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Small-scale land use change modelling using transient groundwater levels and salinities as driving factors – An example from a sub-catchment of Australia's Murray-Darling Basin

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ABSTRACT

Although land-use change (LUC) can have detrimental environmental impacts, very few studies have explored the idea that changes in groundwater conditions and water management directly influence LU. This study models how water management policies, groundwater quality (as salinity) and availability drive and impact LUC at a small scale. The Angas Bremer (AB) irrigation district (Murray-Darling Basin, Australia) was used as a case study because it provides a rare example of complex and transient groundwater management. The key questions raised were (i) how has LU, more specifically agricultural practices, changed groundwater quality and availability; (ii) how have groundwater conditions (salinity and levels) subsequently driven LUC and influenced policy changes; and, (iii) how have groundwater conditions improved as a consequence of LU and policy changes. Using the newly-developed Patch-generating LU Simulation (PLUS) model, LUC was simulated and driving factors analysed for the period 1949–2014. To the best of our knowledge, PLUS was able to successfully model groundwater-driven LUC at a small, local scale for the first time in the international literature. The results show that (i) LUC driving factors depend on groundwater conditions and extent of policy in place, and (ii) changes in groundwater salinity and levels led to new water management policy, which in turn dictated LU changes where more water-efficient crops were favoured. LUC likely contributed to a recovery of groundwater levels and low salinity, i.e. groundwater improved to pre-development conditions. Groundwater-related driving factors are responsible for 5–12% depending on agricultural land use and phase.

1. Introduction

By 2050, the world will face one of its greatest challenges: agricultural production (Elagib et al., 2019; Ayyad and Khalifa, 2021). This challenge is amplified by changing climate and population growth, with increasing competition for water and land resources, especially as rain-fed agriculture plays a crucial role in food supply around the world (Brown et al., 2011). Rain-fed agriculture is particularly vulnerable to droughts, an increasing phenomenon, which affects the socio-economic development of countries worldwide (Peters et al., 2002). Drought onset and end can be difficult to the determine, and the impacts may slowly develop affecting large areas and populations (Minucci, 2021; Ji and Peters, 2003). Irrigation sourced from groundwater is an effective method in counteracting drought impacts in rain-fed agricultural areas (Reshmidevi et al., 2009; Younger, 2007; Dench and Morgan, 2021). Though groundwater resources are deemed more resilient than surface water (Rust et al., 2019), they are also increasingly under threat from overexploitation, drought, pollution (Younger, 2007) and multi-annual rainfall deficits (Rust et al., 2019), which results in reduced groundwater quality and availability (Dench and Morgan, 2021). A key threat arising from groundwater depletion is increased groundwater salinity, as it (i) affects the soil structure so that infiltration and the uptake of water by plants becomes impeded (Younger, 2007); and, (ii) leads to a species-specific reduction in growth and plant productivity, as salt affects photosynthesis, protein synthesis, and energy and lipid metabolism (Parida and Das, 2005).

Overall in the 21st century, conversion of agricultural land is driven by exogenous changes such as urbanisation, environmental regulations,

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agricultural management and climatic conditions (Lambin et al., 2000; Zondag and Borsboom, 2009). Consequently, Land Use Change modelling (LUCM) has emerged as a highly dynamic field of research (Veldkamp and Lambin, 2001) and an important tool to (i) explore possible future LU scenarios, (ii) make LU management decisions, and (iii) analyse the environmental impact of LUC (Promper et al., 2014; Islam et al., 2018; Lourdes et al., 2011; Khan et al., 2018; Elsayed et al., 2020). Previous work from Luo et al. (2010), Berbero et al. (2016) and Tizora et al. (2018) concluded that different modelling approaches have different merits, with no model suitable for all cases – LUCM choice depends on the research question, spatial and/or temporal scale of study and data availability. A key challenge for LUCM is the size of the area modelled (Maria et al., 2014; Veldkamp and Lambin, 2001), with Verburg et al. (2006) arguing that further downscaling of LUCM aspects, such as catchment size, LU classes and management is fundamental to future studies. This is because downscaling provides increased detail on key driving factors, trends and implications of LUC.

LUC can have a significant impact on groundwater quality and availability, through point and non-point pollution, overexploitation (Lerner and Harris, 2009) and recharge dynamics (McCallum et al., 2010; Fu et al., 2019), which can have significant negative socio-economic impacts (Daneshi et al., 2021). Di et al. (2005) used a groundwater model to predict the impacts of LU on nitrate concentrations in groundwater and mapped groundwater management zones according to LU, land surface recharge, river recharge and average nitrate concentrations. Sheikhy Narany et al. (2017) spatially mapped patterns of nitrate within groundwater according to LU. Stein et al. (2010) used fauna and bacteria as ecological indicators for the assessment of groundwater quality under LUC, and Barber et al. (1996) combined GIS methods and groundwater models to evaluate the relationship between LUC and groundwater quality through concentrations of volatile organic compounds. Related to the impact of LUC on water quantity, Mirhosseini et al. (2018) investigated how LUC and land cover would impact the quantity of surface water resources. Shrestha et al. (2020) developed future scenarios of groundwater availability to assess the impact of future LUC on water availability within a river basin. There has been limited research using LUCM to assess the impact groundwater or surface water quality and availability has on LUC. Previous studies have related the impact of LUC on water quantity not the other way around (Barber et al., 1996; Di et al., 2005; Mirhosseini et al., 2018; Sheikhy Narany et al., 2017; Shrestha et al., 2020; Stein et al., 2010). However, Luo et al. (2010) did evaluate the suitability of LU locations by using logistic regression to indicate the probability of an area to be devoted to a single LU given seven potential driving factors, that included groundwater levels and quality. Driving factors are socioeconomic or biophysical variables that influence LU variation and demands, which most LUC models consider (Verburg and Veldkamp, 2002). The effect of policy on managing LUC is complex, and though it is recognised that policy plays an important role when considering driving factors of LUC patterns (Liu et al., 2017a, 2017b), few studies have investigated the direct effects of social-economic policy due to heavy data requirements (Zhu et al., 2010). Normally, the influence of policy is expressed through model constraints, such as nature reserves or other areas where LUC cannot take place. A study by Zhu et al. (2010) found that the implementation of the new policy "Grain for Green Project (GFGP)" in 2000 changed the dominating driving factors from 2001 to 2005, causing the area of cropland to decrease, and the area of grassland and forest to expand when compared to the previous period of 1993–2000. The results implied that the LUC was driven by slope, aspect, elevation, distance to road, soil types, population density in 1993–2000 until GFGP was implemented and became the dominant factor for 2001–2005, impacting LUC through reforestation and biodiversity conservation against urbanisation. Liu et al. (2017a, 2017b) investigated the relationship between government policy and LUC, specifically the implementation of the environmental policy "Returning Farmland to Forest Program". The study looked at different future scenarios, and concluded that though government policy plays an important role as LUC driving factor, it is difficult to consider all policy factors involved and quantify them.

This study addresses several LUCM research gaps (mentioned above and discussed below in more detail) using the case study of the Angas Bremer (AB) irrigation district, in South Australia – a small catchment (250 km^2) at the end of the Murray-Darling Basin (MDB). The MDB covers 14% of Australia land mass and provides 39% of the country's agricultural products, and is arguably the most challenging and important region for water management in Australia (Webster, 2019). AB's history has shown complex interactions between LUC, groundwater quality (salinity) and availability, and groundwater management approaches through changing policy, which have been qualitatively analysed by Shalsi et al. (2019, 2022). This makes it an excellent case study to apply LUCM to quantify the temporal evolution and the complex interactions between LUC (especially crops), groundwater quality (in this work indicated as salinity) and availability, and water management approaches. This is unlike conventional LU studies that adopt a simpler approach and focus on the effect LU has on groundwater. More specifically, the objectives of this study are to (i) model the LUC between 1949 and 2014 for a small catchment of 250 km^2, which is rarely attempted; (ii) quantify the influence of driving factors on LUC; and, (iii) determine whether groundwater quality and/or availability drives or constrains LU distributions. The novelties of this study are using (i) the newly developed PLUS model at a much smaller scale (250 km^2) than previously attempted, and (ii) quantitative maps of groundwater levels and salinity as drivers of LUC. Ultimately, this allows us to (i) understand how LU, more specifically agricultural practices, changed groundwater quality and availability; (ii) quantify how groundwater conditions have subsequently driven LUC and influenced policy changes; and, (iii) discuss how groundwater conditions improved as a consequence of all LU and policy changes. This will hopefully inspire more future studies that combine LUCM with the complex and transient nature of groundwater hydrology and management, at a granular scale that is relevant for groundwater processes and management. At the case-study level, this will allow decision makers to quantitatively understand what drove changes to LUC and better qualitatively understand the impacts of LUC on groundwater conditions. Further, it will allow modelling of future scenarios considering a range of possible LUC and climatic conditions.

2. Case study

Overall, agriculture has created continuous LUC over time in the MDB, which dramatically altered water and salt fluxes creating serious environmental and productivity problems (Dowling et al., 2004). The MDB has been subject to severe droughts, most notoriously the so-called Millennium Drought from 2001 to 2009 and another more recently in 2017–2020 (Holgate et al., 2020). Changes in agricultural practices in South-western Australia have led to increases in groundwater recharge, rising water tables and increased salinization (Zhang et al., 1999) with three quarters of water used sourced from groundwater rather than surface water (Ali et al., 2012). These impacts can be observed at the large MDB scale, but also at small scales such is in basins like AB.

AB, also known as Langhorne Creek, is an economically-thriving famous world-class wine region (Thomson, 2004a), which first vineyards date back to 1860 (Thomson, 2004b). It is located adjacent to Lake Alexandrina, at the mouth of the Murray-Darling river system, and part of the Eastern Mount Lofty Ranges (EMLR) Water Resources Area since 2005 (Fig. 1). The area is situated on the floodplains of the Angas and Bremer ephemeral rivers (Harris, 1993). These rivers have a low salinity of < 1000 mg/L and discharge into Lake Alexandrina. AB's economy is primarily supported by a premium wine-grape industry that historically depended on pumped groundwater for irrigation, and has shifted to surface water as predominant water source since the 1990 s (Cuadrado-Quesda, 2017; Watkins et al., 2006). Other crops include almonds, vegetables, cereals, pasture, lucerne and olives (Harris, 1993;

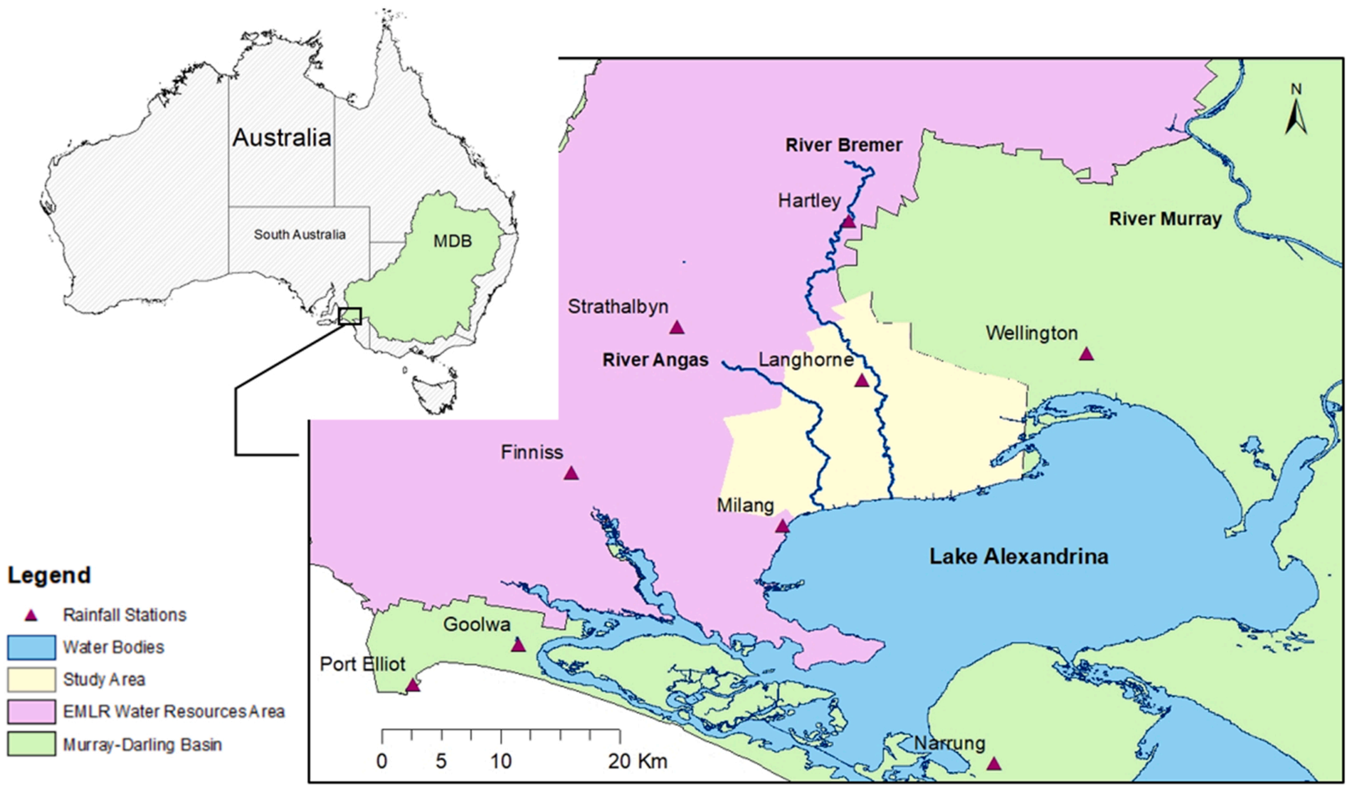

Fig. 1. Location map of AB, including weather stations used in rainfall interpolations.

Watkins et al., 2006). According to Cresswell and Gibson (2004), the region has a Mediterranean climate with hot, dry summers and cool, moist winters. Average rainfall and pan evaporation range from 380 to 490 and 1150 to 1600 mm/year, respectively (Zulfic and Barnett, 2007; Cresswell and Gibson 2004). The area has been subject to severe droughts, most notoriously the so-called Millennium Drought from 2001 to 2009 and another more recently in 2017–2020 (Holgate et al., 2020). Hydrogeologically, the region is formed by two main aquifers (Zulfic and Barnett, 2007). The shallow unconfined aquifer (10–20 thick) is composed of Quaternary sands and gravels, and has a thin, semi-confining clay layer at the bottom. Below, there is a Tertiary limestone aquifer (~100 m thick), which is the main source of groundwater for the region as it provides fresher water and higher yields than the top aquifer. There are water-bearing formations below, which are not used because of high salinities and low yields. The recharge processes are not clear, although Zulfic and Barnett (2007) hypostasize focused recharge from the rivers Angas and Bremer dominates over basin-wide spatially-distributed recharge. The same authors provide a detailed hydrogeological description of the basin.

The evolution of water management in the region is complex and a schematic representation can be seen in Shalsi et al. (2019, 2022). Our analysis is up to 2014 because of LU data availability and LU is considered to have remained stable since. Although we followed the key water management phases from Shalsi et al. (2019), the phases we modelled differ slightly due to data and LU maps availability.

2.1. Phase 1: 1949–1986

The area developed rapidly after the Second World War, and the introduction of electrical groundwater pumps in the 1950 s resulted in the expansion of agricultural irrigation (mainly for lucerne) (Harris, 1993). There was no control over groundwater pumping and by 1981 annual groundwater extraction was unsustainable - four times that of the natural annual recharge (Thomson, 2004b; Howles, 2001; Cuadrado-Quesda, 2017). The irrigators started to observe alarming low groundwater and high salinity levels, and lobbied the South Australian government to proclaim the area as a water management zone under the 1976 Water Resources Act (Howles, 1994). This provided the mechanism to control groundwater extraction through water licenses, with the aim of subsequently reducing salinity levels in the AB area (Shalsi et al., 2019).

2.2. Phase 2: 1986–1993

Through the requirements of the 1976 Water Resources Act, groundwater extraction was reduced by 30% from 29,000 to 20,000 ML/year (Howles, 2001; Shalsi et al., 2019). This was achieved under the first two water management plans (WMPs) (1987 and 1992), which in turn allowed irrigators to access equivalent volumes of surface water from Lake Alexandrina because the (small) volume of surface water pumped was not considered a risk to the lake (Howles, 1994). The WMPs encouraged irrigators to artificially recharge the aquifer with excess water not used for irrigation through a managed aquifer recharge (MAR) scheme. The irrigators had the right to extract 50% of the total recharged volume over a 3-year period (Shalsi et al., 2019). AB irrigators privately funded and constructed pipelines to transport water from Lake Alexandrina, in addition some of the winter flows from Angas and Bremer were diverted and discharged into the aquifer via recharge wells.

2.3. Phase 3: 1993–2003

By the mid-1990 s, surface water had become a significant part of water management plans and an irrigation source for the basin and by 2001, an 80% reduction in groundwater extraction was achieved (Shalsi et al., 2019). The AB Code of Practice (CoP) was introduced in 2001, which meant all AB irrigators were required to monitor root zone salinity and plant 2 ha of native vegetation for every 100 Ml of surface water licence (Howles, 2001; Muller, 2002). The CoP was funded and managed by the irrigators and became a legal requirement of the water licenses.

2.4. Phase 4: 2003–2008

This period includes the longest recorded drought in Australia, the so-called millennium drought, from 2001 to 2009 (Holgate et al., 2020). Due to its negative effects on the lake water quality and availability, the irrigators lobbied for a 110-km pipe to be constructed to pump water from the River Murray instead of the Lake Alexandrina (Shalsi et al., 2019).

2.5. Phase 5: 2008–2014

This period represents the post-drought. The pipe was completed at the end of the drought in 2009 and as such was not effective in addressing the impacts of the millennium drought on water availability, but it is considered important to safeguard future water supply (Shalsi et al., 2019).

3. Methods

3.1. Model selection

Many LUC models use Transition Analysis Strategy (TAS), which are limited in model flexibility when multiple LUs are taken into account. To solve this problem, Pattern Analysis Strategy (PAS) can be used, which calculates the probability of occurrences of a LU within each cell via competition. The Dyna-CLUE and FLUS model are based upon PAS methods. Previous studies using Dyna-CLUE (Shrestha et al., 2020; Trisurat et al., 2019; Adhikari et al., 2020; Pindozzi et al., 2017) and FLUS (Penny et al., 2021; Liang et al., 2018a, 2018b; Yan et al., 2018; Liu et al., 2017a, 2017b) have struggled to allocate and predict multiple LU demands at local scales at a fine resolution, a requirement that is key to future LU planning and policy making (Lourdes et al., 2011; Liang et al., 2021a, 2021b; Verburg et al., 2006). Models that use PAS further lack the ability to reveal how driving factors cause LUC. For example, when using the FLUS model, separate logistic regression analysis is needed to analysis the influence of driving factors on LU (Penny et al., 2021). The novel PLUS model, created by Liang et al. (2021a, 2021b), was developed to promote better understanding of the complex relationships behind LUC, by helping to reveal the underlying drivers and their differing contributions. Unlike previous models, the PLUS model combines TAS and PAS methodology, and can simultaneously provide insights behind the drivers and dynamics of LU types and their transition. As an improvement to previous models, PLUS uses (i) rasters as inputs, (ii) Land Expansion Analysis Strategy and Cellular Automata to simulate multiple patch-based growth at fine scale resolutions, and (iii) TAS and PAS to automatically analysis the influence of driving factors. All the above enable the PLUS model to obtain higher simulation accuracy with smaller local catchment sizes. Liang et al. (2021a, 2021b) previously used the PLUS model on an 8494 km^2 catchment. Consequently, PLUS was chosen for this study, which is available to download from https://github.com/HPSCIL/Patch-generating_Land_Use_Simulation_Model. Although PLUS was designed for small catchments, the AB catchment is significantly smaller than previously attempted, at 250 km^2, which in itself is novelty of this study and required several code modifications and improvements to address calibration errors as explained later.

3.2. Model inputs and driving factors

A large amount of data was compiled from different sources (Table 1). Seven LU classes were determined from the available LU maps: Dryland Farming, Conservation area, Horticulture, Vegetables, Irrigated Crops, Vineyards and Urban/Other. Water body extent remained unchanged throughout the study period, so were not included as a separate LU class. A large number of driving factors were used in this study when compared to other LUCM studies. This was because of the

Table 1
Input data for the PLUS model.

Category	Data	Year	Data source	Data processing (Arc-GIS)
LU/cover data	LU Maps	1949, 1986, 1993, 2003, 2008, 2014	Government of South Australia, Department for Environment and Water	
Driving Factors	Aridity Index	1970–2000	Global-Aridity _ET0 (CGIAR-CSI, 2019)	Extraction - Extract by Mask
	Potential Evapotranspiration	1970–2000	Global Reference Evapotranspiration (Gobal-ET0) (CGIAR-CSI, 2019)	Extraction - Extract by Mask
	DEM / Slope	2007	GEODATA 9 Second Digital Elevation Model (DEM-9S) Version 3 (Hutchinson et al., 2008)	The Surface tool – Slope
	Flow Direction / Drainage Basin	2007	GEODATA 9 Second Flow Direction Grid (D8–9S) (Hutchinson et al., 2008)	Hydrology tools: (i) Basin and (ii) Flow Direction
	Rainfall	1949–2020	Australian Government Bureau of Meteorology (Bureau of Meteorology, 2021)	Interpolation using Kriging. Location of Point data of the nine rainfall stations can be seen in Fig. 1.
	Proximity to Rivers	1949–2014		Created from LU maps - Euclidean Distance used to extract distance
	Proximity to Lake	1949–2014		Created from LU maps - Euclidean Distance used to extract distance
	Groundwater Level	1950, 1977, 2004, 2015	Government of South Australia, Department for Environment and Water Number of wells used: 1950 – no info, 1977 – 146, 2004 – 249, 2015 – 126	Interpolation provided by the Government of South Australia, Department for Environment and Water
	Groundwater Salinity	1950, 1977, 1996, 2006, 2014	Government of South Australia, Department for Environment and Water Number of wells used: 1950 – no info, 1996 – 40, 2006 – 31, 2014–77	Interpolation provided by the Government of South Australia, Department for Environment and Water
	Soil capability/ productivity	2001	Government of South Australia, Department for Environment and Water	Created from soil maps - Euclidean Distance used to extract distance
	Population Density	2000, 2003, 2014	LandScan Datasets (2000); LandScan Datasets, 2003; LandScan Datasets, 2014	Extraction - Extract by Mask
	Urban Area	1949, 1986, 1993, 2003, 2008, 2014	Government of South Australia, Department for Environment and Water	Euclidean Distance used to extract distance from urban areas found within the LU maps. The distance from urban area was then used as a driving factor within the model.

small size of the catchment, which required an increased number of driving factors to improve the accuracy of the results. The 16 driving factors chosen were based on data availability and included Groundwater level, Groundwater salinity, Distance to lake, Slope, Elevation, Distance to Rivers, Distance to urban areas, Population Density, Soil Productivity (defined as 65–100% soil productive potential for Vines and Lucerne), Drainage, Groundwater flow direction, Evapotranspiration, Rainfall and Aridity. Raster maps were created for these attributes in Arc-GIS using a number of tools (Table 1). Practical tips for analytical steps and data preparation for computer processing can be found in the supplementary material (SM1). The model was trained using each of the past LU maps available, to make sure conversion settings were correct all LU maps were utilised. This ultimately determined the phases that were used within the study as these were the dates of the available maps.

3.3. Calibration and validation

Validation of LU models is frequently conducted through Kappa coefficient (Rafiee et al., 2009; Jain et al., 2016; Arsanjani et al., 2011; Huang et al., 2018; Milad et al., 2016; Rawat, 2015). The Kappa coefficient, also known as the KHAT statistic, reflects the degree of similarity, or change, between the simulated LU results and the reference map of actual LU – it ranges from 0 (no agreement between simulated and reference map) to 1 (complete agreement between both maps). When calculating Kappa, an overall accuracy (OA) classification is produced via a confusion or accuracy matrix (Disperati and Virdis, 2015). The accuracy matrix returns Producer's Accuracy and User's Accuracy, which are a measure of agreement between observed and modelled cells. Some argue that this confusion matrix is more helpful than Kappa (Pontius and Millones, 2011) by providing greater accuracy results than Kappa (Disperati and Virdis, 2015). Nevertheless, Liang et al. (2021a, 2021b) and Pontius et al. (2008) argue that Kappa has important flaws and instead figure of merit (FoM) should be use. As a consequence of disagreements in the literature, this study used the three validation methods Kappa, FOM and OA to validate the simulation results and assess the classification and accuracy of results.

4. Results and discussion

4.1. Spatial and temporal evolution of LUC

Fig. 2 shows the % distribution of LUC for the period 1949–2014. The most obvious LUCs are the increases in vineyards that occurred from 1949 to 2003. Dryland farming significantly decreased during the period 1949–2014. Irrigated crops and Vegetables increased up to 2003 and stayed at around a constant level since. Spatially, little change was observed in Horticulture, with Urban and Conservation areas increasing

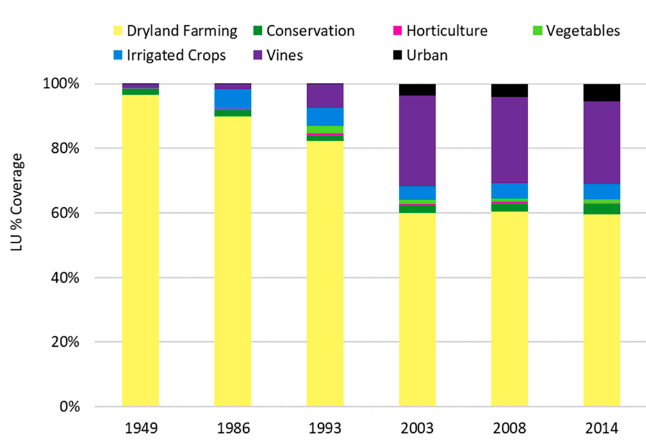

Fig. 2. LU classes for from 1949 to 2014.

after 2003 (Fig. 2). From the total of 16 driving factors used in this modelling exercise (Table 1), the four key ones, which also varied temporally and spatially, were soil productivity, groundwater levels, groundwater salinity and rainfall (Figs. 3, 4, 5 and 6).

The most productive soils (defined as 100% or 65% productive potential for Vines and Lucerne) are alluvial in origin and are located in the central part of the catchment adjacent to the river channels, with soil productivity decreasing with distance to the rivers (Fig. 3). These productive soils require no more than standard management practices to sustain soil productivity and crop growth.

Fig. 4 shows the spatial evolution of groundwater levels from 1950 to 2014 – annual maps are presented according to data availability and were provided by the South Australian Government Department for the Environment and Water already interpolated and without access to primary information – the number of wells used (according to the publicly available data base) is provided in Table 1; some of these maps are described by Zulfic and Barnett (2007). The highest groundwater levels were observed in the NW and the lowest in the SE of the catchment, indicating a general flow in this direction. Groundwater levels were at their lowest in 1986, and have recovered to 1950′s levels by 2014. Fig. 5 shows the spatial evolution of groundwater salinities throughout the study period. Despite the temporal fluctuations, the lowest salinity levels (500–2500 mg/l) are recorded surrounding the rivers and Lake Alexandrina – annual maps are presented according to data availability, and were sourced similarly to the groundwater maps. There is an increase in the recorded annual averaged groundwater salinity from 1950 to 2006 throughout the study area. The salinity levels recorded during this period reached 10,500– 11,500 mg/L. However, by 2014 salinity level have begun to recover returning to those recoded in 1950 and 1977 – this is particularly the case in the central area, where most of groundwater pumping occurs.

For the modelled years, reduced rainfall periods were observed in 1949–1993 and 2008–2014, with the greatest rainfall recorded in 2003 (Fig. 6). Spatially, the highest annual rainfall was in towards the west. Fig. 7 shows the annual rainfall rates in the area for the period 1949–2015. The highest annual rates were observed in 1992 at 623 mm. A total of two years recorded annual rainfall below 250 mm (1957 and 1967), with 6 years recording annual rainfall below 300 mm (1977, 1982, 1994, 1999, 2002 and 2006).

4.2. Land use change modelling

4.2.1. Validation (past and current LU)

A number of different model iterations took place to calibrate the model. Once the optimum initiation parameters were found, a validation process took place that is summarised in Table 2. The improved simulation accuracy was achieved by increasing the Patch generation threshold and decreasing the expansion coefficient (Liang et al., 2021a, 2021b). The best FoM results for validating LUC were found for the period 1986 – 1993 (FoM = 0.61). This period also had the highest overall accuracy when using the confusion matrix (OA = 92%) and second highest KHAT (0.75). In general, validation methods agree – high FoM corresponded to increased accuracies for KHAT and OA. The exception was for the period 2008–2014, where FoM returned the lowest simulation accuracy achieved (0.39), but KHAT and OA returned the highest of 0.87% and 92% respectively. The reason for this could be that this was the period of least LUC. Examples of validation results are illustrated in Fig. 8, which compares the observed and simulated LU patterns in 1993, 2003 and 2014. Using the TAS and PAS methodology, we automatically analyse the influence of driving factors (Fig. 8). The results imply that, throughout the phases, LUC was driven by Productivity distance, Slope, Groundwater level, Groundwater salinity, River Distance and Rainfall.

4.2.2. Phase 1: LUC 1949–1986

Fig. 9 quantifies the contribution of the key driving factors for each

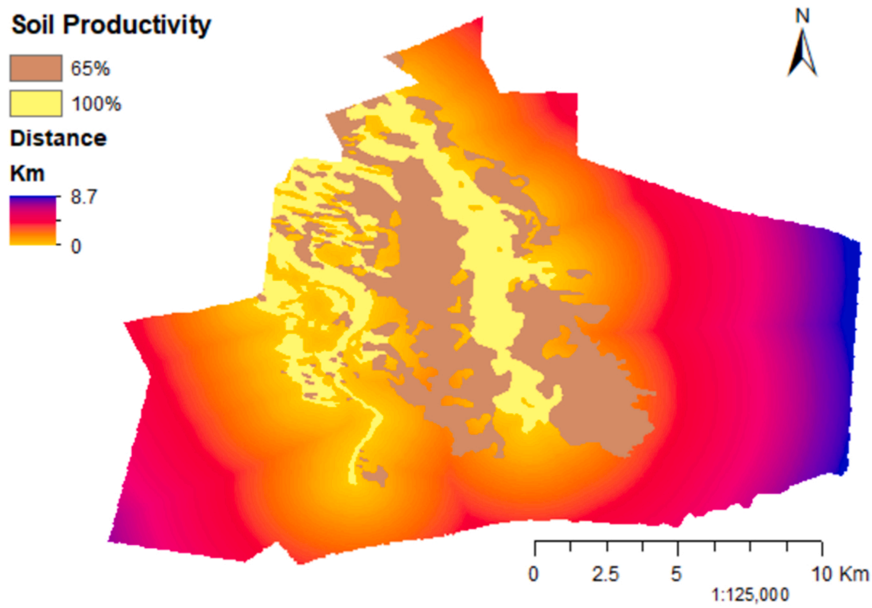

Fig. 3. Most productive soils and distance from the most productive soils (km), where 100% and 65% represent the soil productive potential for Vines and Lucerne.

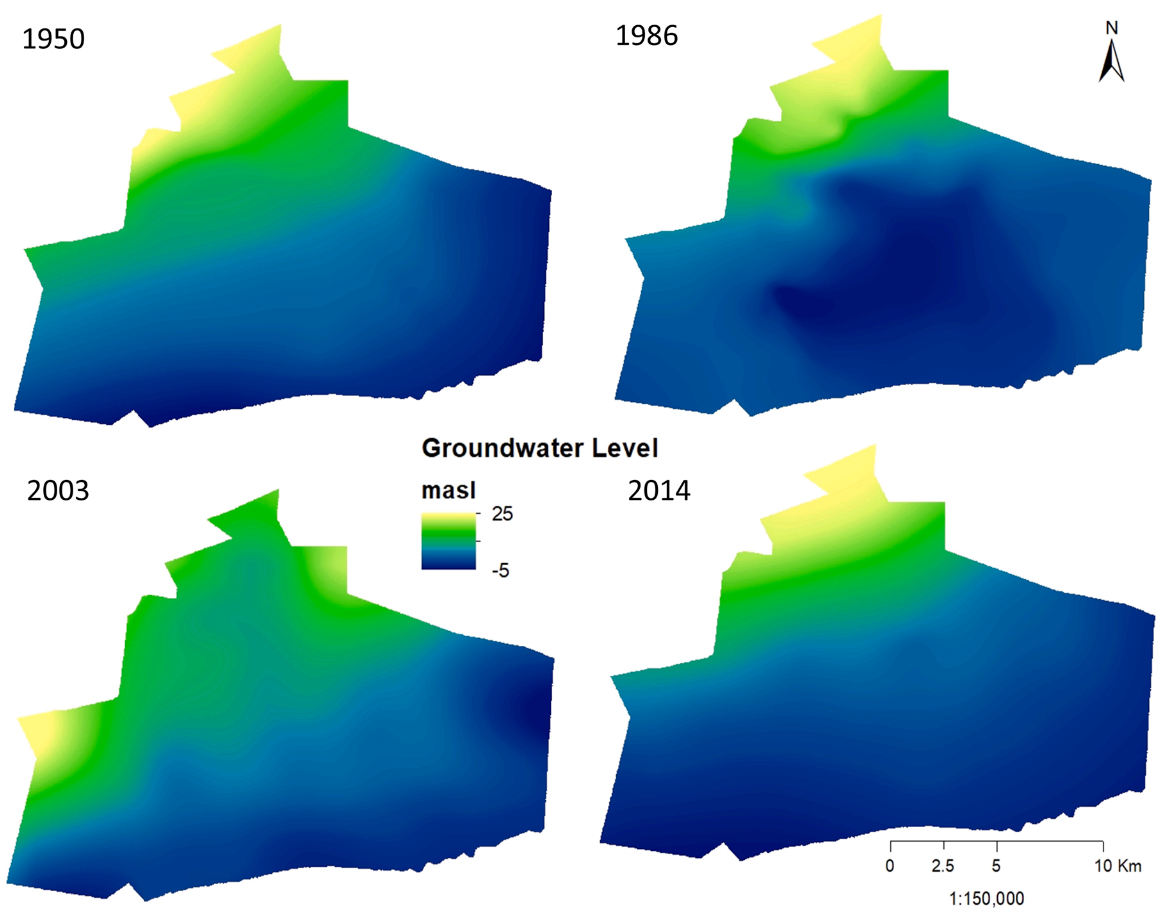

Fig. 4. Groundwater levels from 1950 to 2014.

LUC period. Between 1949 – 1986 the majority of LU remained Dryland farming (cereal crops such as wheat) (Fig. 2), changing from 94% to 87%. Irrigated crops (mostly lucerne) increased from 0.1% to 6%, and Vineyards increased from 1% to 1.4%. Other LUs remained close to unchanged. LUC for both Vineyards and Irrigated crops was driven by soil productivity (11% and 13%, respectively) and proximity to the rivers (17% and 12%, respectively) (Fig. 9). Being situated within or near to the most fertile soil, and distance to the Angas and Bremer Rivers (Fig. 3), where groundwater salinities are typically lower and where there is more access to flood water for irrigation (Zulfic and Barnett,

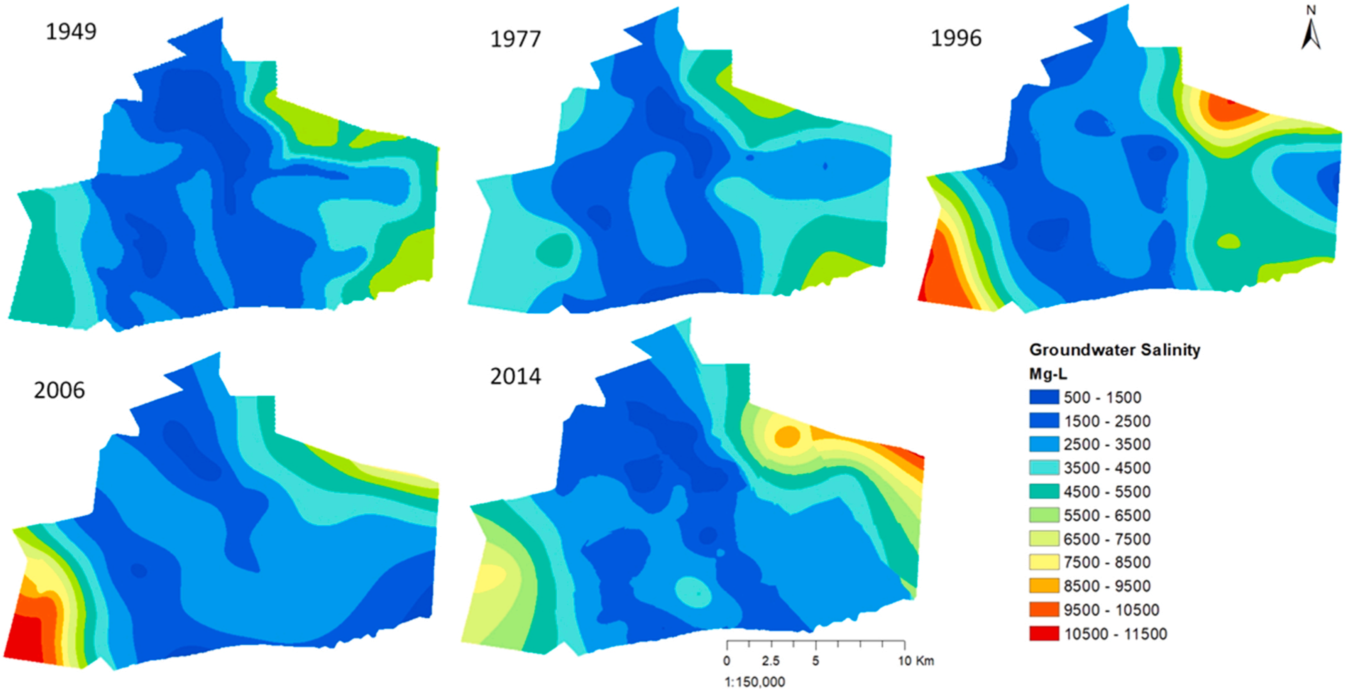

Fig. 5. Groundwater salinity levels from 1949 to 2014.

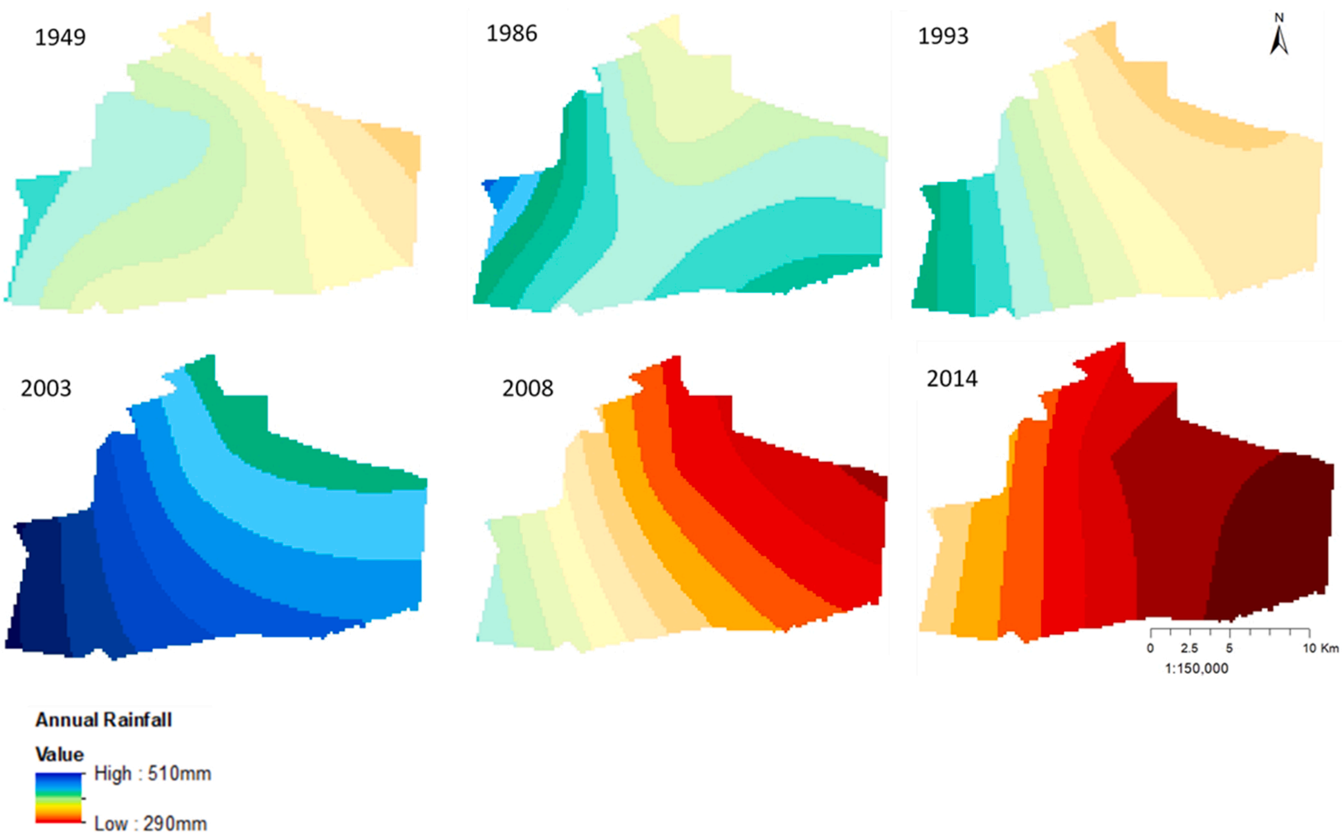

Fig. 6. Annual Rainfall for 1949–2015 using all of rainfall stations identified in Fig. 1.

2007; Howles, 2001; Angas Bremer Water Resource Committee, 2001; Watkins et al., 2006). This is a consequence of favourable conditions for irrigated crop production near the rivers. Vineyards were traditionally planted on the deep, alluvial floodplain soils of the ephemeral Angas and Bremer Rivers (Thomson, 2004b). Other influential drivers for vineyards and irrigated crops included groundwater salinity (9% and 8%, respectively) and level (11% and 6%, respectively) (Fig. 9), with low groundwater salinities (derived from historical recharge from the rivers), more favourable for Irrigated crops and Vineyards, which is also associated to the proximity to the rivers. Furthermore, these areas are

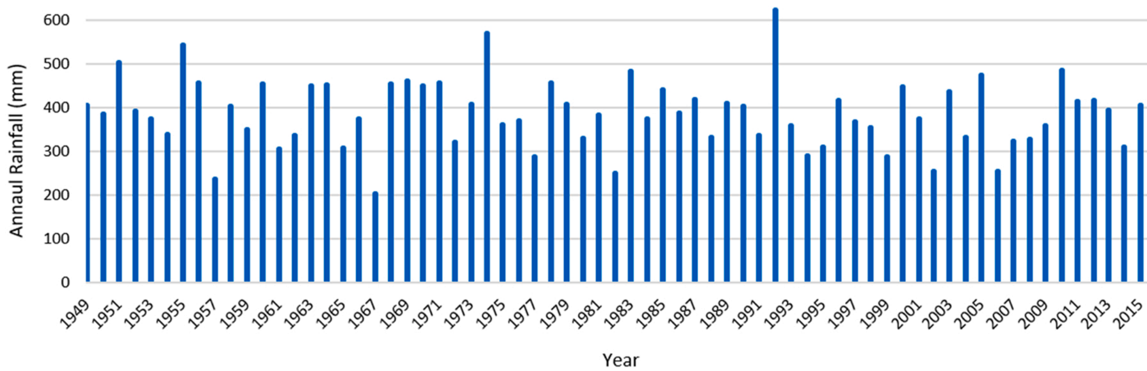

Fig. 7. Annual Rainfall 1949–2015 for Langhorne Creek rainfall station (for location see Fig. 1).

Table 2
Model calibration and validation results.

Year	FOM	Producer's Accuracy	User's Accuracy	Overall Accuracy	KHAT Statistic
Simulated LU for 1993 using 1949 as the models starting point	0.483	0.644	0.658	90%	0.67
Simulated LU for 1993 using 1986 as the models starting point	0.61	0.72	0.79	92%	0.75
Simulated LU for 2003 using 1993 as the models starting point	0.60	0.72	0.78	83%	0.69
Simulated LU for 2014 using 1993 as the models starting point	0.54	0.65	0.76	79%	0.63
Simulated LU for 2014 using 2003 as the models starting point	0.49	0.68	0.64	87%	0.76
Simulated LU for 2014 using 2008 as the models starting point	0.39	0.55	0.56	92%	0.87

characterised by sandy soils, which are also favourable for quality and high-yielding wine grapes production (e.g. Pérez-Álvarez et al., 2019; WenChao et al., 2012). This LUC had consequences for groundwater quality and availability. Groundwater salinities increased by 1977 and levels decreased by 1986 (Figs. 4, 5) in the centre and south of the catchment resulting from heavy groundwater extraction for irrigation of these two crop types. These findings are consistent with the qualitative analysis of Shalsi et al. (2019).

4.2.3. Phase 2: LUC 1986–1993

LU changed dramatically from 1986 to 1993 – Dryland farming was replaced by Vineyards and Vegetables (Fig. 2), however changes in Vineyard area was more dramatic, increasing from 1% in 1986–7% of the catchment by 1993. A socio-economic reason for this change is that Lucerne has a high water demand and a low economic return, whereas crops such as grapes require less irrigation and have a higher economic value (Howles, 1994). This is the main reason for the change from Dryland farming to Vineyards (Shalsi et al., 2019).

Areas associated with increases in Vegetables, Vineyards and Irrigated crops were to the greatest extent driven by increased rainfall (18%, 15% and 13%, respectively) (Fig. 9). Between Phase 1 and Phase 2, a decrease in 20–30 mm mean annual rainfall across the catchment was observed (Figs. 6 and 7). The highest rainfall rates were in the west and south of the catchment. These areas were associated with new Vineyards, Irrigated Crops and Vegetables. In the east, where annual rainfall is less, the catchment has chiefly remained Dryland farming. Locations in the east are also associated with high groundwater salinities, with increase salinity levels observed in 1993 compared to 1986 (Figs. 4 and 5).

Similarly to phase 1, Vineyards and Irrigated crops expansion was driven by groundwater salinity (10% and 7%, respectively) and level (10% for both vineyards and Irrigated crops) (Figs. 9 and 5). These crop types are found in areas of lower groundwater salinity (1500–3500 mg/L), alongside the Rivers Angas and Bremer, and in the south of the catchment near Lake Alexandrina. These finding agree with the Angas Bremer Proclaimed Wells Area Management Plan July 1992- June 1997 where: (i) groundwater salinities over 5000 mg/L have moved to within 1 km of the Langhorne Creek township, (ii) the area of groundwater salinities < 2000 mg/L has decreased from more than 25% of the basin in the 1950 s to about 7% in 1991, and (iii) groundwater salinities on grazing land to the east of the irrigation area have risen to the extent that the water was no longer usable for stock (Angas Bremer Water management Committee, 1997). Between 1986 and 1993, expansion of Vineyard, Irrigated Crops and Vegetables were also driven by distance from the rivers (15%, 8% and 9%, respectively) and the lake (7%, 10% and 15%, respectively) (Fig. 9). Vineyards were found in close proximity to the Rivers and Vegetables near to Lake Alexandrina. These findings link to water management policy because; (i) the 1987 and 1992 water management plans allowed and encouraged irrigators to extract water from Lake Alexandrina, thus crops located close to the lake had easier and more affordable access to fresh water; (ii) the areas close to the rivers have fresher groundwater, access to floodwaters and more productive soils; and, (iii) of suitable locations and water availability for managed aquifer recharge.

4.2.4. Phase 3: LUC 1993–2003

During this period, expansion of Vineyards and Vegetables, and decrease of Dryland Farming were driven by groundwater salinities (6%, 10% and 11%, respectively) and levels (8%, 8% and 7%, respectively) (Fig. 9). Groundwater levels began to return to pre-development levels, especially in the north and centre of the catchment (Fig. 4) (Shalsi et al., 2019). This recovery meant that salinity levels decreased, especially in the east, from a maximum of 5500 mg/L to 3500 mg/L (Fig. 4). By 2001, groundwater extraction had decreased by 80% (Shalsi et al., 2019), partly because of (i) the 1992 water management plan and the conversion of groundwater licences to surface water licences, and (ii) the shift to more water-efficient crops mentioned before. In fact, due to the high

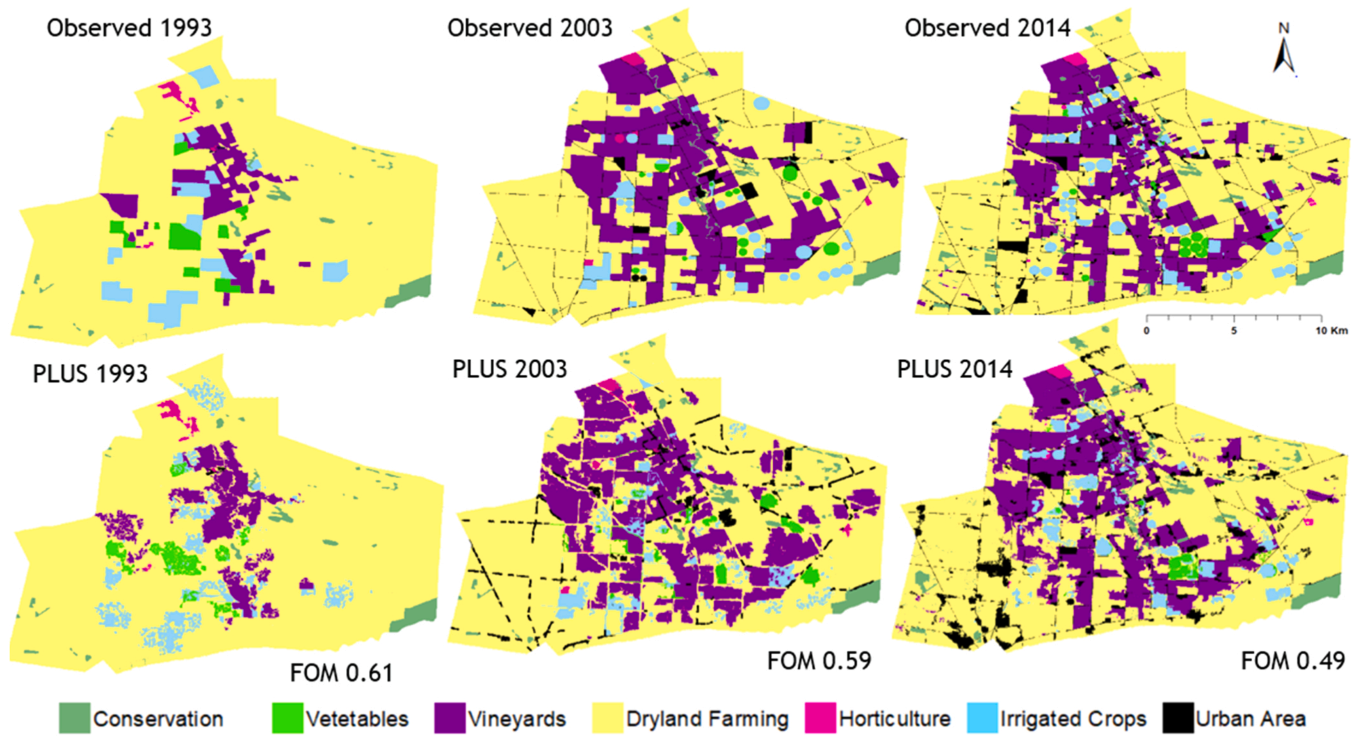

Fig. 8. Comparison of the observed and simulated LU patterns.

economic returns, there was a dramatic change in LU with a boom in the wine grape industry. Covering the centre of the catchment, the Vineyard area increased from 7% to 27% (corresponding to 1700 ha and 6775 ha respectively) (Fig. 2). Dryland Farming area decreased from 80% to 55%. Decreases in LU cover were also found in Vegetables and Irrigated crops (2–1% and 5–4%, respectively), which are related to the introduction of more efficient centre-pivot irrigation method. The increase in Urban area, to 4% of the total area, can mainly be attributed to the growth of the wine industry and associated economic improvement (Howles, 1994), as many large companies bought land and developed vineyards in the district (Thomson, 2008).

These findings concur with data taken from the Langhorne Creek Wine region reports (Phylloxera and Grape Industy Board of South Australia, 2003, 2008, 2014; Wine Australia, 2020), where the area covered by Vineyards sharply increased between 1998 and 2007, after which the area covered by Vineyards remained stable. Thomson (2008) affirms that for the period 1993–2002, the area of wine grapes increased from 400 ha to 5400 ha, and by 1997, the price per tonne of grapes had risen from A$400 to A$1000.

According to the model, rainfall was the main driving factor for LUC during this period (Fig. 9), contributing between 10% and 16% depending on LU type – there was a significant increase in rainfall (Figs. 6 and 7), with the majority of Vineyards are found in the centre and west of the catchment (Fig. 8) where rainfall is higher (Fig. 6). This is in contrast with the eastern part of the catchment where majority of LU remained dryland farming and rainfall is lower (Fig. 6). These findings are interesting because nowhere in the AB-related literature is mentioned rainfall spatial distribution plays a role in crop change – instead the changes are always attributed to soils productivity and access to fresh irrigation (surface and/or ground) water. Similarly, to the previous period, and for the same reasons, vineyards and irrigated crops were found in close proximity to the Angas and Bremer Rivers, and Lake Alexandria (Figs. 1 and 9).

There was an increase from 1% to 2% in Conservation area (Fig. 2). This was a consequence of the CoP requirement of irrigators to plant 2 ha of native vegetation for every 100 ML of water extracted from the Lake Alexandrina (Howles, 2001). Native vegetation was planted to prevent water logging as it reduces groundwater recharge preventing salty groundwater to rise, as well as to protect ecosystems and improve biodiversity (Stirzaker and Thomson, 2004; Thomson, 2004b, 2004a). This occurred alongside the river within the centre and north of the catchment (furthest away from lake Alexandrina (Fig. 7), areas of decreased rainfall (Fig. 6) and in locations where there was a high risk of rising shallow water table (Stirzaker and Thomson, 2004). In fact, Dawes et al. (2004) argue that changes in LU, specifically removing or replanting native vegetation, result in changes to stream flow, groundwater recharge/discharge and salt fluxes. This was confirmed by the model, which found that new areas of conservation were driven by Lake Distance by 22%.

4.2.5. Phase 4: LUC 2003–2008

This period registered a stabilisation of LU, with no significant change in percentage coverage or spatial distribution of LU (Fig. 2), and consequently driving factors have remained similar to the previous period (Fig. 9). This period roughly coincides with the Millennium drought (2001–2009), in which there was a marked reduction in rainfall, especially noticeable in the west of the catchment.

Besides contributing to a dramatic drop in rainfall, the millennium drought also made Lake Alexandrina unsuitable for irrigation because as the water levels dropped the salinities increased dramatically (Gibbs et al., 2018) (Fig. 10). This was mainly due to very low flow rates reaching the lake from the upstream Murray-Darling river system. Increased salinity levels, expressed as electric conductivity (EC), and decrease water levels were observed from the end of 2006 until the end of 2010 (Fig. 10). Gibbs et al. (2018) deduced that water level in Lake Alexandrina plummeted to below 0 m AHD (Australian Height Datum), reaching a minimum —0.88 m AHD on 25 April 2009 that, corresponds to high ECs of 6800–7000 uS/cm, between April and May 2009 (Fig. 10). This meant farmers had to return to using groundwater for irrigation, which over time caused groundwater levels to decrease and salinities to increase (Shalsi et al., 2019) (Figs. 4, 5). Consequently, groundwater became progressively unsuitable for irrigation as salinity levels reached

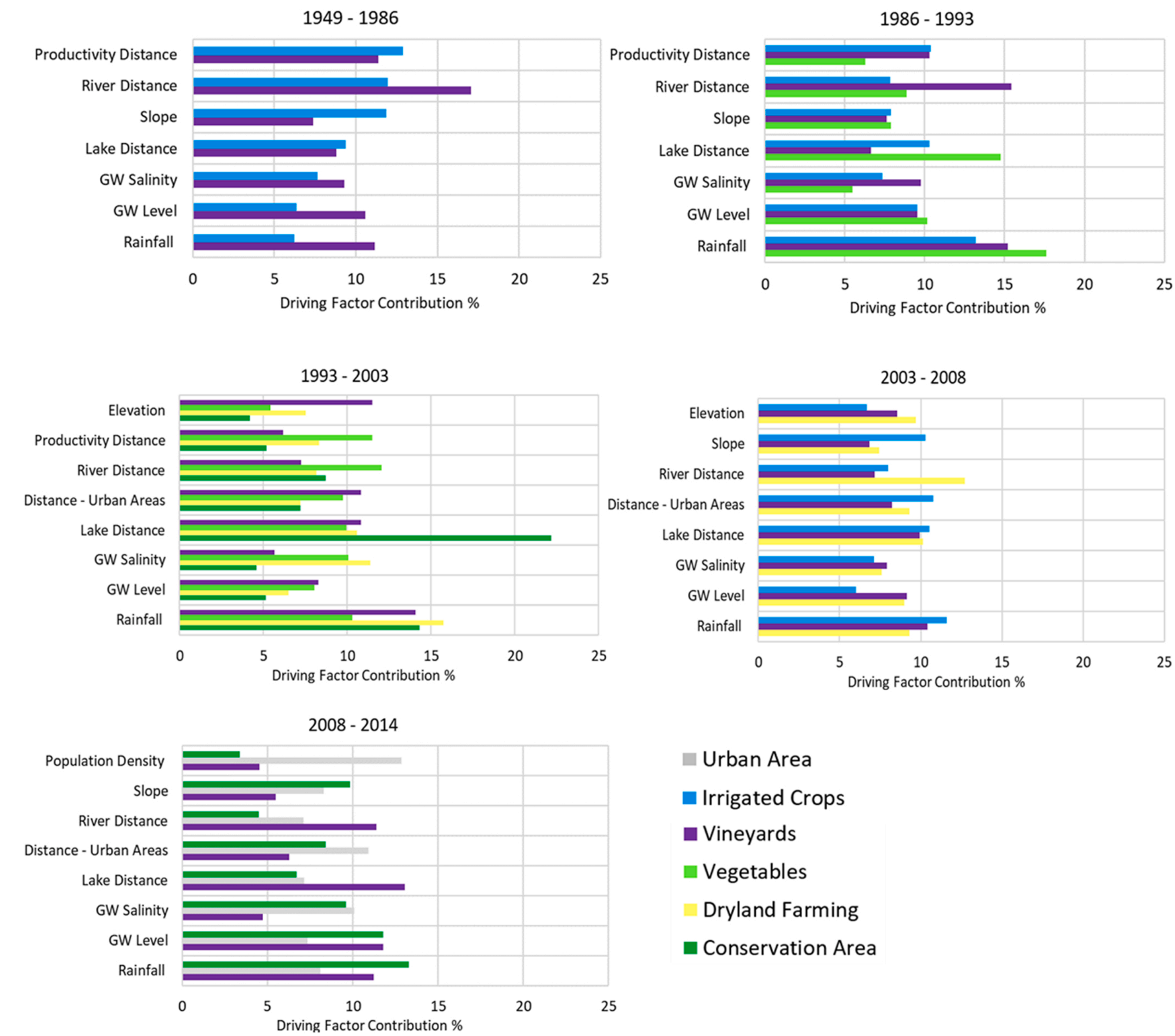

Fig. 9. Results of the key contributing driving factors for each LUC period – horticulture is not represented because it showed very little change.

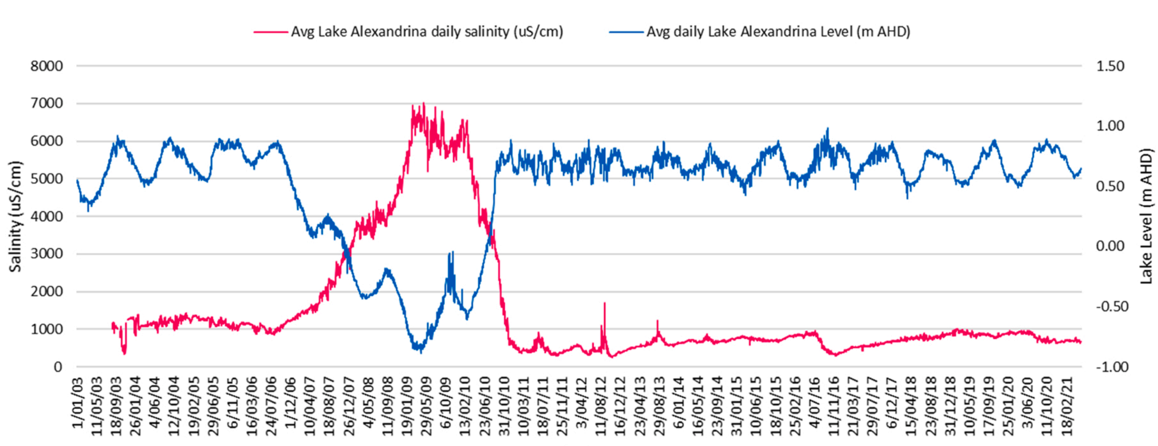

Fig. 10. Daily EC and water levels for Lake Alexandrina between 2003 and 2021.

deleterious levels for vine health (~4000–5000 mg/L) (Stirzaker and Thomson, 2008, 2005). In fact, a study by Stirzaker and Thomson (2005), looking at the average irrigation and salt content of water extracted from 50 and 100 cm depths, found that during the 2002–2003 and 2003–2004 irrigation seasons, 35% and 30% of properties within the study respectively recorded soil water salt contents above 5000 ppm. Groundwater levels and salinities recovered to normal by January 2011 because groundwater extraction was reduced once inflows to Lake Alexandrina returned to normal after the drought ended. Thus, because of the successful water management practices in place, the negative changes that occurred to groundwater (availability and salinity changes), had little influence on LUC distribution.

4.2.6. Phase 5: 2008–2014

LU remained stable for 2008–2014. A slight (~2%) change from Vineyards to Urban areas was observed (Fig. 2), with the Urban area now covering 5% of the catchment, driven by population density (13%) and distances from Road Networks (11%) (Fig. 9). Attributed to the ongoing development of the wine industry and associated facilities and tourism. Even though there was a slight decrease in Vineyard area of 1% (Fig. 2), vineyards productivity increased from 39,546 tonnes in 2011–48,639 tonnes in 2014 (Phylloxera and Grape Industy Board of South Australia, 2014). This increase in productivity despite the decreased area can be attributed to the 110-km long pipeline completed in 2010, that brings water directly from the River Murray. Ironically, the pipeline was proposed to fight the effects of the millennium drought but was only completed after it ended. As such, from 2011, the irrigators were in a much better position to secure good quality water for their crops, meaning that their distribution was less effected by spatial changes in groundwater salinity (5%) and rainfall (11%) (Fig. 9). The addition of the pipeline meant a decrease in groundwater use and recovery to pre-development levels (Fig. 4). Areas of Conservation also increased from 2% to 3%. The new locations of these were found in the west, driven by Rainfall (13%), Groundwater salinities (10%) and levels (12%), and Slope (10%) (Fig. 9). Conservation areas increased in areas less attractive for more productive agriculture LU types.

5. Recommendations and future work

Limitations to the work are related to input data quality and availability. Firstly, the number of LU maps available is limited and not aligned with the key management dates defined by Shalsi et al. (2019), and are only available up to 2014. Secondly, the number of LU classes within all the maps was not consistent. Less LU classes were found in the older maps, with newer maps having a different number and/or new LU classes. Consequently, these LU classes had to be carefully confined to groups or reclassified so LU classes were consistent throughout the study period, which is a requirement of the modelling code. It would have been useful to increase the number of classes throughout the time period to analyse the variation in new crops/farming techniques brought to the area. However, currently no LUC models are able to do this. Despite these limitations, PLUS was able to successfully model LUC at a very small local scale. An important challenge for this modelling exercise were calibration errors related to the small size of the catchment. The source code was improved over four iterations (V1.2.5, V1.2.5 new, V1.3 and V1.3.5) consequently it is now able to predict LUC at a much finer scale. The latest PLUS version is available publicly. This in itself is a significant contribution to the LUCM research community globally.

Unlike previous studies where LUC displays a gradual change through infill, encroachment and expansion (e.g. Liang et al., 2018a, 2018b, 2021a, 2021b; Lourdes et al., 2011; Trisurat et al., 2019; Erdogan et al., 2011; Zhu et al., 2010; Liu et al., 2017a, 2017b), PLUS is able to model sporadic and sudden LUC, whilst determining distinguishing driving factors. We have contributed to LUCM research by demonstrating that local-scale LUCM, at a very high level of detail, is possible, through the application of the calibrated and validated novel PLUS model. Interesting future work would be to simulate future LUs for the Angas Bremer region under different scenarios, which will be particularly useful under the threat and uncertainty of climate change, and evolution of wine demand in international markets. Such study would help to understand future water needs and how they relate to LUC decisions by farmers and managers. This can have important implications for decisions related to the evolution of the wine industry under a changing climate.

As for LUCM research globally, an important contribution would be the development of a code where an increased number of LU classes over time could be modelled. Thus reflecting the possible appearance of new LU classes (e.g. new crops and farming techniques) and the level of spatial resolution that increasingly allows to differentiate between classes (e.g. forest types or urban classifications).

6. Conclusions

This study pioneers the use of the novel PLUS code to model LUC at a small, detailed scale, and contributed for the development of the modelling code to more precisely deal with detailed LUC. It is also unique in the way it analyses the complex relationship between LUC, groundwater conditions and groundwater management approaches, providing parameter importance for each driving factor of LUC. Using the AB irrigation district of Australia's MDB as a case study, it expands on previous knowledge by quantifying groundwater-related driving factors of LUC. This allows decision makers to quantitatively understand what drove changes to LUC and better qualitatively understand the impacts of LUC on groundwater conditions, and will allow modelling of future scenarios considering a range of possible LUC and climatic conditions. Groundwater level and salinity were key drivers for LUC throughout the study period (1949–2014), which are rarely considered in LUCM studies. This reasonably well-known case study allowed us to (i) look at the influence of groundwater salinity and level as a driver of LUC, rather than the impact of LUC on groundwater that occurs frequently in the literature, (ii) model LUC at a detailed local scale, and (iii) analyse the systemic relationship between groundwater policy/management and LUC.

We expand on previous knowledge by quantifying groundwater-related driving factors of LUC. The modelling results confirm groundwater quality (as salinity) and availability as key drivers. Out of the original 16 driving factors used, both salinity (5%−11%) and level (6%−12%) were key contributing drivers to LUC depending on agricultural land use and phase. The most dramatic change was observed between 1993 and 2003 allowing for expansion of irrigated agriculture. Other important factors throughout the study period were areas of most productive soils and areas associated with high rainfall and river flooding. When groundwater salinities increased and groundwater levels decreased due to over-extraction, changes in LU occurred with the most lucrative and less water-demanding crops (Vineyards) expanding to areas close to Lake Alexandrina, which became a new source of freshwater. This was facilitated by policy and water management approaches including MAR, the WMPs and the construction of pipelines that were put in place to combat groundwater salinity rises and level declines. This qualitatively confirms LUC led to change in groundwater conditions, leading to new policies that contributed to a diversification of water sources and a change to more profitable and water-efficient crops, but also the replantation of native vegetation. Ultimately, this resulted in improved groundwater conditions, increased the cover of native vegetation and allowed regional economic growth.

This study demonstrates that LUCM on such a local scale (e.g. 250 km^2) is possible. This was conceivable in the AB region due to good data availability, which may not be the case in data-sparse regions. Our modelling results are well aligned with previous qualitative studies on the factors that influence LUC in the AB region, which is an indication the model performed well and produced robust outcomes. To the best of our knowledge, LUCM was used for the first time to analyse how past transient policies impacted LUC on a local scale catchment over different time periods and climatic conditions. LUCM and groundwater data analysis are not typically conducted together, and this paper provides a demonstration of how it can be done in practice, and at a fine scale enough to be relevant for decision makers. We advocate this to be done elsewhere where groundwater conditions and management approaches, and LUC have such a dynamic, transient and complex relationship.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Jessica Penny reports financial support was provided by Engineering and Physical Sciences Research Council.

Data availability

Data will be made available on request.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.agwat.2023.108174.

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