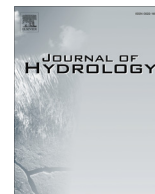




Contents lists available at ScienceDirect

Journal of Hydrology

journal homepage: [www.elsevier.com/locate/jhydrol](http://www.elsevier.com/locate/jhydrol)

## Research papers

# Estimating groundwater recharge and its associated uncertainty: Use of regression kriging and the chloride mass balance method

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## ARTICLE INFO

## Article history:

Available online xxxxx

## Keywords:

 Sydney Basin  
 Gunnedah Basin  
 Gloucester Basin  
 Spatial analysis  
 Upscaling

## ABSTRACT

The chloride mass balance method of estimating groundwater recharge is generally applied at a point scale but water resources management generally requires information at a regional scale. To estimate groundwater recharge regionally previously used upscaling methods have ranged from simple averaging to empirical relationships and geostatistical interpolation. This study combined the best components of these methods by using regression kriging: in data-sparse areas the recharge is upscaled using global regression equations with gridded rainfall and surface geology as covariates, while in data-dense areas the kriging of the regression equation residuals ensures that the upscaled recharge estimates respect the point estimates of recharge. The uncertainty in the recharge estimates was quantified using 1000 stochastic replicates of the chloride deposition of rainfall, the chloride exported in runoff, the chloride concentration of the groundwater and the regression equations used to perform the upscaling. This study focused on the coal bearing Sydney, Gunnedah, Gloucester and Surat Basins of Eastern New South Wales (Australia). Historically, groundwater recharge to the Permian units of these basins has received little attention due to their low yields of poor quality water. The increased potential extraction of regional groundwater due to coal development has demanded a greater understanding of the water balance. We found that recharge is highest in the younger productive aquifers (up to 20% of long-term mean annual rainfall) and lowest in the Permian units (~1% of long-term mean annual rainfall). The magnitude of the uncertainty is often close to the magnitude of the median recharge estimate. The method developed here for upscaling the point estimates of recharge using the chloride mass balance provides robust estimates of recharge and its associated uncertainty. The method is applicable to any regional study with variable density input data.

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## 1. Introduction

Groundwater recharge is very difficult to estimate as it cannot be directly measured (Bakker et al., 2013). While there are numerous techniques to estimate recharge (see Scanlon et al. (2002) and Healy (2010) and the references therein), the chloride mass balance method is the most widely used approach globally (Scanlon et al., 2006) and in Australia (Crosbie et al., 2010). It is popular because it is robust over many climate zones and is cost effective, requiring only analyses of chloride in groundwater and rainfall. Here, we develop an improved approach for estimating regional (i.e., >10,000 km<sup>2</sup>) groundwater recharge by combining chloride

analysis with an uncertainty assessment in a geostatistical framework that accounts for varying input data density.

The first uses of the chloride mass balance were at a point scale and the assumption was that the point estimates represented the area under investigation (Anderson, 1945; HDWB, 1957). Subsequent work (Bresciani et al., 2014; Eriksson and Khunakasem, 1969; Harrington et al., 2002) showed that recharge estimates are not necessarily a point estimate but are an integration of an area upgradient of the sample location; the exact upgradient area being determined by aquifer geometry, depth of screens, and distance to boundaries, amongst other things. Thus, truly representative recharge estimates require some form of upscaling. This could be as simple as a straight average of point estimates of recharge over the entire region of interest (Ordens et al., 2012) or dividing the area of interest into zones (Eriksson and Khunakasem, 1969; Naranjo et al., 2015). Where there is sufficient spatial density of

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input data, a spatially consistent upscaling of recharge estimates to a regular grid becomes possible. This requires that the observations of chloride deposition in rainfall and groundwater chloride concentrations are characteristic of the spatial variability (Ait El Mekki et al., 2015; Alcalá and Custodio, 2015; Davies and Crosbie, 2017; Hornero et al., 2016; Scanlon et al., 2012). Where there is insufficient density of input data to support a regular grid upscaling, covariate regression analyses provides an alternative to overcome the data-sparse shortfall (Crosbie et al., 2015).

Although it is often noted that there is great uncertainty in recharge estimates, the uncertainty is rarely quantified; but there are several examples quantifying the uncertainty in recharge estimates from chloride mass balances in the literature. The simplest method evaluated the range of the recharge rate from a high and low chloride deposition rate and presented the uncertainty as high and low recharge estimates (Ordens et al., 2012). More formal approaches included a linear error propagation of the standard deviations of each of the input variables interpolated to the output recharge estimate grid, which assumes normally distributed errors (Alcalá and Custodio, 2014, 2015). Monto Carlo sampling of a Pearson Type III distribution with a log-normal distribution of chloride concentration allowed to relax the normality assumption and was more representative of the data distribution, but it required extensive computing resources (Davies and Crosbie, 2017). An additional improvement to incorporate data-sparse basins included the use of a regression equation to upscale recharge estimates and account for uncertainty stochastically at a point scale. This included a probability distribution for the chloride deposition and a bootstrapping of the recharge samples in the regression (Crosbie et al., 2015).

In this study, we improve these approaches for groundwater recharge estimates by combining regression analysis with the spatial interpolation. This is known from other disciplines as regression kriging (Hengl et al., 2004), kriging with external drift (Wackernagel, 2013) or partial thin plate splines (McVicar et al., 2010). In this approach the mean of the interpolation becomes an externally defined, often linear, function of a spatially continuous covariate (or covariates). The spatial structure of the residuals of this regression represents the deviation from the externally defined grid at every interpolation location. Bayesian Data Fusion further generalises and improves this approach with relaxing distribution assumptions and improving precision estimates (Bogaert and Fasbender, 2007; Peeters et al., 2010). One of the challenges in spatial interpolation is the quantification of interpolation uncertainty, especially if common assumptions on normality of data are not justified (Schelin and Sjöstedt-de Luna, 2010). Bootstrapping, while being more computationally expensive, provides a much more robust estimation of the interpolation confidence bands than interpolation errors would (den Hertog et al., 2006). In this study we apply these improvements to the estimation of regional groundwater recharge.

This paper aims to: (i) use the chloride mass balance method for estimating recharge regionally with variable density input data; and (ii) estimate the uncertainty in those recharge estimates spatially. The variable density of data means that in some places there is sufficient data to reliably interpolate the recharge estimates directly to a regular grid. In other places recharge estimates are too far apart to allow reliable interpolation. In these data-sparse areas, recharge estimation relies on the relationships with covariates. Regression kriging overcomes the problem of variable data density as it relies on global regression relationships where there is low data density and then conforms to local estimates of recharge through interpolation in areas with high data density. For assessing the uncertainty in the chloride mass balance recharge estimates this study applies the Monte Carlo sampling of the input

variables and bootstrapping of the point data to include the uncertainty in the regression relationships.

## 2. Materials and methods

### 2.1. Study area

This study is conducted in the coal bearing basins of eastern New South Wales, Australia, comprised of the Permian Gloucester, Sydney and Gunnedah Basins and part of the Jurassic Surat Basin that overlies the Gunnedah and Sydney basins (Fig. 1). In the past there has been little groundwater extraction from these basins for irrigation or urban use as the overlying alluvial systems generally have better quality water and higher yielding aquifers (Pena-Arancibia et al., 2016; Zhang et al., 2016). However, due to increasing coal resource development in these basins (Hodgkinson et al., 2015; Hodgkinson et al., 2014; Northey et al., 2014), enhanced understanding of the water balance and hence estimates of groundwater recharge is needed.

The Gloucester Basin contains up to 2500 m of faulted, deformed and eroded Permian sedimentary and volcanic rocks and covers 350 km<sup>2</sup>. There are no productive aquifers within the Gloucester Basin (McVicar et al., 2014).

The Sydney Basin is part of the Permian-Triassic Sydney-Gunnedah-Bowen Basin. The Sydney Basin covers 64,000 km<sup>2</sup> of which 36,000 km<sup>2</sup> is onshore and contains up to 6000 m of sediment. Coal measure sedimentation began in the early Permian and continued to the late Permian. There was no coal deposited in the Triassic but this period saw the deposition of the Hawkesbury Sandstone which is a regionally important aquifer (Herron et al., 2016; McVicar et al., 2015).

The Gunnedah Basin neighbours the Sydney Basin and covers 32,000 km<sup>2</sup>. The Gunnedah Basin consists of up to 2000 m of sediments and contains coal deposits from the early and late Permian. There are no regionally important productive aquifers as part of the Gunnedah Basin (Welsh et al., 2014).

The Surat Basin overlies the western part of the Gunnedah Basin (and part of the northern Sydney Basin) and is part of the Great Artesian Basin which covers nearly one quarter of Australia. The Great Artesian Basin contains nationally important regional aquifers and within the study area the most productive is the Jurassic Pilliga Sandstone (Smerdon and Ransley, 2012). The Surat Basin contains 2500 m of Jurassic to Middle Cretaceous sediments.

Parts of these basins are overlain by Cenozoic volcanics, which can locally form productive aquifers (Welsh et al., 2014). The most productive aquifers within the study region are the alluvium associated with the major rivers (e.g., Namoi, Gwydir and Hunter rivers).

To estimate groundwater recharge the surface geology has been generalised into 11 groups that are primarily based on depositional age (Fig. 2). These groups are consistent with the groundwater management units used in allocating groundwater to users in the study region and are also used in the discretisation of the layers of numerical groundwater models. These surface geology groups along with the 1930–2010 annual average rainfall (Jones et al., 2009) are the covariates in the upscaling of the recharge estimates. The study area has a variable rainfall from below 500 mm/yr in the west to above 2000 mm/yr in the highlands closer to the coast (Fig. 4). Land use is varied, with extensive areas cleared of native vegetation for agriculture as well as the large urban areas of Sydney, Newcastle and Wollongong (Fig. 1). There are also extensive areas of native vegetation covering the surface water catchments supplying the bulk of the drinking water to these major urban areas (Herron et al., 2016; McVicar et al., 2015).

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