluations is defined, the yearly data oscillating trend and additional trends deduced from longer series having incomplete N -year cycles are incorporated to the coincident-in-time short series in order to better reproduce the long-term condition, and several long series are used to compute changing stationary parameters over space.

The paper is organized as follows. Section 2 describes the methodology and data-set treatment. Section 3 analyses the uncertainty associated to the data-series length. Section 4 describes the data-correction procedure. Section 5 describes an example of data correction and the mapping of corrected CMB components in continental Spain. Section 6 contains the discussion. Section 7 presents the main conclusions. Appendix A includes the notation for symbols used.

2. Synthesis of methodology and data sets

Infiltrating water incorporates atmospheric chloride (hereafter Cl^- is simply expressed as Cl) as a conservative, non-volatile solute. The water-mass reduction due to plant transpiration and soil-water evaporation (evapotranspiration) increase the Cl concentration in infiltrating water (evapoconcentration).

For long-term average recharge, the main conditions for the CMB technique are: (1) steady average precipitation, aquifer recharge, and atmospheric Cl deposition rates; (2) no other significant natural or anthropogenic sources of Cl add to the groundwater; (3) short percolation time through the vadose zone; (4) no influence of past climates or major land-use changes; (5) the Cl content at the water table is not significantly changed by diffusion and hydrodynamic dispersion with aquifer water; and (6) no permanent Cl precipitation.

The following notation is used:

- (1) x , X , \bar{X} , and X^T for the extensive variables: P = precipitation, E = surface runoff, and R = aquifer recharge.
- (2) c_x , C_x , \bar{C}_x , and C_x^T for the intensive variable 'chloride concentration' related to the extensive variable denoted in the subscript.
- (3) a_x , A_x , \bar{A}_x , and A_x^T for Cl mass fluxes of the extensive variables: A_p for atmospheric bulk deposition, A_E for export by surface runoff, and A_R for aquifer recharge.

Lowercase c_x and a_x refer to concentration and mass flux of any of the extensive variables X in a sample accumulated over a time interval of d days; for instance, $a_p = c_p \cdot p$, where p and c_p are the rainfall depth and its chloride concentration in d days, respectively. Capitals refer to: (1) X , C_x , and A_x in a given year; (2) \bar{X} , \bar{C}_x , and \bar{A}_x for the mean of n complete (or completed) successive yearly values; and (3) X^T , C_x^T , and A_x^T in a full period of d days (the sum of all the d -day time intervals) of n successive complete (or completed) years.

For the preparation of time series, gaps in data sets may be filled by interpolation or proportional correction. The method used here was the latter (Alcalá and Custodio, 2008a); for a full period of d days with only d' days of data it was assumed that $A_x^T = (d/d') \sum^{d'} a_x$. This correction is easy but if gaps tend to correspond to a given period of the year or omit exceptional events, yearly results may be biased.

Time averages of the variables were preferably calculated: (1) by adding the a_x values (e.g. daily, over some days, etc.) over a long period of n years and dividing the result by the duration of the study period: $\bar{A}_x = A_x^T/n$; and (2) by adding the A_x yearly values, which are afterwards averaged: $\bar{A}_x = (1/n) \sum^n A_x$. The results are the same for complete years without x and c_x gaps. However, some \bar{A}_x values taken from the literature for sparse-data areas were calculated using the arithmetic averages of x and c_x over the full data period. In this case, results do not always coincide, especially for skewed statistical distributions, although it is often assumed that they are close values, as deduced from experimental data (Alcalá and Custodio, 2008a).

\bar{A}_x values derived from variable- n -year series, with and without gaps, and one-year A_x data were used as long-term average values. Consistent units were used, such as g , m , and $year$. Hereafter, \bar{A}_p , \bar{A}_E , and \bar{A}_R are given in $g\ m^{-2}\ year^{-1}$, \bar{P} , \bar{E} , and \bar{R} in $m\ year^{-1}$, and \bar{C}_x in $mg\ L^{-1} \equiv g\ m^{-3}$.

For a long period of n successive complete years under steady-state conditions, the CMB is:

$$A_p^T = A_R^T + A_E^T \quad (1a)$$

or in average values:

$$\bar{A}_p = \bar{A}_R + \bar{A}_E \quad (1b)$$

Recharge was the target and thus it was assumed that $\bar{A}_R = \bar{R} \cdot \bar{C}_R$ (Custodio, 2010). When \bar{A}_p and \bar{A}_E were directly

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