

The impact of deforestation on hydrology and soil salinity

A case study over the South American Dry Chaco



Michiel Maertens

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Dissertation presented in partial
fulfillment of the requirements for the
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Members of the Examination committee:

Prof. dr. ir. M. Roeffaers, KU Leuven (chair)

Prof. dr. A. Van Rompaey, KU Leuven

Prof. dr. E. Lambin, UC Louvain

Dr. M. Dumuzere, RUB

Dr. S. Kumar, NASA GSFC

Dr. I. Gasparri, CONICET

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Preface

‘Wonder is the beginning of wisdom’

Socrates

Verwonderd zijn, daar is het allemaal mee begonnen. Als klein jongetje namen mijn ouders me vele jaren mee, samen met mijn broer, op vakantie naar de Oostenrijkse Alpen. Ik herinner me nog goed hoe ik gefascineerd was door de rotsige bergtoppen, ingesneden riviervalleien en de spectaculaire gletjers. Tot wanhoop van mijn ouders bleef ik hen bestoken met vragen over waar die bergen nu precies vandaan kwamen en waarom we die niet in West-Vlaanderen konden terug vinden. Vragen waar ze helaas geen antwoord op wisten. Daar, in de hoge Alpen, is het zaadje voor de verwondering geplant: de verwondering voor de werking van onze planeet en hoe we daar als mens mee interageren. Die fascinatie heeft er toe geleid dat ik geografie ben gaan studeren, en beetje bij beetje meer inzicht heb gekregen in het functioneren van onze aardbol. Spannender wordt het natuurlijk wanneer je er zelf op kan gaan uittrekken en zelf nieuwe inzichten kan verwerven. De keuze om een doctoraat te beginnen was dan ook een logische stap.

Een logische stap, maar niet altijd de makkelijkste. Een welgemeend woord van dank aan iedereen die heeft meegeholpen aan dit manuscript is dan ook op zijn plaats.

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Challenge accepted!

Michiel

.

Abstract

The Dry Chaco is a semi-arid ecoregion in South America, covering parts of Argentina, Paraguay, and Bolivia. To date, the region hosts one of the largest dry forests in the world, but expansion of dryland agriculture and cattle ranching led to gradual conversion of native vegetation to anthropogenic land cover. The potential impact of these newly established agricultural lands on the surrounding environment is of great concern. Local studies have shown that deforestation leads to changes in the soil-water balance. In the longer term, this can lead to a gradual rise of the groundwater table, mobilising water-soluble salts to the surface, and affecting plant growth and crop productivity.

Therefore, the main objective of this study was to gain insight into spatio-temporal patterns of soil hydrology and salinity of the Dry Chaco using land surface models (LSMs), remote sensing data, and in situ measurements of soil salinity. The central hypotheses were that (i) the impact of deforestation on soil salinity varies with existing climatic and topographic gradients, and (ii) the susceptibility to severe soil salinization following deforestation is spatially-dependent.

First, the impact of deforestation on the different water budget components over the entire Dry Chaco was analyzed using three state-of-the-art LSMs, grouped within the Land Information System (LIS) of NASA. Because most LSMs use climatological vegetation data and static land cover parameters, they lack the ability to correctly represent the ongoing land cover changes in the Dry Chaco. Therefore, land cover changes were implemented using time-varying satellite-derived vegetation indices, together with annually updated land cover information. Our results showed that there are large regional and long-term differences in the simulated water budget components between the three LSMs, mainly due to differences in LSM structures and model-specific parameters. The different LSMs also redistribute water differently in response to the updated vegetation and land cover treatment.

Second, the link between hydrology and soil salinity was studied based on in situ salinity data and environmental variables. In situ salinity data were collected along topographic and climatic gradients across the central Argentinean Dry Chaco in the dry season of 2019. The measurements were associated to LSM output at a regional scale, satellite-derived vegetation indices and topographic data to produce a first physically-based salinity map for the central Argentinean Dry Chaco. Large regional differences in natural soil salinity were observed across the region. In the driest parts, salts are retained in the soil profile as salt leaching is prevented. Severe soil salinization occurs in topographic depressions where groundwater is present near the surface and high evapotranspiration rates enhance the formation of evaporites. With greater precipitation, salts are increasingly leached to deeper layers resulting in low natural soil salinity values. Also in regions with high hydraulic gradients, salts are effectively removed by subsurface flow and regional groundwater transport. Anthropogenic activities can increase the risk for severe soil salinization, especially in agricultural areas with shallow groundwater tables and irrigated croplands.

In the last chapter of this dissertation, we took a closer look at the chemical composition of water-soluble salts in soils of the central Argentinean Dry Chaco, and the link between the chemistry of salt-affected soils and deforestation. Previous studies mainly measured the electrical conductivity or chloride content to quantify soil salinity, and little was known about the chemistry of water-soluble salts that contribute to salt stress. We filled this knowledge gap by analysing the full spectrum of water-soluble salts based on paired soil samples collected in forested and deforested areas. A geochemical analysis revealed that chlorides contribute only 25% to total salinity and that sulphates, calcium, and sodium are equally important. We further showed that the effects of deforestation on soil salinity are spatially dependent and closely related to the geomorphological setting.

Samenvatting

De Dry Chaco in Zuid-Amerika is één van de grootste subtropische bosgebieden ter wereld dat zich uitstrekt over Argentinië, Paraguay en Bolivia. Een snelle toename aan landbouwactiviteiten sinds de jaren 80 van de vorige eeuw heeft de druk op de inheemse bossen snel laten toenemen. De potentiële milieu-impact van deze recente ontbossing op de omgeving baart grote zorgen. Recente studies hebben immers aangetoond dat ontbossing leidt tot veranderingen in de hydrologische cyclus. Op verschillende plaatsen in de Chaco hebben landbouwers ook melding gedaan van ernstige verzilting van hun akkers, verschillende jaren na de boskap. De exacte gevolgen van ontbossing op de waterbalans en bodemsaliniteit op regionale schaal zijn echter nog niet helemaal duidelijk.

Het algemene doel van deze verhandeling is om inzicht te krijgen in spatio-temporele patronen van bodemhydrologie en zoutgehalte van de Dry Chaco met behulp van landoppervlakmodellen, satellietgegevens en experimentele veldmetingen van bodemzoutgehalte. De centrale hypothesen zijn dat (i) de impact van ontbossing op het zoutgehalte van de bodem varieert met de bestaande klimatologische en topografische gradiënten, en (ii) de gevoeligheid voor ernstige bodemverzilting na ontbossing ruimtelijk afhankelijk is.

Om inzicht te krijgen in de hydrologische impact van ontbossing werden drie verschillende landoppervlakmodellen, gegroepeerd in het Land Information System (LIS) van NASA, gebruikt. Omdat de meeste modellen klimatologische vegetatiegegevens en statische landbedekkingsparameters gebruiken, zijn ze niet in staat de effecten van ontbossing correct te modelleren. Daarom hebben we onderzocht of het gebruik van vegetatie-indices afgeleid van satellietdata, samen met jaarlijks bijgewerkte informatie over landbedekking, realistische schattingen geeft van de hydrologische veranderingen na ontbossing. Bovendien zijn we nagegaan hoe de resultaten van de modellen onderling verschillen. Onze resultaten toonden aan dat er grote verschillen zijn in de gesimuleerde waterbalanscomponenten en dat elk model verschillend reageert op de geïmplementeerde ontbossing.

De gesimuleerde waterbalanscomponenten boden een unieke kans om het bodemzoutgehalte in de Dry Chaco in kaart te brengen. In situ data over bodemsaliniteit werden verzameld tijdens een veldcampagne in het centrale deel van de Argentijnse Chaco. Naast hydrologische gegevens werden de saliniteitsmetingen gekoppeld aan vegetatie-indexes afgeleid van satellietdata en topografische variabelen om een eerste saliniteitskaart voor de regio te maken. Onze resultaten toonden aan dat in de droogste gebieden van de Chaco, oplosbare zouten neerslaan in het bodemprofiel omdat uitspoeling door droogte wordt voorkomen. Ernstige natuurlijke bodemverzilting treedt in deze droge gebieden op nabij topografische depressies waar zout grondwater dicht bij het oppervlak komt. Lage zoutconcentraties worden waargenomen in regio's met steilere hellingen, aangezien zouten door regionaal grondwatertransport gemakkelijk uitgespoeld worden. Ook in de nattere delen van de Chaco zijn natuurlijke zoutconcentraties in de bodem laag doordat wateroplosbare zouten worden uitgespoeld naar het grondwater. Landbouwactiviteiten kunnen het risico op ernstige bodemverzilting verhogen, vooral in gebieden met ondiepe grondwatertafels en waar akkers geïrrigeerd worden.

In het laatste hoofdstuk van dit proefschrift zijn we dieper ingegaan op de chemische samenstelling van water-oplosbare zouten in het centrale deel van de Argentijnse Dry Chaco. Daarbij hebben we gekeken hoe die samenstelling wordt beïnvloed door ontbossing. Eerdere studies gebruikten voornamelijk de elektrische geleidbaarheid of het chloor gehalte van de bodem als een proxy voor het totale zoutgehalte. Er was weinig tot geen data beschikbaar over de chemie van de water-oplosbare zouten in de bodem die kunnen bijdragen aan zoutstress. Deze studie heeft nieuwe inzichten opgeleverd door het volledige spectrum van water-oplosbare zouten te analyseren. Uit de geochemische analyse bleek dat chloor slechts voor 25% bijdraagt aan het totale zoutgehalte en dat sulfaten, calcium en natrium even belangrijk zijn. Verder toonden we aan dat de effecten van ontbossing op het zoutgehalte ruimtelijk verschillen en nauw samenhangen met de geomorfologie.

List of Abbreviations and Symbols

Abbreviations

ASCAT	Advanced Scatterometer
AVHRR	Advanced Very High Resolution Radiometer
BELSPO	Belgian Science Policy
CLM	Community Land Model
CLM2.0	Community Land Model version 2.0
CLSM	Catchment land surface model
CLSM-F2.5	Catchment LSM-Fortuna 2.5
EASEv2	Equal-Area Scalable Earth Grid, version 2
EC	Electrical Conductivity
EC _e	Electrical Conductivity from saturated soil-paste extracts
ERI	Electrical Resistivity Imaging
ESA-CCI	European Space Agency Climate Change Initiative
FAO	Food and Agriculture Organization
GGMN	Global Groundwater Monitoring Network
GIMMS	Global Inventory Monitoring and Modelling Study
GLASS	Global LAnd Surface Satellite

GLEAM	Global Land Evaporation Amsterdam Model
GRACE	Gravity Recovery and Climate Experiment
GVF	Greenness Vegetation Fraction
HWSD	Harmonized World Soil Databank
IC	Liquid Phase Ion Chromatography
ICP-AES	Inductively Coupled Plasma-Atomic Emission Spectroscopy
INTA	Instituto Nacional de Tecnología Agropecuaria
ISMN	International Soil Moisture Network
ITCZ	Intertropical Convergence Zone
LAI	Leaf Area Index
LIS	Land Information System
LSMs	Land Surface Models
MARS	Multivariate Adaptive Regression Splines
MERIS	Medium Resolution Imaging Spectrometer
MERIT DEM	Multi-Error-Removed Improved-Terrain Digital Elevation Model
MERRA-2	Modern-Era Retrospective analysis for Research and Applications, version 2
MODIS	Moderate Resolution Imaging Spectroradiometer
NASA	National Aeronautics and Space Administration
NCEP	National Centers for Environmental Prediction
NDVI	Normalized Difference Vegetation Index
Noah	Noah land surface model
Noah 3.6	Noah LSM version 3.6
Noah-MP	Noah-Multiparameterization
OPTRAM	Optical Trapezoid Model
PFT	Plant Functional Type

ppm	parts per million
RDI	Rio Dulce Irrigation Project
ReForCha	Research on Forest dynamics in the Dry Chaco
RMSE	Root-Mean-Square Error
RTM	Radiative Transfer Model
SACZ	South Atlantic Convergence Zone
SALLJ	South American Low-Level Jet
sfmc	Surface soil moisture content
SHP	Soil Hydraulic Properties
SMAP	Soil Moisture Active Passive
SMOS	Soil Moisture and Ocean Salinity
SPOT	Satellite Pour l’Observation de la Terre
STATSGO	State Soil Geographic
Tb	Brightness temperature
Tb _H	Tb at horizontal polarization
Tb _V	Tb at vertical polarization
TDR	Time Domain Reflectometry
TOTRAM	Thermal-Optical Trapezoid Model
UAV	Unmanned Aerial Vehicle
ubRMSD	unbiased Root-Mean-Square Difference
UMD	University of Maryland
VIF	Variable Inflation Factor

Symbols

σ	Standard deviation
ΔS	Change in soil water storage
λET	Latent heat flux

λ	Latent heat of vaporization
ψ_{sat}	Saturated matric potential
θ_{sat}	Soil porosity
θ_{wilt}	Soil wetness at wilting point
aR	anomaly Pearson correlation coefficient
Ca^{2+}	Calcium
Cl^{-}	Chloride
E_B	Bare soil evaporation
E_I	Evaporation from canopy interception
E_V	Vegetation transpiration
ET	Evapotranspiration
K^{+}	Potassium
K_{sat}	Saturated conductivity
mc_{1m}	1 m soil moisture content
mc_{2m}	2 m soil moisture content
Mg^{2+}	Magnesium
Na^{+}	Sodium
NO_3^{2-}	Nitrate
P	Precipitation
Pet	Potential evapotranspiration
Q	Total runoff
Q_{SB}	Subsurface runoff
Q_S	Surface runoff
R	Pearson correlation coefficient
R^2	Coefficient of determination
R_{net}	Net incoming radiation

R_{SP}	Spearman correlation coefficient
SM	Soil moisture
SO_4^{2-}	Sulfate
B	Clapp-Hornberger parameter

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Chapter 1

Introduction

In arid and semi-arid regions, soil salinization is one of the most important environmental causes of soil degradation (Rengasamy, 2006). Soil salinization can be attributed to natural conditions or anthropogenic activities. While natural causes include factors such as climate, lithology, and topography, human causes are usually associated with changes in land use and land cover or irrigation (Ghassemi et al., 1995). The South American Dry Chaco is a semi-arid ecoregion that hosts one of the largest dry forests in the world. Since the 1980s, dryland agriculture and cattle ranching gradually replaced native forests and woodlands. The potential environmental impacts of these recent deforestation processes are not yet well understood (Marchesini et al., 2017). This dissertation focuses on the impacts of deforestation on hydrology and soil salinity in the Dry Chaco to gain better insights into the region's future hazard and risk to dryland salinization.

This dissertation is part of the ReForCha (Research on Forest dynamics in the Dry Chaco) project funded by the Belgian Science Policy (BELSPO), whose central aim is to integrate multi-source remotely sensed data, field observations and land surface models to improve our understanding of ecosystem degradation in dryland forests.

1.1 General context: dry forests and deforestation

Land use changes have become a significant driver of environmental change. They can heavily alter ecosystem functioning and affect the performance of

several ecosystem services, including climate regulation, water quality, timber production, habitat and biodiversity conservation (Costanza et al., 1997; Balthazar et al., 2015; Perera et al., 2018). Therefore, understanding where and why land use has been converted and how it affects ecosystem functioning has become a research priority (Foley et al., 2005; Turner et al., 2007).

Globally, the most important form of land change is forest conversion for expansion of agricultural land (Lambin and Meyfroidt, 2011). Studies on land use and land cover changes have mainly focused on deforestation in tropical regions and little attention has been paid to deforestation in subtropical woodlands and dry forests (Parr et al., 2014; Fehlenberg et al., 2017; Schröder et al., 2021). However, there is evidence that the highest rates of agricultural expansion are recently occurring in these latter biomes (Hansen et al., 2013; Vallejos et al., 2015). A generally accepted definition of dry forests is lacking (Schröder et al., 2021), but they are often described as ‘forests occurring in regions characterized by marked seasonality in precipitation distribution, resulting in multi-month droughts’ (Miles et al., 2006). Hence, they mainly occur in regions with an arid to semi-arid climate. According to the latest global estimates of dry forests, calculated from high-resolution satellite imagery (Quickbird and Ikonos), they cover a total area of 10.790.000 km², similar as tropical rainforests (11.560.000 km²) (Bastin et al., 2017). The global occurrence of dry forests is shown in Figure 1.1.

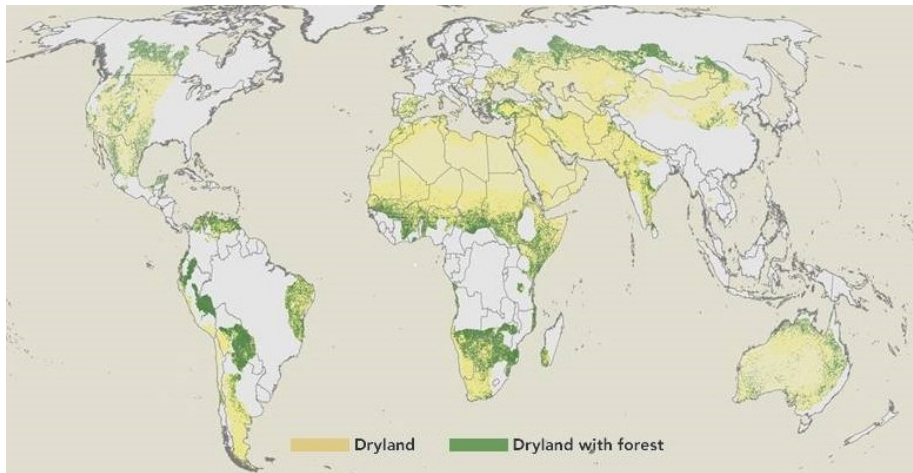


Figure 1.1: Global extent of drylands and dry forests, derived from high-resolution satellite imagery for the year 2015. Source of Figure: Bastin et al. (2017)

Dry forests and woodlands are threatened by a variety of anthropogenic

factors, including agricultural encroachment, human-induced climate change, fire, overgrazing, and population growth (Miles et al., 2006; Siyum, 2020). Over the past five decades, the South American Dry Chaco and Espinal (the largest forests in South America after Amazonia) have experienced particularly high rates of deforestation. Since 1976, more than 158,000 km² of the Dry Chaco forest was transformed into agricultural land, mainly for soybean production, corresponding with a loss of about 20,7% of the original dry forest (Vallejos et al., 2015; De Marzo et al., 2021). Deforestation in the Chaco has affected biodiversity (Mastrangelo and Gavin, 2014), climate regulation (Salazar et al., 2015), and reduced carbon storage (Gasparri et al., 2008). Furthermore, deforestation leads to slow but steady changes in the water balance and, on the longer term, may result in soil salinization with devastating effects on agricultural development as shown by Amdan et al. (2013) and Giménez et al. (2016). Deforestation also alters ecosystem services that support the livelihood of local populations, causing conflicts over the use of resources (Mastrangelo and Lateral, 2015).

1.2 Soil hydrology and salinity in drylands

In semi-arid to sub-humid ecosystems, water is the limiting factor for vegetation growth. Native plant and tree species are adapted to these conditions and tend to optimize their water use, for example, by selectively allocating water to sites of new tissue growth, minimizing water loss to the atmosphere, developing deep-root systems, or using their own water storage systems (Hatton and Nulsen, 1999; Eagleson, 2005; Santoni et al., 2010). In areas where deep-rooted woody plants dominate and soils lack barriers to root development, evapotranspiration equals precipitation input and prevents deep drainage to deeper soil horizons. Extremely low rates of deep drainage and groundwater recharge have been reported in several dry forest and grassland ecosystems of Africa, Australia, Asia, and North and South-America (Santoni et al., 2010).

These specific hydro-ecological conditions of subtropical forests lead to accumulation of water-soluble salts in the soil profile. Salts originate from weathering of parent material, atmospheric deposition (Rengasamy, 2006) or ocean sprays, which can transport salts up to 1400 kilometers from the ocean (Thornton et al., 2010). Because the presence of deep-rooted vegetation limits the percolation of water below the root front, salts can be retained in the vadose zone of the soil mantle. Especially in large and flat sedimentary plains where horizontal groundwater flow is limited, lateral transport and export of salts is negligible (Jobbágy et al., 2020) (Figure 1.2a). The accumulation of salts in the vadose zone is also referred to as primary soil salinity. Natural salinity conditions are further determined by how salts are distributed in the landscape.

The redistribution of these salts within the soil mantle is dependent on the regional climate, hydrogeology and vegetation cover.

In areas where precipitation exceeds the potential evapotranspiration, the water excess results in a net downward water flow and low salinity as salts are leached towards the groundwater table. In arid and semi-arid regions, where potential evapotranspiration exceeds rainfall, the evapotranspiration deficit can be offset by groundwater rise. Together with capillary rise, this can lead to a net upward flux of water and solutes toward the surface and increase salt accumulation in the soil mantle: the higher the water deficit, the higher the risk for soil salinization (Schofield et al., 2001; Nosetto et al., 2008).

Besides climate, the salinity hazard can be increased or weakened by the local hydrogeological context. Flat sedimentary landscapes are more likely to support shallow groundwater levels and thus salinization risks than hilly landscapes with deep groundwater tables and steep hydraulic gradients. Also tectonic activity may have a considerable impact on groundwater movement. For example, tilted or rotated fault blocks can generate topographic depressions in which internally drained lakes can be formed (Leeder and Gawthorpe, 1987). Also, seepage of groundwater along a fault trace can lead to water accumulation in the hanging wall.

Human activities can influence soil salinity, resulting in severe soil salinization (also referred to as secondary salinity). Dryland salinization, a process in which the levels of salinity increase without irrigation, is a common form of secondary soil salinization in drylands and has been documented in western Australia, the Sahel and southwestern United States (Lambers, 2003; Scanlon et al., 2005; Favreau et al., 2009; Leblanc et al., 2008). It is caused by changes in vegetation cover from e.g., deforestation that alter the local soil hydrology by changes in plant transpiration (Allen et al., 1998), phenology (Bisigato and Laphitz, 2009) and rooting depth (Huxman et al., 2005). This process can result in slow but steady changes in the water balance and favor the development of deep drainage pulses during or after wet periods (Jobbágy et al., 2020). Given the tight connection between soil hydrology and salinity, this also has its implication on soil salinity (Figure 1.2). With the downward movement of water from the root zone to deeper soil horizons, salts are leached from the vadose zone, resulting in a decrease of soil salinity. After a prolonged period of time, the increased percolation and deep drainage may result in a gradual rise of the groundwater level. When the phreatic zone gets close to the soil surface, capillary rise and eventually direct evaporation of groundwater can remobilize water-soluble salts to the upper soil horizons. Elevated salt concentrations in the soil mantle have a direct impact on plant growth (Giménez et al., 2016; Marchesini et al., 2017; Jobbágy et al., 2020), and can have devastating impacts on agricultural development as experienced in vast areas of Australia (Lambers, 2003).

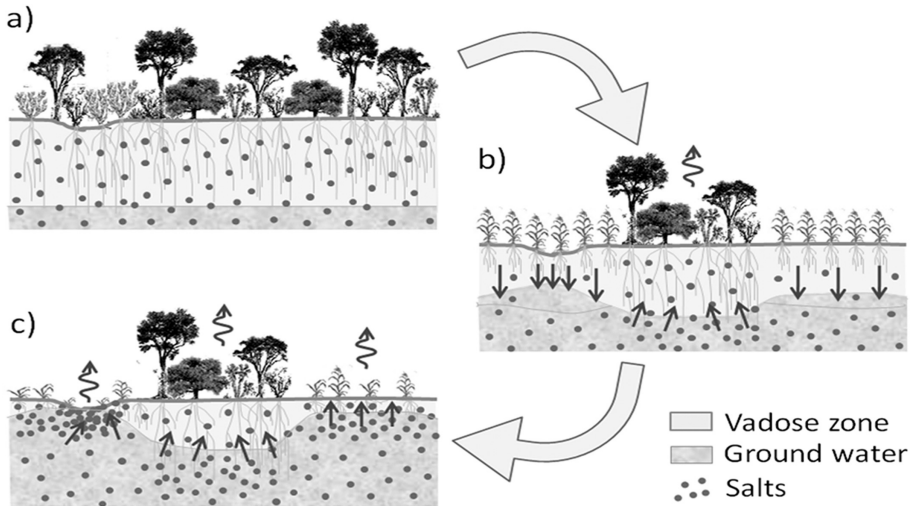


Figure 1.2: Schematic overview of soil salinization due to deforestation in the Dry Chaco. (a) Original situation: dryland forest with deep groundwater table and salts concentrated in the vadose zone. (b) Present conditions: deep percolation, groundwater recharge and leaching of soluble salts from soil mantle to the groundwater table in agriculture plots. (c) Eventual future condition: onset of groundwater evapotranspiration due to very shallow groundwater tables, upward rise and concentration of soluble salts at the surface. Source of Figure: Giménez et al. (2016).

1.3 Bridging the gap: from local to regional estimates of hydrology and soil salinity

1.3.1 Hydrology

To assess the impact of deforestation on the water cycle, information on the partitioning of precipitation into the different water budget components is required. In literature, there are three common approaches to study the hydrological variables.

The first approach is based on observations from hydrometeorological networks that can provide in situ data on rainfall (e.g., via different types of pluviometers), soil moisture (e.g., via gravimetric samples or dielectric technique-based sensors), evapotranspiration (e.g., via eddy covariance measurements on flux towers) and groundwater depth (e.g., via piezometers) among others. They provide the

most reliable and accurate data on temporal variations. Time series of in situ measurements can reveal trends in the hydrological cycle related to e.g., climate or land cover changes. They are also invaluable for the calibration and validation of land surface models and satellite-based retrievals (Dorigo et al., 2011). However, obtaining data from in situ networks is challenging due to high implementation and maintenance costs. Globally, the number of networks and stations measuring hydrological variables, especially on a continuous basis, is limited and measurements remain sparse in space (Dorigo et al., 2011; Shahgedanova et al., 2021). To overcome some of these limitations, international networks such as the International Soil Moisture Network (ISMN) (Dorigo et al., 2011), FLUXNET (Baldocchi et al., 2001) and the Global Groundwater Monitoring Network (GGMN) (Vermooten and Kukuric, 2009) have been initiated to serve as a centralized data hosting facility where globally available in situ measurements from operational networks and validation campaigns are collected, harmonized and made available to users (Dorigo et al., 2011).

Recent advances in remote sensing offer promising data to fill observational gaps in various water budget components. Satellite-derived evapotranspiration estimates are mostly indirect products derived from remotely sensed variables, such as temperature or vegetation, coupled with an energy balance model (Weerasinghe et al., 2020). More recently, evapotranspiration products have also been developed using machine learning in combination with observed flux tower data or model outputs as training sets (Tramontana et al., 2016; Alemohammad et al., 2017). Technological advances in remote sensing also supported a suite of powerful soil moisture monitoring tools (Carlson, 2007). Various methods have been developed to derive soil moisture using a combination of visible and thermal infrared data (e.g., Optical Trapezoid Model (OPTRAM) (Sadeghi et al., 2017) or Thermal-Optical Trapezoid Model (TOTRAM) (Sandholt et al., 2002)). Also microwave remote sensing techniques are widely used to provide continuous surface soil moisture estimates from space (Li et al., 2021). Soil Moisture and Ocean Salinity (SMOS) (Kerr et al., 2010), Soil Moisture Active and Passive (SMAP) (Entekhabi et al., 2010) and Advanced Scatterometer (ASCAT) (Wagner et al., 2013) are some of the main satellite missions carrying an L-band radiometer and currently providing passive soil moisture estimates. These instruments provide soil moisture estimates at coarse spatial resolution but have a very high revisit time (up to 1 day).

In addition to remote sensing products, land surface models (LSMs) can be used to provide spatial and temporal representation of the regional water distribution. They aim to provide a complete and self-consistent description of the temporal and spatial distribution of water and energy over land (Clark et al., 2015). Unlike satellite retrievals, they provide information on all water budget components and close the water balance. The degree to which LSMs are applicable to

particular situations depends on how well their given structure, forcing data, and parameters can represent regional land surface processes (Wood et al., 2011; Clark et al., 2015). There are a variety of LSMs and most of them have evolved significantly in recent years (Clark et al., 2015; Blyth et al., 2021). The most fundamental equations in LSMs are the surface water balance and the energy balance. The surface water balance governs the partitioning of available water into evapotranspiration and runoff, while the surface energy balance governs the partitioning of energy into sensible and latent heat (Pitman, 2003).

Recent studies have found large inconsistencies in the partitioning of the water budget among different LSMs (Wang and Dickinson, 2012; Kumar et al., 2018; Rigden et al., 2018; Zhang et al., 2020). For example, Kumar et al. (2018) showed that modeled transpiration over the continental United States varies from 30 to 84% of the total evapotranspiration depending on the model chosen. Another illustrative example of this diversity is shown by Vereecken et al. (2019), who discussed the wide range of equations that are used among LSMs for estimating infiltration. They reported that different LSM structures and equations have an impact on the modeled soil water balance and energy balance and even modeled land-atmosphere interactions when LSMs are coupled with atmospheric models.

Land cover changes can have significant impacts on different water budget components. However, most large-scale LSMs lack the ability to realistically represent ongoing changes in land cover because they assume that (i) vegetation has a recurring annual cycle and (ii) land cover is static in time. In reality, land cover can change significantly in time over some regions, and alter the vegetation strongly from its climatological representation.

1.3.2 Salinity

There is a variety of studies and methods to measure and map soil salinity. Soil salinity is a measure of the concentration of water-soluble salts in the soil. Soil salinity can be quantified from the chemical analyses of the ions present in soil water extracts, or from electrical conductivity (EC) measurements (Corwin and Yemoto, 2017). EC is commonly used as a proxy for salinity because it is easy to measure, less costly and labour intensive than chemical analyses (Rhoades et al., 1999). The EC measure quantifies the ability of a solution to conduct electricity between electrodes, which is a proxy for salt concentration: the higher the amount of salts present, the greater the current. EC can be measured on an extract of a saturated soil paste, the saturated paste itself, or a soil water sample and is expressed in deci-Siemens per m (dS/m). In addition to techniques based on EC, Time Domain Reflectometry (TDR) and capacitance probes that

measure electrical permittivity can be used to quantify soil salinity indirectly (Corwin and Yemoto, 2017). However, these measurements are applied to field samples: they correspond to point samples, involve intensive field monitoring and often prove difficult to apply on a large scale. To enhance the spatial representation of soil salinity, electrical resistivity imaging (ERI) is commonly used whereby geophysical data are collected along transects. As with TDR and capacitance probes, the measured output is affected not only by the salinity of the soil, but also by the type and amount of clay material, water content, and soil temperature (Shahid et al., 2013).

Maps of soil salinity are often based on a regional extrapolation of point measurements through the use of geostatistical modeling (Fan et al., 2016). Although regional and global maps illustrate the regions affected by salinity, they are static in time and often lack the proper spatial resolution to help policy makers. Moreover, the interpolation technique should be carefully selected to obtain accurate results. Besides geostatistics, remote sensing data have also been used to map soil salinity (e.g., Metternicht and Zinck (2003); Zhang et al. (2011); Scudiero et al. (2015); Zhang et al. (2015)). Early work focused on assessing salinity at or near the soil surface based on differences in surface reflectance between salt crusts and productive topsoil (Allbed and Kumar, 2013). However, in agricultural soils, salts tend to accumulate in the root zone rather than at the surface. This has shifted the paradigm of remote sensing applications towards the use of vegetation indices as indirect measures of soil salinity (Metternicht and Zinck, 2003; Zhang et al., 2011), as excessive salt concentrations in dryland soils affect vegetation growth. In recent work, soil salinity is assessed using vegetation indices calculated from annual to multi-year spectral satellite data (Lobell et al., 2010; Wu et al., 2014; Zhang et al., 2015; Scudiero et al., 2014a, 2015) or from vegetation indices that are integrated over the growing season (Zhang et al., 2015). However, most of these studies have been conducted at local scales, and the locally developed algorithms are not fully extensible to regional-scale assessments due to spatial variability in climate conditions, soil properties, and land use/management (Wu et al., 2014).

1.4 The Dry Chaco ecoregion

The name ‘Chaco’ originates from the word ‘chaku’, which is used by indigenous people and means ‘productive hunting land’. The use of this word refers to the rich variety of wildlife and landscapes as well as to the method of hunting used by natives (Prado, 1993). The Dry Chaco is located east of the Andes mountains. The region has an area of approximately 787,000 km² and covers parts of Argentina, Paraguay and Bolivia and is bordered by the Andes mountains in the

west and the Río Paraná in the east. The location of the Dry Chaco in South America is shown in Figure 1.3. Its elevation ranges from ca. 600 m in the west towards 40 m in the east. The area is drained by 5 principal rivers (Río Parapetí, Pilcomayo, Bermejo, Salado and Dulce) that have their headwaters in the Subandean Ranges (Moretti et al., 2019)) (see Figure 1.5a).

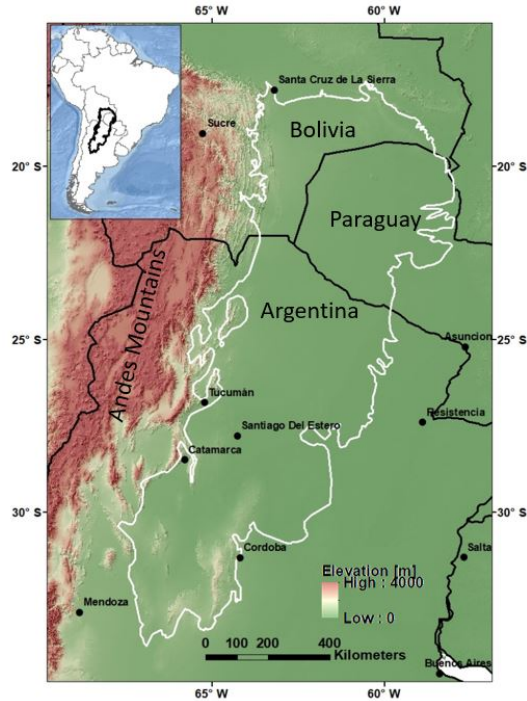


Figure 1.3: Geographic location of the Dry Chaco in South America and the main cities.

1.4.1 Climate

The Dry Chaco ecoregion has a north-south gradient in mean annual temperature from 26 °C to 18 °C (Minetti et al., 1999). Annual mean precipitation ranges from 400 mm/year in the central part to 1000 mm/year in the eastern parts (Minetti et al., 1999). 80% of the annual precipitation falls in the summer season (from October to March). The dry winter season lasts from May to September. The monsoon climate of the region is indirectly determined by the seasonal temperature variations in Central Amazonia (Vera et al., 2006;

Garreaud et al., 2009). In October–November, a deep continental low pressure system (Chaco Low) forms over the Chaco in response to strong convective heating over the Amazon associated with the intertropical convergence zone (ITCZ) (see Figure 1.4). This low pressure system induces the transport of moisture from the tropics to subtropical South America, known as the South American Low-Level Jet (SALLJ) (Paegle and Mo, 2002; Saulo et al., 2004). The SALLJ can be enhanced or inhibited by the South America Convergence Zone (SACZ), which characterizes intraseasonal precipitation variability over South America: enhanced precipitation over the SACZ is associated with decreased precipitation in the subtropical plains, while the opposite phase is associated with more precipitation in the subtropical plains (Ferrero and Villalba, 2019). Between March and May, the ITCZ moves towards the equator and transport of moist air towards the Chaco plain is gradually reduced (Vera et al., 2006).

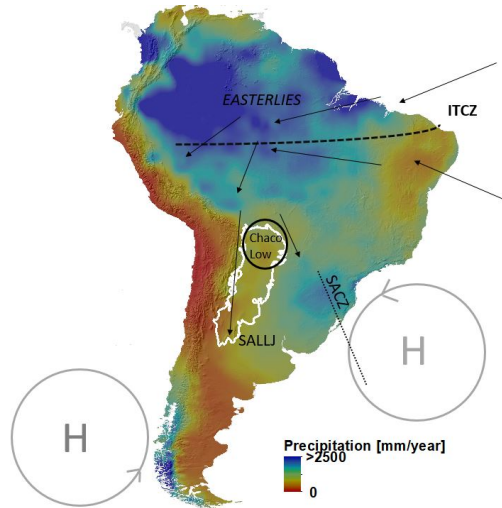


Figure 1.4: General wind circulation systems affecting South America at 850 hPa. Modified from Vera et al. (2006), Savi et al. (2016), Gelbrecht et al. (2017). ITCZ = Intertropical Convergence Zone; SACZ = South Atlantic Convergence Zone; SALLJ = South American Low Level Jet. The background represents the long-term (1992–2017) annual mean precipitation pattern derived from the Modern-Era Retrospective analysis for Research and Applications (MERRA-2) product (Gelaro et al., 2017), interpolated to a 5 km resolution.

1.4.2 Geomorphology

Geologically, the Dry Chaco is an Andean foreland basin filled by fluvial sediments (Latrubesse et al., 2012). The location of the region at the transition between Subandean Ranges and the adjacent lowlands favours the development of alluvial megafans (see Figure 1.5a), resulting in the unique geomorphology of the region (Thalmeier et al., 2021). The Chaco comprises 5 megafans, among the largest in the world, extending approximately 500 - 700 km from the Andean foothills (Thalmeier et al., 2021). The fans show typical microflow patterns and their surface is slightly tilted towards the Paraguay-Paraná River that constitutes the local base level in the region (Kruck et al., 2011). The Chaco rivers that originate in the Andes deposited detrital material in the foreland basin. These rivers transport fine-grained material and remobilize eolian sediments from the headwaters. After excessive rainfall events, the rivers in the lower to middle part of the Chaco plain used to inundate vast areas of land. The fine-grained loamy sediments deposited during floods have regularly blocked the alluvial valley, causing historical river avulsions (Kruck et al., 2011). In contrast to the floodplains, the paleochannels and riverbeds consist of sandy material.

1.4.3 Land cover transformation

The Dry Chaco region has experienced rapid land cover change since the 1980s (Vallejos et al., 2015). Degradation of the native dry forest originally began from traditional settlements (also called 'puestos'), as a result of extensive cattle ranching and the encroachment of shrubs (Gasparri, 2016; Gobbi et al., 2020). Commercial forest exploitation and associated logging activities began in the early 20th century with selective logging of Quebracho Colorado (*Schinopsis quebracho colorado*), a tree species with dense wood used for railroad sleepers and tanning (Bucher and Huszar, 1999; Rueda et al., 2015). Since the 1980s, the rate of deforestation accelerated rapidly: global food demand started to increase and technological improvements together with favourable climatic conditions converted the Dry Chaco in a region that is suitable for agriculture (Marchesini et al., 2017). Since 1976, more than 158.000 km² of Dry Chaco forest have been converted to agricultural land, mainly for soybean cultivation, representing a loss of about 20,7% of the original dry forest (Vallejos et al., 2015; De Marzo et al., 2021). The spatiotemporal pattern of deforestation is shown in Figure 1.5b. Most deforested land is used for intensive cattle ranching and for summer crop monocultures (mainly soybean and corn) (Gasparri and Grau, 2009; Clark et al., 2010).

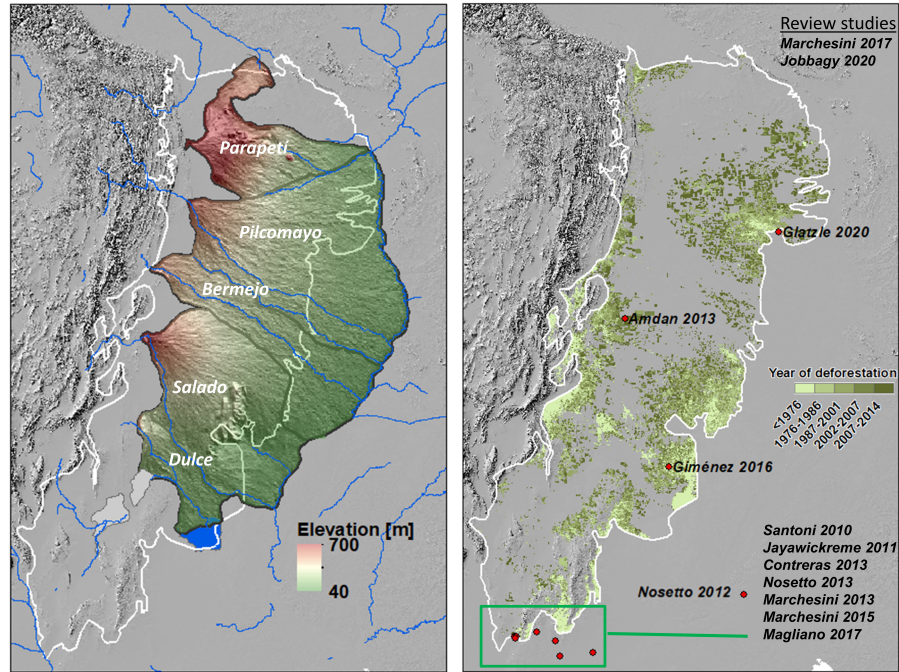


Figure 1.5: (a) Location of the 5 megafans encompassing the Dry Chaco and (b) spatiotemporal pattern of deforestation between 1976 and 2014 obtained from Vallejos et al. (2015) with indication of earlier studies conducted at the plot-level scale.

Only a few studies have been conducted in the Dry Chaco on the hydrological and geochemical consequences following deforestation. The locations of where these studies were conducted are shown in Figure 1.5b. The studies focusing on hydrology reported that the replacement of native dry forests with annual rainfed crops generated changes in soil moisture dynamics (Jobbagy et al., 2008; Santoni et al., 2010; Noretto et al., 2012), excess deep drainage (Amdan et al., 2013; Giménez et al., 2016; Marchesini et al., 2017), and runoff increments (Magliano et al., 2017). The eco-hydrological changes after deforestation are expected to affect the movement of salts in soils. Amdan et al. (2013) reported 94% lower chloride stocks in cropland compared to dry forest. Complete leaching of chloride pools beneath deforested areas was also reported by Giménez et al. (2016).

1.5 Objectives and research questions

The previous mentioned studies on hydrological and soil salinity changes following deforestation in the Dry Chaco were mainly conducted at the local plot-level scale, and did not account for spatial variability in climate and topography across the region. Therefore, this study aims to get a better regional understanding of changes in soil hydrology and salinization after deforestation in the Chaco. Our central hypotheses are that (i) the impact of deforestation on soil salinity varies with existing climatic and topographic gradients, and (ii) the susceptibility to severe soil salinization following deforestation is spatially-dependent. To test these hypotheses, we use an approach that combines LSMs, remote sensing data, and in situ soil salinity data.

More specifically, this study tackles three research questions. The first question is related to the Chaco's hydrology, and the potential use of LSMs to represent regional changes in hydrology after deforestation. The second and third research questions are focusing on the Chaco's soil salinity, and spatial variations in natural and secondary salinity.

RQ.1: What is the impact of land cover changes on water budget components simulated by different LSMs?

In this study, we use LSMs as a tool to estimate the hydrology over the Dry Chaco. Most large-scale LSMs lack the ability to correctly represent the ongoing land cover changes in the Dry Chaco as they use climatological vegetation indices and static land cover information. We aim at implementing land cover changes in different LSMs by using (i) satellite-based interannually varying vegetation indices (leaf area index and green vegetation fraction) instead of climatological vegetation indices and (ii) annually updated land cover information instead of static land cover as illustrated in Figure 1.6. The effect of the implemented changes on the different water budget components is tested in three LSMs embedded in the NASA's Land Information System (LIS). It is also verified if LSMs are capable of simulating the increased deep percolation and higher soil moisture values after deforestation, as reported in field studies of Noretto et al. (2012); Giménez et al. (2016); Magliano et al. (2017) and Marchesini et al. (2017).

The performance of LSMs and the effects of the updated vegetation and land cover parameters are evaluated using independent data. Validation data include in situ soil moisture, satellite-derived estimates of evapotranspiration and brightness temperature. The latter provide an integral assessment of simulated soil moisture, soil temperature, and leaf area index, after passing these variables through a zero-order radiative transfer model.

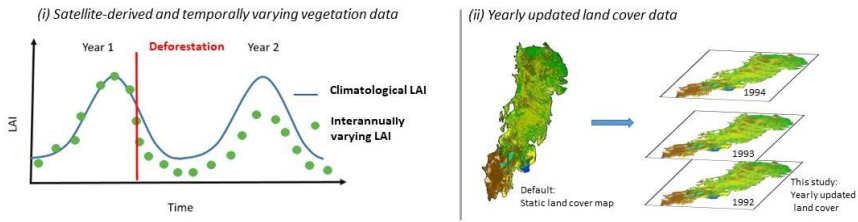


Figure 1.6: Schematic overview on how land cover changes are implemented in LSMs.

RQ.2: To what extent is the Dry Chaco affected by soil salinity and which environmental variables are associated with the regional salinity patterns?

Most studies on soil salinity in the Dry Chaco are conducted on the plot scale and relate soil salinization to forest conversion. To our knowledge, no studies exist on the regional pattern of primary and secondary soil salinity over the region and on how these regional patterns are affected by environmental conditions such as topography and climate. We tested whether spatially explicit data on climate conditions, topography and vegetation can be associated to regional patterns in salinity. To do so, EC measurements collected during a field campaign in 2019 are associated to satellite-derived vegetation indices, topographic information, and meteorological and hydrological variables from a LSM. By using a spatial regression technique, the most relevant variables are identified and a regional soil salinity map for the central Argentinean Dry Chaco is produced.

RQ.3: What is the chemical composition of salts in the vadose zone, and which spatial variations exist in the chemical composition of salts in the Dry Chaco?

Little is known about the chemical composition of salts in the Dry Chaco. In this dissertation, we have a closer look at the chemical composition of water-soluble salts in the region, and the link between the chemistry of salt-affected soils and deforestation. Based on a paired study including agriculture and matched forest sites, we compare the soil chemical signature of cleared areas with nearby intact forested areas across the existing topographical gradients in the Dry Chaco. The chemical composition of water-soluble salts in the soil were determined from Inductively Coupled Plasma-Atomic Emission Spectroscopy and Liquid Phase Ion Chromatography.

1.6 Thesis structure

This PhD dissertation is divided into 5 chapters, including this introduction (Chapter 1). Chapters 2-4 address the three main research questions, whereby each chapter focuses on a different spatial scale and resolution, as illustrated in Figure 1.7.

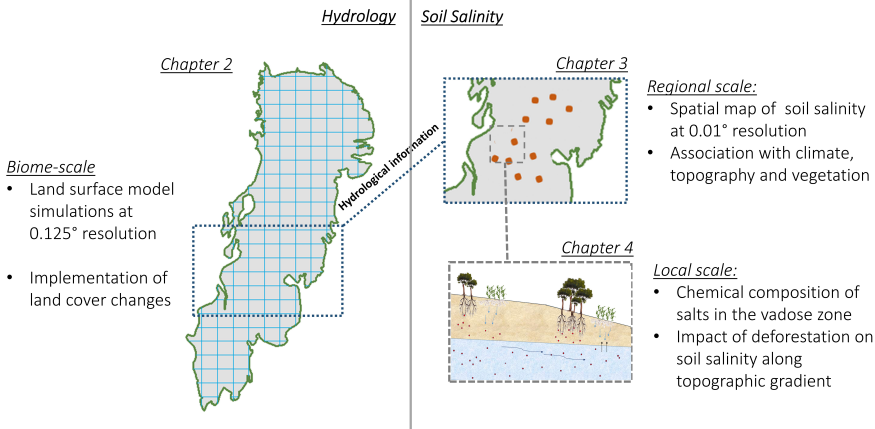


Figure 1.7: Flowchart depicting the links between the different chapters of the PhD thesis.

The LSMs used in Chapter 2 are run at a resolution of 0.125°. The coarse resolution of the simulations allows for a spatial extent that covers the entire Dry Chaco for a long-term period (1992-2015).

Given the extent of the Dry Chaco, it is not feasible to collect salinity data across the entire region. Hence, the area of interest of Chapter 3 is constrained to the central part of the Argentinean Dry Chaco. To produce a physically-based and high-resolution regional salinity map, the LSM output, satellite-derived vegetation indices, and topography data are generated at a spatial resolution of 0.01°.

In Chapter 4, we analyse differences in water-soluble salt compositions between forested and cleared areas. Data are generated from soil samples taken at the plot-level scale in representative sites in the central Argentinean Dry Chaco. The selection of sites is congruent with the spatial framework used in Chapter 3.

Finally, the overall findings and perspectives for further research are summarized in Chapter 5.

Chapter 2

Land surface modeling over the Dry Chaco

Based on:

Maertens, M., De Lannoy, G. J. M., Apers, S., Kumar, S. V., and Mahanama, S. P. P.: Land surface modeling over the Dry Chaco: the impact of model structures, and soil, vegetation and land cover parameters, Hydrol. Earth Syst. Sci., 25, 4099–4125, <https://doi.org/10.5194/hess-25-4099-2021>, 2021

2.1 Introduction

Land surface models (LSMs) aim at providing a complete and self-consistent description of the temporal and spatial distribution of water and energy over land (Clark et al., 2015). The output from LSMs is used for many applications such as the monitoring of water resources, floods and droughts, and their impact on natural hazards, biomass production, ecology or soil salinity. In many cases, the LSM performance is improved by including remotely sensed observations through (i) the dynamic integration of observations into LSMs via data assimilation, (ii) the mapping of model input parameters to characterize the representation of land properties within the model (e.g., soil properties, land cover) and (iii) the validation and development of LSMs. In addition, contrasting model output with remote sensing is a powerful method to identify unmodeled processes in a LSM, such as irrigation (Kumar et al., 2015; Brocca et al., 2018), or groundwater withdrawal (Giroto et al., 2017). Furthermore,

LSMs are an essential part of weather forecast systems and of climate models that simulate past, present and future climate (Pitman, 2003; Clark et al., 2015). They also offer ancillary information to decompose, interpolate and extrapolate sparse ground measurements and remote sensing data. However, the degree to which LSMs can serve these various purposes depends on how well their given structure, forcing data and parameters can represent regional land surface processes (Wood et al., 2011; Clark et al., 2015). This study tests the impact of a revised set of soil, vegetation and land cover parameters on the performance of different LSMs.

Most LSMs use climatological or time-invariant parameters related to vegetation, land cover and soil properties and thereby assume stationary land processes; i.e., given similar meteorological input, the statistical distribution of the land surface variables would by design not change in time. These parameters can be properly calibrated for small-scale applications when suitable historical local data are available. However, for large-scale applications, it is common practice to provide the best possible, often satellite-based, large-scale input datasets to existing modeling systems (Jiang et al., 2010).

Satellite-based green vegetation fraction (GVF) and leaf area index (LAI) are example input datasets that directly or indirectly provide vegetation parameters (also referred to as vegetation indices) to represent the horizontal and vertical density of plant vegetation (Gutman and Ignatov, 1998), used for the calculation of transpiration, interception and radiative shading. Large-scale LSMs without dynamic vegetation modeling are strongly limited by the assumption that vegetation has a recurring annual cycle, i.e., using climatological LAI and GVF input. In reality, the vegetation's response to meteorological and climate conditions varies due to inter- and intra-annual weather and climate anomalies (Case et al., 2013).

The current abundance of satellite-based vegetation datasets allows us to constrain LSMs and account for unmodeled processes in order to better understand the impact of vegetation changes on the water budget components. High-quality and long-term vegetation products from various remote-sensing platforms (Tucker et al., 2005; Liang et al., 2013; Zhu et al., 2013) can provide temporally varying parametric input to LSMs (Boussetta et al., 2015). In addition, they can also be assimilated for state updating in LSMs with dynamic vegetation module, as they have a prognostic representation of vegetation growth (Sabater et al., 2008; Barbu et al., 2011, 2014; Albergel et al., 2017; Kumar et al., 2019). Earlier studies indicated that replacing climatological vegetation by interannually varying satellite-derived indices can improve modeled energy fluxes as well as surface temperature and moisture in both offline LSM simulations (Miller et al., 2006; Case et al., 2013; Yin et al., 2016) and atmosphere-coupled LSMs (Crawford et al., 2001; James et al., 2009; Boussetta et al., 2013; Ge

et al., 2014; Kumar et al., 2014). The largest improvements are obtained during extreme meteorological anomalies (Case et al., 2013). In this study, it is expected that, besides meteorological anomalies, large-scale land cover conversions, such as deforestation, also alter the vegetation strongly from its climatological representation. Therefore, it is tested whether the use of satellite-derived vegetation indices in LSMs is also gainful in regions characterized by land cover changes.

Besides temporally varying vegetation indices, a temporally varying description of land cover is also required over regions with major land cover change. In LSMs, land cover is represented by the use of plant functional types (Kumar et al., 2006; Peters-Lidard et al., 2007). These are groups of plant species that share similar structural, phenological, and physiological traits (Bonan et al., 2002). These features are integrated into several model-specific surface parameters for each land cover type, summarized in lookup tables (Dickinson, 1995). The sensitivity of LSMs to plant functional types or land-cover-related parameters has been illustrated in both offline (Chen et al., 2014) and atmosphere-coupled LSMs (Pitman et al., 2009; Grossman-Clarke et al., 2010; Cao et al., 2015; Ruiz-Vasquez et al., 2020). Most of these studies solely focused on changes in model-specific surface parameters without taking into account changes in LAI or GVF. In contrast, this study aims at implementing large-scale land cover changes in LSMs by feeding them with both temporally varying vegetation indices and land cover parameters.

Soil properties also form a suite of crucial input parameters in LSMs (Dai et al., 2019). Most LSMs derive soil hydraulic properties (SHPs) from lookup tables or pedotransfer functions, using soil texture information. Different LSMs have different soil parameterizations and use model-specific, often historically tuned, SHPs. Dai et al. (2019) stated that popular soil datasets currently used in LSMs are often outdated or have limited accuracy. Furthermore, the derivation of SHPs from soil texture is highly uncertain (Wösten et al., 2001). At the global scale, there are only a few generally accepted global soil maps, such as the Food and Agriculture Organization (FAO) Soil Map of the World (FAO, 1971), the Harmonized World Soil Database (HWSD) product (FAO and ISRIC, 2012) and SoilGrids (Hengl et al., 2017). As shown by De Lannoy et al. (2014), the implementation of more accurate soil texture and related SHPs can lead to reduced bias and error estimates of soil moisture when compared to in situ surface soil moisture and even impact simulated runoff and evaporation estimates. During the last decade, several operational institutes have improved their soil parameters to enhance global land surface simulations (Balsamo et al., 2009; De Lannoy et al., 2014; Chadburn et al., 2015).

In this study, soil, vegetation and land cover parameters are updated in three LSMs. The study domain is the South American Dry Chaco. Given the region's

recent and large-scale deforestation history, it is a unique area to test the impact of temporally evolving vegetation and land cover parameters. It is expected that by feeding LSMs with realistic and time-varying vegetation and land cover, together with an updated set of soil parameters, the most accurate spatial and temporal representation of the Chaco's water distribution could be obtained. Additionally, it is hypothesized that the use of similar soil, vegetation and land cover parameters in various LSMs, would result in similar accurate estimates of the long-term simulated water budgets. Lastly, it is hypothesized that soil and vegetation parameter updates would contribute differently towards the model performance improvement.

The general objectives of this study are (i) to evaluate the simulated water budget components over the Dry Chaco using three different LSMs within the NASA Land Information System (LIS), (ii) to quantify how the simulated water budget components respond when more accurate soil texture and related SHPs are implemented or when the static climatological vegetation (LAI and GVF) indices and land cover map are replaced with interannually varying satellite-based indices and yearly updated land cover maps, and (iii) to identify the remaining deviations in the modeled hydrology compared to different satellite-based and in situ observations of water budget components. Besides these general objectives, the simulated water budget components are further framed within the hydrological context of the Dry Chaco; i.e., it is verified whether the different LSMs simulate the increased deep percolation and higher soil moisture values after deforestation, similarly to the field-based findings of Nosetto et al. (2012); Giménez et al. (2016); Magliano et al. (2017) and Marchesini et al. (2017).

The impact of the revised set of soil parameters and updated vegetation and land cover treatment is analyzed incrementally. In a first phase, models were run with their default model-specific soil parameters, climatological vegetation (LAI and GVF) and static land cover. Next, the models were supplied with more accurate soil texture and related SHPs and their impact on the simulated water budgets was quantified. In a third phase, the ongoing land cover changes were implemented using interannually varying satellite-based indices and yearly updated land cover maps and it was analyzed how the major land cover changes alter the hydrological balance. Lastly, the impact of the various model structures, soil texture and dynamic vegetation input was assessed using the concept of 'efficiency space' and the performance of each set of experiments was evaluated against independent satellite-based estimates of evapotranspiration, brightness temperature and in situ soil moisture.

2.2 Models and datasets

2.2.1 Models

Three LSMs within the NASA LIS (Kumar et al., 2008) were selected to simulate land surface states and fluxes over the Dry Chaco: the Community Land Model version 2 (CLM2.0) (Bonan et al., 2002; Oleson et al., 2004), Catchment LSM-Fortuna 2.5 (CLSM-F2.5) (Koster et al., 2000) and Noah LSM version 3.6 (Ek et al., 2003), hereafter simply referred to as CLM, CLSM and NOAH, respectively. More recent versions of these models are available and might provide better simulations over the Dry Chaco, but are not yet implemented in LIS. This study relied on LIS to facilitate a consistent parameter revision across multiple LSMs, and one of the main goals was to see the impact of various LSM structures, regardless of their version. To demonstrate the impact of the updated soil treatment and dynamically evolving vegetation and land cover, a baseline simulation for each LSM was conducted and followed by various revised experimental runs. For all simulations, the spatial resolution was 0.125° , and the output was created daily (model integration timestep of 15 min). The LSMs were spun up for 10 years from 1 January 1982 through 31 December 1991 using the land cover of 1992. The subsequent simulations from 1 January 1992 through 31 December 2015 were used for further analysis. The meteorological forcing data (precipitation, temperature, specific humidity, radiation, wind and surface pressure) were extracted from the Modern-Era Retrospective analysis for Research and Applications (MERRA-2) product (Gelaro et al., 2017) including gauge-based precipitation corrections (Reichle et al., 2017).

By default, the LIS LSMs use climatological LAI data based on a 4-year average derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) Collection 4 LAI product (Kaufmann et al., 2000), and climatological global GVF data (Gutman and Ignatov, 1998) derived from 5 years of normalized difference vegetation index (NDVI) data from the Advanced Very-High-Resolution Radiometer (AVHRR) (Miller et al., 2006). The default land cover map is the University of Maryland (UMD) global land cover product (Hansen et al., 2000) based on AVHRR data from 1 April 1992 through 31 March 1993. The default soil properties in LIS are derived from the FAO Soil Map of the World (FAO, 1971). In this study, vegetation, land cover and soil input data were revised using the Global Land Surface Satellite (GLASS) LAI (Liang et al., 2013; Xiao et al., 2016), the Global Inventory Modelling and Mapping Studies (GIMMS) NDVI (Tucker et al., 2005; Pinzon and Tucker, 2014), the European Space Agency Climate Change Initiative (ESA-CCI) land cover product (Kirches et al., 2014; ESA, 2017) and soil properties derived from the HWSD v1.2 (FAO and ISRIC, 2012; De Lannoy et al., 2014).

2.2.2 Revised input data

GLASS LAI

The GLASS LAI product is a global spatiotemporally complete dataset, based on MODIS and AVHRR reflectance time series data (Liang et al., 2013). This product is available for the period 1981-2015, with a temporal resolution of eight days and a spatial resolution of 0.05° (Liang et al., 2013). Cloud-contaminated data are filled in using an optimum interpolation algorithm (Xiao et al., 2016). According to Liang et al. (2013) and Xiao et al. (2016), the GLASS LAI features more realistic and smoother seasonal variations than the MODIS LAI product (MOD15) (Knyazikhin et al., 1998) and the first version of the Geoland (GEOV1) LAI product (Baret et al., 2013). For the baseline simulations, a climatological LAI dataset was created using 24 years of GLASS data (1992-2015) to replace the default 4-year AVHRR climatology. This allowed us to solely display the effect of interannual and short-term vegetation variations in the revised experiments with time-varying GLASS data and land cover changes. The LAI observations were upscaled to the 0.125° resolution by spatial averaging.

GIMMS NDVI

The GIMMS NDVI product was assembled from AVHRR NDVI data (Tucker et al., 2005). The GIMMS dataset covers the period 1982-2015 and has a 15-day temporal resolution. The spatial resolution is 0.0833° . The maps are 15-day maximum value composites and cloud-contaminated pixels are replaced by NDVI values derived from either spline interpolation or average season profiles (Pinzon and Tucker, 2014). In this study, the GIMMS GVF was derived from its NDVI and used as input for the LSMs. According to Gutman and Ignatov (1998), the $GVF_{i,j}$ (-) is given by the following equation:

$$GVF_{i,j} = \frac{NDVI_{i,j} - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \quad (2.1)$$

where $NDVI_{i,j}$ is the NDVI value observed at time i and pixel j and $NDVI_{min}$ and $NDVI_{max}$ are NDVI values over barren vegetation classes and fully covered vegetation classes, respectively. For simplicity, we chose to use the values proposed by Gutman and Ignatov (1998), i.e., 0.04 for $NDVI_{min}$ and 0.52 for $NDVI_{max}$, and the GVF is restricted to the 0-1 interval. Multiple other approaches exist to derive GVF from NDVI, each with their own advantages and limitations (Jiang et al., 2010). For the baseline simulations, a climatological GVF dataset was created using 24 years of GIMMS GVF data (1992-2015). For

the revised experiments with inclusion of land cover changes, the time-varying GIMMS data were used. To match the model's 0.125° resolution, NDVI values were upscaled by spatial averaging.

ESA-CCI land cover

The ESA-CCI land cover product offers yearly varying information on 37 land cover classes from 1992 through 2015 at a spatial resolution of 300 m (Kirches et al., 2014; ESA, 2017). This long-term land cover time series was achieved by combining surface reflectance data of different observation systems (Medium Resolution Imaging Spectrometer (MERIS), AVHRR, Satellite Pour l'Observation de la Terre (SPOT) Vegetation and PROBA-V) (Bontemps et al., 2012; Kirches et al., 2014). In this study, the ESA-CCI land cover maps were reclassified into 13 UMD classes (see Appendix A.1) and upscaled to a 0.125° resolution assigning the most dominant land cover to each pixel. Figure 2.1 shows how deforestation in the Dry Chaco has progressed in both time and space, based on this ESA-CCI land cover information. The derived spatiotemporal pattern of deforestation agrees well with the 30 to 60 m resolution deforestation product of Vallejos et al. (2015) (Figure 1.5b). The deforested area of the Dry Chaco in the overlapping period (1992-2013) of both products is 23% for the 0.125° ESA-CCI data and only 15% for the finer-scaled dataset of Vallejos et al. (2015). The main reasons for this discrepancy are the different spatial resolutions of both products. A static water mask file was created based on pixels that were classified as water at least once during the period 1992-2015. For CLSM, the UMD land cover classes were further combined into model-specific classes.

HWSD soil texture and SHPs

The global 1 km soil texture data were taken from the Soil and Terrain database for Latin America and the Caribbean as part of the HWSD v1.21 and were translated to 0.125° dominant soil texture. Similarly to in De Lannoy et al. (2014), the soil texture and organic matter data were used to estimate SHPs using the pedotransfer functions of Wösten et al. (1999). The derived SHPs include the soil porosity, bulk density, Clapp-Hornberger parameter B, saturated hydraulic conductivity, saturated matric potential, soil wilting point and field capacity (see section 2.3.2). These HWSD-based soil parameters are also used in the operational Soil Moisture Active Passive (SMAP) Level-4 soil moisture product (Reichle et al., 2019).

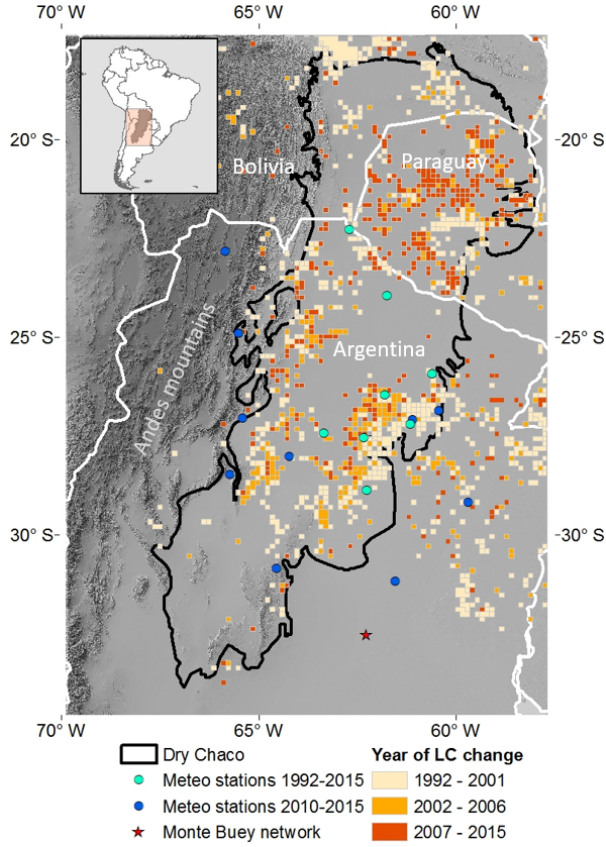


Figure 2.1: Geographic location of the Dry Chaco ecoregion together with the spatiotemporal pattern of land cover (LC) changes obtained from the ESA-CCI land cover product (upscaled to 0.125° resolution) together with the location of the Monte Buey soil moisture site and in situ meteorological stations used for validation of soil moisture and precipitation, respectively.

2.2.3 Evaluation data

Precipitation input, and surface soil moisture and evapotranspiration output were evaluated against in situ measurements and satellite-based estimates. Furthermore, an integrated evaluation of surface soil moisture, surface temperature and LAI was performed through the comparison of diagnosed L-band brightness temperature (Tb) simulations against satellite-observed Tb obtained from Soil Moisture and Ocean Salinity (SMOS).

Precipitation

The quality of the MERRA-2 precipitation over the Argentinean Chaco was evaluated against in situ data obtained from the Instituto Nacional de Tecnología Agropecuaria (INTA, 2020). Two sets of daily precipitation data were downloaded: data from meteorological stations covering the period 1992-2015 (10 stations) and data covering the period 2010-2015 (8 stations). The exact locations of these stations are shown in Figure 2.1. As this study mainly focused on long-term simulations, the precipitation evaluation was conducted using monthly averaged data.

Monte Buey soil moisture

Pixel-scale in situ surface soil moisture was obtained from 17 nodes of the Monte Buey soil moisture network. The network is located in fields surrounding the town of Monte Buey, Cordoba, Argentina, just outside the Dry Chaco (Figure 2.1), and covers three 0.125° model pixels. At each node, the surface soil moisture is measured using a Hydra Probe II buried at a depth of 5 cm. The network adopts the highest quality standards (Thibeault et al., 2015) and serves as a calibration and validation site for various satellite missions, e.g., the SATélite de Observación CON Microondas and SMAP. To allow for comparison with the daily modeled surface soil moisture, averaged over three 0.125° model pixels, the hourly in situ measurements were averaged to daily values across the 17 nodes. The period of validation was from 1 January 2013 through 31 December 2015.

Evapotranspiration

The modeled evapotranspiration components were evaluated against Global Land Evaporation Amsterdam Model (GLEAM) data. The GLEAM model consists of a set of algorithms that are driven by satellite-based observations and globally estimate all the daily evapotranspiration components at 0.25° spatial resolution (Miralles et al., 2011; Martens et al., 2017). Central in the GLEAM model is the use of the modified Priestley and Taylor (1972) equation. Daily LIS simulations of latent heat flux were upscaled to 0.25° to allow for comparison to GLEAM data for the entire simulation period, i.e., 1992-2015.

L-band microwave brightness temperature

The satellite-observed L-band Tb data were extracted from the SMOS SCLF1C product, version 620, projected onto the 36 km Equal-Area Scalable Earth Grid, version 2 (EASEv2), angular fitted and quality controlled as in De Lannoy et al. (2015), e.g., excluding areas close to open water, urban areas, and areas with high radiofrequency interference or with a poor angular fit. Both the horizontally (H) and vertically (V) polarized data at a 40° incidence angle were used for evaluation of the daily simulations (see section 2.3.5) from 1 January 2011 through 31 December 2015, using both ascending (6 am) and descending (6 pm) half-orbits.

2.3 Methodology

Table 1 summarizes the different experiments that were performed for each of the three selected LSMs. The experiments include a baseline (*BL*) simulation and two revised simulations, one with updated soil parameters (*REV_S*) and one with both updated soil, vegetation and land cover parameters (*REV_{SV}*), and two sensitivity simulations (*SENS_V*, *SENS_{LC}*), which are explained in section 2.3.2.

Table 2.1: Overview of experiments.

Name	Soil data	Vegetation	Land cover
<i>BL</i>	FAO	Climatology	ESA-CCI 1992
<i>REV_S</i>	HWSD	Climatology	ESA-CCI 1992
<i>REV_{SV}</i>	HWSD	Time-varying	ESA-CCI yearly updated
<i>SENS_V</i>	HWSD	Increasing climatology	ESA-CCI 1992
<i>SENS_{LC}</i>	HWSD	Climatology	Forest or agriculture

2.3.1 Baseline simulations

The set of baseline (*BL* in Table 2.1) simulations used the default FAO surface soil texture data and the related default model-specific SHPs, assuming a vertically homogeneous soil profile for CLM and NOAH. By design, CLSM uses the 0-30 cm soil texture to compute parameters related to surface water transport, whereas the 0-100 cm soil texture is used for computation of all other parameters (Ducharne et al., 2000; De Lannoy et al., 2014). The vegetation input for the *BL* simulations consisted of monthly climatological vegetation datasets newly created based on GLASS LAI and GIMMS GVF, together with

the ESA-CCI 1992 land cover map. This specific setup with climatological vegetation and static land cover does not account for major interannual changes in vegetation, e.g., due to deforestation. Note that CLM only requires LAI data, and GVF is not an input parameter.

2.3.2 Simulations with updated parameters

Revised soil parameters

In a first set of revised experiments, we replaced the model-specific SHPs (derived from FAO surface texture) for each LSM with the ‘topsoil’ SHPs associated with a vertically homogeneous 0-100 cm HWSD soil texture and organic matter similar to in De Lannoy et al. (2014). Corresponding to the default structure of CLSM, only the 0-30 cm HWSD soil texture is used to obtain model-specific parameters for the surface soil water transport. In these experiments, only the soil parameters were revised (REV_S in Table 2.1), whereas the climatological vegetation and land cover information was the same as in the BL simulations. Our hypothesis was that by feeding the different LSMs with similar SHPs, differences between model output could be reduced.

It is important to note that the different LSMs do not use the same subsets of SHPs. By default, CLM uses pedotransfer functions (Cosby et al., 1984) to relate sand and clay fractions to SHPs. The used SHPs in CLM are the saturated conductivity (K_{sat}), porosity (θ_{sat}), Clapp-Hornberger parameter B, and saturated matric potential (ψ_{sat}) (Han et al., 2014). The soil profile is divided into 10 layers and K_{sat} decreases exponentially with depth throughout those layers.

CLSM’s soil parameterization differs fundamentally from the other two LSMs. It uses several model parameters and moisture deficit model prognostic variables to dynamically partition the computational pixel into three distinctly different moisture regimes (saturated, transpiring and wilting regimes) to account for spatial variability of soil moisture within that pixel. CLSM’s soil parameterization uses the spatial distribution of topographic indices and SHPs to derive model parameters (Ducharne et al., 2000). For baseflow generation only, CLSM assumes an exponential decay of K_{sat} with depth, with the decay factor $\nu=2.17$ in the BL simulations and $\nu=1$ in the REV_S simulations, whereas for the vertical moisture transport, CLSM assumes K_{sat} to be vertically homogenous. Other important SHPs in CLSM are ψ_{sat} , the parameter B and soil wetness at wilting point θ_{wilt} .

The soil parameters in NOAH are discussed by Kishné et al. (2017) and the

default SHPs are calculated from texture-based lookup tables (Cosby et al., 1984). The SHPs include the parameter B , θ_{sat} , ψ_{sat} , and K_{sat} . The soil profile is divided into four layers but with a constant K_{sat} value over depth (Ek et al., 2003). Other parameters include the soil water content threshold for ceasing evaporation from the top soil layer (DRYSMC), the saturated hydraulic diffusivity (SATDW), the soil water content at field capacity (REFSMC), soil wetness at wilting point θ_{wilt} , parameter for soil thermal diffusivity (F11) and quartz content (QTZ). Note that DRYSMC, SATDW, F11 and QTZ are not included in the SHPs of De Lannoy et al. (2014), and their values for the revised SHPs were derived from lookup tables based on the HWSD soil texture data.

The spatial boxplots in Figures 2.2a-c show three SHPs used in the BL simulations of each LSM and their updated values used for the REV_S and REV_{SV} simulations over the Dry Chaco. The mean values for the updated B parameter, θ_{sat} and ψ_{sat} are smaller than for BL , but have larger spatial variances. The slightly higher mean and standard deviation in the associated HWSD 0-100 cm sand fraction map (REV_S : $43 \pm 25\%$, Figure 2.2e), compared to that of the FAO surface sand fraction map (BL : $41 \pm 15\%$, Figure 2.2d), explain the change in these updated parameter values.

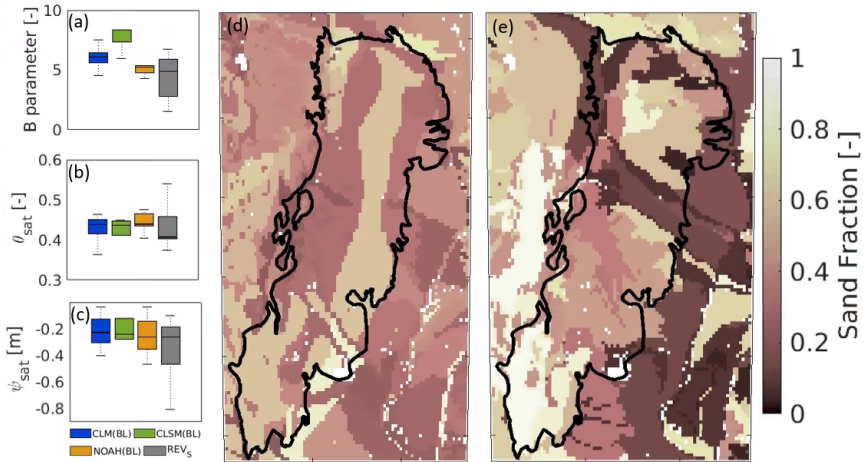


Figure 2.2: Spatial boxplots of soil parameters: (a) B parameter, (b) porosity θ_{sat} and (c) saturated matric potential ψ_{sat} used in BL and REV_S simulations. Sand fraction maps associated with (d) BL (FAO surface texture), and (e) REV_S and REV_{SV} (HWSDv1.21 0-100 cm texture).

Revised vegetation and land cover parameters

To analyze the response of the Chaco's hydrology to deforestation or vegetation changes in general, time-varying vegetation observations from GLASS and GIMMS were incorporated into the LSMs together with yearly updated ESA-CCI land cover maps in a second set of revised experiments (REV_{SV} in Table 2.1). This specific setup includes the effect of vegetation changes (such as deforestation) compared to the use of climatological vegetation parameters and static land cover in the BL simulations. As described in section 2.2.2, the GLASS LAI and GIMMS NDVI were available every 8 and 15 days, respectively. However, the data were linearly interpolated to obtain daily parameter updates in LIS. The ESA-CCI land cover maps were updated each year on 1 January. LSMs only use land cover information to define model-specific parameters associated with each land cover type; i.e., ESA-CCI land cover is used as predictor of parameters such as rooting depth, stomatal conductance and surface roughness. The exact values and implementation of each parameter are model-dependent.

Note that albedo calculations in each model were kept unchanged, as the focus of this study is primarily on the water balance. In CLM, the albedo for vegetated areas is calculated based on soil properties, LAI and plant functional types (Oleson et al., 2003). CLSM uses a surface albedo parameterization scheme (based on the Simple Biosphere Model, (Sellers et al., 1986)) that incorporates LAI, GVF and sun incidence angle to calculate the albedo and is rescaled to fit the annual cycle of MODIS-observed albedo. NOAH uses an albedo climatology based on 5 years (1985-1989) of visible and near-infrared radiation from AVHRR (Csiszar and Gutman, 1999). To see how deforestation influences the water budget component, the water budget analysis of the REV_{SV} output mainly focused on the subset of 197 pixels that were deforested between 2002 and 2006 (based on the ESA-CCI land cover).

Sensitivity experiments

Our results will indicate (see section 2.4.1) that the various LSMs react differently to the simultaneously updated interannually varying vegetation and land cover parameters. To disentangle the impact of vegetation and land cover parameters separately for each LSM, two sets of synthetic sensitivity experiments were conducted. A first set of sensitivity experiments ($SENS_V$ in Table 2.1) included five experiments ('exp1' through 'exp5') in which monthly spatially distributed climatological GLASS LAI values of the BL simulations were systematically increased by 1 and GVF values were raised proportionately. To estimate the corresponding GVF values, an empirical exponential relationship between LAI

and GVF ($GVF = a + (b * \exp(c * LAI))$) was derived for each individual pixel based on daily LAI and GVF values from 1992 to 2000. LAI values much larger than about 6 do not occur in reality, nevertheless, they are kept in this sensitivity analysis to understand the LSM response in a synthetic setting. In CLM only the LAI was altered because CLM does not use GVF as an input, whereas both LAI and GVF were altered in CLSM and NOAH. Each experiment was run for the years 1992-2015 with a fixed ESA-CCI land cover map of 1992.

To test the sensitivity to land cover ($SENS_{LC}$ in Table 2.1), two simulations were conducted per LSM. In a first simulation, the entire Dry Chaco was assumed to be covered by deciduous broadleaf forest, whereas in the second scenario cropland was assumed. These vegetation classes are associated with the major land cover conversion in the Dry Chaco. It must be mentioned that in the drier areas of the Chaco, deforested areas are also used for intensive cattle ranching. As cropland and grazing areas have similar land cover parameterizations in the LSMs, their impact was not tested separately. The climatological GLASS LAI and GIMMS GVF datasets were used in $SENS_{LC}$ simulations.

2.3.3 Model evaluation in terms of water budget components

To assess the relative impact of different LSM structures, vegetation and land cover parameters, various water budget components were compared in each simulation:

$$P = ET + Q + \Delta S \quad (2.2)$$

where P is the precipitation [mm], ET is the total evapotranspiration [mm], Q is the total runoff [mm], and ΔS is the change in soil water storage [mm] for a given time period. The total ET and Q in the water budget equation (3.3) can be written as the sum of their different components:

$$ET = E_V + E_B + E_I \quad (2.3)$$

$$Q = Q_S + Q_{SB} \quad (2.4)$$

where E_V is the vegetation transpiration [mm], E_B is the bare soil evaporation [mm], E_I is the evaporation from canopy interception [mm], Q_S is the surface runoff [mm], and Q_{SB} is the subsurface runoff [mm].

2.3.4 Model evaluation with efficiency curves

The relative differences in the various LSM behaviors were further analyzed using efficiency curves, without associating any performance assessment. Q and ET are strongly regulated by soil moisture. However, soil moisture is also a highly model-dependent quantity (Koster et al., 2009), complicating the evaluation of the modeled Q and ET . To avoid this issue, Koster et al. (2012) and Koster (2015) proposed to evaluate hydrological behavior in terms of ‘efficiency space’. The main reasoning behind this approach is that higher soil moisture content generally leads to both increased ET for a given amount of net incoming radiation (ET efficiency) and increased Q for a given amount of P (Q efficiency). The ET efficiency [-] is the ratio of the latent heat flux to the net radiation:

$$\lambda ET / R_{net} = \beta(mc_{1m}) \quad (2.5)$$

where λ [J kg^{-1}] is the latent heat of vaporization, λET [J m^{-2}] is the latent heat flux, R_{net} [J m^{-2}] is net incoming radiation and $\beta(\cdot)$ [-] is a function of moisture content, here assumed to be the 1 m soil moisture content mc_{1m} . The Q efficiency [-] is the ratio of the total Q production to the total P :

$$Q/P = F(mc_{1m}) \quad (2.6)$$

where Q is total runoff, P is the precipitation and $F(\cdot)$ [-] again is a function of mc_{1m} . By plotting the Q efficiency against ET efficiency, and identifying their relationship, a unique signature of the hydrological behavior (without model-dependent soil moisture) of a LSM can be obtained. Ideally, this would allow us to shift a LSM signature towards an in situ observed land surface signature. Due to lack of suitable and publicly available Q measurements for the Dry Chaco, this study uses the efficiency space to relatively compare the hydrological behavior of different LSMs with various parameter settings (BL , REV_S , REV_{SV}).

For each pixel, water budget components (λET , R_{net} , Q , mc_{1m} and P) were averaged over each month for the period 1992-2015. Different locations had different minimum mc_{1m} values, induced by differences in soil texture. Prior to plotting, the mc_{1m} values for each pixel were normalized to reduce spatial differences in mc_{1m} and to dominantly focus on the temporal LSM signature. Both the Q and ET efficiency were plotted as a function of the normalized mc_{1m} for each LSM to visualize the model-specific soil moisture dependencies. For each pixel, a curve drawn through the points was constructed by computing the median of the ET and Q efficiencies over narrow bins of normalized mc_{1m} . The combination of all fitted curves for all pixels was visualized using a scatter density cloud. The resulting ‘efficiency space’ plots (showing the obtained ET efficiency

as a function of Q efficiency) show how evaporation and runoff efficiencies vary with each other, as the soil gets drier or wetter. The efficiency plots are used to see whether the three LSMs provide a consensus on the simulated hydrological behavior and on the impact of the updated soil, vegetation and land cover treatment.

2.3.5 Model evaluation with independent data

For each experiment, the quality of model input P , and the model performance in terms of output surface soil moisture content (sfmc) and ET were evaluated against independent data (section 2.2.3), for simplicity referred to as ‘observations’, using four skill metrics:

- bias: long-term mean difference between simulations and observations (i.e., model minus observation),
- ubRMSD: unbiased root-mean-square difference, calculated by first removing the bias from both the simulated and observed time series (Entekhabi et al., 2010),
- R: temporal Pearson correlation coefficient between simulations and observations,
- aR: temporal anomaly Pearson correlation coefficient between simulations and observations, calculated after removing the mean climatology from each time series. The climatology is computed as the multi-year average of 30-day smoothed time series of daily values. This removed the trivial agreement in seasonality and allowed us to focus on interannual and short-term dynamics.

For an integrated evaluation of the model sfmc, surface temperature and LAI of the various experiments, a zero-order tau-omega microwave Radiative Transfer Model (RTM) was used to convert these modeled variables into L-band Tb [K] estimates. The modeled Tb were compared to SMOS Tb observations, similarly to the approach presented by Albergel et al. (2012). For a detailed description of the tau-omega RTM we refer to De Lannoy et al. (2013). Feldman et al. (2018) showed that a zero-order tau-omega model would suffice for the dry forests of the Dry Chaco. Instantaneous sfmc, surface temperature and LAI at 6 am and 6 pm were used as input in the RTM and simulated Tb were evaluated against 6 am and 6 pm SMOS-observed Tb (both at the top of vegetation). The Tb simulations were computed at the 0.125° model resolution and then spatially averaged to the 36-km EASEv2 grid for comparison to SMOS-observed

Tb for the period 2011-2015. Short-term variability in both simulations and observations was reduced using a 1-month averaging window. This allowed us to focus on the effect of the implemented vegetation changes, which occur on a longer seasonal timescale.

The RTM required specific input parameters related to soil properties (Wang and Schmugge, 1980) and vegetation classes. The related soil parameters differ thus for the *BL* and *REV_S* simulations, and the parameters related to land cover class also vary in time for the *REV_{SV}* simulations due to yearly updated land cover. The literature offers various lookup tables to estimate the RTM parameters related to vegetation classes (soil roughness, scattering albedo, vegetation structure parameters). Here, we used the lookup tables of the SMAP soil moisture retrieval (O'Neill et al., 2016; Quets et al., 2019). Another choice would affect the overall Tb bias for all experiments, but would minimally affect the relative comparison of the various experiments with revised soil and vegetation parameters.

2.4 Results

2.4.1 Model evaluation in terms of water budget components

Baseline simulations

The annual and seasonal distributions of the different water budget components for each *BL* model simulation are summarized in Table 2.2. The values are calculated for a 24-year period (1992-2015) and averaged over all pixels within the Dry Chaco, excluding open-water pixels. The Dry Chaco receives an average yearly P of 809 mm with most P (643 mm) during the wet season (October-March), in line with the findings of Marchesini et al. (2020) and Minetti et al. (1999). All LSMs confirm a water storage (ΔS) deficit for the dry season (April-September), which is compensated for during the wetter months with a water surplus.

Table 2.2: Long-term (1992-2015) distribution of the BL water budget components [mm] for CLM, CLSM and NOAH over the Dry Chaco, year-round (annual), for the months April-September (dry season) and the months October-March (wet season), respectively.

	CLM			CLSM			NOAH		
	Annual	Dry	Wet	Annual	Dry	Wet	Annual	Dry	Wet
P	809	166	643	809	166	643	809	166	643
ET	698	162	536	599	172	427	773	221	552
Q_S	91	16	75	210	35	175	18	3	15
Q_{SB}	20	6	14	0	0	0	18	8	10
ΔS	0	-18	18	0	-41	41	0	-66	66

Figure 2.3a shows the corresponding yearly averaged water budget components relative to the total P whereby the total ET is subdivided into its three components (see section 2.3.3). The variation in the total amount of ET and its components shows that there is large variability between the models, even though all of them use the same forcing data, land cover, vegetation, soil texture (not SHP) and topography input. In addition, there are significant disagreements in the ET partitioning. The largest ET component is different in each LSM; i.e., E_I is largest for CLM, E_B for CLSM and E_V for NOAH. The high fraction of E_I for CLM is physically unrealistic (see section 3.3.3). CLM and NOAH both have a Q_{SB} component, whereas CLSM does not. The latter has a very large fraction of Q_S .

Revised soil parameters

The impact of the revised soil parameters (REV_S) on the yearly mean relative water budget components is shown in Figure 2.3b, again for the period 1992-2015. Most striking is that, despite the similarity in SHPs, the various models still produce a very different partitioning of the water budget components. For CLM, the revised SHPs cause a yearly reduction in Q_S by 4% which is compensated for by an increase in E_V and Q_{SB} . For CLSM, the mean water budget components hardly change. For NOAH, there is a small increase in Q_{SB} and decrease in ET , mainly due to a large decrease in E_B (-9%) of which 6% is compensated for by extra E_V . For each model, the differences in the water budget components between the BL and REV_S simulations, averaged over the entire Dry Chaco, are relatively small. However, within the study domain, there is a large local spatial variability in the changes in the various water budget components (not shown).

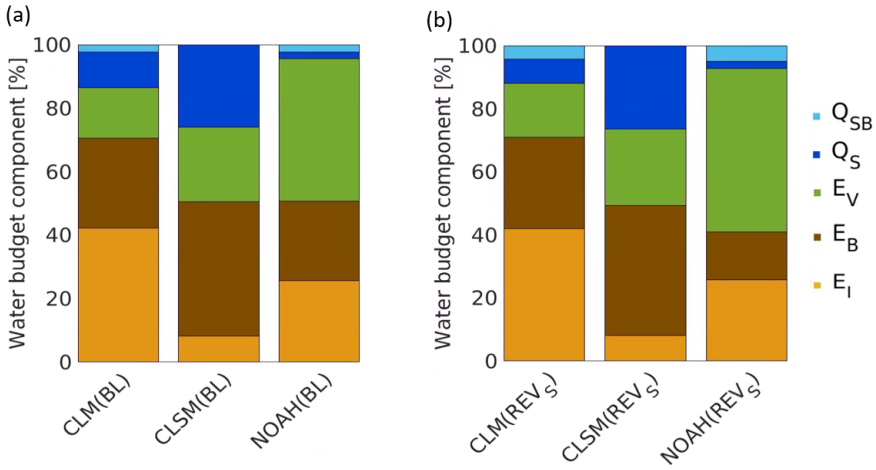


Figure 2.3: Long-term (1992-2015) annual water budget components averaged over the Dry Chaco relative to the total precipitation for (a) *BL* and (b) *REV_S* experiments (Q_{SB} : subsurface runoff, Q_S : surface runoff, E_V : vegetation transpiration, E_B : bare soil evaporation, E_I : interception evaporation).

Figure 2.4 summarizes the impact of the updated SHPs on the soil moisture content in the first meter of the soil (mc_{1m}). The boxplots of time-averaged (1992-2015) mc_{1m} over the Dry Chaco (Figure 2.4a) show that the *REV_S* simulations are drier than for *BL*: the mc_{1m} decreases from 0.16 to 0.11 m^3/m^3 for CLM, from 0.22 to 0.13 m^3/m^3 for CLSM and from 0.19 to 0.17 m^3/m^3 for NOAH. These lower mean soil moisture values can be related to the larger fraction of sandy soils (Figures 2.2d and e) and the associated reduced water retention (SHPs) in the *REV_S* simulations. However, again, at the local scale, some areas become wetter and others drier. Despite the relatively large difference in long-term mean soil moisture between *BL* and *REV_S*, the differences in ET and Q_S fluxes are small: the meteorological forcings are the primary drivers of these fluxes, whereas the SHPs only have a secondary impact. Figures 2.4c and d show how the texture pattern dominates the long-term averaged mc_{1m} for the period 1992-2015 for the NOAH *BL* and *REV_S* simulations (similarly for CLM and CLSM). Figure 2.4b illustrates that the updated SHPs change the temporal standard deviation of mc_{1m} , which significantly decreased for NOAH.

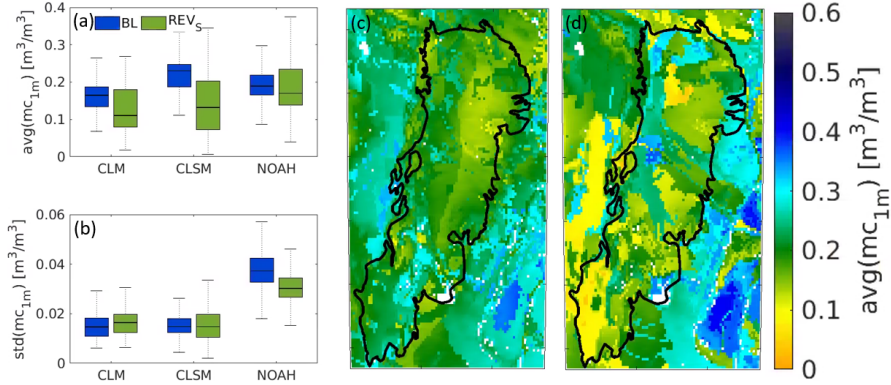


Figure 2.4: Boxplots of long-term (1992-2015) (a) average (avg) and (b) standard deviation (std) of BL and REV_S moisture content in the upper 1 m (mc_{1m}) for CLM, CLSM and NOAH. Maps of long-term (1992-2015) average NOAH mc_{1m} , obtained with (c) BL and (d) REV_S parameters.

Revised vegetation and land cover parameters

The impact of deforestation over the Dry Chaco was assessed via a relative comparison of the water budget components of the REV_S and REV_{SV} simulations for each LSM, using a subset of 197 pixels that were deforested between 2002 and 2006. Keep in mind that the REV_S uses climatological vegetation indices and a static land cover map, which do not account for interannual vegetation changes. The REV_{SV} simulations include the effects of vegetation changes by the implementation of satellite-derived dynamic vegetation indices as well as yearly updated land cover parameters. The differences between the REV_S and REV_{SV} simulations thus solely stem from interannual vegetation variations and land cover changes. By design, the former would only introduce minimal long-term differences over the entire simulation period. Therefore, the output differences were only analyzed after deforestation, i.e., for the period 2007-2015. Figure 2.5 compares the water budget components for the REV_S and REV_{SV} simulations after deforestation, i.e., for the period 2007-2015. For CLM, we observed a relative decrease in E_V (-6%), that is compensated for by an increase in E_B and E_I , maintaining a constant amount of ET . For CLSM, there is a 5% decrease in total ET (with a similar relative distribution of the ET components), which is compensated for by a Q_S increase of 5%. For NOAH, deforestation also resulted in smaller ET (-3%), which is compensated for by an increase in Q_{SB} . Regarding the relative ET distribution of NOAH, there is an increase in E_B of 4% and a decrease in E_V of 6%.

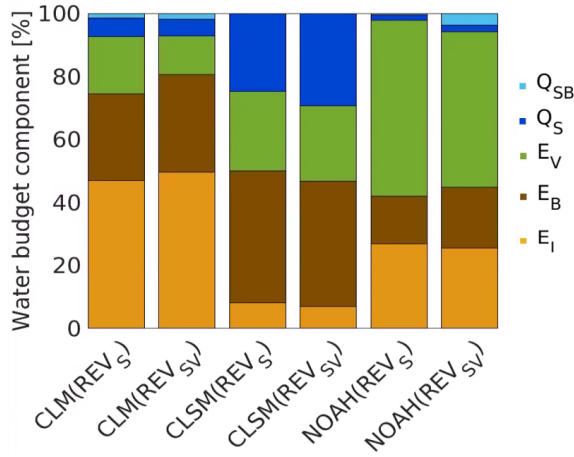


Figure 2.5: Annual water budget components for the period 2007-2015 relative to the total precipitation for the 197 pixels deforested between 2002 and 2006 for REV_S and REV_{SV} simulations (Q_{SB} : subsurface runoff, Q_S : surface runoff, E_V : vegetation transpiration, E_B : bare soil evaporation, E_I : interception evaporation).

The impact of vegetation changes on the temporal evolution of LAI and moisture content in the first two meters of the soil (mc_{2m}) is illustrated in Figure 2.6 for a representative pixel (28.0625° S, 63.6875° W). Figure 2.6a shows the climatological REV_S LAI and the interannually varying REV_{SV} LAI, together with P for a pixel that was deforested in 2004 (based on ESA-CCI land cover). The LAI values are generally low both before and after deforestation. Years where the REV_{SV} LAI is larger than its climatology, mainly correspond to wetter years. Deforestation does not cause a sudden drop in LAI, probably because the LAI for fully developed crops is not very different from that of dry forests, or the smaller-scale deforestation signal may be suppressed in the upscaled 0.125° LAI values. However, the REV_{SV} LAI is significantly smaller than its climatology in drier years after 2004, which may be indicative of less crop cover and earlier deforestation. In short, the coarse-resolution LAI does not necessarily reflect land cover changes and is strongly influenced by P .

The combined impact of time-varying LAI and land cover on mc_{2m} is shown in Figures 2.6b-d for the REV_S and REV_{SV} simulations of each LSM. From the deforestation in 2004 onwards, the mc_{2m} of the REV_{SV} simulations increases for each model, but at a different rate. The main driver for the increase in mc_{2m} is the change in land cover. The updated parameters related to a land cover change

push the model out of its equilibrium and water is gradually redistributed to achieve a new balance with a higher soil moisture content. Considering all pixels deforested between 2002 and 2006, mc_{2m} increases on average by $0.0035 \text{ m}^3/\text{m}^3$ (maximum change of $0.016 \text{ m}^3/\text{m}^3$) for CLM, by $0.03 \text{ m}^3/\text{m}^3$ (maximum change of $0.08 \text{ m}^3/\text{m}^3$) for CLSM and by $0.07 \text{ m}^3/\text{m}^3$ (maximum change of $0.1 \text{ m}^3/\text{m}^3$) for NOAH. The reason for the different behavior of each LSM will be explained in the following paragraph.

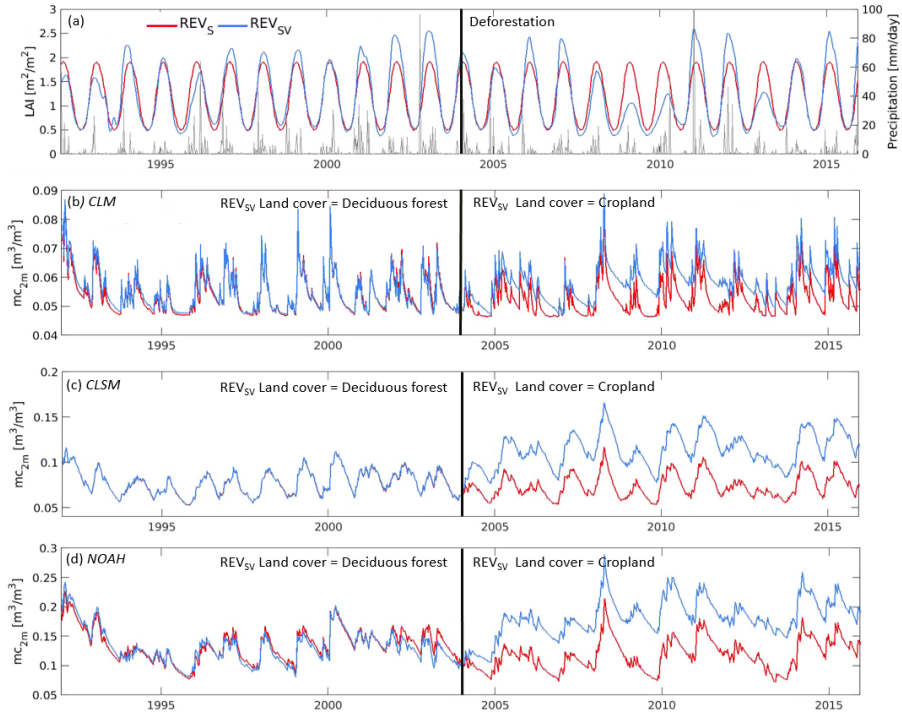


Figure 2.6: Time series of REV_S and REV_{SV} land surface variables for a pixel deforested in 2004 (28.0625° S , 63.6875° W): (a) LAI and precipitation, (b-c-d) 2 m moisture content (mc_{2m}) for CLM, CLSM and NOAH, respectively.

Sensitivity experiments

Sensitivity experiments with synthetic vegetation and land cover parameters were conducted to get more insight into the distinct behavior of soil moisture for the different LSMs in response to dynamic vegetation and land cover input. Figure 2.7a-c illustrate how domain-averaged water budget components change

when the LAI is systematically increased by 1 to 5 units ('exp1' through 'exp5') as explained in section 2.3.2. To mimic the effect of deforestation, assumed to result in smaller LAI values, one should read the figure from exp5 (high LAI) to exp1 (low LAI). For CLM, a reduction in LAI introduces a reduction in E_I , an increase in E_B and a slight decrease in E_V . For CLSM, a reduction in LAI and GVF yields a strong decrease in E_I , fully compensated by an increase in E_B whereas E_V is barely affected. Concerning NOAH, smaller LAI and GVF values result in a significant decrease in E_V . When the LAI and/or GVF are reduced, the Q_{SB} increases in both CLM and NOAH.

Figure 2.7d-f illustrate how the various LSM soil moisture profiles respond to changing LAI (and corresponding GVF for CLSM and NOAH). A decrease in LAI barely affects soil moisture in CLSM, whereas it increases soil moisture for CLM (moderately) and NOAH (strongly), in line with the respective LSM's degree of decrease in E_V (water extraction from the soil). The increase in soil moisture climatology for an imposed decrease in LAI (while assuming a persistent vegetation type) is partly an artifact resulting from a one-way dependency of soil moisture to vegetation in the absence of a dynamic vegetation growth module. In nature, LAI and soil moisture evolve together.

Figure 2.7g-i show soil moisture profiles for the sensitivity experiment in which the land cover was either uniformly cropland or forest. For CLM, there is almost no difference in soil moisture between both. CLSM has a slightly wetter soil moisture profile for cropland than for forest. For NOAH, the soil moisture content is higher under cropland than forest in the deeper layers. The distinct model response to land cover changes is related to the fact that each model uses a model-specific set of land cover parameters, each with different values and behavior. These parameters impact the total E_V (not shown) and the related water extraction from the soil. For example, the rooting depth (the depth to which roots of plants can extract water from the soil profile) is defined differently in each LSM. In NOAH, the forest land cover class has a rooting depth of 2 m; i.e., roots take up water over the whole profile. Roots of crop are parameterized to 1 m and are not able to extract water from the deepest soil layers, resulting in wetter soils at the bottom of the soil profile (Figure 2.7i). CLM makes use of a root fraction distribution whereby root fraction is a function of depth and land cover type as described in Zeng (2001). CLSM uses a rooting depth of 1 m, regardless of the land cover.

The sensitivity experiments were designed to explain the distinct behavior of soil moisture in response to changing land cover or vegetation parameters separately and do not provide insights into possible interactions between both. The relative change in the water budget components of REV_{SV} against REV_S , as shown in Figure 2.5, originates from changes in LAI and GVF, land cover, and their interactions. This explains, for example, the increase in model Q_S and decrease

in total ET after deforestation for CLSM. This cannot be explained by the CLSM results of the $SENS_V$ (Figure 2.7b) or $SENS_{LC}$ experiments alone.

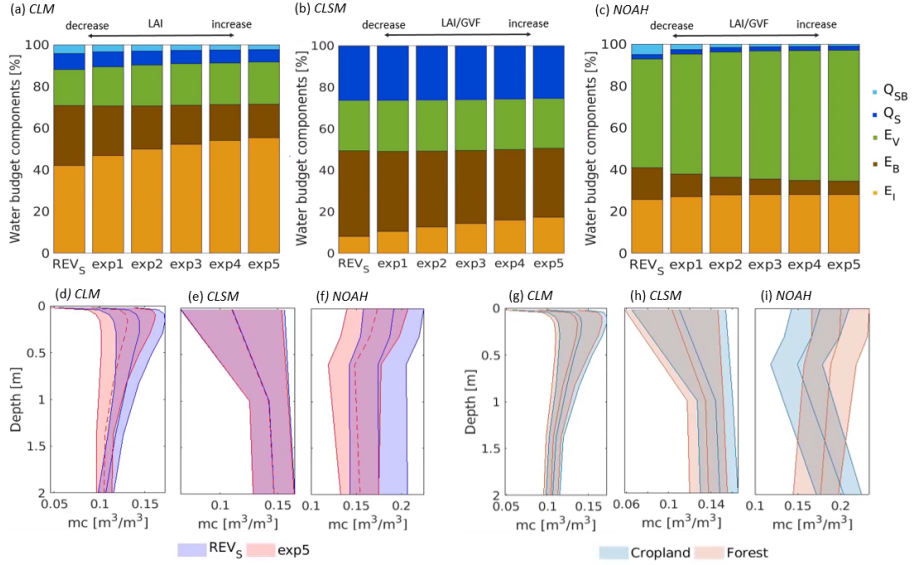


Figure 2.7: (a-b-c) Long-term (1992-2015) water budget components averaged over the Dry Chaco for $SENS_V$ experiments, for CLM, CLSM and Noah, respectively. Exp1 to exp5 refer to simulations whereby the monthly climatological LAI maps were increased with respectively 1 to 5 units (Q_{SB} : subsurface runoff, Q_S : surface runoff, E_V : vegetation transpiration, E_B : bare soil evaporation, E_I : interception evaporation). (d-e-f) Associated impact on the soil moisture profile (spatially averaged profile) for CLM, CLSM and Noah, respectively. (g-h-i) Impact of changing land cover parameters ($SENS_{LC}$) from deciduous forest to cropland on the soil moisture profile for CLM, CLSM and Noah, respectively.

2.4.2 Model evaluation with efficiency curves

Baseline simulations

To compare the BL hydrological behavior of the three different LSMs, Figure 2.8 presents the Q and ET efficiency as a function of mc_{1m} along with the ‘efficiency space’. For each pixel within the Dry Chaco, these quantities are computed for each month across the 24-year time period, and a curve is fitted using a simple

binning procedure. Figure 2.8 summarizes the hydrological signature of the Chaco by showing the density scatter cloud of all fitted curves.

Figure 2.8a, d and g show a very different Q efficiency as a function of mc_{1m} for the three LSMs. For CLSM, a majority of the curves reaches Q efficiency values up to 0.4, whereas the median values are around 0.2 for CLM and even below 0.1 for NOAH. This different behavior was also observed in the annual water budget analysis (see Table 2.2). Note that for CLM and NOAH, some high Q efficiencies are found at relatively low mc_{1m} values (black circle). This is caused by high Q_{SB} rates, which allow precipitation from the wet season to run off during the dry season months even if P in the latter period is small.

For all LSMs, the ET efficiency (Figures 2.8b, e, h) is larger than the Q efficiency and the relationship of the ET efficiency with mc_{1m} is more similar across the three LSMs than that of the Q efficiency. The distinct BL signature of the three LSMs in efficiency space is summarized in Figures 2.8c, f, i and mainly explained by differences in Q .

Revised simulations

Figure 2.9 shows the impact of the REV_S and REV_{SV} experiments in efficiency space. The impact of the updated SHPs is summarized by a small shift between the mean values of the BL and REV_S in efficiency space, with a decrease in Q efficiency for CLM, and increase for CLSM and NOAH.

Figure 2.9 also shows the REV_S and REV_{SV} scatter density clouds (and mean value) in efficiency space for the 197 pixels deforested between 2002 and 2006 for the period 2007-2015. The inclusion of vegetation changes (REV_{SV}) causes a shift towards larger Q efficiencies for CLSM (increased Q_S) and NOAH (increased Q_{SB}). The opposite is found for CLM. When analyzing the effect of deforestation on ET efficiency, it is important to keep in mind that these efficiencies are calculated as the ratio of the latent heat flux to the net incoming radiation (available energy). By definition, the net radiation is also impacted by vegetation changes. Therefore, one cannot directly relate changes in ET efficiency to changes in total ET . For CLM, the REV_{SV} density cloud tends to larger ET efficiencies, indicating that croplands need less energy than forests for the same amount of ET . For CLSM and NOAH, the scatter cloud shows a slight shift to the right: croplands use a slightly larger portion of the available energy than forest for ET .

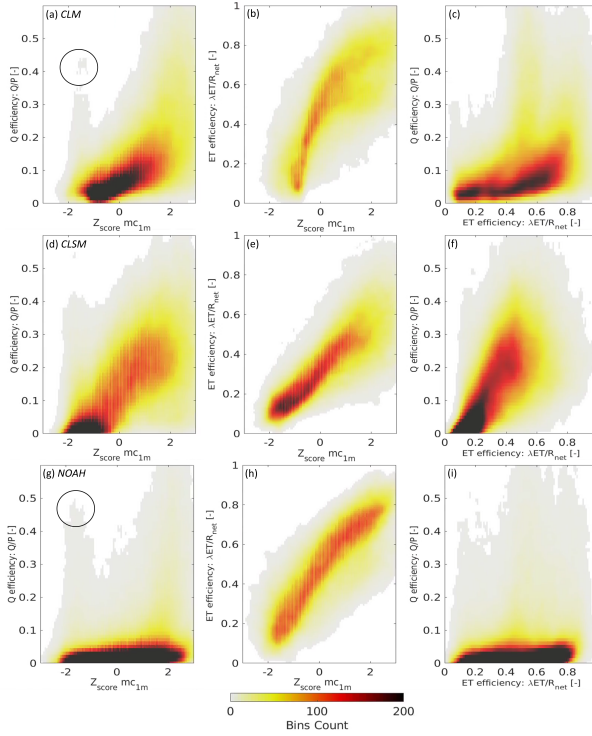


Figure 2.8: Scatter density clouds representing the fitted curves in efficiency space of all pixels inside the Dry Chaco for the *BL* experiment for the period 1992-2015 for (a-b-c) CLM, (d-e-f) CLSM and (g-h-i) NOAH, respectively. (Left) *Q* efficiency, (middle) *ET* efficiency and (right) *ET* vs *Q* efficiency.

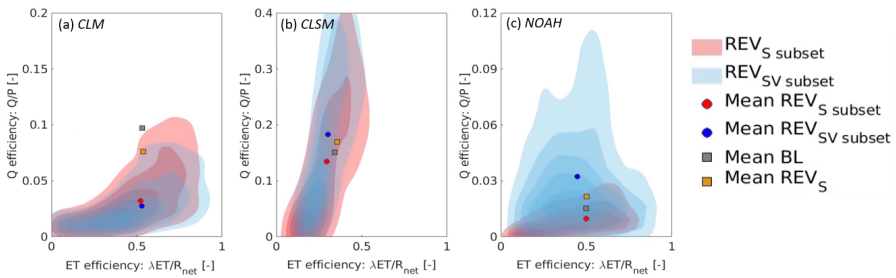


Figure 2.9: Scatter clouds in efficiency space for the *REV_S* (red) and *REV_{SV}* (blue) experiment for a subset of 197 pixels (corresponding with deforested pixels between 2002-2006) for the period 2007-2015, together with the mean value for (a-b-c) CLM, CLSM and NOAH, respectively. The gray and orange dots represent the shift in mean efficiency between the *BL* and *REV_S* simulations, based on all pixels inside the Dry Chaco, i.e., the mean *BL* values correspond to those in Figure 2.8 (c-f-i).

2.4.3 Model evaluation with independent data

Precipitation

Because the quality of input P will greatly influence the quality of ET , $sfmc$ and Tb simulations, independently of the used LSM, the quality of the MERRA-2 P product was first evaluated against in situ P data. Table 2.3 summarizes how well the monthly averaged MERRA-2 P corresponds to in situ observations for two types of stations. For the 10 stations that cover the 1992-2015 period, the mean correlation coefficient is $0.83 (\pm 0.07)$, the mean monthly bias is $5 (\pm 11)$ mm/month and the mean ubRMSD equals $38 (\pm 17)$ mm/month. For the 2010-2015 stations ($n=8$), the overall skill metrics are lower: a mean correlation of $0.74 (\pm 0.11)$ a mean bias of $18 (\pm 13)$ mm/month and a mean ubRMSD of $42 (\pm 14)$ mm/month, respectively. The positive bias indicates that MERRA-2 P is overestimated.

Table 2.3: Skill metrics for monthly MERRA-2 relative to in situ precipitation: spatial average $\pm$ spatial standard deviation.

	Bias [mm/month]	ubRMSD [mm/month]	R [-]
Stations ₁₉₉₂₋₂₀₁₅ (n=10)	5 ± 11	38 ± 17	0.83 ± 0.07
Stations ₂₀₁₀₋₂₀₁₅ (n=8)	18 ± 13	42 ± 14	0.74 ± 0.11

Monte Buey soil moisture

Figure 2.10 shows daily modeled $sfmc$ time series for CLM, CLSM and NOAH, together with in situ Monte Buey $sfmc$ (5 cm) observations (both averaged over the three pixels) for the period 2013-2015. For CLSM and NOAH, the $sfmc$ depths are 2 and 10 cm, respectively. For CLM, the soil moisture content in the 4 upper soil layers was averaged to obtain a 5-cm $sfmc$ value.

The largest R and aR values between observed and modeled $sfmc$ are obtained with CLM and NOAH (R and aR values between 0.72 and 0.81 for BL). By updating the soil parameters (REV_S), some R and aR values increase, but others decrease. However, the bias is decreased for all models. For NOAH, the updated soil parameters result in substantially wetter $sfmc$ during the dry season. Note that these results are only valid for the three model pixels covering the Monte Buey site and cannot be extended to the entire Dry Chaco.

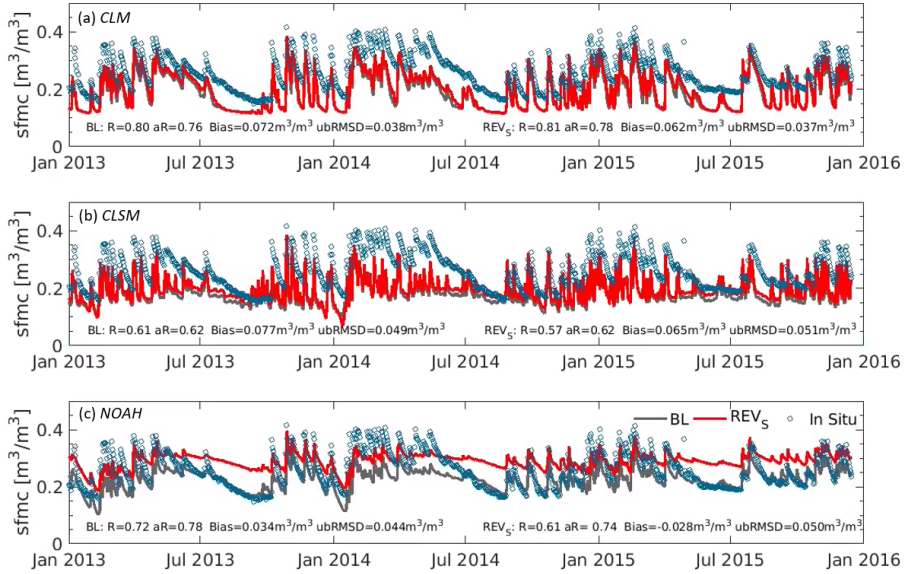


Figure 2.10: Simulated (BL and REV_S) and in situ observed surface soil moisture (sfmc) time series at Monte Buey, Argentina (32.91° S, 62.44° W), for the period January 2013-December 2015, for (a-b-c) CLM, CLSM and Noah, respectively.

Evapotranspiration

The skill of daily simulated total ET relative to that of GLEAM-based ET estimates is shown in Figures 2.11a-d for the period 1992-2015 over the entire Dry Chaco. In general, Noah has the largest R and aR and the smallest ubRMSD. When averaged across the entire region and time period, the impact of the updated soil, vegetation and land cover parameters on the total ET is negligible and even deteriorates the overall CLSM performance relative to GLEAM.

The relative distribution of the different ET components is very different for GLEAM than for the selected LSMs. Figure 2.11e shows that all the models (REV_S) are possibly underestimating the E_V . For GLEAM, 89% of the total ET is E_V , whereas this is only 47% for Noah, 31% for CLSM and 18% for CLM. E_I is the second largest component in GLEAM (7%). CLM (48%) and Noah (27%) are likely overestimating the E_I , whereas CLSM overestimates the E_B .

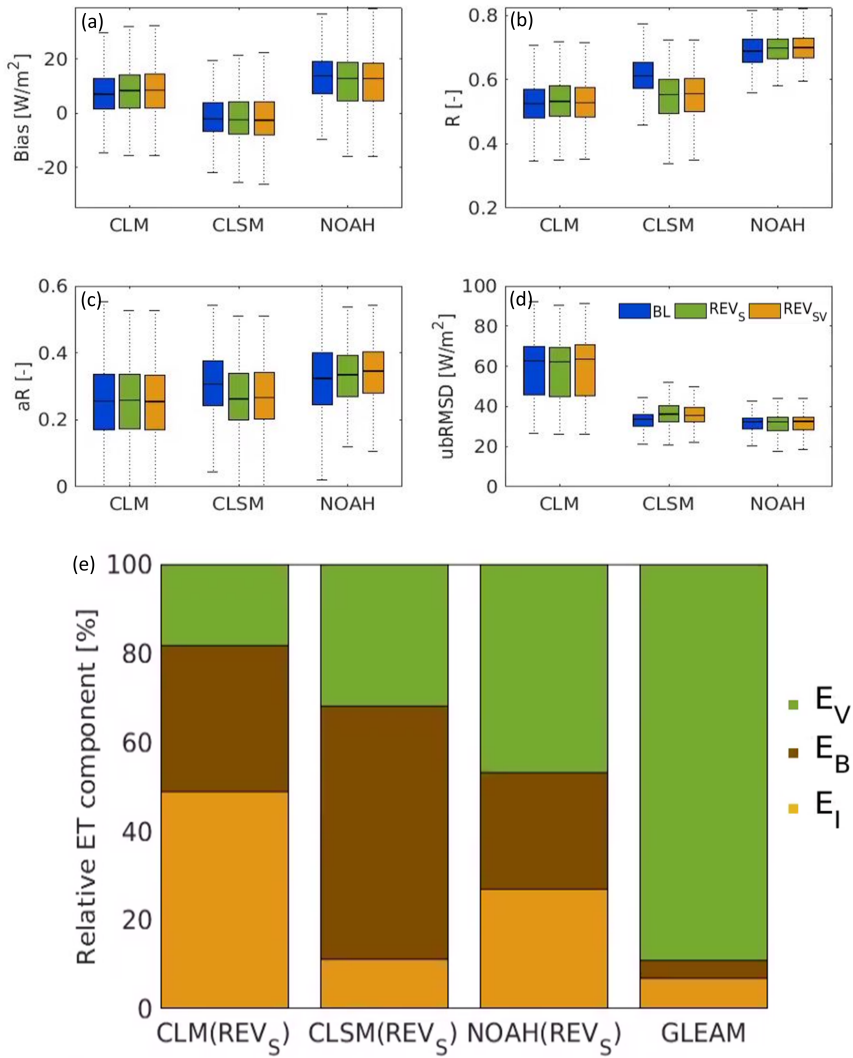


Figure 2.11: (a-d) Skill metrics for total ET from CLM, CLSM, NOAH (BL , REV_S and REV_{SV}) relative to GLEAM, calculated for the period 1992-2015 over all pixels inside the Dry Chaco. (e) Long-term (1992-2015) relative ET components (E_V : vegetation transpiration, E_B : bare soil evaporation, E_I : interception evaporation) spatially averaged over the Dry Chaco for REV_S CLM, CLSM, NOAH and GLEAM.

L-band microwave brightness temperature

Time series of the simulated 40° Tb at horizontal polarization (Tb_H) with NOAH BL , REV_S and REV_{SV} input, and SMOS Tb_H are shown in Figure 2.12a. The inputs used in the RTM for the simulated Tb include simulated surface soil moisture (using FAO texture and related SHPs in the BL simulations, HWSD-based texture and SHPs in the REV_S and REV_{SV} simulations), temperature, LAI (climatological in BL and REV_S , interannually varying in REV_{SV}), land cover (static in BL and REV_S , yearly updated in REV_{SV}) and the associated literature-based lookup RTM parameters. These time series are for the 36-km EASEv2 pixel that includes the deforested 0.125° pixel shown in Figure 2.6. The corresponding sfmc and LAI are shown in Figures 2.12b and 2.12c. Time series of NOAH Tb at vertical polarization (Tb_V) and the simulations for CLM and CLSM showed similar behavior and are not shown. Figure 2.12 highlights how the REV_{SV} LAI deviates from the long-term climatology (REV_S) during the SMOS observation period. Not shown here is that the LAI also deviates from the climatology earlier in time, i.e., on average the interannual variations cancel each other out by design, as in Figure 2.6.

The updated soil parameters (REV_S) affect the sfmc and RTM parameters, causing a different behavior in simulated Tb_H . The reduced LAI and changes in land cover (REV_{SV}) result in wetter sfmc but the sfmc increase is not as pronounced as for the mc_{2m} in Figure 2.6d. This wetter sfmc and reduced LAI propagate through the RTM and result in colder simulated Tb_H .

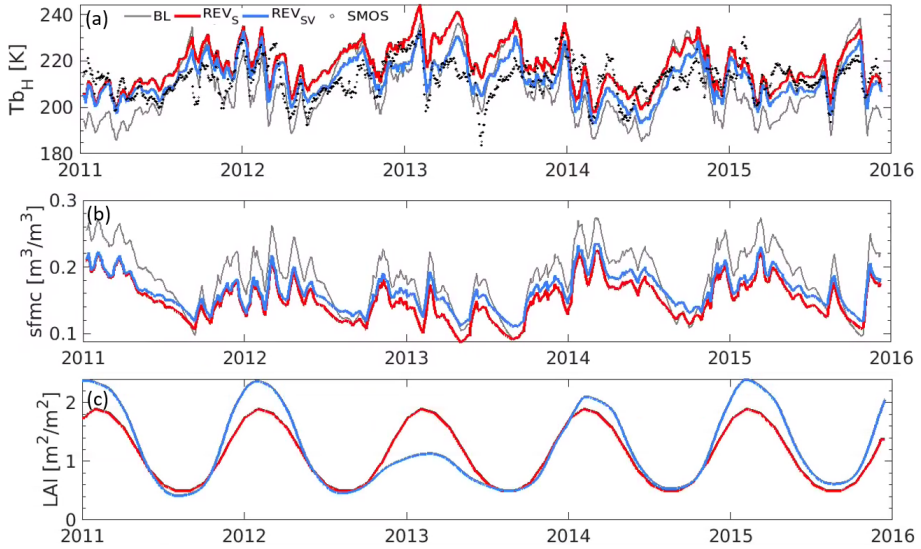


Figure 2.12: Time series of simulated (gray) BL , (red) REV_S , (blue) REV_{SV} NOAH-based (a) Tb_H , (b) $sfmc$ and (c) LAI input at the same location as in Figure 2.6, but upscaled to the 36-km EASEv2-grid resolution. Also shown are (black dots) SMOS observed Tb_H in subplot (a).

Figure 2.13a-d summarize the Tb skill metrics for the different experiments, only for the subset of pixels that were deforested between 2002 and 2006. The metrics for both polarizations (Tb_H and Tb_V) were averaged before creating the spatial boxplots. In general, the Tb bias for each model is negative, indicating that the simulated Tb is colder than the SMOS Tb . NOAH has the largest absolute bias and the updated soil treatment reduces the Tb bias of each model. CLSM has the best R and aR values, but the updated soil parameters reduce its performance in terms of R , aR and $ubRMSD$ values. This is in line with the reduced performance of CLSM relative to the GLEAM ET . For NOAH, the updated soil treatment increases the R and aR values, and reduces the $ubRMSD$. The additional impact of the updated vegetation and land cover treatment is small.

To visualize the local effects of the vegetation changes, spatial maps of the differences in temporal R values (ΔR) between the REV_{SV} and REV_S are shown for each model in Figures 2.13e-g. The modeled Tb and the spatial pattern of ΔR , over the Dry Chaco are mainly driven by changes in $sfmc$, and these are driven by vegetation and land cover changes. The ΔR values are relatively small for CLM because the model $sfmc$ is only slightly sensitive to changes

in vegetation and land cover parameters. For CLSM, the REV_{SV} simulations yield larger R values over certain areas compared to the REV_S simulations because temporal changes in modeled sfmc mainly result from changes in land cover parameters. Consequently, the ΔR pattern is similar to the deforestation pattern (see Figure 2.1). In NOAH, the sfmc is sensitive to land cover and LAI changes and, therefore, the ΔR pattern depends on both land cover and LAI changes. For NOAH, the ΔR values do not increase everywhere. At some pixels with reduced REV_{SV} performance, we noticed unexpected trends in the LAI time series (not shown), i.e., LAI would not show the expected decrease during the dry season. This possibly deteriorated the Tb simulations. In short, the extent of the simulated Tb response to vegetation and land cover changes is model-specific and is mainly driven by the sensitivity of the model's sfmc to vegetation and land cover parameters.

2.5 Discussion

2.5.1 LSM comparison

The relative evaluation of LIS CLM, CLSM and NOAH in terms of their water budget components (Table 2.2 and Figure 2.3) and efficiency space (Figure 2.8) highlights that each LSM has a distinct hydrological signature. CLSM has more Q_S than NOAH and CLM, but CLSM has no Q_{SB} component, unlike NOAH and CLM. It is striking how the various LSMs partition the total ET very differently into its three components, as was reported before by Wang and Dickinson (2012); Kumar et al. (2018); Rigden et al. (2018); Zhang et al. (2020). For example, we found that CLM strongly overestimates E_I and E_B compared to GLEAM over the Dry Chaco (Figure 2.11e). Lawrence et al. (2007) came to similar findings and indicated that by reducing the tuning parameter α_l from 1 to 0.25 in the canopy interception equation, the amount of E_I could be reduced to more realistic values at the global scale. They also indicated that the relative contribution of E_V and E_B in vegetated regions could be improved by altering two parameters ($C_{s,dense}$ and α) in the equation to calculate the turbulent transfer coefficient between the soil and canopy air. For CLSM, the portion of E_I over the Dry Chaco is similar to that of the GLEAM product. Reichle et al. (2011) described how the amount of interception evaporation is influenced by the rainfall interception parameters FWETL and FWETC and that realistic interception rates are found when both parameters equal 0.02 (applied in our simulations). These parameters describe the fractional areas of canopy leaves (interception reservoir) on which large-scale and convective rainfall is applied. The bias between modeled ET and GLEAM is high for NOAH, indicating an

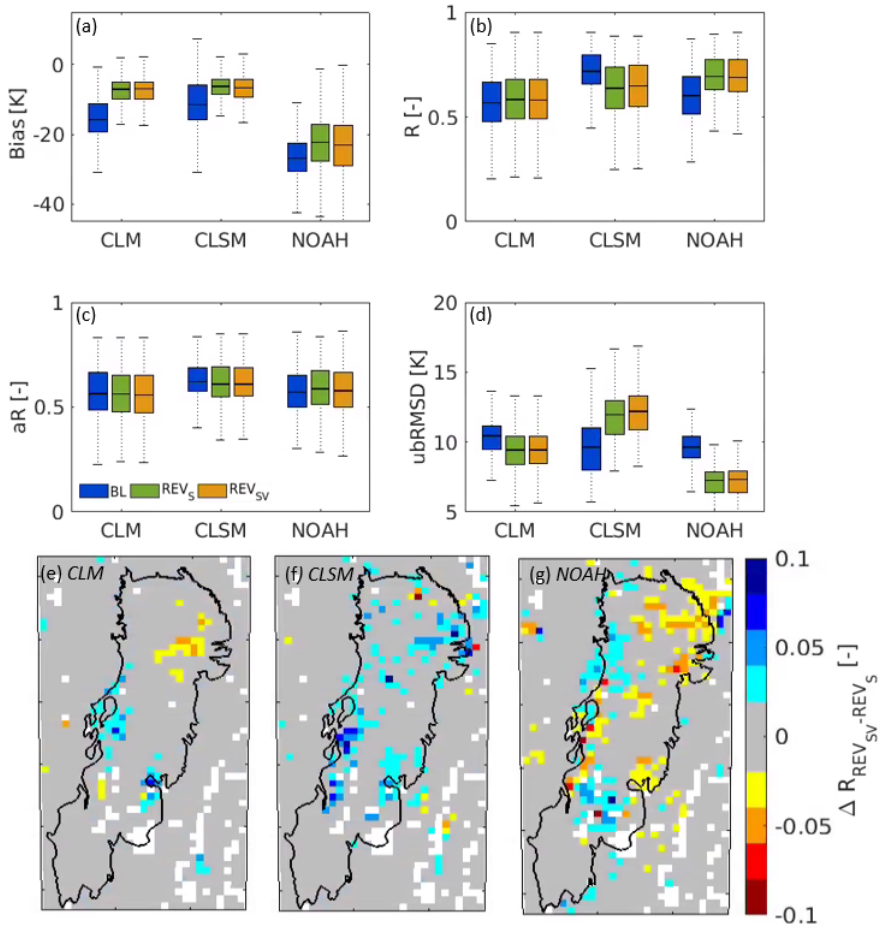


Figure 2.13: (a-d) Skill metrics for CLM, CLSM, NOAH (BL , REV_S and REV_{SV}) Tb relative to SMOS Tb, calculated for the period 2011-2015 over pixels deforested between 2002 and 2006. (e-f-g) difference between the R metric for REV_{SV} and REV_S for CLM, CLSM and NOAH, respectively.

overestimation of the total ET . Wei et al. (2013) observed that NOAH yields substantial biases in latent heat flux, total Q and land surface skin temperature when compared to independent data over the United States. They showed that adapting model parameterizations, such as including a seasonal factor for the root distribution and selecting optimal model parameters related to the canopy resistance calculations (an important factor for E_V simulation), could reduce

these biases.

Our results show that constraining the LSMs with the same, optimal soil, vegetation and land cover parameter input (REV_S and REV_{SV}) does not result in more similar water budget partitioning, because the results are dominated by internal model-specific equations and parameters. The latter have historically been tuned globally with particular input datasets and may compensate for errors in those datasets, so that ‘better’ input does not necessarily lead to ‘better’ output. In addition, some LSMs are inherently more or less sensitive to time-varying parameters and therefore climatological vegetation input may suffice if the LSM is simply not very sensitive to vegetation changes (Jarlan et al., 2008), or if the vegetation changes are not extensive. LSMs could benefit from further development to obtain a more realistic hydrologic response to vegetation changes and to better include dynamic vegetation phenology. This should lead to more realistic simulations of the interaction between the carbon and water cycles.

Lack of sufficient in situ Q and ET measurements over the Dry Chaco, prevents identification of which LSM setup best approaches the long-term observed water budget and its components. However, our study highlights the large estimation uncertainty due to model structures and the secondary impact of (soil and vegetation) input parameter uncertainties. It is important to mention again that LSMs are continuously upgrading and that our study provides a relative comparison of older LSM versions within LIS.

2.5.2 Effects of soil and vegetation parameters on soil moisture

Despite soil moisture being a highly model-dependent variable, it is important that soil moisture simulations closely mimic natural patterns to allow their use as underlying information in applications such as soil salinity monitoring over the Dry Chaco. Providing LSMs with the best available soil and vegetation parameters is one step towards this goal. The soil parameters strongly determine the spatial (horizontal and vertical) pattern of soil moisture (Figure 2.4), and only have a secondary impact on its temporal variability, which is mainly driven by meteorology. This was also reported by Morgan et al. (2017); Kishné et al. (2017); Zhao et al. (2018). The long-term soil moisture response to revised vegetation and land cover parameters differs among the three LSMs for two reasons:

- Soil moisture sensitivity to LAI and GVF indices ($SENS_V$): a decrease in LAI and GVF barely affects soil moisture in CLSM, whereas it increases soil moisture for CLM (moderately) and NOAH (strongly). This is in

line with the respective LSM's degree of E_V extracting more or less water from the soil.

- Soil moisture sensitivity to land cover parameters ($SENS_{LC}$): a land cover change from forest to cropland barely affects CLM soil moisture, slightly increases soil moisture in CLSM, and mainly increases deep soil moisture in NOAH. This is related to the distinct root distribution and root water uptake (controlled by the stomatal conductance and rooting depth) in the various LSMs, impacting the E_V and related water extraction from the soil.

The REV_{SV} simulations showed that all three LSMs simulate wetter soils after deforestation in the Dry Chaco. In addition, larger values of total Q are found for two LSMs, which might implicitly be indicative of groundwater recharge (groundwater is only simulated in CLSM). This is in agreement with studies that have been carried out on a local scale by Giménez et al. (2016), Marchesini et al. (2017), Magliano et al. (2017) and Nosetto et al. (2012). They all reported wetter soils on agricultural land compared to forest across different regions of the Chaco. However, it must be mentioned that deforestation itself does not necessarily lead to wetter soils. The impact of deforestation on soil moisture is a combination of an increased rate of E_B (drier soils) and a decreased rate of E_V (wetter soils). The net effect depends on the local climate and the length of the wet or dry periods (Chen et al., 2009). The impact may also vary across the vertical soil profile depending on the change in root distribution and soil characteristics after deforestation (de Queiroz et al., 2020). Amdan et al. (2013) stated that the agriculture system applied in northwestern Argentina also influences the soil moisture status. The prevalent agriculture system in the Dry Chaco is mostly based on no-tillage management followed by fallow seasons. The crop residue that remains on the field decreases E_B and therefore increases available soil water content (Villegas et al., 2010). During the fallow season, there is no consumption of soil water over agriculture areas, increasing deep percolation of water towards the groundwater table. These changes in soil characteristics, soil management and natural mulching are not included in LSM simulations.

2.5.3 Model evaluation using independent data

The reasonable agreement between MERRA-2 and the long-term in situ P data supports an analysis of the water budget components in absolute values (as in Table 2.2), but with caution: the more recent P stations suggest larger biases and may possibly not have been included in the gauge-based P corrections of

MERRA-2. Due to its coarse resolution, MERRA-2 does not take into account microclimatic effects over the mosaic landscape associated with deforestation.

Relative to independent data, there is no LSM setup that yields significantly better output for the entire Dry Chaco in terms of time series metrics. CLM sfmc yields the largest R and aR values when compared to the in situ Monte Buey sfmc. NOAH outperforms both CLM and CLSM in terms of ET (when compared to GLEAM ET), whereas CLSM yields the best Tb results (when compared to SMOS Tb). Updating the model soil parameters with more recent (assumed to be more accurate) information reduces the sfmc bias relative to in situ observations for the 3 Monte Buey pixels, as well as the Tb bias relative to region-wide SMOS observations for all models. On the other hand, the update reduces the R values between CLSM and GLEAM ET and between CLSM and SMOS Tb .

The spatially complete time series evaluation with long-term SMOS Tb observations is unique to assess model performance over areas with limited long-term in situ data. A similar approach was conducted by Albergel et al. (2012) over the United States. The high R values between the SMOS Tb observations and RTM simulations indicate that LSMs simulate realistic temporal variations and that their use over the Dry Chaco is justified (despite the lower agreement between MERRA-2 and recent in situ P). After implementation of time-varying vegetation and land cover changes, we found no significant or unanimous model improvement when compared to independent data. This is most likely due to the coarse spatial resolution of the satellite-based evaluation, which suppresses the signal of the rather small-scale mosaic deforestation activities over the Chaco, and to the fact that model simulations do not necessarily perform better when given supposedly better input parameters. Furthermore, removal of subtropical dry forest is likely to only have a little impact on L-band Tb , whereas the removal of dense tropical rainforest would probably have a much stronger impact on both Tb simulations and observations. However, Figure 2.13 indicates that time-varying vegetation and land cover parameters did introduce slightly better agreements between simulated and SMOS-observed Tb for some deforested areas. Local calibration of different RTM parameters, could possibly further improve the agreements between modeled and observed Tb .

An evaluation with finer-scale sfmc retrievals e.g., obtained from Sentinel-1 or after downscaling passive microwave products, is not included in this study because by design, sfmc retrievals do not necessarily account well for deforestation, are prone to vegetation bias in general (Zwieback et al., 2018), and would thus not serve well as reference data. A finer-scale evaluation in terms of land surface temperature would add value, but an analysis of the energy budget was beyond the scope of this study.

2.5.4 Shortcomings and scope for further research

Our simulations of the Dry Chaco's hydrology with revised soil, vegetation and land cover parameters have some shortcomings and caveats that could partly be overcome in future research. First, feeding the models with similar, e.g., satellite-based, albedo input could further lead to a homogenization in model output, as this is a key parameter in the calculation of the land surface energy budget (Alton, 2009; Yin et al., 2016; Houspanossian et al., 2017). Second, we showed that the spatial pattern of simulated soil moisture is closely related to the spatial pattern of the soil texture data. Regional simulations could thus benefit from regional soil maps, where available. In addition, land cover changes can affect soil properties (Wickenkamp et al., 2020), which means that the adjustment of SHPs in response to vegetation changes (such as deforestation) could further improve LSM simulations. Third, the relatively coarse spatial resolution of our simulations (0.125°) required an upscaling of the LAI, GVF and land cover input data, and the satellite-based evaluation even required an aggregation to 36 km. This caused a suppression of the deforestation signature in our simulations. Fourth, our LSM simulations did not include any dynamic vegetation growth module, which would couple soil moisture and vegetation in two ways, instead of only one way. More generally, LSMs can benefit from further developments to better represent soil-water-vegetation processes, because the three tested LSMs now show a questionable range in their partitioning of the water budget components and in their response to parameter changes. Some of the above caveats will be addressed in future research towards using LSM output as underlying information for the assessment of dryland salinity over the Dry Chaco.

2.6 Conclusions

In this study, we updated the soil- and vegetation-related parameters of three LSMs (CLM2.0, CLSM-F2.5 and Noah3.6), grouped within NASA's LIS, to obtain the best modeled representation of the hydrology over the South American Dry Chaco. We used HWSD v1.21 soil texture and time-varying satellite-based GLASS and GIMMS vegetation indices, along with yearly updated ESA-CCI land cover information. The impact of the various model structures, soil texture and dynamic vegetation input was assessed in terms of water budget partitioning and efficiency space. Our results indicate that:

- the three LSMs yield a different partitioning of the water budget, with 74% to 95% of the total annual P over the Dry Chaco contributing to ET ;

- the soil texture pattern is the main driver of the spatial pattern of soil moisture;
- introducing similar soil, vegetation and land cover parameters in the various LSMs does not result in a homogenization of the long-term water budget components, i.e., the various LSM structures primarily determine the water distribution whereas soil, vegetation and land cover parameters only have a secondary impact.

The updated vegetation and land cover treatment allowed us to explore to which extent large-scale land cover changes in the Dry Chaco affect the different water budget components. It was found that:

- deforestation increases soil moisture for all LSMs, but the degree of increase depends on the model structure;
- a change in land cover results in a shift of the model climatology and a (non-stationary) redistribution of the water budget, which is different for each LSM; and
- the implemented satellite-based vegetation indices do not fully depict deforestation, because the 0.125° spatial resolution partially suppresses the deforestation signal, and the replacing agricultural crop may have similar LAI and GVF values to the initial dry forest.

The model input and output were further evaluated against independent data of in situ P and sfmc and spatially covering GLEAM ET and SMOS Tb. The latter offers the unique possibility for an integral evaluation of simulated soil moisture, soil temperature and LAI after forwarding these variables through a zero-order RTM. Relative to independent data, no specific LSM structure, soil or vegetation input is significantly better than another in terms of time series metrics. Updated soil parameters reduce Tb bias relative to region-wide SMOS observations for all models, improve the R and ubRMSD values for CLSM and NOAH, but reduce the R values between CLSM and GLEAM ET and CLSM and SMOS Tb. Interannually varying vegetation and land cover input generally have a marginal impact.

Our methodology is a first step towards a better representation of the Dry Chaco ecosystem using dynamic LSM simulations. The assimilation of multi-source remote-sensing data for state (e.g., soil moisture and temperature) and parameter (e.g., albedo) updating may help to further constrain the models and correct for unmodeled processes, such as land cover changes. However, the impact of such updates will depend on the used LSM, and on the optimization

of data assimilation systems in the presence of non-stationary processes that are associated with land cover changes (such as deforestation). Vegetation data assimilation can only have the desired impact if the sensitivity of simulated hydrological fluxes to vegetation changes is realistic and this may need further research, especially at the global scale. To better represent small-scale land cover conversions and their impact on the water distribution for research on dryland salinity or ecology, simulations should also be conducted at a finer spatial resolution.

Chapter 3

Spatial patterns of soil salinity in the central Argentinean Dry Chaco

Based on:

Maertens, M., De Lannoy, G. J. M., Vincent, F., Massart, S., Giménez, R., Houspanossian, J., Gasparri, I., and Vanacker, V.: Spatial patterns of soil salinity in the central Argentinean Dry Chaco, Anthropocene, in review, 2021

3.1 Introduction

Soil salinization is the process whereby water-soluble salts accumulate in the soil mantle. Salinization degrades the soil when the concentration of salts rises above a level that impacts agricultural production or threatens ecosystems (Rengasamy, 2006). A soil is defined as saline when the electrical conductivity (EC) of the saturation extract in the root zone exceeds 4 deciSiemens per meter (dS/m), a level at which most crops experience reduced yield (Richards, 1954) due to root osmotic stress, ion-toxicity, and anoxia (Turnbull et al., 2012; Walker et al., 1999). In advanced stages, severe salinization can lead to the transformation of fertile soils to barren land (Chesworth, 2008; Jones et al., 2012; Tóth et al., 2008). On a global scale, salinization is one of the major soil degradation threats and affects an area of approximately 8.322.000 km² (6% of

the world's total land area) (Munns, 2005; Rengasamy, 2006).

Multiple processes are involved in the development of saline soils, whereby a distinction can be made between natural (so-called primary) and human-induced (secondary) salinity (Daliakopoulos et al., 2016). Natural salinity is determined by how chemical weathering processes release salts from the parent material, depending on the mineralogy of rock or sediment constituents (Daliakopoulos et al., 2016), and how salts are distributed in the landscape. The redistribution of these salts within the soil mantle is dependent on the regional climate, hydrogeology and vegetation cover. The annual climatic water balance, here represented by precipitation minus potential evapotranspiration ($P - P_{et}$) strongly influences salinization (Nosetto et al., 2008). A positive water balance results in a net downward water flux and low salinity, whereas a negative water balance leads to evapotranspiration deficits that can be offset by groundwater rise. Together with capillary rise, this can cause a net upward flux of water and solutes towards the surface and enhance salt accumulation in the soil mantle. The higher the water deficit, the higher the soil salinization risk (Schofield et al., 2001; Nosetto et al., 2008). Specific hydrogeological circumstances, such as the depth of the groundwater table may further amplify or weaken the hazard (Domenico and Schwartz, 1998). Flat sedimentary plains with shallow water tables and slow (sub)horizontal movement of groundwater are more prone to salinization than high-relief landscapes with deep groundwater tables and steep hydraulic gradients (Marchesini et al., 2017; Jobbágy et al., 2020). Also tectonic activity may have a considerable impact on groundwater movement. For example, tilted or rotated fault blocks can generate topographic depressions in which internally drained lakes can be formed (Leeder and Gawthorpe, 1987). On top of that, seepage of groundwater along a fault trace can lead to water accumulation in the hanging wall.

Besides natural contributing factors (Nosetto et al., 2008), anthropogenic activities can influence soil salinity. Human-induced vegetation changes can alter the local water balance through changes in transpiration rates (Peña-Angulo et al., 2021), and influence salt accumulation and distribution in the soil subsurface. Deforestation, for example, may lead to dryland salinization as experienced in Western Australia. By the end of the 1980s, almost 40 % of the Australian dry forests was converted to cropland and pasture, causing the salinization of more than 2 million hectares of productive lands (Lambers, 2003). Furthermore, irrigation with saline water and poorly managed irrigation schemes (often coupled with poor drainage conditions) are an important source of secondary salinization and major factor limiting crop production (Fan et al., 2012; Trnka et al., 2013).

Mapping and monitoring soil salinity is important for sustainable management of drylands (Scudiero et al., 2014b). A plethora of studies and methods exist

to map soil salinity but in many cases, remote sensing data has been used (e.g., Metternicht and Zinck (2003); Zhang et al. (2011); Scudiero et al. (2015); Zhang et al. (2015)). Early works focused on salinity assessment at or near the soil surface, and are based on the differences in surface reflectance between salt crusts and productive topsoil (Allbed and Kumar, 2013). However, in agricultural soils, salts tend to accumulate in the root zone rather than at the surface. This has shifted the paradigm of remote sensing applications towards the use of vegetation indices as indirect measures of soil salinity (Metternicht and Zinck, 2003; Zhang et al., 2011), as excessive salt concentrations in dryland soils affect vegetation growth. In most cases, soil salinity is assessed using vegetation indices computed from yearly to multi-year spectral data (Lobell et al., 2010; Wu et al., 2014; Zhang et al., 2015; Scudiero et al., 2014a, 2015), or integrated vegetation indices over the growing season (Zhang et al., 2015). However, most of these studies were conducted at a local scale and the locally developed algorithms are not fully extendable for regional-scale assessments due to spatial variability in climate conditions, soil properties, and land use/management (Wu et al., 2014). Besides, a major problem with indirect salinity detection methods is that remotely sensed vegetation indices generally cannot differentiate salinity-induced crop stress from stress caused by other factors such as weather conditions, pests, and water management (Hopmans et al., 2021). It has been shown that using environmental covariates as additional predictor variables besides vegetation indices in regression equations and classifiers can improve the accuracy of salinity maps (Furby et al., 2010; Taghizadeh-Mehrjardi et al., 2014). For example, Scudiero et al. (2015) developed a linear regression equation for estimating soil salinity using spatial precipitation and temperature data and multitemporal Landsat 7 canopy reflectance data. Recently, Taghizadeh-Mehrjardi et al. (2021) showed that topography and climate data are useful covariates in regional-scale soil salinity assessments from remote sensing data, using machine learning algorithms.

A region that is characterized by primary and secondary salinity is the Dry Chaco in South America. The Dry Chaco covers one of the most extensive and flat sedimentary plains in the world including parts of Argentina, Paraguay and Bolivia (787,000 km²). This low-relief region is prone to salinization because of its subhumid to semi-arid climate (Jobbágy et al., 2020). The Dry Chaco still hosts large remnants of dry forests (Marchesini et al., 2017), but has long been one of the largest deforestation hotspots in the world (Hansen et al., 2013). In total, 158,000 km² of forests has been converted to agricultural land during the period 1976–2012, corresponding with 20.7% of the total area (Vallejos et al., 2015).

Large-scale land cover change in the Chaco affects local hydrology and may introduce dryland salinity. Native dry forests consume water intensively,

preventing deep drainage of rain water to the groundwater table (Amdan et al., 2013; Jobbágy et al., 2020). As a result, salts remain or accumulate in the soil mantle (Giménez et al., 2020b). When forests are converted to agricultural land, soil moisture and deep drainage increase, resulting in a rise in the groundwater table. If this trend continues over time, it may result in salt accumulation close to the soil surface and eventually result in reduced plant growth and soil degradation (Giménez et al., 2016; Marchesini et al., 2017; Jobbágy et al., 2020).

The above-mentioned studies from the Dry Chaco are mostly conducted on plot-level scale and relate soil salinization to forest conversion. To our knowledge, no studies exist on the regional pattern of primary and secondary soil salinity over the Dry Chaco or on how environmental conditions such as topography and climate influence this pattern. This study is guided by the following research questions: (i) Which environmental variables are associated with the observed regional salinity patterns over the Dry Chaco? (ii) Which processes explain the observed differences in salinity across the study area? (iii) Which remote-sensed vegetation indices are relevant predictors of regional salinity? To answer these questions, we collected 492 surface and 142 subsurface EC measurements along east-west transects covering the existing topographic and climatic gradients in the region. The EC measurements were associated to vegetation indices, topographic and climatic variables. The climatic information was obtained from a state-of-the-art land surface model (LSM). A spatial regression technique was used to associate the environmental variables to the EC measurements, and to create a regionally interpolated soil salinity map.

3.2 Methodology

3.2.1 The Dry Chaco's geomorphology

This chapter focuses on soil salinity patterns in the central Argentinean Dry Chaco (Figure 3.1). Given the close relationship between soil salinity and geomorphology, we first provide a brief summary of the main geological and geomorphological features. Geologically, the Dry Chaco can be considered as an Andean foreland basin that is predominantly filled by fluvial sediments (Latrubesse et al., 2012). The region has a unique geomorphology as it is located at the transition between the Subandean Ranges and the adjacent lowlands favoring the formation of alluvial megafans (Thalmeier et al., 2021). The Chaco encompasses 5 megafans that are amongst the largest in the world and extend ca. 500 - 700 km from the Andean foothills (Thalmeier et al., 2021).

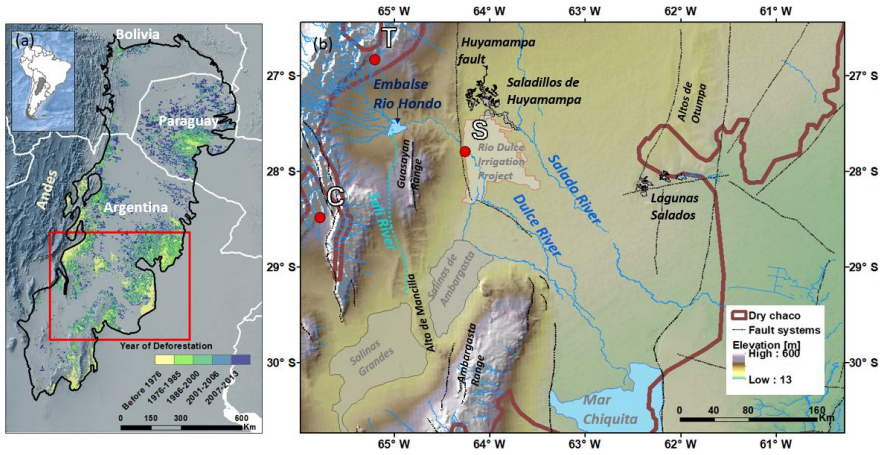


Figure 3.1: (a) Geographic location of the Dry Chaco in South-America, with spatiotemporal pattern of deforestation between 1976 and 2013 as derived from Vallejos et al. (2015). (b) Topography and main geomorphological features of the central Argentinean Dry Chaco. The largest cities are (T) San Miguel de Tucumán, (S) Santiago Del Estero and (C) Catamarca.

The geomorphology of the study area shows tectonic imprints related to the flat subduction of the Nazca plate beneath the South-American Plate (Ramos et al., 2002). Tectonic deformation has been active throughout the Quaternary and mainly includes east-west compression (Mon and Gutiérrez, 2009; Gutiérrez et al., 2017). The fault scarp of the 60 km long Huyamampa Fault is the result of this compression and is clearly visible in the landscape with an offset of approximately 150 to 200 m (Miro and Gonfiantini, 1980). According to Gutiérrez et al. (2017), the thrust fault causes subsidence of the eastern block. To the west of the fault, Pliocene and Miocene sediments are covered by Pampean loess, whereas east of the fault, Quaternary sediments occur that mainly consist of gravel and sands (Miro and Gonfiantini, 1980). The adjacent salt lakes, Saladillos de Huyamampa, are likely formed as a result of water accumulation (water seepage and blocked drainage) in the fault-bounded depression. Near Santiago Del Estero, the Huyamampa Fault forms the border of the alluvial deposits of the Dulce river. This alluvial megafan has a thickness of about 150 m at its apex and it thins eastward over a distance of 50 km (Bhattacharya et al., 2006). Quaternary tectonic activity in the northeastern part of the study area initiated the progressive uplift of the Altos de Otumpa Range, a topographic high with north-south orientation (Peri, 2012). In the topographic depression that formed south of the Altos de Otumpa, a series of small salt lakes developed,

the Lagunas Saladas (Peri, 2012).

In the southern Dry Chaco, Quaternary morphotectonic processes resulted in the salt lakes of Salinas Grandes and Salinas de Ambargasta, which make up remarkable landscape features (Gutiérrez et al., 2017). Pleistocene east-northeast transtension resulted in the formation of a large topographic depression. The depression was first filled by the Sali River (also referred to as the Sali-San Bernardo River) that drained west of the Guasayan Range forming the Lagunas Grandes. Note that the Lagunas Grandes covered the area of the current Salinas Grandes and Salinas de Ambargasta that were originally connected to each other. The uplift of the Guasayan Range led to the diversion of the Sali River towards the east (North of Guasayan Range on Figure 3.1b), filling the Lagunas Grandes from the north. Progressive east-west compression led to the uplift of the Alto de Mancilla Range that bisected the Lagunas Grandes, and a second diversion of the Sali River (from then on called the Dulce River) towards the Mar Chiquita. It is estimated that the final diversion of the Dulce/Sali River from the Lagunas Grandes and Lagunas de Ambargasta occurred 250 to 300 years ago (Gutiérrez et al., 2017). The old lakes dried-up forming the Salinas Grandes and Salinas de Ambargasta (Figuroa et al., 2020). South of 28°S, the Dulce and Salado Rivers currently flow in the same floodplain over a length of 200 km. Channel avulsions frequently occur because of the low slope gradient of the river channel and the flat topography (Bucher, 1982; Mon and Gutiérrez, 2009).

Near Santiago Del Estero, numerous small-sized farms intensively use the Rio Dulce alluvial cone for irrigated agriculture, supported by a canal system. The project is known as the Rio Dulce Irrigation Project (see Figure 3.1b). With an irrigable area of 1,200 km², it is one of the most important irrigation systems in Argentina (Prieto, 2006). The Rio Hondo Reservoir (Embalse Rio Hondo on Figure 3.1b) functions as the source of water supply.

3.2.2 Data collection

Data on soil salinity was collected during a two-month field campaign in July-August 2019 across the central part of the Argentinean Chaco. Samples were collected along multiple east-west transects through the provinces of San Miguel de Tucumán, Santiago Del Estero and Chaco. The exact location of the transects was conditioned by road accessibility. To avoid direct influence of the road, all soil samples were taken at > 50 m from the road. As a proxy for soil salinity, we measured the EC of soil samples of 50 grams that were taken from the surface 5 cm and at 1 m depth. To determine the EC of the soil, we used the 1:1 method whereby we added 50 ml of distilled water to 50 grams of

soil. The samples were shaken and left to rest for 15 minutes, after which we measured the temperature corrected EC (expressed in dS/m) with a YSI proDSS probe. The YSI proDSS EC sensor measures EC values in a range from 0 to 200 dS/m with an accuracy of 0.001 dS/m. The sensor was calibrated daily. The dataset contains 492 surface and 142 subsurface measurements (at 1 m depth). Despite the relatively low amount of subsurface samples, we ensured the maximum coverage of topographic and climatic conditions by comparing the spatial distribution of multiple environmental variables over the entire study area with the spatial distribution of the sampling points as described in more detail in section 3.3.2.

During the field campaign, we observed soil salt crusts at the surface. In agriculture land, the crusts were small (<2 m in diameter), patchy, and with irregular shapes. In topographic depressions however, they covered extensive areas (>1 km²). After the field campaign, we used Google Earth imagery covering the period of 2013 through 2019 to locate clusters of saline topsoils in the study area. The visual identification of salt crusts was based on differences in surface reflectance between salt and non-salt affected soil surfaces (see Appendix A.2.1). Figures 3.2a-d illustrate how salt crusts encountered during the field campaign appear in Google Earth imagery. The aim of the identification was not to identify each saline spot individually across the entire study area but rather to identify different clusters where soil salt crusts are present.

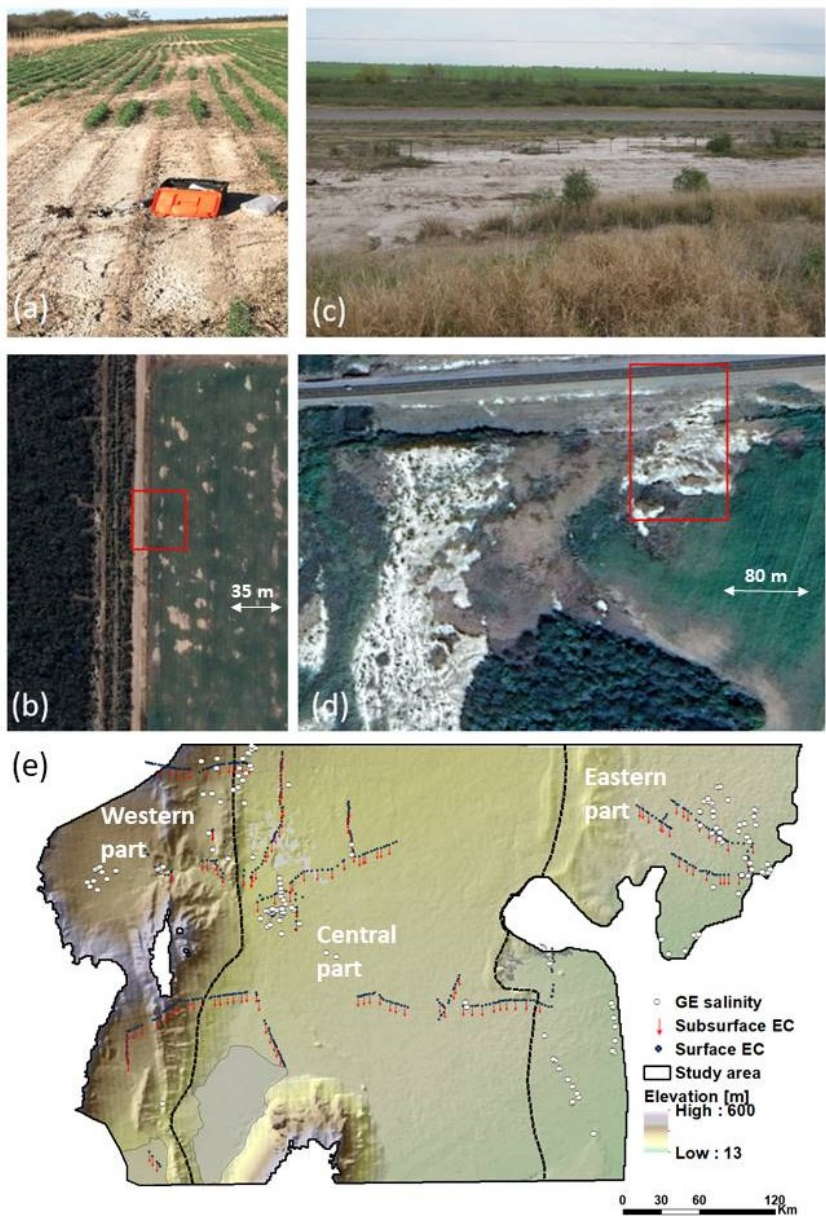


Figure 3.2: (a-b) Signs of surface salinity observed during the field campaign (a: 26°42'50" S, 64°16'20" W, b: 26°40'40" S, 64°28'10" W) and (c-d) how they appear on Google Earth (GE) imagery. (e) Overview of the location of soil samples collected during the field campaign of 2019, with indication of surface (blue dot) and subsurface (red arrow) samples. White dots correspond to the areas where signs of surface salinity were detected based on Google Earth imagery. The north-south dotted lines mark a division into geomorphological subregions.

The spatial distribution of the field samples is given in Figure 3.2e. The northern and southern boundaries were delineated based on the upper and lower latitude of the dataset. The eastern and western boundaries were based on the limits of the Dry Chaco ecosystem whereby areas above > 500 m a.s.l. were excluded. To facilitate the interpretation of our results, the area of interest was further divided into three geomorphological subregions (dotted lines): (i) a western part, including the areas to the west of the Huyamampa Fault and the Alto de Mancilla, (ii) a central part corresponding with the flat lowlands of the Chaco plain, and (iii) an eastern part with the areas east of the Altos de Otumpa and related fault systems.

Our results will indicate (see section 3.3.1) that EC measurements in the surface 5 cm are generally low. In addition, surface salinity crusts in agriculture lands are small and showed irregular shapes. This impedes the accurate mapping of surface salinity on a regional scale. Therefore, the analysis of the large-scale salinity patterns and the development of the regional salinity map will be based on subsurface EC measurements solely. The surface salinity spots derived on Google Earth will be used in the discussion where a spatial interpretation of the surface and subsurface salinity patterns is presented.

3.2.3 Environmental variables

To gain more insights in the spatial pattern of subsurface soil salinity, the EC values were associated to different environmental variables related to soil salinity. Based on literature (Nosetto et al., 2008; Glatzle et al., 2020), we selected the topography, satellite-derived leaf area index (*LAI*) and greenness vegetation fraction (*GVF*), the climatic water balance (represented as $P - Pet$), and soil moisture (*SM*) as potentially relevant variables. For each variable a spatial map at 1-km resolution was created. Maps that showed a significant correlation with the collected point-scale EC measurements were used in a regression analysis to regionally interpolate the measurements to a soil salinity map of the region. More specifically, for $Pet - P$, *SM* and vegetation, spatial maps of the mean and standard deviation over the previous hydrological year (September 2018-2019) were used.

Topographic data

Topographic information was derived from the Multi-Error-Removed Improved-Terrain Digital Elevation Model (MERIT DEM) (Yamazaki et al., 2019). This product removed multiple error components (absolute bias, stripe noise, speckle noise, and tree height bias) from existing spaceborne DEMs (Shuttle Radar

Topography Mission 3v2.1 and Advanced Land Observing Satellite World 3D-30m v1). It represents terrain elevations at a 3 arcsec resolution (~ 90 m at the equator). As local depressions, where groundwater is close to the surface, are hypothesised to be more prone to salinization, we detrended the DEM to better represent local topography. To do so, first, we created a surface by interpolating the altitude of the lowest points in the landscape (river profiles, lakes). Second, we subtracted the interpolated surface from the original DEM. In the detrended DEM, topographic depressions also obtained the lowest absolute elevation values. We will further refer to this detrended DEM as $DEM_{detrend}$. The DEM was upscaled to 1 km to match the resolution of the hydrological data.

Vegetation data

This study used two satellite-derived vegetation indices as indirect indicators of soil salinity: the Leaf Area Index (LAI) and the Greenness Vegetation Fraction (GVF). The LAI characterizes plant canopies, and expresses the leaf area per unit ground area (Smets et al., 2016). Satellite-derived LAI values correspond to the total green LAI of all canopy layers, including the understory which may be significant in forests. The GVF corresponds to the fraction of ground covered by green vegetation. It is computed from the LAI and other canopy structural variables. The GVF and LAI data used in this study are obtained from the Copernicus Global Land Service. The datasets have a resolution of 300 m and spatially complete maps are available every 14 days from January 2009 onwards. From 2014 onwards, the indices were derived from the Top of Atmosphere PROBA-V reflectances in three visual-near infrared spectral bands allowing to distinguish healthy from unhealthy vegetation (Smets et al., 2016). To match the model's 1 km resolution, LAI and GVF values were upscaled by spatial averaging.

Precipitation, evapotranspiration and soil moisture data

Spatio-temporal information on soil moisture (SM) was obtained from the NOAA LSM version 3.6 (Ek et al., 2003), embedded in the NASA Land Information System (Kumar et al., 2008). NOAA produces daily fluxes and states of the surface water and energy budget. We used a spatial resolution of 1 km for the simulations and aggregated information on a daily basis using a model integration timestep of 15 min. The meteorological forcing data (precipitation, air temperature, specific humidity, radiation, wind and surface pressure) were extracted from the Modern-Era Retrospective analysis for Research and Applications (MERRA-2) product (Gelaro et al., 2017) with inclusion of gauge-based precipitation corrections (Reichle et al., 2017). To

represent vegetation density, we used the satellite-derived *LAI* and *GVF* as described above. The LSM was run with yearly updated land cover information derived from the European Space Agency-Climate Change Initiative (ESA-CCI) land cover product (Kirches et al., 2014). The time-varying vegetation and land cover data allow for an up-to-date and accurate description of the land surface (Maertens et al., 2021). Based on a simplification of soil information taken from Moretti et al. (2019), soil texture in the LSM was defined as loamy sand for the entire study area. Massart (2020) showed that soil texture is a main controlling factor for the spatial pattern of soil moisture in NOAH 3.6, but that implementation of a detailed regional soil map over the Dry Chaco did not necessarily improve the correlation with in-situ soil moisture. The LSM was spun up for 7.5 years from 1 January 2011 through 31 August 2018. The simulations covering the period from 1 September 2018 through 1 September 2019 were used for further analysis.

P_{et} in this study is defined as the reference crop evapotranspiration and was calculated using the Food and Agriculture Organization (FAO) Penman-Monteith method (Allen et al., 1998). The necessary climate data (temperature, windspeed, atmospheric pressure and solar radiation) for the calculations were derived from the MERRA-2 product (Gelaro et al., 2017), bilinearly interpolated to 1 km resolution. The annual water balance was calculated by subtracting the annual *P_{et}* from the annual *P* derived from MERRA-2 (also downscaled to a 1 km resolution). Negative values result in a water deficit, whereas positive values indicate water excess. We did not use the ratio of *P_{et}/P*, as very low *P* values during the dry months caused unrealistic *P_{et}/P* ratios when calculating monthly means.

Assumptions about temporal variability

Soil salinity - just as other physico-chemical soil properties - varies over time. Temporal variation typically occurs at different timescales ranging from multi-annual over inter-annual or seasonal variation (Pennington and Chavez, 2000; Nasetto et al., 2013) to event-based variation (Glatzle et al., 2020). The multi-annual or first-order variation is associated with cyclical changes in climate (Gutierrez and Johnson, 2010) or land cover change (Jobbágy et al., 2020). Inter-annual hydrometeorological variability such as extreme wet years can generate second-order variation in soil salinity. Individual hydrometeorological events (such as significant rainfall events, after which salts are diluted or leached by rainwater infiltration) generate third-order temporal variations in soil salinity. By design, most soil salinity maps are static in time, focus on spatial variations and make abstractions of temporal variations in salinity.

In this study, the EC measurements were collected in July-August 2019. As such, the large-scale salinity map will closely mimic the soil salinity as it was observed in the dry season of 2019 and might not be fully representative for long-term annual mean salinity patterns. Given the wide spread in EC values measured across the study area (see section 3.3.1), we assume that the inter-annual variations at a given location are small compared to the spatial variations in EC over the study area.

The EC measurements were associated with data on soil moisture, the climatic water balance and vegetation from the previous hydrological year (September 2018-2019). It is important to mention that the eastern part of the study area had an anomalous wet period (May-June 2019) prior to the field campaign, possibly resulting in salt dilution. This wet period is partially included in the associated hydrological data as it covers the period September 2018-2019. Besides averaged annual hydrometeorological data, seasonal variation was taken into account by the use of an annual standard deviation map for each variable. This was done by first calculating monthly mean maps for each variable for the period September 2018-2019, and then deriving the standard deviation over the 12 months of data for each pixel. The standard deviation maps allow to distinguish areas with low and high seasonality, and they can identify potential bias related to cropping cycles. Agriculture plots that are fallow for part of the year can incorrectly be interpreted as saline areas if only the annual mean vegetation GVF or LAI is included. The use of standard deviations maps (further referred to as $\sigma_{variable}$) allows to overcome this issue as they incorporate the effect of seasonal vegetation cycles. In short, the 1-year means and standard deviations of 4 variables and a detrended DEM (nine variables in total) at 1-km resolution are used as predictor variables in the subsequent regression analysis: $P - Pet$, σ_{P-Pet} , GVF , σ_{GVF} , LAI , σ_{LAI} , SM , σ_{SM} and $DEM_{detrend}$.

3.2.4 Regression analysis

Prior to the regression analysis, the nine variables were standardized using a spatial Z-score transformation: for each pixel, the study area's spatial mean was subtracted from the original value, and the difference was divided by the study area's spatial standard deviation. The nine environmental variables were tested on multicollinearity and their correlation with soil salinity. The variable inflation factor (VIF) was calculated and variables with a $VIF > 3$ were omitted in the final regression model. To determine the correlation between the different variables and EC measurements, the Spearman correlation coefficient (R_{SP}) was computed. Variables with a $R_{SP} \geq 0.40$ and P value ≤ 0.05 were considered

as significant variables and selected as input in the regression model. The other variables were omitted from the analysis.

We used the Multivariate Adaptive Regression Splines (MARS) technique, developed by Friedman (1991), to relate EC values to the environmental variables. The advantage of this technique is that it allows us to account for the non-linear and non-parametric relation between the continuous environmental variables and the dependent variable. The building elements in the MARS model are piece-wise spline functions. These functions divide the data range into separate piece-wise linear or cubic segments, called splines, and are defined as (Rounaghi et al., 2015):

$$h_1(x) = (t - x) = \begin{cases} t - x, & \text{if } t \geq x \\ 0, & \text{otherwise} \end{cases} \quad (3.1)$$

$$h_2(x) = (x - t) = \begin{cases} x - t, & \text{if } x > t \\ 0, & \text{otherwise} \end{cases} \quad (3.2)$$

for a model with two basic functions h_1 and h_2 , whereby x represents the independent variable and t is the location of the knot (the point where two splines meet). In general, the MARS-based model can be described as the sum of different splines and has the following structure:

$$f(x) = \beta_0 + \sum_{m=1}^M \beta_m h_m(x) \quad (3.3)$$

in which, $h_m(x)$ are spline functions, M is the number of functions in the model as identified after the forward stage, β_0 and β_m are coefficients that are optimised based on the sum of squared errors from the h_m functions. In the forward stage of the MARS regression, a high number of stepwise functions are fitted. The unnecessary functions are then eliminated in the backward stage (pruning stage) using the generalized cross-validation criterion to improve the forecasting accuracy. Hence, the final number of functions (M) is determined (Kisi and Parmar, 2016; Roy et al., 2018; Adnan et al., 2020). We used the ARESLab toolbox for Matlab for the MARS regression, allowing for piecewise-linear and piecewise-cubic regression models (Jekabsons, 2016).

The final salinity map is the result of a cross-validation approach. A total of 100 model simulations were conducted whereby for each iteration, 4/5 of the subsurface EC measurements was randomly selected for model calibration and 1/5 for internal model validation. By calculating the ensemble-mean over the 100 simulations, the mean salinity over the dry season was obtained. The standard deviation on the mean is an indicator of the uncertainty on the

modelled salinity values, but since our random cross-validation does not ensure independent sampling, the ensemble uncertainty will be a strong underestimation of the actual prediction uncertainty (Roberts et al., 2017). We evaluated the model output against the measured EC-values by means of the coefficient of determination (R^2) and Root Mean Square Error (RMSE).

3.3 Results

3.3.1 Spatial variability in observed surface and subsurface salinity

The patterns of surface and subsurface EC measurements are shown in Figure 3.3. Figure 3.3a visualizes the EC values from the surface measurements together with the salinity spots derived from Google Earth imagery (white dots). Generally, the western part is characterized by low EC values (majority of the values ranges between 0 and 2 dS/m), but extremely high values occur near the Salinas Grandes (> 40 dS/m) in the South. In the central part, the mean surface EC values are higher but show higher spatial variability (mean of $4.3 \text{ dS/m} \pm 7.7 \text{ dS/m}$). The highest EC values are found over the Salinas de Ambargasta and the Saladillos de Huyamampa. Observed EC values over the eastern part are generally low ($0.58 \pm 1.46 \text{ dS/m}$). Agricultural fields with salinization were identified on Google Earth imagery west of the Rio Hondo Reservoir, near the Huyamampa Fault at the transition from the western to the central part and on the irrigated croplands of the Rio Dulce Irrigation project. Despite the fact that low EC values were measured, numerous saline spots were also identified over the lowest areas of the eastern part. This is likely a result of the seasonal character of surface salinity in this part of the Chaco (see section 3.4.1).

The subsurface measurements show large-scale patterns similar to the surface measurements but with less variability. The largest EC values are observed in the central part with a mean EC of $6.87 \pm 5.34 \text{ dS/m}$. Much lower values are found in the eastern and western parts : 0.81 ± 1.41 and $3.30 \pm 7.83 \text{ dS/m}$ respectively. The most saline subsoils are found close to the Salinas Grandes and Ambargasta reaching values up to 32 dS/m.

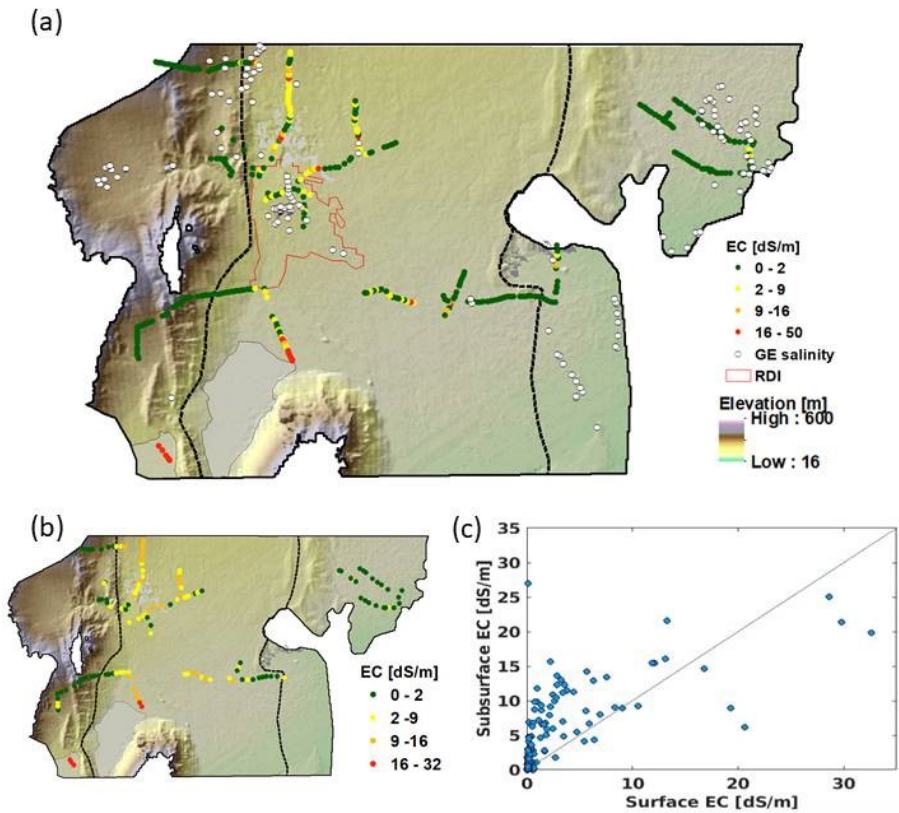


Figure 3.3: (a) Spatial pattern of surface soil EC values. White dots indicate locations where saline areas were identified based on Google Earth (GE) imagery. The red lines show the extent of the Rio Dulce Irrigation Project (RDI), (b) same as in (a) but for subsurface EC measurements, (c) relation between the EC of subsurface and corresponding surface samples.

Figure 3.3c shows the relation between the subsurface EC values and their corresponding surface measurements. Surface soil salinity is generally low compared to the subsurface EC values, except for those samples taken in the Salinas where salt crusts are forming as result of evaporation. As shown in Figure 3.2, salinity crusts in agriculture lands are small and show irregular forms. This impedes accurate detection of surface salinity at regional scale. Therefore, the analysis of the large-scale salinity patterns and its association with environmental variables is conducted based on the subsurface samples only.

In the discussion, the link between surface and subsurface salinity is elaborated in more detail.

3.3.2 Subsurface salinity and relation with environmental variables

To gain more insights into the spatial patterns of salinity, the subsurface EC measurements were compared to the environmental variables described in section 3.2.3. Figure 4.3 shows the scatterplots between the measured EC values of the subsurface soils and the environmental variables. Note that the relation between EC, LAI and σ_{LAI} is not shown due to the high multicollinearity between LAI and GVF (VIF > 3). In each scatterplot, the Spearman correlation coefficient and P value are also shown. The $P - Pet$, σ_{GVF} and $DEM_{detrend}$ have an absolute $R_{SP} \geq 0.40$ and P value < 0.05, and are used in the ensuing regression analysis (variables are indicated in red). The $DEM_{detrend}$ has the highest absolute correlation with EC (-0.50) followed by σ_{GVF} (-0.43) and $Pet - P$ (-0.41). The annual mean SM , and its temporal standard deviation, have low correlations with EC and are omitted in further analysis, just as the annual mean GVF map and σ_{P-Pet} .

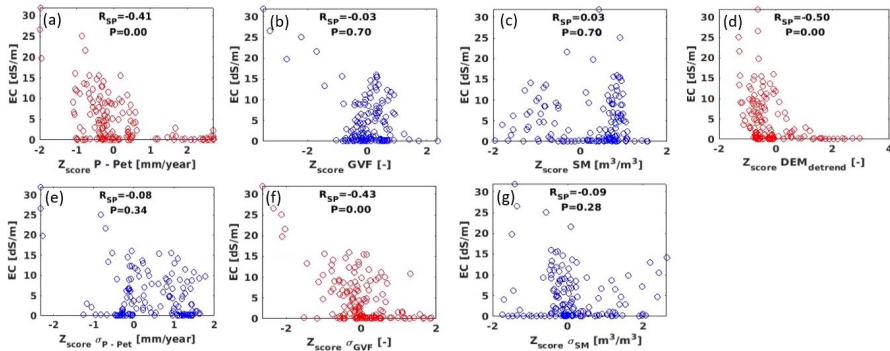


Figure 3.4: Scatterplots between the EC values of the subsurface soil samples and environmental variables with indication of the Spearman correlation coefficient (R_{SP}) and P value. Variables in red are used in the spatial interpolation (regression) analysis.

We verified if the spatial coverage of visited areas during the field campaign is representative for the entire study area. The spatial distribution of the selected environmental variables over the entire study area was compared with the spatial distribution of the sampling points (Figure 3.5a-c). The bars in 3.5a-c represent the distribution of the environmental variables for the sampling

points (green bars) and the entire study area (gray bars). The histograms illustrate that the EC dataset covers most of the study area's variability for the three selected variables. This is confirmed by the student's t-values indicating that the null-hypothesis of the t-test cannot be rejected and that the mean differences in the distributions are not significant.

The maps of the three selected variables are shown in Figure 3.5d-f. The $P - Pet$ map (3.5d) shows a potential water deficit in the central part (mean deficit = -1115 mm/year), in contrast with the lower deficit in the eastern part (mean deficit of -825 mm/year). The western part has a strong north-south deficit-gradient with an annual mean deficit of -1107 mm/year. Figure 3.5e shows the annual standard deviation of the fraction of ground covered by green vegetation, GVF, and represents the vegetation's phenology. The western part, dominated by croplands, has high σ_{GVF} values, reflecting a strong seasonal cycle in vegetation growth. The central part is characterized by low σ_{GVF} values, especially over the Salinas de Amabargasta, the alluvial plain of the Rio Dulce and the Saladillos de Huyamampa. The remaining areas in the central part, mainly consisting of dry forest, have intermediate σ_{GVF} values. The Altos de Otumpa in the east are characterized by high σ_{GVF} , as a result of croplands with strong seasonal cycle. East of Altos de Otumpa, the land cover is dominated by croplands with low σ_{GVF} values. The detrended DEM shows the geomorphological units: the western part has a significantly higher topographic roughness and elevation than the eastern and central part. In the central part, lower areas correspond to the Salinas de Ambargasta, the Saladillos de Huyamampa and the alluvial plain of the Rio Dulce.

3.3.3 Regression analysis

The adjusted response plots of the three selected variables are shown in Figure 3.6, and illustrate the relationship between the EC subsurface values and each variable as it was derived by MARS regression over 100 model simulations (the ensemble-mean and one and two standard deviations are shown). The functions describe the relationship between EC and one of the selected environmental variables, whereby the other predictor variables are averaged out. Figure 3.6a shows a negative relationship between EC and $P - Pet$: the more negative the water balance (higher water deficit), the higher the EC values. The modeled relationship between EC and σ_{GVF} is also negative: areas with low seasonal variability in GVF are most likely affected by salinity in the subsurface layers. Figure 3.6c shows that the relation between $DEM_{detrend}$ and EC is also negative: topographic lows tend to be more saline.

Figure 3.7a shows the modeled subsurface salinity over the study domain. The

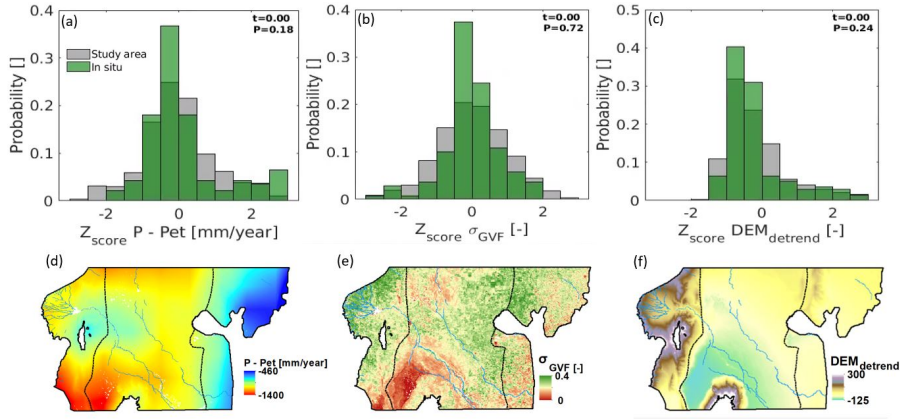


Figure 3.5: (a-c) Histograms representing the distribution of the 1-km environmental variables for the sampling points (green bars) and the entire study area (gray) for $P - Pet$, σ_{GVF} and $DEM_{detrend}$ respectively. (d-f) Maps of the annual mean water balance ($Pet - P$), σ_{GVF} and $DEM_{detrend}$.

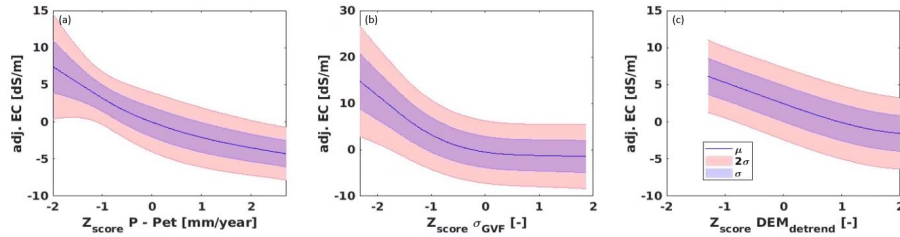


Figure 3.6: Adjusted response plots between EC and (a) $Pet - P$, (b) σ_{GVF} and (c) $DEM_{detrend}$. The ensemble-mean (blue line) and one (purple) and two (red) standard deviations are shown.

map represents the ensemble-mean over the 100 individual regressions. A clear spatial pattern appears: most of the western part is characterized by low salinity values (with mean value of 4.46 dS/m) but a strong increase in EC towards the south (corresponding with the northern edge of Salinas Grandes). The central part is characterized by higher EC values (7.42 dS/m) compared to the western and eastern part. The Salinas de Ambargasta stand out by very high EC values (>32 dS/m), followed by the Saladillos de Huyamampa and the alluvial plain of the Rio Dulce. The eastern part of the Chaco has again lower modelled EC values (2.30 dS/cm). The Altos de Otumpa have very low EC values, while east of the Altos de Otumpa, a mosaic of low and intermediate EC values appears.

The intermediate EC values mainly correspond with agriculture plots with low σ_{GVF} values. The low vegetation phenology can be related to reduced crop performance by soil salinity but also by specific crop management practices (see section 3.4.2).

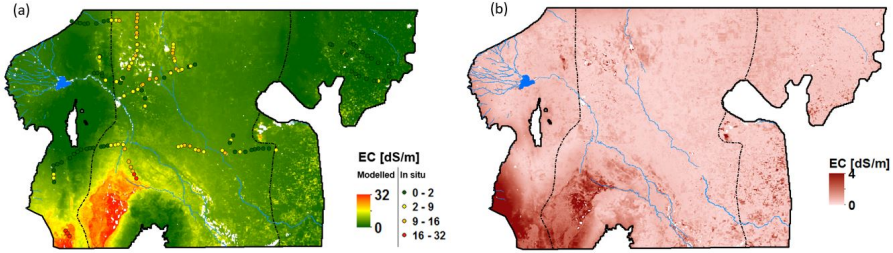


Figure 3.7: (a) Ensemble mean and (b) standard deviation map of modeled soil salinity (EC) at 1 km resolution, based on 100 simulations.

The standard deviation map shows the uncertainty on the regression estimates (Figure 3.7b). The map represents only the uncertainty related to the MARS-regression and underestimates the total salinity uncertainties (see section 3.4.3). Overall, the standard deviations related to the regression analysis are very small with a mean value of 0.8 dS/m. This suggests that the results are only weakly influenced by selecting different subsets for model calibration. The performance of each ensemble member was assessed by calculating the R^2 and RMSE. Figure 3.8 shows violin plots whereby each point represents one model simulation (out of 100). For each simulation, the R^2 and RMSE for both the calibration and validation dataset are shown. The mean R^2 of the calibration and validation dataset are 0.67 and 0.59 respectively, with a larger spread for the validation dataset. Similar results are observed for the RMSE, whereby the mean and standard deviation on the RMSE are lower for the calibration (3.44 ± 0.13 dS/m) compared to the validation dataset (3.66 ± 0.54 dS/m). Given the limited number of EC measurements, the validation dataset in each model-member strongly correlates to the training data, partially explaining the good performance of the model. The average RMSE values (3.44 and 3.66 dS/m for calibration and validation respectively) are larger than the mean ensemble standard deviation (0.8 dS/m). This indicates that the uncertainty of the ensemble model underestimates the actual uncertainty. An independent validation dataset would improve the uncertainty assessment and allow us to evaluate the real uncertainties on modeled soil salinity.

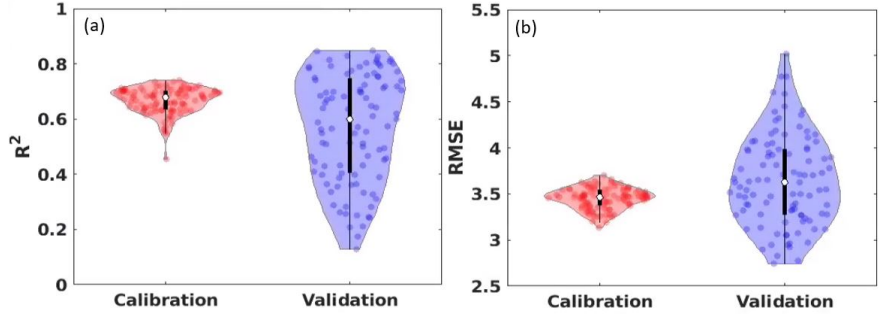


Figure 3.8: Violin plots of (a) R^2 and (b) RMSE for 100 model simulations. For all simulations, the dataset was randomly divided in a calibration (4/5) and internal validation (1/5) part. Each dot represents a model-member.

3.4 Discussion

3.4.1 Spatial patterns of soil salinity over the Dry Chaco

By associating the subsurface EC measurements to different environmental variables in a regression model, we found four variables that significantly contributed to the observed EC-pattern: the annual mean precipitation and potential evapotranspiration (combined in $Pet - P$), the geomorphological setting, and temporal standard deviation in GVF (as proxy for vegetation phenology). The EC measurements and salinity map highlight strong spatial differences in salinity across region, whereby the observed soil salinity pattern is the result of primary and secondary salinity processes. The EC dataset used in this study did not include sufficient datapoints to quantitatively disentangle secondary from primary salinity. However, based on the theoretical concepts of arrested drainage and landscape stagnation introduced by Jobbágy et al. (2020), relevant insights in the susceptibility to soil salinity can be obtained and are discussed below. A schematic representation of the main salinity processes and patterns found in this study is presented in Figure 3.9. In appendix A.2.2, high resolution imagery illustrates the expression of these processes.

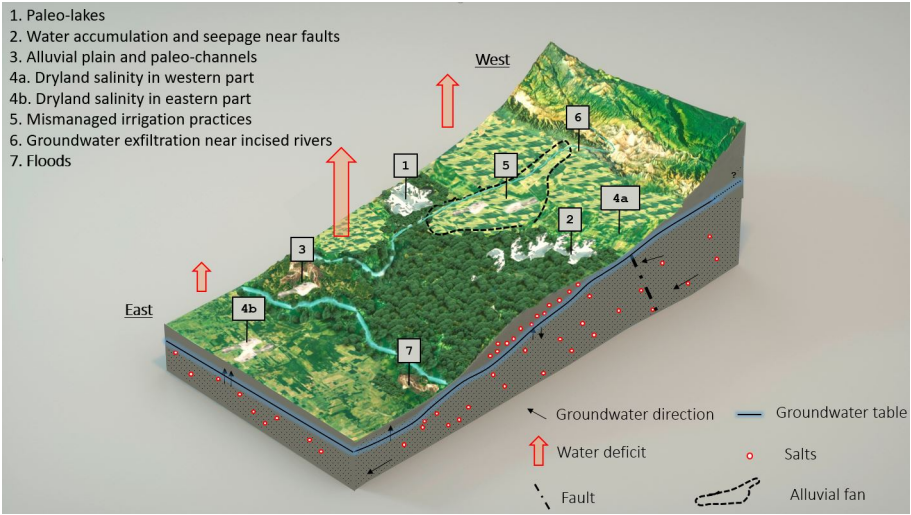


Figure 3.9: Schematic overview of main processes of soil salinization over the Dry Chaco. High resolution satellite-images showing a visual imprints of the described processes are shown in Appendix A.2.2.

Primary salinity: Arrested drainage

The results showed that EC was correlated with $P - Pet$ ($R=-0.41$). The importance of water deficits in explaining soil salinity patterns is congruent with the concept of arrested drainage as explained in Jobbágy et al. (2020). They state that in regions with dry to semi-arid climates, there is a total restriction of deep drainage as vegetation has the ability to use rainfall inputs exhaustively, either in near-real time or with seasonal or inter-annual deferrals. This mechanism limits water percolation beyond the front of the root zone and favours accumulation of solutes in the upper horizons of the soil mantle. As deep drainage towards the ground water is reduced, leaching of salts towards deeper layers is prevented. The modeled soil water balances showed the highest water deficits in the central part of the study area (-1115 mm/year), whereas much lower water deficits occur in the eastern part (-825 mm/year). The western part has a strong north-south gradient in water deficit with mean value of -1107 mm/year. These large-scale patterns in soil water balance are also reflected in the subsurface salinity map with mean EC values ranging from 7.42, 2.30 and 4.46 dS/m for the central, eastern and western part respectively. The high water deficits that we report for the central part of the Dry Chaco are likely impeding deep drainage and salt leaching as rainfall inputs (500 to 1000 mm/year) are

largely lost through evapotranspiration. Compared to the central part, the higher rainfall inputs in the eastern part result in lower water deficit and higher water excess during the wet season.

Primary salinity: Landscape stagnation

The EC values of the subsurface soil horizons are strongly correlated with local topography ($R=-0.50$). This relation is congruent with the concept of landscape stagnation as explained in Jobbágy et al. (2020): flat sedimentary plains are characterized by low hydraulic gradients and slow subsurface lateral transport of solutes. Even if the arrested drainage condition is not met, the lack of horizontal (ground)water flow in stagnated landscapes (Jobbágy et al., 2020) efficiently limits the export of salts.

The western part of the Dry Chaco is located at the margin of the Subandean Ranges: the elevation ranges between 180 and 450 m whereby groundwater is relatively deep (between 10 to 40 m according Nicolli et al. (2008)). Slope gradients are up to 6% whereby the main regional subsurface flow direction is towards the southeast (García et al., 2001). Hence, salts can effectively be evacuated through regional groundwater transport in this part of the Chaco. Note that west of the Rio Hondo Reservoir, higher EC values were modeled and multiple saline crusts were identified on Google Earth imagery. The area is located in a topographic depression where regional groundwater flow paths may accumulate and create shallow groundwater conditions. Possibly, the Rio Hondo Reservoir enhanced conditions for landscape stagnation. The presence of saline soils in this area was reported earlier by Puchulu and Fernández (2014).

The flat topography of the central part is an ideal setting for primary salinity due to landscape stagnation. Salts that cannot be exported by the river system will accumulate in topographic depressions such as the Salinas de Ambargasta, the Saladillos de Huyamampa and the Rio Dulce's alluvial plain. The Salinas de Ambargasta (number 1 on Figure 3.9 and Appendix A.2.2) stand out as the most saline area in the region (see Figure 3.7a). The salt lake is formed in an endorheic basin: the water inflow mainly consists of saline groundwater that seeps out along major tectonic structures. The evaporation exceeds water input resulting in ongoing salt accumulation at the surface (Figuroa et al., 2020). The formation of the Saladillos de Huyamampa (number 2 on Figure 3.9 and Appendix A.2.2) is most likely related to groundwater seepage and blocked drainage in the neighborhood of the Huyamampa Fault. The saline open water that accumulates in small topographic depressions is affected by high evaporation rates (caused by the high water deficit) leading to the formation of evaporites. The third topographic depression is the Rio Dulce's alluvial plain

(number 3 on Figure 3.9 and Appendix A.2.2). The plain is considered as one of the few remaining saline wetlands (Bucher, 2019). Because of its topographic position, the area is flooded occasionally, and the groundwater table is very close to the surface (Bucher, 2019).

The eastern part is characterised by high annual mean precipitation (between 1180 and 1684 mm) and a flat topography (slopes are generally less than 0.1%). Despite the high precipitation and low water deficit, the flat topography prevents effective removal of salts from the river basins. Groundwater depths in this part of the Chaco are relatively shallow (between 2 and 3 m depth), as recently shown by Giménez et al. (2020a) and Giménez et al. (2021). Marked rainfall seasonality is expected to result in seasonally fluctuating groundwater tables. At the end of the rainy season, groundwater tables are highest and salts are mobilised to the upper soil horizons. At the beginning of the dry season, salinization of the surface is expected to occur due to shallow groundwater levels, resulting in capillary rise and direct evaporation of saline groundwater. As long as the dry period lasts, the accumulated salts will not be diluted. Also in topographic depressions, such as Lagunas Saladas, groundwater tables are shallow, resulting in saline topsoils. Note that the majority of EC values we measured in the dry season of 2019 are consistently low (0.8 dS/cm). We attribute this to the very wet conditions prior to the field campaign, which resulted in the dilution of salts.

Secondary salinity: land cover changes

Land cover conversions in the Dry Chaco result in deviations from the primary salinity conditions as reported by Amdan et al. (2013); Giménez et al. (2016); Marchesini et al. (2017). However, the exact impact of anthropogenic change will depend on local climate and geomorphology that condition soil water balance and salt mobilization. Regardless of the original salt concentration in the soil mantle, it is plausible that deforestation in the western part increased deep percolation and salt leaching from the vadose zone to the water table. The risk of severe soil salinization in the near future is likely to be low: the water table is at depths of 10 to 40 m which does not pose a direct threat for remobilization of salts from the groundwater to the soil mantle. According to Amdan et al. (2013), it may take between 30 and 120 years before the rise in the water table affects the upper soil horizons in this part of the Chaco. In addition, it is still unclear whether the increased deep percolation will cause groundwater levels to rise as the excess of infiltration water can also be evacuated via regional groundwater flow. Disruption of regional groundwater flow by tectonic activity (Huyamampa Fault) results in exfiltration of groundwater along the fault trace. Local seepage of groundwater can enhance soil salinization, as observed in the agricultural

lands in the transition between the western and central parts (number 4a on Figure 3.9 and 4 in Appendix A.2.2).

In the central part, where landscape stagnation is likely to occur, the flat topography inhibits salt removal by lateral groundwater flow. It is expected that the hazard of secondary soil salinity will increase with deforestation in three areas that are prone to primary salinity (i.e., Salinas de Ambargasta, Saladillos de Huyamampa and alluvial plain of the Río Dulce). The shorter the distance to these areas, the shallower the groundwater table, and the higher the risk for capillary rise and mobilization of salts to the soil surface.

The eastern part is also characterised by flat topography but is more humid compared to the central part. A study conducted near the village of Bandera, located at the transition between the central and eastern part, indicated that deforested areas show clear signs of groundwater recharge and salt leaching (Giménez et al., 2016). Given the shallow water tables in the eastern part, there is an elevated hazard for severe soil salinization as small increases in deep percolation can result in rapid rise of the water table. The observations from satellite imagery support this statement, as numerous salt crusts were observed in agriculture plots (number 4b on Figure 3.9 and 4 in Appendix A.2.2). Changing hydrological conditions were reported in recent work by Giménez et al. (2020b) who documented a massive waterlogging event in the eastern part that was caused by recent rise of the groundwater table after large-scale deforestation.

Besides deforestation, irrigation schemes artificially change the soil water balance in agricultural plots and can enhance secondary salinization (number 5 on Figure 3.9 and Appendix A.2.2). In the transition between the western and central parts, the alluvial fan of the Río Dulce forms an elevated area. The fan is occupied by numerous small-sized farms for irrigation-fed agriculture. The satellite-based assessment (Figure 3.3) shows the occurrence of salt patches in numerous agricultural plots. This confirms earlier statements by Prieto et al. (2005) about the unsatisfactory performance of the Río Dulce irrigation project, related to lack of maintenance of irrigation and drainage canals and inadequate water management at the field level with excessive application depths.

Small scale salinity processes

Although salt crusts are barely present in the western part due to high elevation and intense salt leaching after deforestation, several small patches of salt crusts were identified during the field campaign and on Google Earth imagery. These patches are associated to local exfiltration of groundwater in incised river valleys (number 6 on Figure 3.9 and Appendix A.2.2). In the eastern part, the

flat topography and poorly incised river network increase the hazard of soil salinization by impeding regional groundwater flow. This favours pounding of water during flood events, followed by precipitation of dissolved salts after evaporation of saline groundwater. Several flooding events can be observed on satellite-imagery during the rainy season, leaving visible traces during the dry season in the form of salt crusting and reduced vegetation growth (number 7 on Figure 3.9 and Appendix A.2.2).

3.4.2 Vegetation phenology in relation to soil salinity

In addition to the geomorphological and hydrometeorological controls on soil salinity, we also explored the relation between the EC values and the density of green vegetation (and its seasonal variation represented by σ_{GVF}). This allows us to test if remotely sensed vegetation indices can be used as an indirect indicator of soil salinity. The satellite-derived σ_{GVF} pattern (as shown in Figure 3.5e) shows vegetation phenology for natural vegetation (including xerophytic forests, savannah and halophytic shrublands) and agricultural lands. The results from the MARS regression show a negative relation between the subsurface EC and the seasonal cycle in GVF (represented by σ_{GVF}). This indicates that vegetation can grow to its full potential, when it is not affected by any form of (salt) stress. In contrast, areas with low temporal standard deviations in GVF, are characterized by high EC values.

In the Dry Chaco, the natural vegetation pattern is a patchwork of seasonally dry and xerophytic forests with *Aspidosperma quebracho blanco* and *Schinopsis lorentzii* species to halophytic shrublands and herbaceous plants in saline-affected areas (Gobbi et al., 2020). Figure 3.10b shows a scatter density cloud of the σ_{GVF} and the modelled subsurface EC values, classified according to the three major land cover types: forest (n=21588), herbaceous plants (n=4405), and agricultural lands (n=31358) as derived from the ESA-CCI landcover map. The field measurements are plotted with their corresponding σ_{GVF} . Figure 3.10b illustrates that forests have intermediate σ_{GVF} and EC values. Dry forests have relatively high annual means of GVF , without much variability throughout the year. Forests tend to present high subsurface EC values from arrested drainage conditions. Herbaceous vegetation with lower σ_{GVF} values is predominant on soils with EC values above 15 dS/m. These areas with halophytic vegetation have low GVF along the year, and low variability in GVF over the year. The scatter density cloud illustrates the interaction between plant functional types and soil salinity, where plant types and phenological activity differ with soil salinity.

In addition to primary salinity, anthropogenic activities create secondary

salinization patterns. This pathway is represented with green and blue arrows in Figure 3.10a and b. In a first phase (green arrow), deforestation can lead to an increase in the σ_{GVF} , as croplands are characterised by a higher seasonality in GVF compared to forests and herbaceous plants. Figure 3.10b illustrates that croplands with above-average σ_{GVF} values have modelled EC values below 5 dS/m. A negative relation between σ_{GVF} and the modelled EC is observed: increasing soil salt levels are coinciding with decreasing σ_{GVF} of the crops (blue arrow). Although this could be interpreted as the first effects of secondary salinization on crop growth, detailed analyses are needed to account for crop management. Relatively low σ_{GVF} values for croplands can be the result of poor crop performance but also of intensified crop system with high GVF in the case of e.g. highly productive double-crop systems (Giménez et al., 2020b).

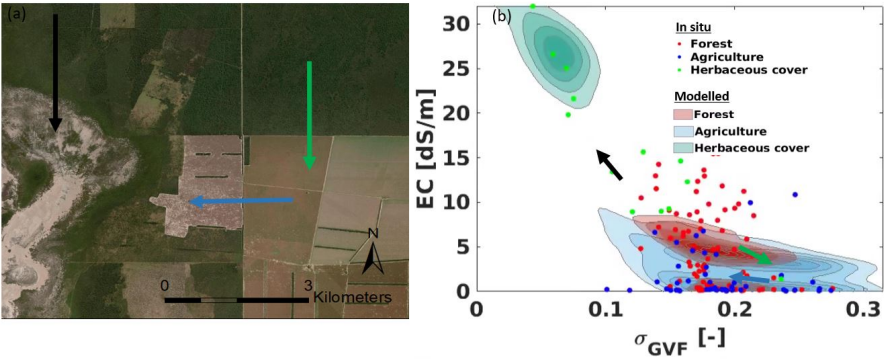


Figure 3.10: (a) Illustration of gradients in soil salinity as observed in very high resolution satellite imagery. The black arrow shows changes in vegetation along a natural gradient in salinity, while the green and blue arrows illustrate the effect of deforestation on secondary salinization. (b) Relation between σ_{GVF} and modelled subsurface EC values for three land cover types: with increasing soil salinity (black arrow), salt-tolerant herbaceous plants become dominant showing low σ_{GVF} . Conversion of forest to cropland causes first an increase in σ_{GVF} and decrease in EC (green arrow). When dryland salinization occurs, the EC increases and σ_{GVF} decreases (blue arrow).

The observed association between the modelled subsurface EC and the remotely sensed σ_{GVF} demonstrates the potential of remote sensing indices to track soil salinity, but the relation itself does not provide additional information about the driving processes. Hence, the methodological set-up, i.e., associating EC measurements to different environmental variables, should be considered as a mere spatial association rather than an analytical model that aims to predict soil

salinity based on explanatory variables *sensu stricto*. It must be mentioned that the use of σ_{GVF} as ‘explanatory’ variable in the regression model introduces a degree of endogeneity, as σ_{GVF} is not a primary driver, but rather a consequence of soil salinity conditions. In further research, each of the processes mentioned (deforestation, flooding, irrigation, groundwater seepage,...) needs to be studied in more detail to gain more insight into the physical mechanisms and how they lead to soil salinity in time and space.

As the main objective of this chapter was to gain insights into spatial patterns of soil salinity, we decided to not include a land cover map in our analysis. The implementation of a land cover map, or even better a map indicating the number of years since deforestation (such as the one of Vallejos et al. (2015)), could be useful in a model that attempts to predict areas affected by dryland salinization after deforestation. Combined with data on groundwater recharge, depth to groundwater, regional groundwater flows, and climate, it must be possible to develop a model that identifies agricultural areas suffering from surface salinization due to rising groundwater tables. However, such a model will not be applicable to other types of salinization processes (e.g.: how floods deposit salts on the surface, as observed in the eastern part of the Chaco, or the accumulation of evaporites in topographic depressions).

3.4.3 Uncertainties and scope for further research

The regional assessment provides insights into the spatial pattern of soil salinity (Figure 3.7a), and the salinization processes across the Dry Chaco. Based on the outcomes of the study, we identified three ways that can contribute to resolve the uncertainties that are associated with a spatial regression approach. First, there is a spatial mismatch between our point-measurements and the 1 km resolution of the final salinity-map, whereby the point measurements are not fully representative for the ‘real’ EC value of the entire pixel. The representativeness of the in situ salinity measurements can be addressed by studying the spatial variability of soil salinity measurements at the 1 km scale.

Second, time series analyses of soil salinity, groundwater level and water quality data can contribute to unravel the intra- and inter-annual variations in soil salinity. In this study, the EC measurements were taken during the 2019 dry season and contain imprints of first, second and third order temporal variability. The intra- and inter-annual variations due to e.g. precipitation-events were not fully accounted for in the hydrometeorological and vegetation data. For the salinization processes described above, the temporal variations in soil salinity are expected to be small for the central and western part. As shown by Jobbágy and Jackson (2004), temporal EC variations over forested areas (such as the central

part) tend to be minimal. Also, over agricultural areas where the groundwater table is deep (such as in the western part of the study area), most salts are leached from the upper soil horizons, and one can expect low EC-variations over time. In contrast, over the eastern part, there is field evidence for large temporal variation in soil salinity. During the field campaign, low EC values of around 0.58 dS/m were measured. Most likely, the extremely wet conditions of May and June 2019 caused a dilution of soil salts resulting in low EC values. The temporal variability in EC values can also explain the discrepancy that we observed between the EC measurements and the Google Earth assessment: although we reported low EC values in the field, numerous salt patches were identified based on Google Earth imagery. We attribute this variation to the shallow and fluctuating groundwater levels whereby salts are mobilised as a function of soil and groundwater fluxes. Continuous monitoring of soil salinity, groundwater level and water quality across the Dry Chaco will remain important. Given the extensiveness of this data-scarce region, land surface models combined with satellite retrievals and field data from monitoring networks may provide complementary information. Especially recent advances in the detection of shallow groundwater tables based on space-borne soil moisture observations can be promising for further regional salinity assessments (Soylu and Bras, 2021).

Third, a comprehensive analysis of salinity variations with depth is needed to evaluate the soil salinity hazard over the Dry Chaco. Recent work by Jobbágy et al. (2020) stated that soil profiles under natural vegetation can display a strong increase in salt content below the first or second meter. Therefore, a regional salinity map based on samples taken in the upper 1 m of soil material might underestimate the overall salinity hazard. Besides, Jobbágy et al. (2011) found that also soil texture plays an important role in determining the salinization hazard as soil chloride accumulation was not observed in much drier but extremely sandy environments (sand dunes). Future work is needed to quantify soil salinity variations with depth and how it relates to soil texture, as this will be informative for understanding the salinization processes.

3.5 Conclusions

The aim of this study was to gain insights into the spatial pattern of soil salinity over the central Dry Chaco. The study started from the hypothesis that spatial variation in topography, climate and vegetation will cause regional variations in soil salinity. The conducted approach included the collection of EC measurements, as a proxy for soil salinity, along multiple east-west transects covering the existing topographic and climatic gradients. The collected data contains both surface and subsurface (1 m depth) measurements. Data on

surface salinity was further expanded with the identification of salt crusts on Google Earth imagery. Compared to surface salinity that was generally low but noisy, the subsurface salinity was systematically higher and showed clear regional spatial patterns. A correlation analysis between the subsurface EC measurements and multiple environmental variables showed that subsurface EC was closely related to the annual water budget (represented as $P - Pet$), the annual standard deviation of the Greenness Vegetation Fraction (as proxy for vegetation phenology) and topography. Remotely-sensed vegetation indices such as the seasonal variation in the density of green vegetation, σ_{GVF} , are shown to be particularly suitable for identifying primary soil salinity at regional scale. The environmental variables were further used in a regression model to create an interpolated subsurface salinity map for the region. The regional salinity analysis showed that the sensitivity to soil salinization is not spatially uniform. Over flat areas with high water deficits, salts get retained in the soil profile and are prevented from leaching. Severe natural soil salinization processes occur in these dry areas when the groundwater table is high, water stagnates and high evapotranspiration leads to the formation of evaporites. Low natural salinity values are observed in regions with higher slope gradients as salts are effectively leached from the catchments by regional groundwater transport. Also over areas with higher rainfall inputs, low salinity conditions are observed due to salt leaching. The data show how secondary salinity is imprinted on the primary salinity pattern, particularly in agricultural areas with shallow groundwater tables, and irrigated croplands. The results can provide a basis for further research on the spatial variations of natural and secondary salinity in dryland ecosystems and can inform the development of adequate land use planning and groundwater/salinity monitoring networks. Although this study focused on the central Argentinean Dry Chaco, the methods can be applied to nearby places where regional salinity studies are lacking.

Chapter 4

Spatiotemporal analysis of secondary soil salinity over the central Argentinean Dry Chaco

Based on:

Maertens, M., Vanacker, V., De Lannoy, G. J. M., Galindo, M., Gasparri, I., Giménez, R., (in prep.): Spatiotemporal analysis of secondary soil salinity over the central Argentinean Dry Chaco, 2021

4.1 Introduction

In semi-arid to sub-humid ecosystems, water is the limiting factor for vegetation growth. Native plant and tree species are adapted to these arid conditions and tend to optimize their water use, for example, by selectively allocating water to sites of new tissue growth, minimizing water loss to the atmosphere, developing deep root networks, or using their own water storage systems (Hatton and Nulsen, 1999; Eagleson, 2005; Santoni et al., 2010). These ecosystems consume water input from precipitation by transpiration and direct evaporation, preventing deep drainage to deeper soil horizons (Seyfried et al., 2005; Small, 2005). Extremely low rates of deep drainage and groundwater recharge have

been reported in dry forests and grassland ecosystems of Africa, Australia, Asia and North and South America (Santoni et al., 2010).

The specific hydro-ecological conditions of subtropical forests may lead to accumulation of salts in the soil profile. Salts in the soil mantle originate from (weathering of) parent material or atmospheric deposition (Rengasamy, 2006). Plant traits such as deep root systems, perennial life cycles and phenologies adapted to local hydroclimatic seasonality limit the percolation of water below the root front. As a result salts are retained in the vadose zone (Kim and Jackson, 2012). This is particularly the case in flat sedimentary plains where horizontal groundwater flow is limited, and lateral transport and export of salts is negligible (Jobbágy et al., 2020).

Modification of natural vegetation cover, by e.g., human-driven deforestation, can affect the local hydrology of semi-arid ecosystems through changes in evapotranspiration (Allen et al., 1998), plant phenology (Bisigato and Laphitz, 2009), and rooting depth (Huxman et al., 2005). They can lead to slow but steady changes in the soil-water balance and favor the development of deep drainage during or after wet periods (Jobbágy et al., 2020). Changes in soil hydrology have implications for the storage and mobilization of water-soluble salts in the soil column, and soil salinity. A reduction of evapotranspiration after deforestation can increase deep drainage. The percolation of water below the root zone facilitates leaching of water-soluble salts from the upper soil horizons towards the groundwater table and can lead to a decrease in soil salinity. Over time, progressive percolation and deep drainage drive a gradual rise of the groundwater table. Once the phreatic zone is at or very close to the soil surface, the upward capillary rise of water from plant transpiration or evaporation remobilizes dissolved salts to the soil surface. When elevated salt concentrations are observed in the upper soil horizons, chemical degradation has a direct impact on plant growth (Giménez et al., 2016; Marchesini et al., 2017; Jobbágy et al., 2020) and can have devastating effects on agricultural development, as experienced in large areas of Australia (Lambers, 2003).

In Chapter 3, we examined large-scale salinity patterns over the central Argentinean Dry Chaco. When analysing the empirical data on soil salinity with a spatial regression technique, we found that the salinity patterns are determined by topography (as proxy for the geomorphological context) and regional climate. As shown by Milione et al. (2020) for the Pampas Plains in Argentina, the natural salinity pattern can condition the sensitivity to secondary salinization after land cover change. In the Dry Chaco and Espinal, local case studies reported lower salinity values in agriculture lands compared to adjacent forest stands. For example, Amdan et al. (2013) reported 94% lower chloride stocks in cropland compared to dry forest. More recent work by e.g., Giménez et al. (2016) in the Dry Chaco reported complete leaching of chloride pools

beneath deforested areas down to the water table. The studies in the Dry Chaco and Espinal have in common that they analyzed individual cases at the plot-level scale, and did not account for spatial variability in climate and topography across the region. In addition, they characterized the soil salinity based on electrical conductivity (EC) and chloride concentration in the soil column (Amdan et al., 2013; Marchesini et al., 2013; Santoni et al., 2010; Contreras et al., 2013). Hence, few data is available on the chemical signature of the water-soluble salts in Dry Chaco soils, and its spatial variation across the region. Recent work by Jobbágy et al. (2020) found that only 50% of the accumulated salts is due to chloride accumulation, highlighting the need to explore the full range of dissolved salts that contribute to salinity stress.

Based on the findings of Chapter 3, we hypothesize that the regional climatic and geomorphological context conditions the sensitivity for dryland salinity after deforestation, and that the impact of deforestation on soil salinity is spatially dependent. The risk of dryland salinization is expected to be high when deforestation takes place near areas prone to primary salinity, corresponding to topographic depressions and areas with high water deficits. The closer to these areas, the shallower the groundwater table, and the higher the risk of capillary rise and mobilization of salts from the vadose zone to the upper soil horizons. At the contrary, the risk for secondary salinity is expected to be low in landscapes with high topographic gradients and deep groundwater tables. Increased percolation after deforestation tends to mobilize salts to the groundwater table, and evacuate dissolved salts by regional groundwater flow. Similarly, in areas with low water deficits, the risk for dryland salinization is considered to be low.

Based on the above-mentioned research gaps and hypotheses, our research questions are: (i) How is the geomorphological context controlling the sensitivity to secondary soil salinization after deforestation? (ii) How do soil salt concentrations evolve over time after deforestation, (iii) What is the chemical composition of salts in the vadose zone, and (iv) Which variation exists in soil salt chemical composition over the Dry Chaco?

To address these questions, a paired study including agriculture and matched forest sites was set up in the Dry Chaco. Soil samples were taken during the dry season of 2015 and 2019 across the existing topographical gradient in the Dry Chaco. These gradients are closely related with geomorphology and depth to the groundwater table. Hence, the samples were pooled into distinct geomorphological clusters characterized by different elevation and groundwater depth.

Soil salinity was determined based on the total concentration of water-soluble salts in bulk soil samples and on the EC of the soil saturated paste extracts.

The elemental composition of the saturated paste extracts was determined using Coupled Plasma-Atomic-Emission Spectroscopy and Liquid Phase Ion Chromatography measurements at the Earth and Life Institute (UCLouvain).

4.2 Methodology

4.2.1 In situ data collection

Field sampling was done in 2015 and 2019 in the provinces of Tucuman, Santiago del Estero, and Salta (Figure 4.1). The two datasets used a similar control and treatment sampling strategy, with soil samples collected in agricultural and matched forest sites. Seasonally dry forest is the natural vegetation type of this part of the Chaco, with *Aspidosperma quebracho blanco*, *Schinopsis quebracho colorado*, *Chlorisia speciosa* and *Caesalpinea paraquariensis* as dominant species. The year of deforestation for each agriculture site was derived from the plot-level geodatabase of Vallejos et al. (2015) covering the deforestation history of the Dry Chaco since the 1970s.

Chapter 3 showed that natural salinity patterns in the central Argentinean Dry Chaco are mainly determined by geomorphology and climate. This chapter focuses on a subregion of the central Argentinean Dry Chaco with a homogeneous climate. Hence, differences in soil chemical signature between forest and agriculture are analysed as a function of the geomorphological context.

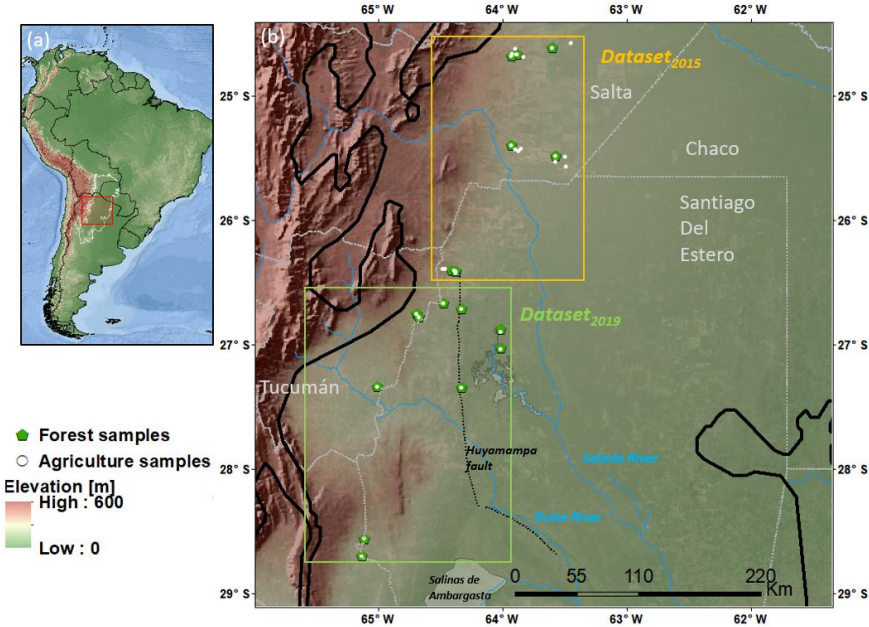


Figure 4.1: (a) Location of the Dry Chaco in South America and (b) location of sites sampled in 2015 and 2019.

The soil samples of 2019 (Vincent et al., 2021) were taken in the southern part of the study area, in cropland and matched sites of dry forest to a depth of 2 m. The dataset contains measurements at 10 paired sites taken at 4 depths (0-20 cm, 20-40 cm, 80-100 cm, and 200 cm). The paired samples were divided in three geomorphological clusters based on elevation and depth to groundwater (see Figure 4.2). The upper cluster corresponds to the region above 300 m where groundwater levels are considered to be at 10 to 40 m depth (Nicolli et al., 2008). The landscape in this cluster is dominated by agricultural lands, and there are only a few and small forest sites remaining. The mean area of the sampled forest sites in this cluster is 0.36 km². The middle cluster encompasses the region with altitudes between 200 and 300 m, and sits at the transition between the upper and lower clusters. Agriculture and forest sites form a mosaic pattern and the size of the visited forest sites is larger (5.76 km²) compared to the upper cluster. The lower cluster groups the samples east of the Huyamampa Fault where the elevation is below 200 m and where shallow groundwater levels (< 2 m depth) were observed during the field campaign. Native forests and shrublands are the dominant land cover, and small salt lakes are abundant (like e.g., Saladillos de Huyamampa). In this cluster, the agricultural sites are small,

and embedded in large areas covered by native forests.

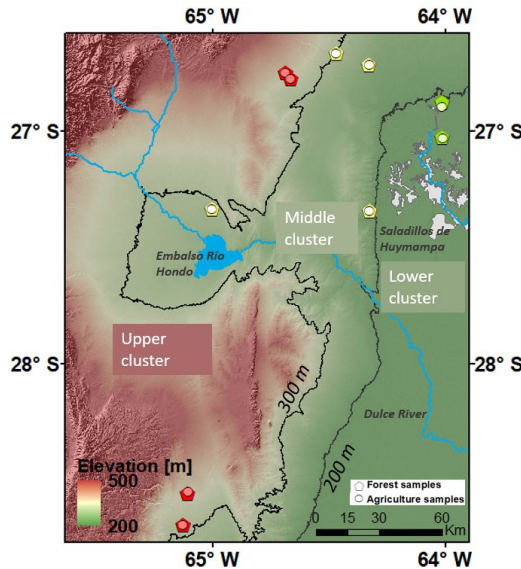


Figure 4.2: Location of the three geomorphological clusters of the dataset₂₀₁₉ and indication of the sampled forest and agriculture sites.

The samples of 2015 were collected in the southern part of Salta province near the villages of Las Lajitas, El Quebrachal and Rapelli. Near each village, the dataset includes samples from 6 to 8 croplands and 2 to 3 matched forest sites to control for natural soil salinity. In total, the dataset contains samples from 30 sites at 3 depths (0-15, 15-30, and 30-35 cm). The elevation of the samples ranges from 391 m in the west to 256 m in the east. Given the different depths at which the samples are collected compared to *dataset*₂₀₁₉, the two datasets are analyzed separately. Groundwater levels in this part of the Chaco are reported to be at a depth of 12 to 20 m (Amdan et al., 2013) and are not affecting the upper soil horizons. Hence, the samples of this dataset are not further divided into different geomorphological clusters. Given the high number of samples collected in agriculture plots, the dataset can provide relevant insights in how salinity concentrations evolve over time after deforestation. Note that such a temporal analysis is not feasible for the dataset₂₀₁₉, as the number of paired samples is limited and samples were collected in different geomorphological settings.

4.2.2 Chemical and statistical analysis

From saturated soil-paste extracts, we determined the electrical conductivity (EC_e) and the total concentration of water-soluble salts. Saturated paste extractions simulate the environment of naturally occurring moisture-saturated soils and are considered to be most representative to study plant and soil response to salinity (Pansu and Gautheyrou, 2007). Saturated pastes were prepared according to standard methods by adding deionized water to approximately 10 g of soil sample until a state of complete saturation is reached (Richards, 1954; Longenecker and Lyster, 1964). Pastes were left to rest and equilibrate for 1 h. An extract of the saturated paste was obtained by vacuum filtration. The extracts were diluted to 50 ml. The temperature-corrected EC (expressed in dS/m) of the solution was measured using a YSI proDSS probe. The YSI proDSS EC sensor measures values in the range of 0 to 200 dS/m with an accuracy of 0.001 dS/m. The proDSS probe was tested and calibrated daily with a KCl (Potassium chloride) conductivity standard solution of 1 dS/m. Samples were bias-corrected by subtracting the EC from blank samples containing water of Type I. By multiplying the bias-corrected EC with the dilution factor of the solution, we obtained the EC of the saturated paste extracts.

The ion concentrations of the saturated paste extracts were determined using Inductively Coupled Plasma-Atomic Emission Spectroscopy (ICP-AES) and Liquid Phase Ion Chromatography (IC). The measurements were realized with the ICP-AES (Thermo Scientific iCAP 6000 Series) and IC (Thermo Scientific Dionex) of the Earth and Life Institute, UCLouvain. The analyses included calcium (Ca^{2+}), magnesium (Mg^{2+}), sodium (Na^+), potassium (K^+), chloride (Cl^-), sulfate (SO_4^{2-}), and nitrate (NO_3^{2-}). The concentrations of the major elements (ppm) were blank-corrected and converted to mass concentrations (mg/kg) following the ISO 22036 protocol:

$$W_e = \frac{(\rho_1 - \rho_0)}{m} \cdot f \cdot V \quad (4.1)$$

where W_e is the mass concentration of an element in the sample (mg/kg of dry mass), ρ_1 is the concentration (ppm or mg/kg) of the diluted sample, ρ_0 is the mean concentration of the blank (ppm or mg/kg), f is the dilution factor, V is the volume (ml or g) of the sample taken for analysis, m is the mass of the soil sample (g).

We tested for differences between control (forest) and treatment (agriculture) in terms of EC_e values and chemical composition of the saturated paste extracts. Given the small amount of data, a Student's t-test could not be performed because the assumptions of normality and homoscedasticity could not be met. Therefore, its non-parametric counterpart, the Wilcoxon test, was applied. The

Wilcoxon test is a paired difference test and is used to assess whether the population mean rank between two samples differs.

4.3 Results

4.3.1 EC_e vs concentrations

The EC_e of the saturated paste extract and the total concentration of water-soluble salts are two independent measures of soil salinity. The measured EC_e is expected to be proportional to the ion concentration of the soil extracts (Pansu and Gautheyrou, 2007), whereby the proportionality depends on the type of salts. The total ion concentration was here derived as the sum of the ions mentioned in section 4.2.2 and does not include carbonates and bicarbonates. Figure 4.3 shows that the EC_e values (expressed in dS/m) are significantly correlated with the ion concentrations ($R=0.99$, $P<0.001$). The linear relationship is consistent with the empirical relationship reported by Pansu and Gautheyrou (2007). The slope of the regression line (568 ppm*dS/m) is somewhat lower than the values reported by Pansu (600 to 650 ppm*dS/m), which is expected because carbonates and bicarbonates were not accounted for.

Given the strong correlation between the total ion concentration and EC_e values, the following sections only report on the results that are based on the total ion concentrations.

4.3.2 Spatial variability in the dataset₂₀₁₉

The total ion concentrations of the paired sites (expressed in mg/kg) are shown in Figure 4.4, where the data are represented by cluster and categorized by depth. In the upper cluster, agricultural sites have concentrations of water-soluble salts between 34 and 60 mg/kg that do not vary with depth (Figure 4.4). Under forests, the mean salt concentration increases with depth: the mean concentration is 51 mg/kg at the surface while it increases to an average value of 813 mg/kg at two meters depth. The salt concentration at a depth of 2 m strongly varies in forests with concentrations ranging from 22 to 2350 mg/kg. Compared to the forest sites, the scatter is much smaller under agriculture. The Wilcoxon test showed that there are no significant differences in soil salinity between forests and agricultural sites (P value = 0.84).

In the middle cluster (200 to 300 m), the mean salt concentrations are higher than in the upper cluster. Similar differences between forest and agriculture

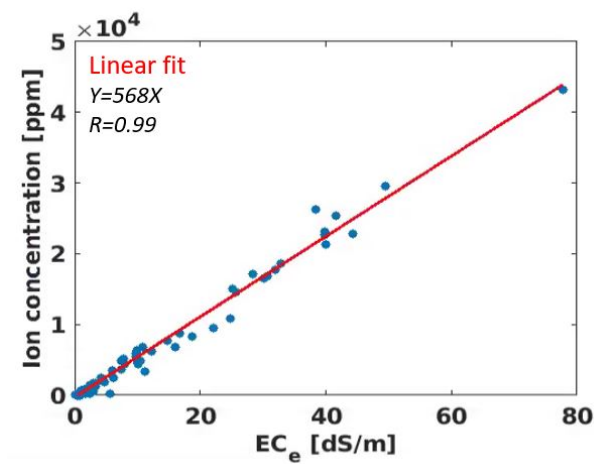


Figure 4.3: Scatterplot between EC_e and total ion concentration in soil extracts, including all samples of the dataset₂₀₁₅ and dataset₂₀₁₉, with indication of correlation coefficient (R) and linear regression equation.

sites are observed with the latter having lower salt concentrations than adjacent forest sites with mean concentrations of 515 and 1750 mg/kg at 1 m depth respectively. Note that the large spread in salt concentrations among forests was also observed here. The differences in salinity between forest and agriculture were significant (p-value=0.002).

Soils in the lower cluster are characterized by the highest concentrations of water-soluble salts in the saturated paste extracts with values above 3000 mg/kg at 1 and 2 meters depth (Figure 4.4c). Differences in salt concentrations between forests and agriculture are much smaller than in the middle cluster, and are not significant at the 0.05 level. At the surface, the mean salt concentration of the agricultural soils exceeds this of forests (1440 vs. 922 mg/kg).

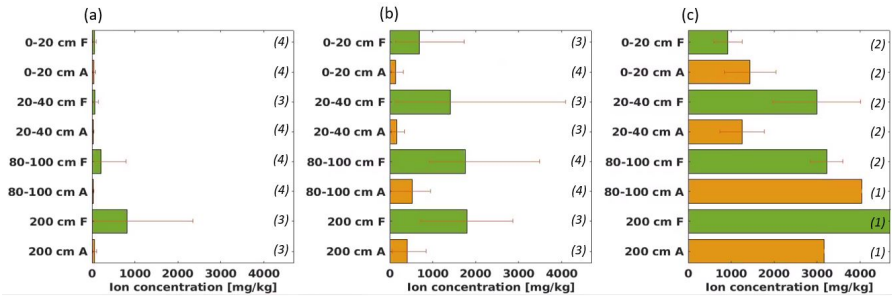


Figure 4.4: Mean total ion concentrations for the three clusters of dataset₂₀₁₉ (a: upper cluster, b: middle cluster, c: lower cluster) shown per soil depth for paired forest (F) and agriculture (A) sites. The horizontal line represents the spread in each category by indicating the minimum and maximum salt concentrations. The number between brackets indicates the amount of samples in each class.

4.3.3 Chemical fingerprint of water-soluble salts in the dataset₂₀₁₉

Figure 4.5 shows the relative contribution of each chemical element to the ion concentration measured in the three clusters. The data are grouped per soil depth and classified in control and treatment sites (a-c= forest, d-f= agriculture). Ca^{2+} and Na^{+} are the major cations contributing respectively 10%, and 21% to the total ion concentration. The Ca^{2+} concentration decreases with depth beneath forests. SO_4^{2-} (32%) and Cl^{-} (24%) are the major anions, followed by NO_3^{-} , which has a relative contribution of 7%. The concentration of SO_4^{2-} shows an increase with depth in forested areas, and this increase in SO_4^{2-} is partially compensated by a decrease in Cl^{-} . The proportion of K^{+} and Mg^{2+} is generally below 2%.

There are differences in the chemical composition of the soil extracts between the three clusters. In the upper cluster, the relative contribution of Ca^{2+} is larger compared to the middle and lower clusters. In the agricultural sites of the upper and middle cluster, relative high concentrations of NO_3^{-} are measured (up to 30% at the surface in the upper cluster). Most likely this can be explained by the use of fertilizers in croplands and/or atmospheric N deposition as nearby forest topsoils also contain considerable amounts of NO_3^{-} (22% in the upper cluster).

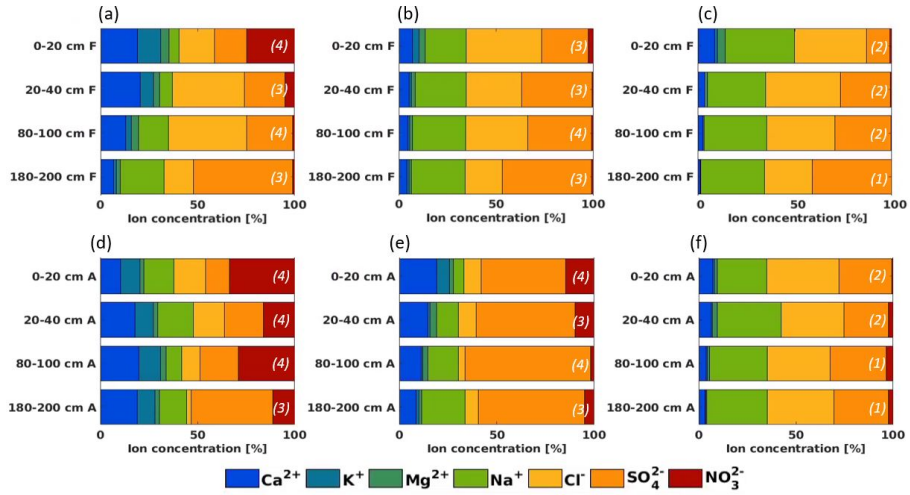


Figure 4.5: Chemical fingerprint of water-soluble salts for the three clusters of dataset₂₀₁₉ (a,d: upper cluster, b,e: middle cluster, c,f: lower cluster) for paired agriculture (A) and forest (F) sites. The values were grouped per soil depth. The number between brackets indicates the amount of samples in each class.

4.3.4 Spatial and temporal variability in the dataset₂₀₁₅

The differences in soil salinity between forest and agriculture sites derived from the dataset₂₀₁₅ are shown in Figure 4.6. In contrast to the dataset₂₀₁₉, the measurements cover only topsoil material sampled between 0 and 35 cm depth. Mean salt concentrations under forest are relatively constant in the first few centimeters of the soil, with mean values around 155 mg/kg. Note that there is a large spread in the forest measurements, similar to what we observed in the dataset₂₀₁₉. Mean ion concentrations under agriculture sites range from 40 to 50 mg/kg, but individual samples can reach values up to 250 mg/kg. The values are in the range of concentrations measured in the upper cluster of dataset₂₀₁₉. The dataset₂₀₁₅ shows significant differences in soil salinity between forest and agriculture sites at all depths with P values ≤ 0.05 .

In the dataset₂₀₁₅, Ca^{2+} makes up 20% of the total ion load, followed by Na^+ (12%) and K^+ (5%) (see Figure 4.6b and c). All other cations have percentages lower than 3%. The major anions are NO_3^- (23%), followed by Cl^- (19%) and SO_4^{2-} (17%). As the samples were taken over a depth of only 35 cm below the surface, there are no important differences with depth. When comparing forest

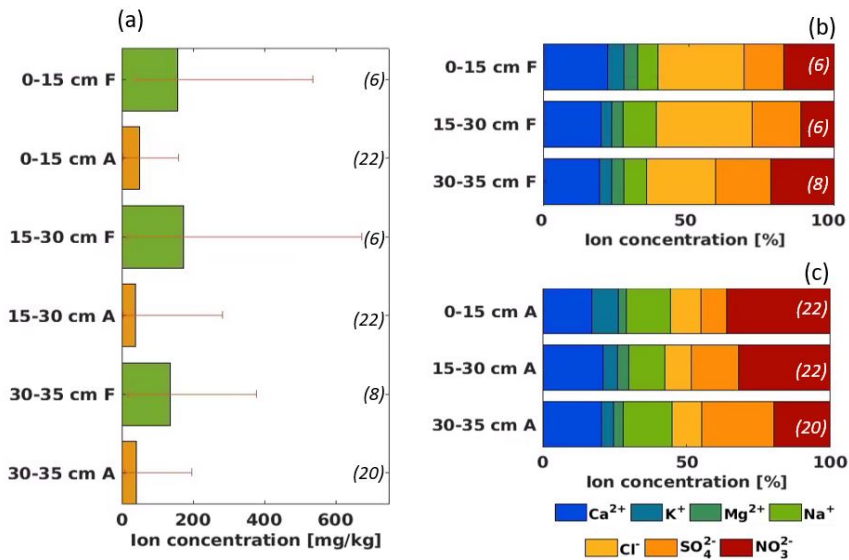


Figure 4.6: (a) Mean total ion concentrations per depth for forests (F) and agriculture (A) sites. The horizontal line represents the spread in each category by indicating the minimum and maximum salt concentration. (b-c) Relative contribution of the water-soluble salts to the total ion concentration for forest and agriculture.

with agricultural sites, NO_3^- concentrations are twice as high in croplands, and the opposite is true for Cl^- .

The concentration of water-soluble salts in the soil extracts strongly decreases after deforestation. Figure 4.7a shows the exponential decrease of the total salt concentrations with time since clearing and cultivation. Based on the empirical dataset, we estimated that water-soluble salts are almost completely leached from the topsoil in approximately 30-40 years after deforestation. When analyzing the chemical signature of the element mobility, it is clear that the mean Cl^- concentration decreases most strongly (from 43 mg/kg to 5 mg/kg) and abruptly after land clearing, whereas the decrease of the other ions is much more gradual (figure 4.7b). At the same time, the NO_3^- concentration peaks during the first years after land clearing. This observation further emphasizes the role of fertilizers in changing the soil chemical properties during the first years after land clearing.

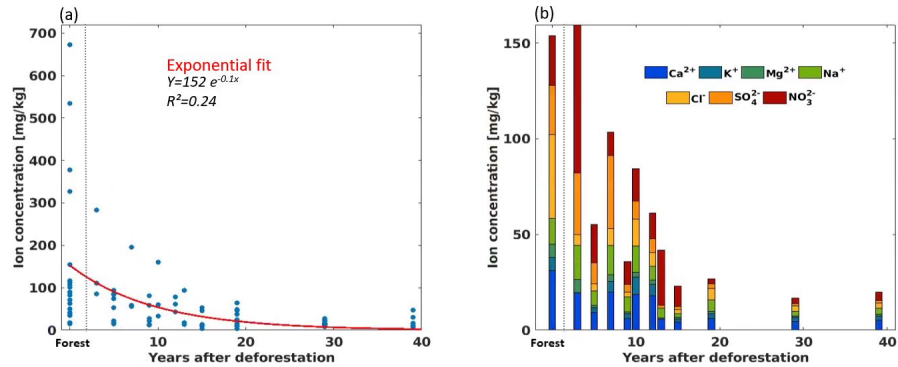


Figure 4.7: (a) Temporal evolution of total ion concentrations after deforestation for the samples of dataset₂₀₁₅, for all depths. (b) Mean contribution of the different ions to the total ion concentration. For each year, means are calculated over the number of data-points available as shown in figure (a).

4.4 Discussion

4.4.1 Spatial context

Along the geomorphological gradient, there are clear differences in the sensitivity to soil salinity after deforestation. In the upper and middle clusters, differences in total ion concentration between forest and agriculture are highest, whereby salt concentrations are significantly lower in the agriculture sites compared to the adjacent forests. In the lower cluster, salt concentrations were generally higher compared to the other two clusters, with smaller differences between forest and agriculture. These spatial differences are most likely associated with differences in groundwater depth as summarized in Figure 4.8.

The area of the upper cluster has relatively deep groundwater tables (between 10 to 40 m according Nicolli et al. (2008)). Increased deep percolation of water following logging may cause groundwater levels to rise, but likely not significantly enough to reach the top two meters of the soil profile. Besides, studies of groundwater movement south of San Miguel de Tucuman indicate that the main groundwater flow direction in this area is to the southeast (García et al., 2001), suggesting that salts may be exported at depth via groundwater transport. Finally, the small size of the remaining forest patches in this area might lead to a certain amount of salt leaching under forest sites. Most likely, their size is too small to sustain the condition of arrested drainage and deep percolation. Hence, salt leaching is expected to occur during the wet periods

(see section 4.4.4).

In the middle cluster, salt concentrations in agricultural soils are lower than in forests. This difference between control and treatment is indicative of enhanced salt leaching towards the groundwater table after deforestation. The forest stands in the middle cluster yield significantly higher salt concentrations than the upper cluster, which could be due to their larger size. It is expected that larger and dense forests plots are more efficient in their water consumption than smaller plots, avoiding deep drainage and salt leaching to deeper soil horizons.

These findings in the upper and middle cluster are consistent with the results of Amdan et al. (2013); Giménez et al. (2016, 2020b), who observed lower salinity values under croplands compared to forests. In-depth temporal analyses of soil salinity near the village of Bandera (Santiago Del Estero, Argentina) showed that deep percolation and salt leaching in croplands occur mainly in anomalously wet years (rainfall > 1000 mm) and are unlikely to occur in relatively dry years (rainfall < 800 mm) (Giménez et al., 2020b).

In the lower cluster, corresponding to areas east of the Huyamampa Fault, we observed the highest salt concentrations in the area. No statistical differences were found between agriculture lands and forests. In our dataset, salt accumulation is observed in the upper soil horizons of agricultural sites, where the soil salinity of agricultural lands sometimes exceeds that of forests. Given the shallow groundwater table in the lower cluster, it is expected that capillary rise of salt water increases the risk for dryland salinization. However, these results should be interpreted with caution due to the small sample size.

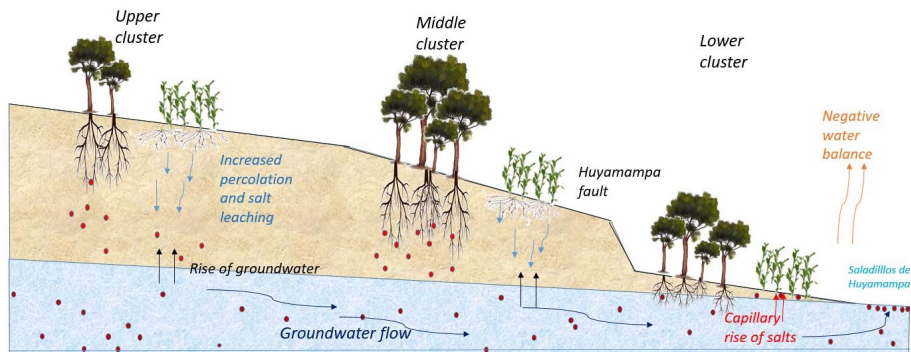


Figure 4.8: Schematic overview of the impact of topography, groundwater and land cover on soil salinity.

In short, our data show a spatial east-west trend in the concentrations of

water-soluble salts that corresponds with the existing trend in topography and groundwater depth. It is mainly the depth of the groundwater table that determines the soil salinity following deforestation. Climate is also expected to have an important influence on the reaction of soil salinity following deforestation. However, due to the relatively small area covered in this chapter, not enough spatial variability in climate was included to test this hypothesis.

When extrapolating these findings to the regional salinity patterns as discussed in Chapter 3, it is expected that also the alluvial plain of the Rio Dulce and areas adjacent to Salinas Grandes and Ambargasta are prone to rapid soil salinization after deforestation, as these areas are also characterized by shallow groundwater tables.

It is important to mention that there is a whole range of land uses that can be applied after deforestation. In the the Dry Chaco, forests are mainly converted to pasture and cropland. In our analysis, we did not make a distinction between both land uses as our dataset was too small to draw statistically significant conclusions regarding the effect of land use. Although there may be small differences in the soil-water balance between croplands and pasture, we believe that the overall effect, i.e., leaching of salts due to increased deep percolation, takes place in both classes, and that the type of conversion will only have a secondary impact. This is confirmed by findings of Amdan et al. (2013), who reported that agricultural soybean stands have higher rates of groundwater recharge (values between 27 and 87 mm per year) compared to the ones of pasture (10.4 mm per year).

4.4.2 Temporal context

Temporal analysis of ion concentrations from the dataset₂₀₁₅ showed a clear dependence of the salt concentrations on the number of years after deforestation: the concentration of water-soluble salts in the soil decreases with the time after deforestation. The negative exponential trend in the data points to a nonlinear behavior whereby a rapid leaching of water-soluble salts occurs during the first 5 to 10 years after forest conversion to agriculture. Our data show little variation in salt concentrations in sites that were deforested between 15 to 40 years. This suggests that salt levels in the upper 40 cm of soil are not yet affected by rising groundwater levels and associated salt intrusions in this specific part of the Chaco. Given that the groundwater table is assumed to be 12 to 20 m deep in this area (Amdan et al., 2013), it is not surprising that the uppermost soil horizons are not yet affected by severe soil salinization.

Our results are consistent with the findings of Amdan et al. (2013), who analyzed the chloride stock in forests and agriculture sites in Salta province, covering

the same area as the dataset₂₀₁₅. They analyzed seven paired stands of natural dry forests and agriculture, with different age of clearance (>30 years, 20 and 3 years) Their measurements went down to 6 m depth and they concluded that chloride peaks migrated down to 6 m depth 30 years after deforestation and that a draining surplus of about 30-60 mm per year is necessary to explain such differences.

Based on the calculated draining surplus, they estimated that it would take 30 to 120 years for the water table to reach the surface in this part of the Chaco. In contrast to our results, they focused exclusively on chlorides and observed a linear decrease in chlorides with time since clearing. Our results suggest an exponential decline of total salt stocks, with abrupt changes for chloride concentrations shortly after logging, but smoother decreases for the other water-soluble salts. Similar to Jayawickreme et al. (2011) (Espinal region), we found delayed transport of sulfate (and other major ions) compared to chloride, likely related to the lower solubility of sulfate-containing gypsum salts (Jobbágy et al., 2020).

Temporal changes in soil salinity depend on the (re-)mobilization of salts in the soil mantle, and the (re-)mobilization rates are closely related to local groundwater dynamics. In areas with shallow groundwater tables, such as the lower cluster, salt leaching is expected to be minimal and upward rise of salts and groundwater to occur earlier.

4.4.3 Types and origin of salts

Our study provides unprecedented insight into the chemical signature of water-soluble salts in soils of the central Argentinean Dry Chaco. The major ions in the saturated paste extracts are Ca^{2+} , Na^+ , Cl^- and, SO_4^{2-} whereby their relative contribution depends on land cover, topography and depth of sampling.

The chemical composition of the saturated paste extracts is consistent with groundwater studies conducted in the region. Nicolli et al. (2008, 2012) analyzed groundwater samples in the wide region of San Miguel de Tucuman (corresponding with the areas of the upper cluster). Raychowdhury et al. (2014) did similar research in the area near Santiago del Estero and the Saladillos de Huyamampa (lower cluster). The chemical composition of groundwater in the region is well studied because of the high concentrations of arsenic which can have adverse health effects. Table 4.1 compares the concentrations as they were measured in the saturated paste extracts with the groundwater composition reported in above-mentioned studies. Note that the percentages are calculated solely for the ions considered in the three studies.

Table 4.1: Individual ion contribution (in %) to the total ion concentrations found in this study and percentage of each ion observed in groundwater by other studies.

Ion	Upper cluster		Lower Cluster	
	This study	Nicolli 2008	This study	Raychowdhury 2014
SO_4^{2-}	41	40	30	33
Cl^-	20	12	33	18
Na^+	19	29	31	34
Ca^{2+}	10	12	4	10
NO_3^-	5	2	1	0
K^+	3	2	0	2
Mg^{2+}	2	3	1	2
Mn^{2+}	0	0	0	0

There is still an ongoing debate on the origin of the salts in the Dry Chaco (Jobbágy et al., 2020). In areas with deep groundwater tables, chlorides in the vadose zone are expected to have an atmospheric origin that are deposited via precipitation or dust (Santoni et al., 2010). Their concentration tends to increase with depth in response to the coupled effects of water uptake by plants and chloride exclusion by roots.

In addition to an atmospheric origin, salts may also originate from chemical weathering of parent material. In the Dry Chaco, soils are mainly composed of feldspars (between 45 and 70%). Smaller amounts of quartz, muscovite and calcite are also present.

The feldspar minerals can dissolve upon contact with water, which mainly explains the observed ionic contribution of Na^+ and Ca^{2+} . The relative increase in Na^+ concentrations towards the east (lower cluster) is most likely further influenced by weathering of Na feldspars and regional groundwater transport. Based on the topographic gradients and hydraulic gradients mentioned in (García et al., 2001), we argue that percolated water in the upper and middle cluster is transported eastward to reach the surface (groundwater discharge) near the Huyamampa Fault and adjacent Saladillos (lower cluster). Considering the longer residence time, the influx of Na^+ most likely increases through weathering of feldspar present in soil's parent material as the reaction of albite (Na feldspar) to kaolinite, is responsible for Na^+ enrichment (Nicolli et al., 2012). In contrast to the Na^+ enrichment towards the lower cluster, our results show that concentrations of Ca^{2+} are the lowest in the lower cluster. As reported by Jobbágy et al. (2020), concentrations of Ca^{2+} in groundwater, together with HCO_3^- and CO_3^{2-} (not considered in this study) favors the precipitation of $CaCO_3$, possibly explaining the observed low Ca^{2+} concentrations in the lower cluster.

Studies also mention the presence of volcanic glass material in the loess, whereby the amount of volcanic glass shards can range between 25 to 50% (Nicolli et al.,

2012). In the Espinal region, the volcanic material is reported to contain S (sulphur) bearing minerals (Jayawickreme et al., 2011), but no studies were found supporting this hypothesis for the Dry Chaco. However, it is likely that the source of sulphates found in this study is related to the weathering of these S-bearing minerals.

Besides the chemical weathering of parent material and volcanic glass material, it is expected that also secondary weathering contributes to the observed chemical concentrations of water-soluble salts. For example, in the neighbourhood of the lower cluster, evaporites are formed where groundwater reaches the surface (e.g., Saladillos de Huyamampa). These evaporates mainly include halite and gypsum (Raychowdhury et al., 2014), which on their turn can also get dissolved during rainfall events.

4.4.4 Variation in soil salinity in forests

On top of the large-scale spatial variations in soil salinity related to the geomorphological context, our results showed a remarkable variation in salt concentrations in forests. Similar strong spatial variations in salinity were observed by Jayawickreme et al. (2011); Giménez et al. (2016); Amdan et al. (2013) in soils, and in groundwater-related studies. We propose three reasons for these spatial variations:

First, microtopographical features (e.g., paleochannels, small streams, and local topographic depressions) may lead to local variations in near-surface soil salinity and groundwater composition. As reported by Giménez et al. (2016), variations at the plot-level scale such as micro-sites of concentrated recharge can lead to increased salt leaching. These small areas are difficult to distinguish in the field at the time of sampling. The establishment of artificial channels and drainage networks can also lead to enhanced salt removal through surface or subsurface water transport, (Jobbágy et al., 2020) or to salt accumulation in artificial water basins.

Second, we argue that the size of the remaining forested areas also plays a critical role in the retention of salts. On the one hand, and as noted by Giménez et al. (2016), it is likely that the hydrological control of few and sparse forest remnants (such as those in the upper cluster), is limited, leading to a certain amount of salt leaching under forest sites. However, no data are available on this, and further research is needed to determine whether exhaustive consumption of rainwater is reduced when forest patches are degraded and fragmented. On the other hand, it is likely that edge effects occur when sampling forest patches. Due to dense understorey vegetation, deep penetration into the forest stands is not always possible. Therefore, forest samples might suffer from edge effects,

whereby soils in the outer edges of the forests are different from the core areas. Further research is needed to verify the existence of edge effects.

Third, local to regional variations in parent material might cause variations in soil chemical weathering and soil elemental composition (Jayawickreme et al., 2011). In particular, the presence of evaporites (e.g., gypsum, halite) might strongly affect the chemical composition of soils and groundwater.

In future research, attention needs to be paid to small-scale variations in soil salinity. This can be done by integrating point data with continuous data collected in transects by e.g., electrical resistivity imaging (ERI). ERI can be used to map soil conductivity patterns, which are strongly influenced by the distribution of salts and water in the subsurface. It is also useful for accessing deeper parts of the subsurface that are beyond the reach of augers. The utility of the method is illustrated by Jayawickreme et al. (2011); Giménez et al. (2016).

4.5 Conclusions

The objective of this chapter was to gain insights into differences in soil salinity between forest and agriculture sites in the central Argentinean Dry Chaco. Our study hypothesized that the geomorphological context conditions the sensitivity for dryland salinity after deforestation, and that the impact of deforestation on soil salinity is spatially dependent. To test this hypothesis, soil samples were collected in the area, using a control and treatment sampling strategy. The samples were analysed for the concentration of major water-soluble ions and EC of extracts of the saturated paste. Our results show that salts are leached in agriculture sites with deep groundwater tables. In topographically low areas, salt accumulation is observed in the upper soil horizons of agricultural sites, whereby their concentrations can exceed those of forests. However, these results should be interpreted with caution due to the small sample size used in this study.

In addition to this spatial effect, we also analysed the temporal evolution of salinity after deforestation. Agricultural plots that were logged 15 to 30 years ago had significantly lower salt concentrations than more recently logged plots. While chloride concentrations decrease shortly after deforestation, other ions show a much more gradual decrease over time. We also gained insight into the chemical composition of total ion concentrations. Chlorides correspond to 20 to 25% of the total salt content, suggesting that previous studies have greatly underestimated the total stock of salts in the vadose zone. Calcium, sodium, sulphates and nitrates are the other major ions present. Lastly, it must be mentioned that our results are representative for the central Argentinian Dry Chaco but more research is needed for other parts of the region.

Chapter 5

Discussion and conclusions

This doctoral dissertation aimed to gain new insights into changes in hydrology and soil salinity after deforestation in the Dry Chaco. The scientific contributions of this work are twofold. First, the comparison of three land surface models (LSMs) implemented in the NASA LIS system showed that they respond differently to vegetation changes, illustrating the need for further model development and validation with independent datasets to obtain the most realistic model outcomes. However, we found that LSMs simulate temporal variations in soil hydrology realistically and that their use for studying temporal dynamics of the different water budget components is justified. Second, the regional assessment of soil salinity over the Dry Chaco provided unprecedented insights into the spatial pattern of primary and secondary salinity. By integrating soil salinity data with LSM output, satellite derived vegetation indices, and environmental data, we revealed how the sensitivity for soil salinization depends on climate, geomorphology, and land cover. Although our analysis of salinity focused on the central part of the Argentinean Dry Chaco, our approach and findings can be useful for other parts of the region or areas prone to soil salinization.

In the following sections, we will take a closer look at what the future may hold for the Dry Chaco in terms of soil salinity. A critical issue in the analysis of dryland salinization remains the time lag between land use change and the actual or perceived onset of environmental degradation (Amdan et al., 2013). Shifts in soil water balance and soil salinization are the consequences of land use changes that occurred years to decades earlier. Because of this time lag and the uncertainty on future deforestation in the Chaco, it is difficult to predict how fast dryland salinization will evolve in the future. Hence, it is currently unclear

whether dryland salinization in the region will be of a similar magnitude as in Western Australia, where more than 2 million hectares of productive lands suffer from severe salinization (Lambers, 2003). Below, we discuss current and future trends in land cover change, and the risk for severe salinization in the Dry Chaco. We further provide some key priorities for further research. Finally, we conclude by revisiting the main research questions.

5.1 Trends in deforestation and land use planning

In the last decades, large-scale soy and beef production by agribusinesses was the main cause of deforestation in the Dry Chaco (Gasparri and Grau, 2009). Technological advances made it easier to grow crops in the Dry Chaco, which had previously been difficult to cultivate because of hydroclimatological limitations and accessibility (Grau et al., 2005; Volante et al., 2016; Marchesini et al., 2017). At the end of 2012, the deforested area in the Dry Chaco totaled 15.8 million ha, representing 20.7% of the natural area of the entire ecoregion (Vallejos et al., 2015). The areas that were converted from natural vegetation to agricultural land in Argentina, Paraguay and Bolivia represent 68%, 27% and 4% of the total converted area, respectively. Annual deforestation rates in the Chaco were the highest between 2000-2012 but, as shown in Figure 5.1, the total deforested area tends to stabilize in Argentina and Paraguay from 2010 onwards (Vallejos et al., 2015).

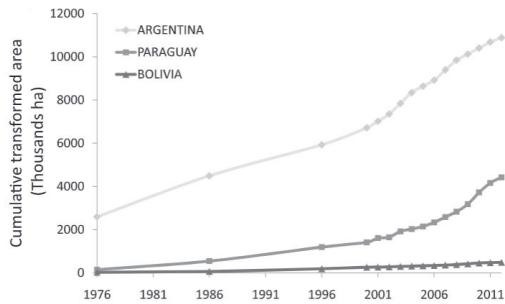


Figure 5.1: Cumulative transformed area in hectares (ha) as a function of time from 1976 to 2012 at country level in the South American Dry Chaco ecoregion. Source of Figure: Vallejos et al. (2015).

In Argentina, the annual rate of deforestation still increased between 2006 and 2012 in the provinces of Formosa, Salta, and San Luis, but a downward trend has been observed since 2006 in the provinces of Catamarca, Chaco, Córdoba, Santa Fe and Tucuman (Vallejos et al., 2015). This can be related to the fact that

most of the remaining forest has been cleared or is located in areas with severe topographic and/or climatic constraints for agriculture (Vallejos et al., 2015). The implementation of the National Forest Law (*Ley de Protección ambiental de Bosques nativos*), enacted in November 2007, is also cited as an important factor in stabilizing deforestation rates in Argentina (Nolte et al., 2017; Vallejos et al., 2021). This law mandated provincial governments to regulate the expansion of large-scale agriculture and establish practices to protect native forests.

The effective implementation of the law encountered significant difficulties, and e.g., Vallejos et al. (2021) showed that local governments were not always able to enforce the law in protected areas, as some of them experienced an increase in illegal logging after the law passed. The exact impact of the law and whether it significantly reduced deforestation is still highly debated (Nolte et al., 2017; Volante and Seghezzo, 2018). Nolte et al. (2017) concluded that land use zoning at the provincial level significantly reduced deforestation in three provinces that accounted for more than three quarters of deforestation before the law passed: Salta, Santiago del Estero and Chaco.

However, according to Volante and Seghezzo (2018), it is too simplistic to attribute the declining deforestation rates to a single driver such as law enforcement, as a variety of factors (such as international commodity prices, political aspects, spatial constraints, judicial interventions, export regulations, foreign exchange rates, and the level of taxation on agricultural products, among others) also play an important role in land use decisions. Instead, this team of scientists suggested that falling international prices and the steady decline of the real effective exchange rate in Argentina since 2002 have affected the growth of the agricultural sector.

Based on the sensitivity of the Dry Chaco for primary and secondary soil salinity, it is a sustainable land use practice to protect areas that are prone to salinization from logging. In the most sensitive areas with shallow groundwater tables and high water deficits, small rises in the groundwater level can lead to severe soil salinization as shown by case studies in Western Australia by e.g., McFarlane and George (1992) and Coram (1998). Therefore, protecting forests in areas with elevated risk for salinization can reduce further environmental degradation and associated societal costs. For example, over Western Australia, it is estimated that the opportunity cost of lost agricultural production alone is \$ 519 million per year. The costs to maintain salt-damaged rail and roads is about \$175 million (Auditor General, 2018). Between 2002 and 2009 in Western Australia, the state and federal governments invested \$724 million in ecosystem restoration to manage salinity and agricultural land degradation (State NRM Office, 2010). In areas with severe salt-induced land degradation, farmers tend to abandon their fields and possibly have to clear new arable land, adding extra pressure to natural ecosystems and biodiversity (Negacz and Vellinga, 2021).

5.2 Risk for future dryland salinization in the central Argentinean Dry Chaco

Our regional analysis (Chapter 3) showed that the sensitivity to soil salinization is not spatially uniform. In the western Chaco, the risk of severe soil salinization in the near future is likely to be low, as the presence of a deep water table (at 10 to 40 m depth) does not pose a direct threat for remobilization of salts from the ground water to the soil mantle. Based on the assessment of Amdan et al. (2013), it can take between 30 to 120 years till the potential rise in phreatic level would affect the soils in this part of the Chaco. Besides, it is still unclear whether the increased deep percolation will lead to a rise in groundwater levels in this part as the excess of infiltration water can also be discharged via regional groundwater flow. Therefore, it will be important to monitor groundwater levels closely as to detect when critical groundwater levels are reached. Topographic depressions might need special attention, as first signs of surface soil salinization were already observed in the topographic depression east of the Rio Hondo Reservoir where shallow groundwater conditions occur (Puchulu and Fernández, 2014).

In the central part, we consider it necessary to maintain and protect natural forests in the wide surroundings of the topographic depressions where shallow groundwater tables occur. This includes the regions surrounding the Salinas de Ambargasta and Grandes, the Saladillos de Huyamampa, and the alluvial plain of the Rio Dulce. This will help maintain saline groundwater at a relatively low level and reduce the risk of capillary rise of saline groundwater and consequent salinization. This practice is already considered an important, effective, and now widely accepted land use planning tool for the Chaco in Paraguay (Glatzle et al., 2020). However, this practice is not yet implemented or enforced in the most vulnerable parts of the Argentinean Dry Chaco, as we could observe from Google Earth Imagery taken near the Saladillos de Huyamapa and the Rio Dulce alluvial plain.

In the eastern part of the area, high temporal variations in soil salinity are expected due to the seasonally fluctuating groundwater table. The extremely flat topography and poorly incised river network further increase the risk of soil salinization by impeding regional groundwater flow. This favours pounding of water during flood events, followed by precipitation of dissolved salts after evaporation of the saline water. Spatiotemporal assessments of groundwater and soil salinity are crucial in this part of the Chaco, as saline topsoils are visible on Google Earth satellite imagery, as shown in Chapter 3. Evidence of the changing hydrological conditions was given by Giménez et al. (2020b) who reported a massive waterlogging event near the city of Bandera in Santiago Del

Estero in 2015 that was caused by recent rise of the groundwater table after large-scale deforestation.

In a more distant future, also climate change can have an impact on soil salinization. According to Verga and Lauenstein (2021), the Chaco is currently in a state of great vulnerability to climate change. In the last years, the occurrence of extreme drought events and heavy rains is observed across the region (Barros et al., 2014). The risks for such extreme events is expected to increase in the future based on moderate future climate scenarios, such as the A2 scenario, according to the report of the Intergovernmental Panel on Climate Change (Ortega et al., 2021). With respect to the period 1960–2010, the Chaco is expected to be prone to warming with temperature increases to 1 °C in the near future (year 2050) and up to 2.5–3.5 °C in the distant future (year 2100). No major changes in the average annual precipitation are expected, but changes in the annual distribution of rainfall with rainfall increase in the wet season and decrease in the dry season are predicted (Ortega et al., 2021).

The change in climate conditions can affect the Chaco's soil water balance in two ways: (i) the rise of temperature may increase the potential evapotranspiration, and at the same time decreases runoff, infiltration, groundwater recharge and water storage, especially if accompanied by low precipitation (Viglizzo and Ricard, 2021) ; (ii) the decrease in precipitation during the dry season is expected to increase the sensitivity of crops and pastures to severe droughts, whereas extreme rainfall in the wet season can result in damaging flood events. How these effects impact soil salinity will likely depend on the local conditions. In the western part, where the groundwater table is deep, increased transpiration and decrease in runoff and infiltration can reduce the amount of salt leaching toward deeper soil layers, but groundwater recharge and salt leaching can be enhanced during extreme wet events. In the drier central part, the rise in temperature can lead to an increased rate of upward water fluxes, and accompanied upward salt transport. In the eastern part, the increase in rainfall seasonality is expected to result in more pronounced seasonally fluctuating groundwater tables. At the beginning of the dry season this may increase the risk for soil salinization as shallower groundwater tables (due to increased precipitation in the wet season) may enhance capillary rise and direct evaporation of saline groundwater.

In short, the extent of future dryland salinization in the Dry Chaco will mainly depend on (i) whether areas prone to natural soil salinity are further protected, (ii) the magnitude and rate of the rise in groundwater levels after deforestation. Our findings suggest that this will be dependent on the local climate and geomorphology that conditions the depth of the groundwater table. This dissertation can provide a basis for further research on the spatial variations of natural and secondary salinity in dryland ecosystems and the development of adequate land use planning and groundwater/salinity monitoring networks.

Although this study focused on the central Argentinean Dry Chaco, the methods can be applied to nearby places where regional salinity studies are lacking. The identification of the different soil salinity processes may also help to better assess the risk for soil salinization in the view of a changing climate.

5.3 Bridging the spatial gap: monitoring hydrology and soil salinity

This dissertation illustrates the power of combining in situ data, satellite observations, and LSMs to gain insight into regional hydrology and soil salinity. This section addresses prospects for further research on hydrology and soil salinity in the Dry Chaco. Good estimates on the different hydrological components and surface and subsurface salinity are needed to detect early signs of severe salinization as summarized in Figure 5.2.

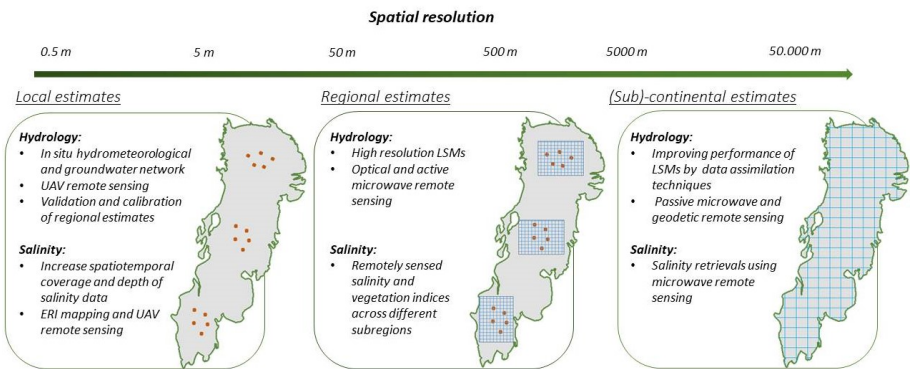


Figure 5.2: Overview of multiple approaches at different spatial resolutions to monitor the water cycle and soil salinity.

5.3.1 Local point estimates

At the local scale, field measurements of precipitation, soil moisture and evapotranspiration are invaluable to monitor the hydrology. Whereas INTA, the national institute of agricultural technology, has an extended network of precipitation stations (which are used in Chapter 2), timeseries of observed soil moisture and evapotranspiration data are barely present for the region. Besides providing crucial hydrometeorological information, conventional measurement

networks consisting of point measurements are crucial for the calibration and validation of e.g., climate and land surface models and satellite-based retrievals on the regional and sub-continental scale.

The link between hydrology and soil salinity is mainly driven by the depth and salinity of the groundwater. Hence, a measuring network with physical measurements of the groundwater level and its quality is of crucial importance to better understand the interactions among topography, land cover, precipitation, groundwater depth, salinity and surface salinization as shown recently by Glatzle et al. (2020). There is a need to invest in a dense network of monitoring wells that is adapted to the spatial context of the Dry Chaco, and that provides continuous measurements of groundwater levels and water quality for prolonged periods of time.

The quantification of the total salt stocks and the types of water soluble salts in dryland soils requires further research. This study provided first information on the chemical composition of water soluble salts in the upper soil horizons. Due to its extent and scope, the study only covered part of the central Argentinean Dry Chaco and monitored soil salinity from bulk soil samples. As stated in Jobbágy et al. (2020), soil profiles under natural vegetation display a strong increase in salt content below the first or second meter. Besides, soil texture can play an important role in determining the salinization hazard as Jobbágy et al. (2020) did not observe soil chloride accumulation in much drier but extremely sandy environments (sand dunes). Hence, research on dryland salinity in the Dry Chaco would benefit from an extensive soil survey with high sampling density whereby the full range of environmental gradients (climate, topography, soils) is covered. In addition, a permanent network of soil EC measurements can help to provide useful information on the temporal variability of soil salinity.

The integration of point data into spatially continuous fields from e.g., transects derived from electrical resistivity imaging (ERI) can provide complementary information on soil depth, texture and composition. ERI can be used to map soil conductivity patterns, which are strongly influenced by water and salts in the subsurface. Geophysical techniques such as ERI can be useful for accessing deeper parts of the subsurface that are beyond the reach of augers (Jayawickreme et al., 2011; Giménez et al., 2016). New technological advances based on very high resolution imagery collected by Unmanned Aerial Vehicles (UAV) can offer alternatives to monitor surface soil salinity and soil moisture (Wang et al., 2018; Hu et al., 2019; Ivushkin et al., 2019).

5.3.2 Regional fine-resolution estimates

Information from monitoring networks and punctual field data can be inter- and extrapolated to a larger spatial extent, e.g., over several hundreds of km², using remote sensing and LSMs.

As shown in Chapter 2, the relatively coarse resolution (0.125°) of the LSM simulations partially suppressed the deforestation signal, which limited an accurate representation of the ongoing deforestation processes. It is currently being verified whether model simulations at a spatial resolution of 0.01° are able to correctly represent hydrological changes following deforestation. To this end, satellite derived vegetation indices and albedo at high spatial resolution were implemented to replace the default climatological vegetation and albedo input. The first results indicated that the hydrological impact of deforestation is spatially dependent, whereby deep percolation under croplands significantly increased in the wetter areas, but remained negligible in the drier central Dry Chaco.

Besides LSMs, the water balance at the regional scale can further be assessed by remote sensing data. In the last decades, advances in remote sensing technology has helped to monitor and understand different aspects of the terrestrial water cycle. Monitoring of spatial and temporal variations of soil moisture and evapotranspiration of the land surface has become possible due to new satellite missions and instruments. For example, it is now possible to retrieve surface soil moisture at 1 km resolution based on Sentinel-1 backscatter values (Bauer-Marschallinger et al., 2018). Also different evapotranspiration products are available at high spatial resolution (e.g., the MODIS-derived MOD16A2 evapotranspiration product (Mu et al., 2011)). These satellite retrievals can further be integrated in LSMs via data assimilation or be used as evaluation products.

High-resolution satellite remote sensing data are very promising for measuring and monitoring soil salinity over time. At present, many satellite remote sensing data exist with high to moderate spatial and temporal resolutions. Previous studies have shown the possibilities of satellite derived salinity and vegetation indices to retrieve soil salinity. They included a wide set of sensors onboard of e.g., IKONOS (Allbed et al., 2014), Quickbird (Eldeiry and Garcia, 2008; Sidike et al., 2014), Landsat (Peng et al., 2019) and a wide range of techniques to retrieve soil salinity from spectral data (e.g., neural networks (Habibi et al., 2021), random forests (Wang et al., 2021) or support vector regression models (Taghizadeh-Mehrjardi et al., 2021)). These satellite-based salinity retrievals need to be evaluated by in situ salinity data from the plot-level scale.

5.3.3 (Sub)-continental coarse-resolution estimates

Currently, one of the most effective ways to assess the water balance over the entire Dry Chaco is through microwave remote sensing products and LSMs. Chapter 2 showed that LSMs are capable to realistically simulate temporal dynamics in different water budget components over the Dry Chaco. However, they can benefit from further developments to better represent soil-water-vegetation processes, because the three tested LSMs in this study show a questionable range in their partitioning of the water budget components and in their response to parameter changes. Feeding the models with similar, e.g., satellite-based, albedo input could further lead to a homogenization in model output, as this is a key parameter in the calculation of the land surface energy budget. However, as shown in Chapter 2, ‘better’ input does not necessarily lead to ‘better’ output. In future research, the use of more recent versions of the three selected LSMs might provide better simulations over the Dry Chaco as following processes are represented in greater detail:

- The depth of the soil profile as it is encoded in the three selected LSMs is a major limitation to correctly represent the hydrological functioning of the dry forests. As reported by Nosetto et al. (2008); Jobbagy et al. (2008) and Marchesini et al. (2017), the roots of native trees can attain depths up to 6 m; enhancing evapotranspiration during dry periods and limiting percolation of water below the vadose zone. In the applied LSMs, the soil profile depths range from 3.4 m (CLM), 2 m (NOAH) to 1 m (CLSM). By design, the rooting depth cannot exceed the prescribed soil thickness values. This representation of the rooting depth may lead to underestimated rates of total transpiration and associated water extraction from the soil (and hence overestimation of deep percolation). In further studies, this can be remediated by using newer versions of the LSMs such as CLM 5 (Lawrence et al., 2019). To account for spatial variation in soil thickness, CLM 5 allows the application of different soil thicknesses (ranging from 0.4 up to 8.5 m depth) for each pixel (Brunke et al., 2016; Swenson and Lawrence, 2015).
- Another important limitation in the used LSMs, is the absence of a groundwater module. More recent model versions, such as NOAH-MP (Niu et al., 2011) and CLM 5 (Lawrence et al., 2019), include 1D groundwater modules (i.e., groundwater can move vertically, but not flow to neighbouring grid cells). In further research, it could be interesting to see if these 1D modules correctly represent the rise in the groundwater table after deforestation. However, it must be mentioned that 1-dimensional groundwater modules do not account for lateral groundwater movement, limiting the correct representation of hydrological conditions and fluxes in

areas where groundwater converge and accumulate. As shown in Chapter 3, this can have significant implications for soil salinity.

- The implementation of a dynamic vegetation module, available in NOAH-MP and CLM 5, can also help to better represent the coupling between soil moisture and vegetation in two ways rather than just one way. In water-scarce ecosystems such as the Dry Chaco, this could improve the interplay between vegetation and soil moisture, whereby high soil moisture values can stimulate vegetation growth.

An important remark has to be made here. Clark et al. (2015) reported that there is an important trade-off between model complexity and model fidelity. They defined model complexity as the extent to which physical processes are represented explicitly as well as the discretization and representation of the physical landscape. Model fidelity refers to the extent to which models faithfully represent observed processes. They make the remark that including additional processes may not necessarily lead to improvements in model performance if there is not enough information on the spatial variability of model parameters. Especially in data-scarce regions such as the Dry Chaco, the correct calibration of LSMs remains a difficult task as shown in Chapter 2.

The spatial and temporal performance of LSMs could further benefit from the assimilation of multi-source remote-sensing data for state (e.g., soil moisture and temperature) to correct for unmodeled processes, such as land cover changes. However, the impact of such updates will depend on the used LSM, and on the optimization of data assimilation systems in the presence of non-stationary processes that are associated with land cover changes (such as deforestation). The results of Chapter 2 also suggest that vegetation data assimilation can only have the desired impact if the sensitivity of simulated hydrological fluxes to vegetation changes is realistic and this may need further research, especially at the global scale.

Besides LSMs, soil and vegetation water contents at the sub-continental scale can be measured through microwave remote sensing data. Monitoring of spatial and temporal variations of the surface soil moisture at a (sub)-continental scale has become possible due to several satellite missions and instruments including SMOS (Kerr et al., 2010), SMAP (Entekhabi et al., 2010), and ASCAT (Wagner et al., 2013). These instruments provide soil moisture estimates at coarse spatial resolution but have a very high revisit time (up to 1 day). The Gravity Recovery and Climate Experiment (GRACE) can provide spatiotemporal data on Terrestrial water storage (TWS), based on the detections of variations in Earth's gravity field. GRACE data has been successfully used as indicator of groundwater depletion, drought and flood conditions at regional scale and across the globe (Syed et al., 2008; Rodell et al., 2009; Khaki and Awange, 2019).

GRACE is also a valuable tool to study water dynamics at large scales with a good temporal monthly resolution (Landerer and Swenson, 2012; Felfelani et al., 2017).

For salinity, coarse-scale satellite-based monitoring has not been established yet. Vincent et al. (2021) tested if microwave remote sensing data could be used to map soil salinity over the Dry Chaco, because salinity strongly influences the imaginary part of the dielectric constant at L-band (Hallikainen et al., 1985). Since L-band satellite observations give an integrated large-scale view of soil moisture, vegetation, salinity and other land surface properties, the potential of retrieving these properties from long time series of SMOS brightness temperature (Tb) data was explored. The retrieval of surface salinity was not successful due to the low sensitivity of Tb to salinity, and the limited accuracy of the background information, and because of the relatively low surface salinity in the Chaco. By better defining background information (i.e., mainly about soil texture, ponding water and heterogeneity within the footprint), it might be possible to gain information about salinity in areas with higher salinity levels in the future.

5.4 Conclusions

The main objective of this dissertation was to gain new insights into changes in hydrology and soil salinity after deforestation in the Dry Chaco. For this purpose, we combined land surface models (LSMs), remote sensing data, and in situ soil salinity data. In the following section, we provide an answer to the main research questions formulated in the introduction of this dissertation.

RQ 1: What is the impact of land cover changes on water budget components simulated by different LSMs?

Chapter 2 used LSMs as a tool to estimate the hydrology over the Dry Chaco and showed that vegetation and land cover parameters only have a secondary impact on the simulated water budget components, whereas the various LSM structures primarily determined the water distribution. In addition, it was found that the three selected LSMs reacted differently to the updated vegetation and land cover treatment. A change in land cover resulted in a shift of the model climatology and a (non-stationary) redistribution of the water budget, which is different for each LSM. However, all LSMs indicated an increase in soil moisture for deforested pixels. When compared to independent data, we concluded that LSMs simulate temporal variations realistically but that no specific LSM structure, soil or vegetation input performed significantly better than another.

RQ.2: To what extent is the Dry Chaco affected by soil salinity and which environmental variables are associated with the regional salinity patterns?

The results of Chapter 3 showed that surface salinity (i.e., between 0 and 5 cm depth) in the Dry Chaco is generally low, but shows large variability, whereas subsurface salinity (i.e., 100 cm depth) is systematically higher with clear regional patterns. A correlation analysis between the subsurface EC measurements and several environmental variables indicated that subsurface salinity is closely related to the annual water balance (represented as $P - Pet$), the annual standard deviation of the Greenness Vegetation Fraction (representative of vegetation phenology), and topography. The observed variability in salt concentration can be explained by the concepts of arrested drainage and landscape stagnation. In flat areas with high water deficit, corresponding with the central part of the Chaco, salts are retained in the soil profile and prevented from leaching. Severe natural soil salinization occurs when groundwater accumulates near the surface and high evapotranspiration leads to the formation of evaporites. This is the case in topographic depressions due to tectonic activity or alluvial plains. Low natural salinity is observed in regions with higher slope gradients (western Chaco), as salts are effectively removed from the landscape by regional groundwater transport. Low salinity is also observed in areas with higher precipitation due to salt leaching (eastern Chaco). However, our data also showed how these wetter parts are susceptible for secondary salinization following deforestation due to their shallow groundwater tables.

RQ.3: What is the chemical composition of salts in the vadose zone, and which spatial variations exist in the chemical composition of salts in the Dry Chaco?

The results of Chapter 4 indicated that chlorides correspond to 25% of the total salt content, suggesting that previous studies have greatly underestimated the total stock of salts in the vadose zone. Calcium, sodium, and sulphates are the other major ions present. Given that geomorphology is one of the main variables that controls soil salinity, we further explored how soil salinity is impacted by deforestation across a topographic gradient. We found that salts are leached in agriculture sites with deep groundwater tables. In topographically low areas, salt accumulation is observed in the upper soil horizons of agricultural sites, whereby their concentrations can exceed those of forests. In addition to this spatial effect, we also analysed the temporal evolution of salinity after deforestation. Agricultural plots that were logged 15 to 30 years ago had significantly lower salt concentrations than more recently logged plots. While chloride concentrations decreased shortly after deforestation, other ions showed a much more gradual decrease over time.

Appendix A

Supporting Information

A.1 Chapter 2

Table A.1: Conversion from the ESA-CCI to the UMD land cover classification

ESA CCI	UMD
No data	No data
Cropland, rainfed	Cropland
Cropland, herbaceous cover	Cropland
Cropland, tree or shrub cover	Cropland
Cropland, irrigated or post-flooding	Cropland
Mosaic cropland (>50%) natural vegetation (tree, shrub, herbaceous cover) (<50%)	Cropland
Mosaic natural vegetation (tree, shrub, herbaceous cover) (>50%), cropland (<50%)	Open shrubland
Tree cover, broadleaved, evergreen, closed to open (>15%)	Evergreen broadleaf forest
Tree cover, broadleaved, deciduous, closed to open (>15%)	Deciduous broadleaf forest
Tree cover, broadleaved, deciduous, closed (>40%)	Deciduous broadleaf forest
Tree cover, broadleaved, deciduous, open (15-40%)	Deciduous broadleaf forest
Tree cover, needleleaved, evergreen, closed to open (>15%)	Evergreen needleleaf forest
Tree cover, needleleaved, evergreen, closed (>40%)	Evergreen needleleaf forest
Tree cover, needleleaved, evergreen, open (15-40%)	Evergreen needleleaf forest
Tree cover, needleleaved, deciduous, closed to open (>15%)	Deciduous needleleaf forest
Tree cover, needleleaved, deciduous, closed (>40%)	Deciduous needleleaf forest
Tree cover, needleleaved, deciduous, open (15-40%)	Deciduous needleleaf forest
Tree cover, mixed leaf type (broadleaved and needleleaved)	Mixed cover
Mosaic tree and shrub (>50%), herbaceous cover (<50%)	Woodland
Mosaic herbaceous cover (>50%), tree and shrub (<50%)	Woodland
Shrubland	Closed shrubland
Evergreen shrubland	Closed shrubland
Deciduous shrubland	Closed shrubland
Grassland	Grassland
Lichens and mosses	Grassland
Sparse vegetation (tree, shrub, herbaceous cover) (<15%)	Open shrubland
Sparse shrub (<15%)	Open shrubland
Sparse herbaceous cover (<15%)	Open shrubland
Tree cover, flooded, fresh or brakish water	Open shrubland
Tree cover, flooded, saline water	Open shrubland
Shrub or herbaceous cover, flooded, fresh/saline/brakish water	Open shrubland
Urban areas	Urban
Bare areas	Bare ground
Consolidated bare areas	Bare ground
Unconsolidated bare areas	Bare ground
Water bodies	Water

A.2 Chapter 3

A.2.1 Identification of saline topsoils on Google Earth imagery

As mentioned in section 3.2.2, the identification of salt-crusts on agriculture plots was hindered to their small irregular shape and the wet period prior to the field campaign. To gain more insights into their spatial distribution, Google Earth imagery was consulted to localize salt crusts across the study area. Based on the differences in surface reflectance between salt and non-salt affected areas, soil crusts at the soil’s surface were detected. Note that their identification can be complicated and may yield unreliable results when soil moisture is high or the crust salt is mixed with other soil constituents. Therefore, the ‘historical imagery’ function in Google Earth was used, allowing to monitor soil conditions over multiple years. We mainly focused on images of the period 2013-2019. The criteria to separate salt and non-salt affected areas on high resolution satellite-imagery is shown in Figure A.1.

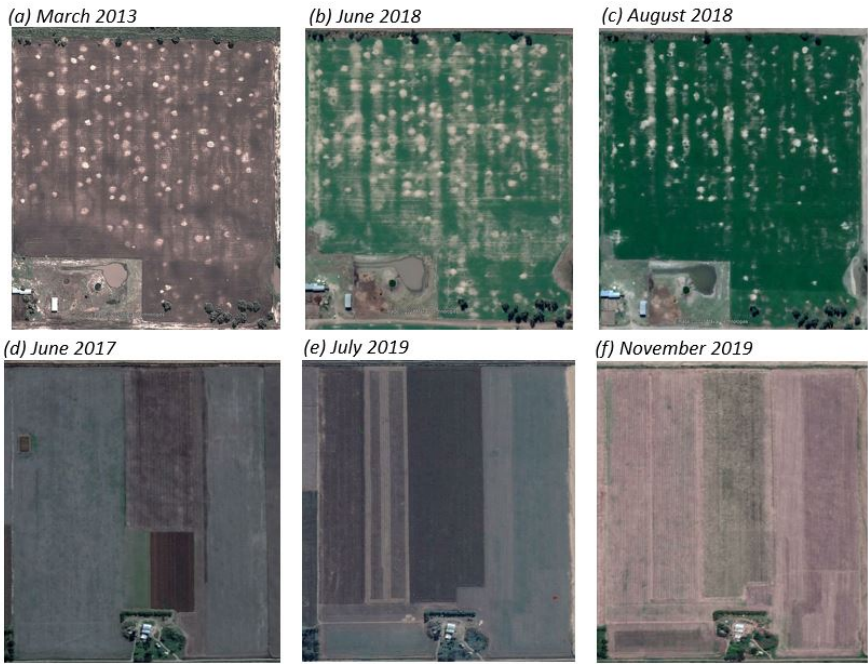


Figure A.1: Illustration of differences in surface reflectance for salt (a-c) and non-salt affected cropland (d-f) as observed on Google Earth Imagery over multiple years.

Figures a-c show an agriculture plot that was considered as saline based on the appearance of white irregular patches across the field. The color of the spots evolves over time (ranging from white to brown) but their location is relatively fixed. For comparison, Figures d-f show an agriculture plot without any signs of soil salinity. It is important to mention that most of the spots identified on Google Earth were not validated in the field. Consequently, the used approach only identified areas that are 'most likely' saline topsoils.

A.2.2 Different salinity processes as observed on satellite imagery

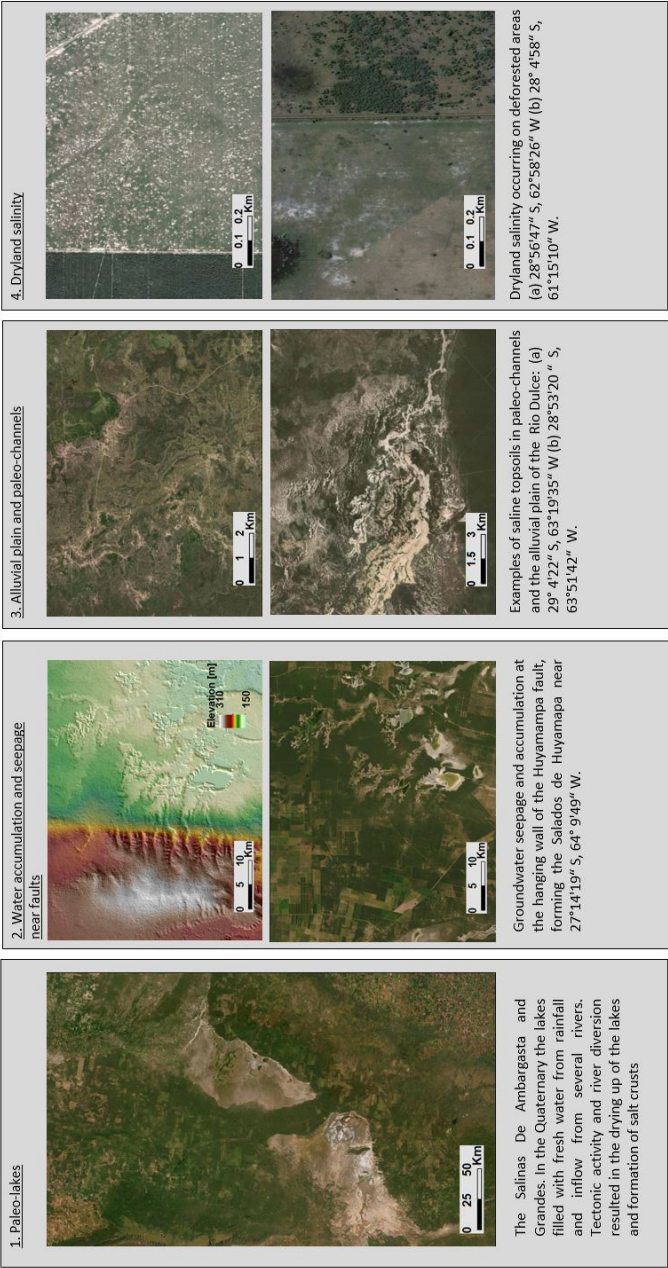


Figure A.2: Overview of different processes leading to surface soil salinity (part 1).

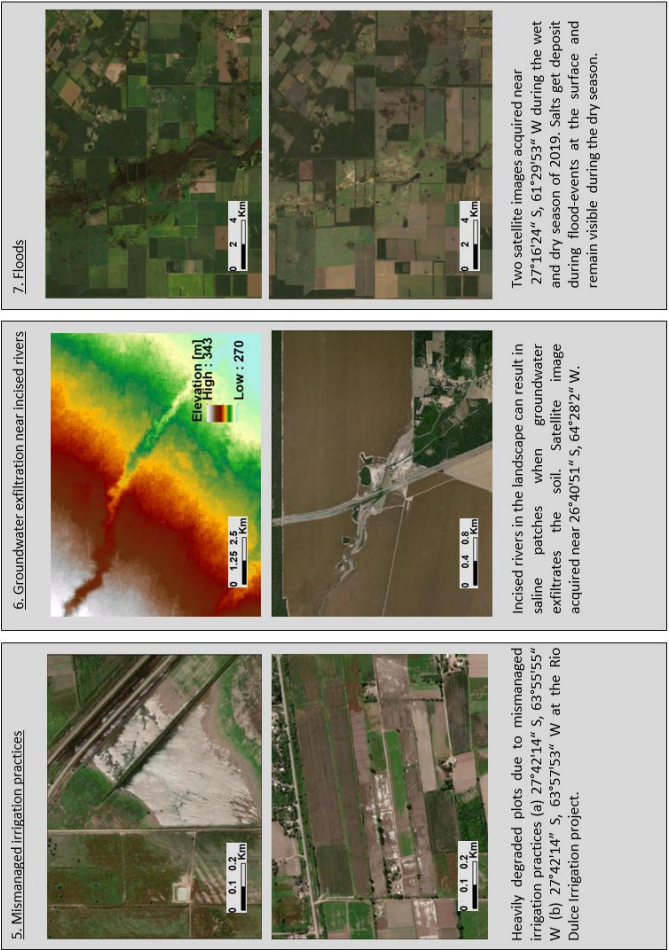


Figure A.2: Overview of different processes leading to surface soil salinity (part 2).

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FACULTY OF BIOSCIENCE ENGINEERING
DEPARTMENT OF EARTH AND ENVIRONMENTAL SCIENCES
DIVISION OF SOIL AND WATER MANAGEMENT
Celestijnenlaan 200E
B-3001 Leuven

